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Review

New solutions for automated image recognition and identification: Challenges to radiologic technology and forensic pathology

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Abstract

This paper outlines the history of biometrics for personal identification, the current status of the initial biological fingerprint techniques for digital chest radiography, and patient verification during medical imaging, such as computed tomography and magnetic resonance imaging. Automated image recognition and identification developed for clinical images without metadata could also be applied to the identification of victims in mass disasters or other unidentified individuals. The development of methods that are adaptive to a wide range of recent imaging modalities in the fields of radiologic technology, patient safety, forensic pathology, and forensic odontology is still in its early stages. However, its importance in practice will continue to increase in the future.

(110 words)

Key words: image recognition, biometrics, biological fingerprints, biometric verification, positive identification, forensic identification

1. History of personal identification using biometrics

Personal identification using fingerprinting, DNA analysis, and dental records has been used for multiple purposes, such as forensic identification and identity verification. Several researchers, including medical examiners/coroners, forensic pathologists, and forensic anthologists, are continually working to establish standards and systematic analysis methods for application to unknown cases and human remains [1]. However, daily activities often require rapid, reliable, and convenient personal identification. Thus, personal identification is becoming the fundamental of today's society, and ongoing research contributes more secure services to prevent fraud and crime while improving accessibility and convenience.

Research regarding personal identification using biometrics originated in the 1600s, when human fingerprint patterns were used. In 1684, Grew conducted extensive research on the ridge patterns of fingerprints to distinguish different human beings [2]. In 1685, Bidloo described the details of the fingerprint in the book *Anatomy of the Human Body* [3]. Around that time, the fact that fingerprint patterns are unique to individuals began to be recognized. Mayer wrote a book in 1788, entitled *Anatomical Copper-plates with Appropriate Explanations*, asserting that the pattern of fingerprints is unique to each human [4]. He wrote, "Although the arrangement of skin ridges is never duplicated in two persons, nevertheless the similarities are closer among some individuals." The differences have been well identified; despite all persons having similar patterns, the specific arrangements show slight differences [5]. Thus, fingerprints were applied as the first commercially available biometric identification method in 1858 by Herschel, who prompted local Indian businessmen to sign binding contracts with a print of their own palm. The fingerprint was used as a system of identification equivalent to official signatures in the magistrate court [6]. In the late 1800s, although not yet fingerprint authorization, Bertillon reported that the combination of 11 anthropometric measurements was unique to the individual [7]. That was the first attempt to use specific anatomical characteristics to identify reoffending criminals. As for the criminal history records in the Justice system, Galton developed a fingerprint-classification system and published a book, *Finger Prints*, in 1892 [8]. Edward Richard Henry published *Classification and Uses of Finger Prints* in 1900 [9]. In 1903, fingerprinting was used to identify prisoners in the New York State Prison. Subsequently, an increasing number of local police identification bureaus established fingerprint systems [10, 11]. In 1986, the National Bureau of Standards (NBS) and the American National Standards Institute (ANSI) published a standard for the exchange of fingerprint minutiae (ANSI/ NBS-I CST 1-1986). However, personal identification using biometrics was implemented manually, at that time, without the numerical computation of biometric characteristics.

Image recognition for personal identification is rapidly progressing with image digitization and evolution in computer vision. There is no doubt that computers can identify images in a shorter time for a greater number of samples with higher accuracy than humans can. **Figure 1** shows several practical features that are commonly implemented for biometric information. It is important to note that several features, including those for biometric technology, are still in varying stages of development and assessment.

2. Environment and patient safety in medical imaging

In 1982, Dwyer *et al*. proposed the concept of a picture archiving and communication system (PACS) to reduce the cost of medical image management [12–14]. In medical safety, the following changes have been observed over the past 20 years. The idea has rapidly spread worldwide to achieve efficient medical care services with the aid of the popularization of digital imaging and progress in information and communication technology. PACS has become an indispensable image-management system in modern hospitals as it improves convenience and medical efficiency. Several medical images obtained by various modalities are available on a local area network in a hospital or hospital group. Moreover, some images are available on a cloud system, as needed. The volume of medical images has been rapidly increasing, and radiologists and physicians are struggling to keep up with the sheer number of images to review. For most medical images, accurate and reproducible interpretations can be provided by utilizing advanced systems, such as computer-aided diagnosis systems, that can efficiently and correctly gather useful image information based on the quantitative analysis of the image as a diagnostic reference [15].

