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

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1	New solutions for automated image recognition and identification: Challenges to
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17 Abstract

18 This paper outlines the history of biometrics for personal identification, the current status 19 of the initial biological fingerprint techniques for digital chest radiography, and patient verification during medical imaging, such as computed tomography and magnetic 20 21 resonance imaging. Automated image recognition and identification developed for 22 clinical images without metadata could also be applied to the identification of victims in 23 mass disasters or other unidentified individuals. The development of methods that are 24 adaptive to a wide range of recent imaging modalities in the fields of radiologic 25 technology, patient safety, forensic pathology, and forensic odontology is still in its early 26 stages. However, its importance in practice will continue to increase in the future. 27 (110 words) 28 29

30 Key words: image recognition, biometrics, biological fingerprints, biometric verification,

31	positive	identification,	forensic	identification
-	1			

32 1. History of personal identification using biometrics

33 Personal identification using fingerprinting, DNA analysis, and dental records has been 34 used for multiple purposes, such as forensic identification and identity verification. 35 Several researchers, including medical examiners/coroners, forensic pathologists, and 36 forensic anthologists, are continually working to establish standards and systematic 37 analysis methods for application to unknown cases and human remains [1]. However, 38 daily activities often require rapid, reliable, and convenient personal identification. Thus, 39 personal identification is becoming the fundamental of today's society, and ongoing 40 research contributes more secure services to prevent fraud and crime while improving 41 accessibility and convenience.

42 Research regarding personal identification using biometrics originated in the 1600s, 43 when human fingerprint patterns were used. In 1684, Grew conducted extensive research 44 on the ridge patterns of fingerprints to distinguish different human beings [2]. In 1685, 45 Bidloo described the details of the fingerprint in the book Anatomy of the Human Body 46 [3]. Around that time, the fact that fingerprint patterns are unique to individuals began to 47 be recognized. Mayer wrote a book in 1788, entitled Anatomical Copper-plates with 48 Appropriate Explanations, asserting that the pattern of fingerprints is unique to each 49 human [4]. He wrote, "Although the arrangement of skin ridges is never duplicated in two

50	persons, nevertheless the similarities are closer among some individuals." The differences
51	have been well identified; despite all persons having similar patterns, the specific
52	arrangements show slight differences [5]. Thus, fingerprints were applied as the first
53	commercially available biometric identification method in 1858 by Herschel, who
54	prompted local Indian businessmen to sign binding contracts with a print of their own
55	palm. The fingerprint was used as a system of identification equivalent to official
56	signatures in the magistrate court [6]. In the late 1800s, although not yet fingerprint
57	authorization, Bertillon reported that the combination of 11 anthropometric
58	measurements was unique to the individual [7]. That was the first attempt to use specific
59	anatomical characteristics to identify reoffending criminals. As for the criminal history
60	records in the Justice system, Galton developed a fingerprint-classification system and
61	published a book, Finger Prints, in 1892 [8]. Edward Richard Henry published
62	Classification and Uses of Finger Prints in 1900 [9]. In 1903, fingerprinting was used to
63	identify prisoners in the New York State Prison. Subsequently, an increasing number of
64	local police identification bureaus established fingerprint systems [10, 11]. In 1986, the
65	National Bureau of Standards (NBS) and the American National Standards Institute
66	(ANSI) published a standard for the exchange of fingerprint minutiae (ANSI/NBS-ICST
67	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.

76

77 2. Environment and patient safety in medical imaging

78 In 1982, Dwyer et al. proposed the concept of a picture archiving and communication 79 system (PACS) to reduce the cost of medical image management [12–14]. In medical 80 safety, the following changes have been observed over the past 20 years. The idea has 81 rapidly spread worldwide to achieve efficient medical care services with the aid of the 82 popularization of digital imaging and progress in information and communication 83 technology. PACS has become an indispensable image-management system in modern 84 hospitals as it improves convenience and medical efficiency. Several medical images 85 obtained by various modalities are available on a local area network in a hospital or