The Institute of Medicine of the National Academy of Sciences in the USA declared its intent to strengthen efforts to prevent medical accidents in the report “To Err is Human: Building a Safer Health System” in November 1999. Since then, various actions have been taken in hospitals for patient safety, not only in the USA, but also worldwide. The most serious mistake in hospitals is the wrong-patient error, which is mainly caused by human errors and can occur in virtually all stages of diagnosis and treatment. The consequences of patient misidentification can be severe, ranging from medical errors to adverse effects on the bottom line. As of 2020, the National Patient Safety Goals effective July 2020 for the hospital program recommends the use of at least two patient identifiers when providing care, treatment, and services to improve the accuracy of patient identification [16]. A key problem with the use of two patient identifiers has been identified [17], and thus, biometrics are to be introduced in clinical care to prevent patient misidentification. However, the ever-increasing number of patient-verification tasks using biometrics to daily workflow increase the burden on healthcare providers, which can result in other human errors or clinical problems in patients. It is believed that the application of biometrics in healthcare can significantly improve both patient convenience and healthcare provider productivity within a short time, thus acting as a solution to the increasing workload. However, it has the following operational concerns for its clinical use. According to the Japan Medical Imaging and Radiological Systems Industries Association (JESRA) guidelines [18], the anonymization of medical images states that "consideration should be given to rare cases with small number of patients and the face as information that can identify the individual." The image data itself is not considered to be patient-specific information ethically; however, the tag information associated with the medical image is defined as patient-specific information. When biometric information using medical images is introduced, it is supposed that the guidelines and regulations are revised such that the image itself will be subject to patient information protection. It is also necessary to establish a secure environment in practice for the secondary use of patient medical images.

3. Utilization and evaluation of similar images

In the field of computer vision, various methods for retrieving interesting images, such as content-based image retrieval (CBIR) [19], query by image and video content [20], and content-based multimedia information [21], have been utilized to query a specific image on the web or numerous photographs in a database. Although the concept of CBIR, which originated in 1992, is a unique and useful idea to search for similar images, most techniques are based on the examination distance of two images in image-feature spaces, such as the color, shape, and texture of images. Therefore, certain cases did not match in terms of resemblance, as judged by human observers. Muramatsu and Doi investigated similarity measures and methods for the similar image retrieval of breast lesions on mammograms at the beginning of the 21st century. Furthermore, a group at the University of Chicago proposed psychological measures to evaluate similar images [22–27]. Their studies clearly demonstrated the importance of examining the resemblance between medical images.

4. Image recognition and identification for medical imaging

At the end of the 20th century, Morishita *et al.* initiated a study of automated patient recognition and identification for digital chest radiographs (CXRs), and the first paper on this subject was published in 2001 [28]. The study focused on CXRs, which are the most frequent X-ray examinations in hospitals, and was based on a template-matching technique between current and previous CXRs (**Fig. 2 left**) and the histogram analysis of the correlation values that indicate similarity between the CXRs (**Fig. 3**). A thousand pairs of CXRs with an image matrix size of 64 × 64 for the same patients and different patients were evaluated and exhibited promising results, with a 47.8% correct identification of correct patients without any misidentification as the wrong patients [28]. A comparison of the similarity of the corresponding areas in the two images by evaluating the normalized cross-correlation value and histogram analysis can be used to determine a specific image or similar image in a database that includes several images of the same type [28]. Moreover, it is also possible to reduce the time required to search for a specific patient image from a database containing several images by using a query ranked by image similarities.

Transparency to the public about mistakes in image acquisitions was considered taboo until the end of the 20th century; however, after the 1999 academic report by the US Institute of Medicine, such issues have been reported in newspapers and articles in Japan. PACS has evolved over time and has been improved for each hospital environment, which includes access to archive images and links to corresponding patient information. The actual occurrence of filing errors with an initial version of the PACS environment in a hospital was examined in Japan [29]. The implementation of the PACS clearly contributes to a decrease in misfiling errors by healthcare providers. Currently, in Japan, a verification system before images are stored on the PACS server, called the "KENZO system," is now operating, and misfiling of patients has been reduced considerably. Nevertheless, the wrong-patient problem still occurs occasionally in hospitals because of unavoidable human errors.

To further improve the performance of the method developed by Morishita *et al.* [28], edge-enhanced image-based matching [30] (**Fig. 2, middle**) and biological fingerprints (BFs) (**Figs. 2 right and 4**) were applied. The BFs are useful image information that can be used to recognize and identify a specific patient as part of the radiographs [31]. A comparison of the corresponding BFs in two images (current and previous CXRs) is based on the evaluation of the normalized cross-correlation value and histogram analysis. Although the method used a limited number of normal CXRs without abnormalities, it was promising for searching for a specific or similar image in a database containing several similar images. Because BF is a concept that describes the physique, anatomic features, and specific abnormalities of an individual, it can be applied to image matching with other types of radiological imaging.

Various BFs on CXRs (**Fig. 4**), namely, whole-lung fields (WLF), cardiac shadows, the superior mediastinum, lung apices, part of the right lung, and the lower right lung, which includes the costophrenic angle, were cropped and tested to identify correct and incorrect patients. The method was based on comparing the BFs in a target CXR to those of other CXRs in the database [31]. To examine the resemblance for each BF between the current CXR, $A(i, j)$, and the previous CXR, $B(i, j)$, for the presumed corresponding patient is determined by the following equation, called the normalized cross-correlation value (C):

$$C = \frac{1}{IJ}\sum_{j=1}^{J}\sum_{i=1}^{I}\frac{\{A(i,j)-\bar{a}\}\{B(i,j)-\bar{b}\}}{\sigma_A \cdot \sigma_B},$$

where

$$\bar{a} = \frac{1}{IJ}\sum_{j=1}^{J}\sum_{i=1}^{I}A(i,j),\ \bar{b} = \frac{1}{IJ}\sum_{j=1}^{J}\sum_{i=1}^{I}B(i,j),$$

$$\sigma_A = \sqrt{\frac{\sum_{j=1}^{J}\sum_{i=1}^{I}\{A(i,j)-\bar{a}\}^2}{IJ}},\ \sigma_B = \sqrt{\frac{\sum_{j=1}^{J}\sum_{i=1}^{I}\{B(i,j)-\bar{b}\}^2}{IJ}}.$$