86	hospital group. Moreover, some images are available on a cloud system, as needed. The
87	volume of medical images has been rapidly increasing, and radiologists and physicians
88	are struggling to keep up with the sheer number of images to review. For most medical
89	images, accurate and reproducible interpretations can be provided by utilizing advanced
90	systems, such as computer-aided diagnosis systems, that can efficiently and correctly
91	gather useful image information based on the quantitative analysis of the image as a
92	diagnostic reference [15].
93	The Institute of Medicine of the National Academy of Sciences in the USA declared its
94	intent to strengthen efforts to prevent medical accidents in the report "To Err is Human:
95	Building a Safer Health System" in November 1999. Since then, various actions have
96	been taken in hospitals for patient safety, not only in the USA, but also worldwide. The
97	most serious mistake in hospitals is the wrong-patient error, which is mainly caused by
98	human errors and can occur in virtually all stages of diagnosis and treatment. The
99	consequences of patient misidentification can be severe, ranging from medical errors to
100	adverse effects on the bottom line. As of 2020, the National Patient Safety Goals effective
101	July 2020 for the hospital program recommends the use of at least two patient identifiers
102	when providing care, treatment, and services to improve the accuracy of patient
103	identification [16]. A key problem with the use of two patient identifiers has been

104	identified [17], and thus, biometrics are to be introduced in clinical care to prevent patient
105	misidentification. However, the ever-increasing number of patient-verification tasks
106	using biometrics to daily workflow increase the burden on healthcare providers, which
107	can result in other human errors or clinical problems in patients. It is believed that the
108	application of biometrics in healthcare can significantly improve both patient
109	convenience and healthcare provider productivity within a short time, thus acting as a
110	solution to the increasing workload. However, it has the following operational concerns
111	for its clinical use. According to the Japan Medical Imaging and Radiological Systems
112	Industries Association (JESRA) guidelines [18], the anonymization of medical images
113	states that "consideration should be given to rare cases with small number of patients and
114	the face as information that can identify the individual." The image data itself is not
115	considered to be patient-specific information ethically; however, the tag information
116	associated with the medical image is defined as patient-specific information. When
117	biometric information using medical images is introduced, it is supposed that the
118	guidelines and regulations are revised such that the image itself will be subject to patient
119	information protection. It is also necessary to establish a secure environment in practice
120	for the secondary use of patient medical images.

122 **3.** Utilization and evaluation of similar images

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

136

137 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

140	this subject was published in 2001 [28]. The study focused on CXRs, which are the most
141	frequent X-ray examinations in hospitals, and was based on a template-matching
142	technique between current and previous CXRs (Fig. 2 left) and the histogram analysis of
143	the correlation values that indicate similarity between the CXRs (Fig. 3). A thousand pairs
144	of CXRs with an image matrix size of 64×64 for the same patients and different patients
145	were evaluated and exhibited promising results, with a 47.8% correct identification of
146	correct patients without any misidentification as the wrong patients [28]. A comparison
147	of the similarity of the corresponding areas in the two images by evaluating the
148	normalized cross-correlation value and histogram analysis can be used to determine a
149	specific image or similar image in a database that includes several images of the same
150	type [28]. Moreover, it is also possible to reduce the time required to search for a specific
151	patient image from a database containing several images by using a query ranked by
152	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

158	actual occurrence of filing errors with an initial version of the PACS environment in a
159	hospital was examined in Japan [29]. The implementation of the PACS clearly contributes
160	to a decrease in misfiling errors by healthcare providers. Currently, in Japan, a verification
161	system before images are stored on the PACS server, called the "KENZO system," is now
162	operating, and misfiling of patients has been reduced considerably. Nevertheless, the
163	wrong-patient problem still occurs occasionally in hospitals because of unavoidable
164	human errors.
165	To further improve the performance of the method developed by Morishita et al. [28],
166	edge-enhanced image-based matching [30] (Fig. 2, middle) and biological fingerprints
167	(BFs) (Figs. 2 right and 4) were applied. The BFs are useful image information that can
168	be used to recognize and identify a specific patient as part of the radiographs [31]. A
169	comparison of the corresponding BFs in two images (current and previous CXRs) is based
170	on the evaluation of the normalized cross-correlation value and histogram analysis.
171	Although the method used a limited number of normal CXRs without abnormalities, it
172	was promising for searching for a specific or similar image in a database containing
173	several similar images. Because BF is a concept that describes the physique, anatomic
174	features, and specific abnormalities of an individual, it can be applied to image matching
175	with other types of radiological imaging.