I and *J* indicate the matrix size of the area selected for each BF of the current images *A* and *B, respectively.* If images *A* and *B* are identical, then *C* is set to 1.0. The correlation value indicates the resemblance between the two images, where a higher correlation value indicates a greater similarity. Among several BFs, only a part of the right lung did not work well for identifying the correct patient owing to fewer differences in image contrasts in the BF. Then, the sum of the other five correlation values is used as a correlation index to rank similar images. Finally, a combination of the index and artificial neural networks achieved 58% correct warning rates for different patients.

Toge *et al.* improved the overall performance of the correct recognition of the same patients up to 87.5% without incorrect warnings for the same patients by using a weighting factor for each correlation index for the similarity measure. Additionally, an additional 5.0% of the same patients were included in the top-10 ranking of the correlation index in the database [32]. Shimizu *et al.* modified the shape of WLF to improve its performance and applicability for unknown individuals [33] and developed an automatic extraction method for BFs, including the detection of image orientation in digital CXRs [34]. These techniques are introduced in a book entitled *New Perspectives in Forensic Human Skeletal Identification* [35] as examples of computer-assisted biometric matching of radiological imaging in non-forensic fields. Kao *et al.* also demonstrated automated patient recognition of CXRs in 2013 [35] by evaluating six characteristics, including the anatomical length and area. The upper part of **Table 1** presents the performance of the automated patient recognition and identification methods using CXRs.

5. Patient verification using routine torso CT and brain MR imaging

Cross-sectional imaging systems, such as computed tomography (CT) and magnetic resonance (MR) imaging, are expanding rapidly to become the first-choice examinations for X-ray imaging in several cases. CT and MR imaging produce hundreds to thousands of images per examination. In addition, several CT/MR series images might be sent to an external system for secondary use, or the original dataset may be used for multi-planar reconstruction and volume rendering. Hence, a single wrong-patient registration of an exam could potentially lead to a fatal medical accident. Biometrics in healthcare are preferred as a simple verification/identification task under various patient conditions because routine work for healthcare providers is already complicated.

Ueda *et al.* [37, 38] suggested the use of scout images, which are acquired for scan planning purposes, for biometric verification. This makes the examination process convenient for both healthcare providers and patients. The benefits of scout images for biometrics are: high versatility, no additional scanning, and possible automatic execution during an examination. Their use is a novel technique for positive patient verification using routine torso CT and brain MR images. A study entitled “Biological fingerprint using scout computed tomographic images for positive” [37] evaluated the temporal scout CT images of the chest, abdomen, and pelvis scans. In this challenge, the resemblance between the follow-up and baseline images was evaluated by comparing the estimates of the image characteristics using local feature extraction and matching algorithms.

Figure 5 demonstrates the examples of the same- and different-pair analyses using chest–pelvis scout CT images. In this example, the correspondence rates, which are defined as similarity indexes, are 80.6% for the genuine pair and 18.0% for the impostor pair. The highest area under the curve (AUC), equal error rate (EER), and rank-one identification rate (R1) achieved in this study were 0.998, 1.22%, and 99.7%, respectively.

Moreover, another study entitled "Usefulness of biological fingerprint in magnetic resonance imaging for patient verification" evaluated eight anatomical multi-planar reconstruction images of the right and left halves of the brain—including the temporal lobe and optic nerve for the sagittal section; optic nerve, optic chiasm, and internal auditory canal (IAC) for the coronal section; IAC, basal ganglia, and lateral fissure for the axial section—and midsagittal images generated from temporal three-dimensional (3D) MR imaging of the brain, as illustrated in **Fig. 6** [38]. In this study, the IAC image exhibited the best performance and yielded AUC, EER, and R1 values of 0.998, 1.37%, and 98.6%, respectively. In this study, the evaluation of the images of patients who underwent surgery between two temporal scans exhibited lower performance; however, those of patients who had undergone surgery before the prior scan exhibited high performance levels, as did those of patients who did not undergo surgery. These methods have the potential to discover the misfiled patient information under/after examination and confirm the patient identity, despite the patient being unable to communicate.

The lower part of **Table 1** summarizes the biometric technology using CT and MR imaging. The verification performance for biometrics is evaluated in terms of the receiver operating characteristic (ROC) curve and its corresponding EERs and AUCs. The EER indicates a point that has an equal probability for the misclassification of genuine or impostor pairs on the ROC curve. The lower the value of EER, the better the biometric system is for verification. The close-set identification performance for biometrics was evaluated using R1, which indicates that the rank of the genuine patient pair is higher than that of all the impostor patient pairs. The higher the value of R1, the better the biometric system is for closed-set identification. In a good biometric system, EER, AUC, and R1 are low, high, and high, respectively.