176 Various BFs on CXRs (Fig. 4), namely, whole-lung fields (WLF), cardiac shadows, the 177 superior mediastinum, lung apices, part of the right lung, and the lower right lung, which 178 includes the costophrenic angle, were cropped and tested to identify correct and incorrect 179 patients. The method was based on comparing the BFs in a target CXR to those of other 180 CXRs in the database [31]. To examine the resemblance for each BF between the current 181 CXR, A(i, j), and the previous CXR, B(i, j), for the presumed corresponding patient is 182 determined by the following equation, called the normalized cross-correlation value (C): $C = \frac{1}{IJ} \sum_{j=1}^{J} \sum_{i=1}^{I} \frac{\{A(i,j) - \bar{a}\}\{B(i,j) - \bar{b}\}}{\sigma_A \cdot \sigma_B},$ 183 184 where

185
$$\bar{a} = \frac{1}{IJ} \sum_{j=1}^{J} \sum_{i=1}^{I} A(i,j), \ \bar{b} = \frac{1}{IJ} \sum_{j=1}^{J} \sum_{i=1}^{I} B(i,j),$$

186
$$\sigma_A = \sqrt{\frac{\sum_{j=1}^J \sum_{i=1}^I \{A(i,j) - \bar{a}\}^2}{IJ}}, \ \sigma_B = \sqrt{\frac{\sum_{j=1}^J \sum_{i=1}^I \{B(i,j) - \bar{b}\}^2}{IJ}}.$$

187 I and J indicate the matrix size of the area selected for each BF of the current images 188 A and B, respectively. If images A and B are identical, then C is set to 1.0. The correlation 189 value indicates the resemblance between the two images, where a higher correlation value 190 indicates a greater similarity. Among several BFs, only a part of the right lung did not 191 work well for identifying the correct patient owing to fewer differences in image contrasts 192 in the BF. Then, the sum of the other five correlation values is used as a correlation index 193 to rank similar images. Finally, a combination of the index and artificial neural networks

achieved 58% correct warning rates for different patients.

195 Toge et al. improved the overall performance of the correct recognition of the same 196 patients up to 87.5% without incorrect warnings for the same patients by using a 197 weighting factor for each correlation index for the similarity measure. Additionally, an 198 additional 5.0% of the same patients were included in the top-10 ranking of the correlation 199 index in the database [32]. Shimizu et al. modified the shape of WLF to improve its 200 performance and applicability for unknown individuals [33] and developed an automatic 201 extraction method for BFs, including the detection of image orientation in digital CXRs 202 [34]. These techniques are introduced in a book entitled New Perspectives in Forensic 203 Human Skeletal Identification [35] as examples of computer-assisted biometric matching 204 of radiological imaging in non-forensic fields. Kao et al. also demonstrated automated 205 patient recognition of CXRs in 2013 [35] by evaluating six characteristics, including the 206 anatomical length and area. The upper part of Table 1 presents the performance of the 207 automated patient recognition and identification methods using CXRs.

208

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

Cross-sectional imaging systems, such as computed tomography (CT) and magneticresonance (MR) imaging, are expanding rapidly to become the first-choice examinations

212	for X-ray imaging in several cases. CT and MR imaging produce hundreds to thousands
213	of images per examination. In addition, several CT/MR series images might be sent to an
214	external system for secondary use, or the original dataset may be used for multi-planar
215	reconstruction and volume rendering. Hence, a single wrong-patient registration of an
216	exam could potentially lead to a fatal medical accident. Biometrics in healthcare are
217	preferred as a simple verification/identification task under various patient conditions
218	because routine work for healthcare providers is already complicated.
219	Ueda et al. [37, 38] suggested the use of scout images, which are acquired for scan
220	planning purposes, for biometric verification. This makes the examination process
221	convenient for both healthcare providers and patients. The benefits of scout images for
222	biometrics are: high versatility, no additional scanning, and possible automatic execution
223	during an examination. Their use is a novel technique for positive patient verification
224	using routine torso CT and brain MR images. A study entitled "Biological fingerprint
225	using scout computed tomographic images for positive" [37] evaluated the temporal scout
226	CT images of the chest, abdomen, and pelvis scans. In this challenge, the resemblance
227	between the follow-up and baseline images was evaluated by comparing the estimates of
228	the image characteristics using local feature extraction and matching algorithms.
229	Figure 5 demonstrates the examples of the same- and different-pair analyses using