6. Applications of image recognition and identification in forensic pathology

The personal identification of decedents or human remains has been of important scientific interest for forensic anthropologists to answer legal questions since 1850 [35]. The Scientific Working Group for Forensic Anthropology (SWGANTH) [39] and the Organization of Scientific Area Committees for Forensic Science (OSAC) [40] have been working together to systematize, provide best practices for, and develop a consensus standard since 2008. Image matching between postmortem (PM) and antemortem (AM) images is called positive identification and is also used for identification in forensic pathology, where PM and AM images, such as radiography or photography, are compared. Forensic skeletal identification has been researched for a century since Schuller suggested its usefulness in observing the frontal sinus in 1921 [41, 42]. Forensic identification of unknown bodies and human remains using advanced imaging techniques, such as postmortem computed tomography (PMCT), is expected [43–47].

Matsunobu *et al.* demonstrated the potential usefulness of the reconstructed two-dimensional (2D) images of ribs and vertebrae from 3D CT images for positive identification of CXRs (**Figs. 7 and 8 c, d**) [48]. Tsubaki *et al.* showed the potential usefulness of sex determination based on morphological features obtained from the 2D CXRs of the ribs and thoracic vertebrae (**Fig. 8 a, b**) [49]. To further utilize CT images for forensic cases, Kawazoe *et al.* proposed an accurate and reproducible semi-automated method to correct the positioning of the brain PMCT compared to that of AMCT, as PMCT positioning is made difficult by covering the corpse with a cadaver bag or changes in rigidity after death (**Fig. 8 e–h**) [50]. For accurate image comparison of the human body, if such correction is installed in the CT system for automatic preprocessing, positioning correction can be easier and more reproducible for operators with different skills.

In Japan, the Act of Promotion of Policy about Death Investigation was legislated and enforced in April 2020 to utilize scientific methods to investigate the cause of death and prepare a database for personal identification of corpses [51]. O'Donnell *et al.* identified the potential usefulness of PMCT and MR imaging for personal identification [52]. Furthermore, another study reported that whole-body CT images of victims were a valid approach for rapid personal identification during a large fire in Australia in 2009 [53]. Interpol established guidelines for disaster-victim identification (DVI) and noted that it was difficult to identify such victims by visual recognition. Therefore, fingerprinting, dental records, DNA profiling, and physical indications are required for conclusive identification [54]. Implanted metals are also important for identifying unknown bodies that are difficult to recognize from visual observations. Wada *et al.* reported a preprocessing method using a CT scout image to check for the existence of implanted metals (**Fig. 8 i**) [55]. Scout images under CT imaging have the advantage of fewer artifacts around the metal implant; therefore, it may be useful for quickly finding metals implanted in the body. Although CT imaging techniques, such as a mobile CT scanner, are required on site, the scout image would be useful in the case of a mass disaster because panoramic dental imaging systems and cone-beam CT, frequently used in dental clinics for dental examination, are unavailable in the field.

7. Future expectations and issues

Because most studies on personal identification have used a closed set of cases, with either few cases or only a single case, there is no guarantee of their effectiveness for unknown cases or samples with different conditions. To overcome this problem, as well as to develop a method for personal identification, various types of large databases are required that can be used in the case of mass disasters worldwide.

Currently, conventional radiography using screen-film systems in medically advanced countries has almost completely shifted to computed radiography (CR) and flat-panel detectors (FPDs). The number of imaging modalities for medical imaging has increased, and all images are stored digitally. Therefore, various accurate and reproducible image recognition and personal identification are expected to be achieved using automated computer-assisted technologies, including artificial intelligence (AI), as well as image comparison using digital radiography. These changes indicate the requirement for various large databases that can be used for training AIs or positive identification in mass disasters worldwide, as well as in cases of other unidentified persons.

The authors concluded that biometrics using advanced medical imaging are the key solutions to the incorrect identification of patients in radiology and the identification of unknown bodies or human remains in forensic pathology.

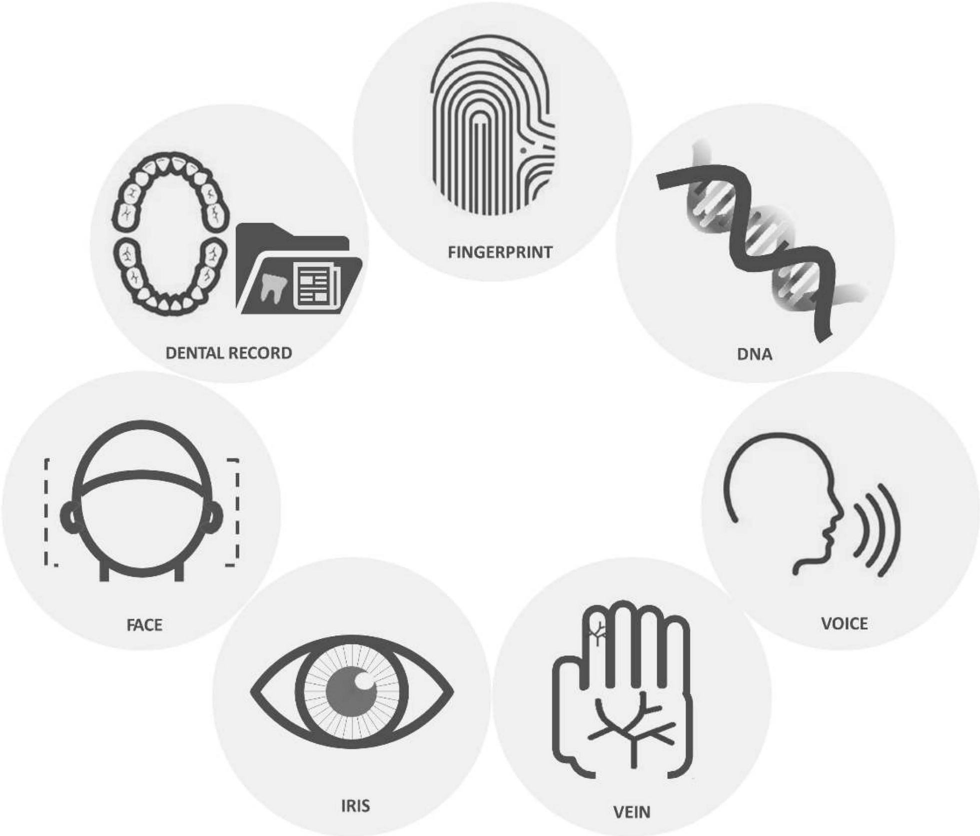

Figure 1. Schematic illustration of various biometric traits for personal identification and authentication.

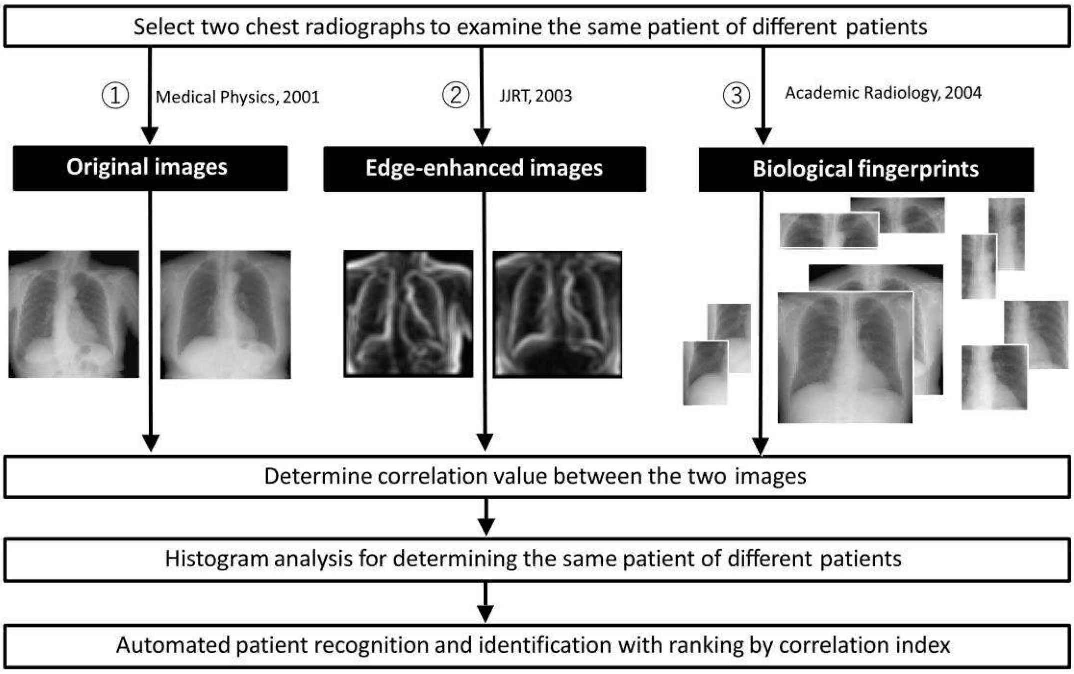

Figure 2. Overall scheme for three different automated patient recognition and identification methods for comparing chest radiographs, based on various template-matching techniques and the histogram analysis of correlation values.

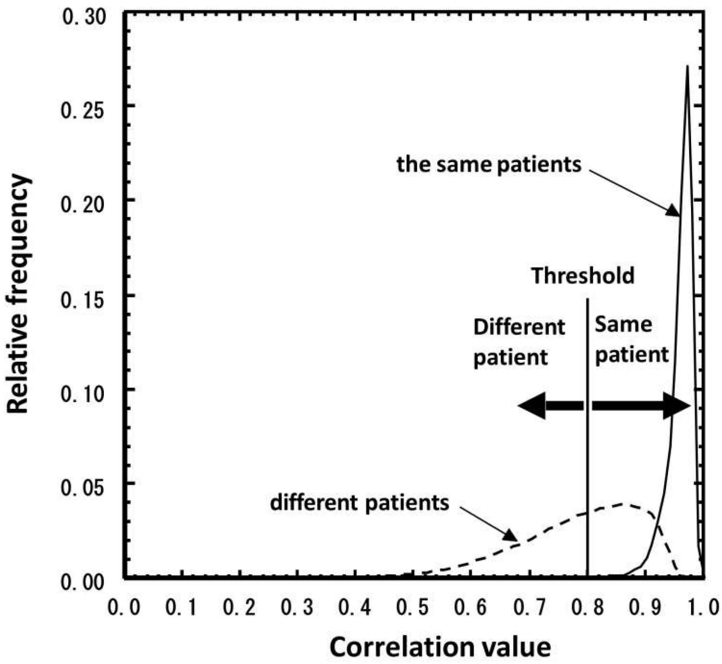

Figure 3. Histograms for correlation values obtained with two chest radiographs for the same patients and for different patients. The threshold value was set at the lowest correlation value for the same patient. However, it can be changed to control the valance of true positives and false negatives.

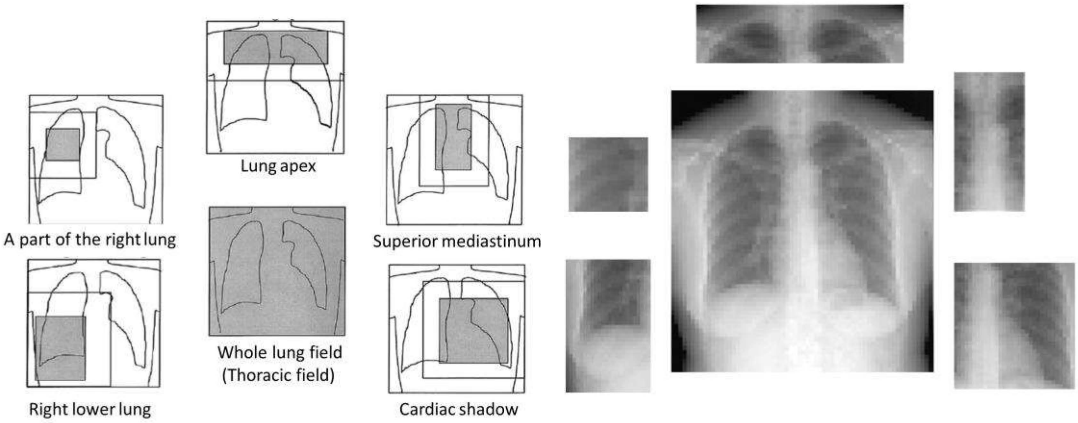

Figure 4. Illustrations of locations for six different BFs, namely, whole-lung field, cardiac shadow, lung apex, the superior mediastinum, part of the right lung, and the lower right lung. The surrounding regions for each BF indicate search areas used in the template-matching technique. An example of BFs extracted from a CXR is shown on the right.

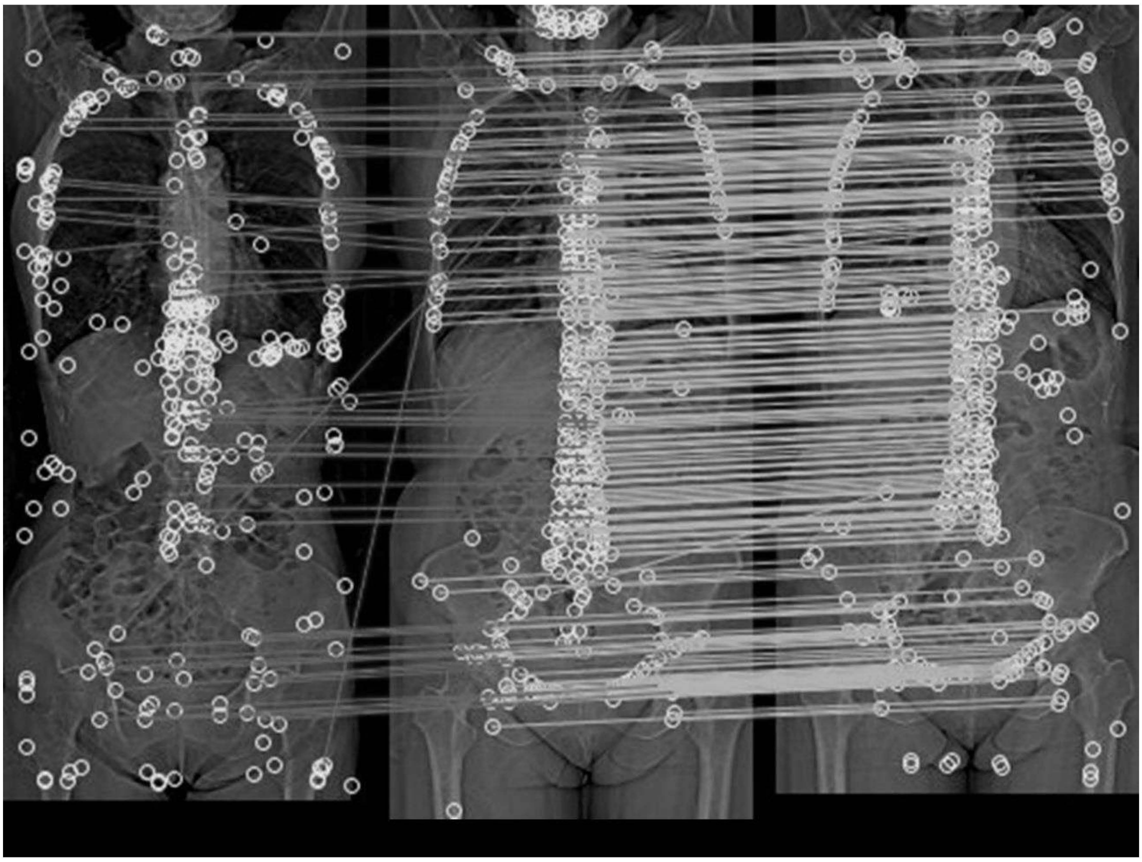

Figure 5. Example of a novel BF technique for biometric verification in CT scout images of the chest, abdomen, and pelvis under a clinical setting. Scout views of follow-up (center) and baseline (right) scans of the same patient are shown. A follow-up (center) and baseline (left) scans corresponding to different patients are shown. Yellow circles indicate the local feature points. Lines connecting pairs of yellow circles in the pairs of images are valid corresponding feature points of the same-patient pair (cyan lines) and different-patients pair (magenta lines). The number of such lines indicates the similarity score. The more the number of lines connecting the feature points, the more

likely they are to be the same patient.

Note: Original figure adapted from data from Ueda et al. [37].

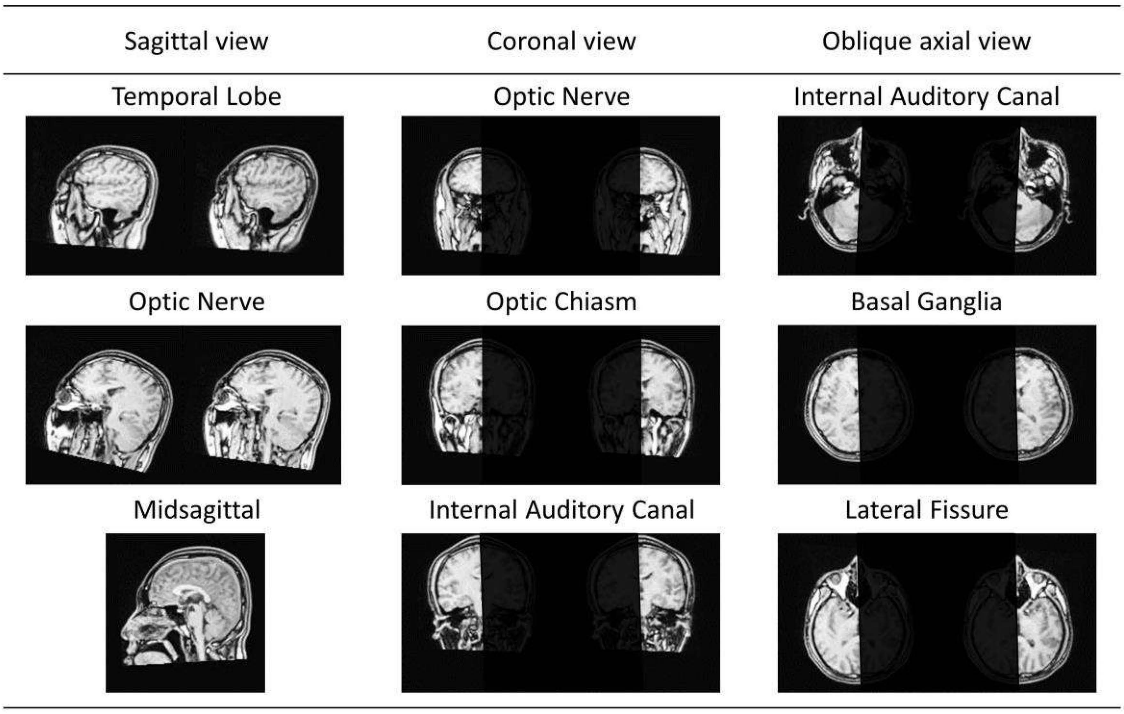

Figure 6. Examples of nine BF images reconstructed from a 3D MR image of the brain. Each 2D BF image was determined comparing each right or left 2D image. The resemblance between the 2D BF images of each identical section was used for biometric verification.

Note: Images were adapted from data from Ueda [38].

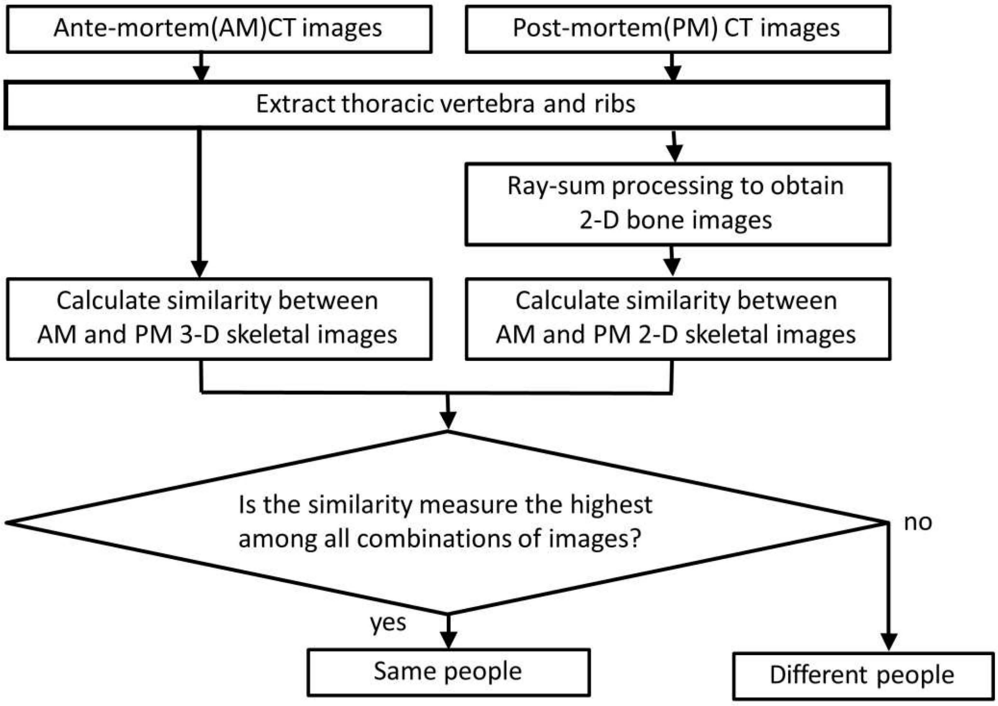

Figure 7. Overall scheme for positive forensic identification using 2D and 3D skeletal images extracted from antemortem (AM) and postmortem (PM) CT images. The normalized cross-correlation value was used as a similarity measure.

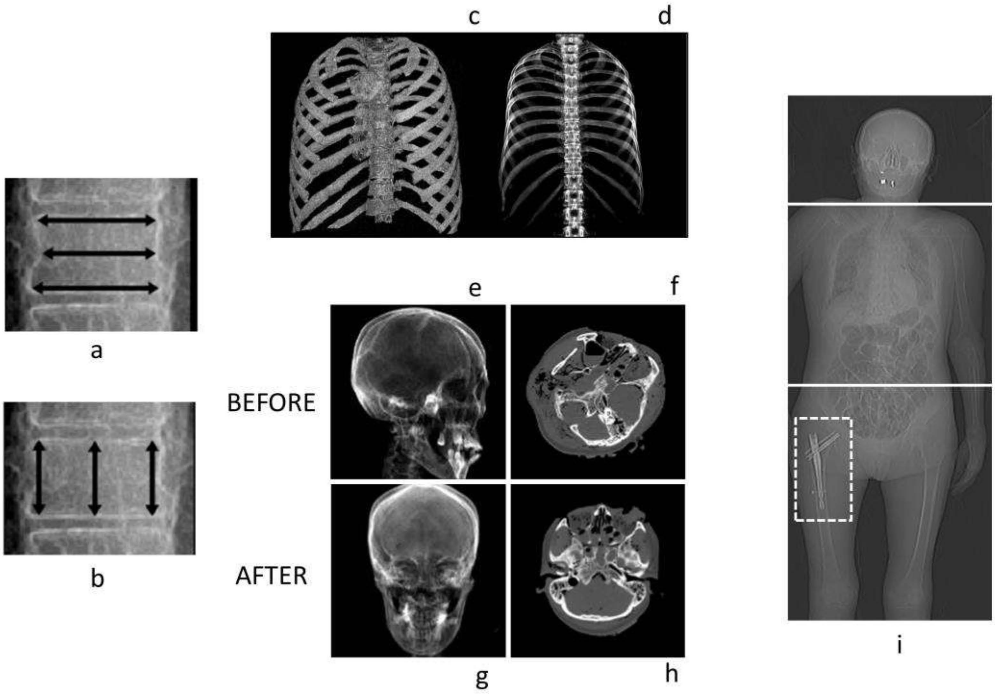

Figure 8. Examples of forensic skeletal identification for sex determination using thoracic vertebra (a, b), 3D and 2D skeletal images (c, d), head PMCT images before and after semiautomated position readjustment (e, f, g, h), and an example of three automatically roughly classified body parts for PMCT scout view, including an artificial hip joint, as shown in the dashed rectangle (i).

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Ethics declarations

Conflict of interest

All authors declare that they have no conflict of interest.

Ethical statement

All procedures conducted the studies, which involved human participants of introducing in this paper, were in conformance with the ethical standards of the Institutional Review Board at each authors' affiliated institutions and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed consent

Written informed consent of the studies, which involved human participants of introducing in this paper, were not required owing to the retrospective design.

Animal rights

The studies, which are introduced in this paper, did not involve animal model.

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