230	chest-pelvis scout CT images. In this example, the correspondence rates, which are
231	defined as similarity indexes, are 80.6% for the genuine pair and 18.0% for the impostor
232	pair. The highest area under the curve (AUC), equal error rate (EER), and rank-one
233	identification rate (R1) achieved in this study were 0.998, 1.22%, and 99.7%, respectively.
234	Moreover, another study entitled "Usefulness of biological fingerprint in magnetic
235	resonance imaging for patient verification" evaluated eight anatomical multi-planar
236	reconstruction images of the right and left halves of the brain-including the temporal
237	lobe and optic nerve for the sagittal section; optic nerve, optic chiasm, and internal
238	auditory canal (IAC) for the coronal section; IAC, basal ganglia, and lateral fissure for
239	the axial section-and midsagittal images generated from temporal three-dimensional
240	(3D) MR imaging of the brain, as illustrated in Fig. 6 [38]. In this study, the IAC image
241	exhibited the best performance and yielded AUC, EER, and R1 values of 0.998, 1.37%,
242	and 98.6%, respectively. In this study, the evaluation of the images of patients who
243	underwent surgery between two temporal scans exhibited lower performance; however,
244	those of patients who had undergone surgery before the prior scan exhibited high
245	performance levels, as did those of patients who did not undergo surgery. These methods
246	have the potential to discover the misfiled patient information under/after examination
247	and confirm the patient identity, despite the patient being unable to communicate.

248	The lower part of Table 1 summarizes the biometric technology using CT and MR
249	imaging. The verification performance for biometrics is evaluated in terms of the receiver
250	operating characteristic (ROC) curve and its corresponding EERs and AUCs. The EER
251	indicates a point that has an equal probability for the misclassification of genuine or
252	impostor pairs on the ROC curve. The lower the value of EER, the better the biometric
253	system is for verification. The close-set identification performance for biometrics was
254	evaluated using R1, which indicates that the rank of the genuine patient pair is higher than
255	that of all the impostor patient pairs. The higher the value of R1, the better the biometric
256	system is for closed-set identification. In a good biometric system, EER, AUC, and R1
257	are low, high, and high, respectively.
258	
259	6. Applications of image recognition and identification in forensic pathology
260	The personal identification of decedents or human remains has been of important
261	scientific interest for forensic anthropologists to answer legal questions since 1850 [35].
262	The Scientific Working Group for Forensic Anthropology (SWGANTH) [39] and the
263	Organization of Scientific Area Committees for Forensic Science (OSAC)[40] have been

264 working together to systematize, provide best practices for, and develop a consensus

standard since 2008. Image matching between postmortem (PM) and antemortem (AM)

266	images is called positive identification and is also used for identification in forensic
267	pathology, where PM and AM images, such as radiography or photography, are compared.
268	Forensic skeletal identification has been researched for a century since Schuller suggested
269	its usefulness in observing the frontal sinus in 1921 [41, 42]. Forensic identification of
270	unknown bodies and human remains using advanced imaging techniques, such as
271	postmortem computed tomography (PMCT), is expected [43-47].
272	Matsunobu et al. demonstrated the potential usefulness of the reconstructed two-
273	dimensional (2D) images of ribs and vertebrae from 3D CT images for positive
274	identification of CXRs (Figs. 7 and 8 c, d) [48]. Tsubaki et al. showed the potential
275	usefulness of sex determination based on morphological features obtained from the 2D
276	CXRs of the ribs and thoracic vertebrae (Fig. 8 a, b) [49]. To further utilize CT images
277	for forensic cases, Kawazoe et al. proposed an accurate and reproducible semi-automated
278	method to correct the positioning of the brain PMCT compared to that of AMCT, as
279	PMCT positioning is made difficult by covering the corpse with a cadaver bag or changes
280	in rigidity after death (Fig. 8 e-h) [50]. For accurate image comparison of the human
281	body, if such correction is installed in the CT system for automatic preprocessing,
282	positioning correction can be easier and more reproducible for operators with different
283	skills.

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

302

303 7. Future expectations and issues

304 Because most studies on personal identification have used a closed set of cases, with 305 either few cases or only a single case, there is no guarantee of their effectiveness for 306 unknown cases or samples with different conditions. To overcome this problem, as well 307 as to develop a method for personal identification, various types of large databases are 308 required that can be used in the case of mass disasters worldwide. 309 Currently, conventional radiography using screen-film systems in medically advanced 310 countries has almost completely shifted to computed radiography (CR) and flat-panel 311 detectors (FPDs). The number of imaging modalities for medical imaging has increased, 312 and all images are stored digitally. Therefore, various accurate and reproducible image 313 recognition and personal identification are expected to be achieved using automated 314 computer-assisted technologies, including artificial intelligence (AI), as well as image 315 comparison using digital radiography. These changes indicate the requirement for various 316 large databases that can be used for training AIs or positive identification in mass disasters 317 worldwide, as well as in cases of other unidentified persons. 318 The authors concluded that biometrics using advanced medical imaging are the key

319 solutions to the incorrect identification of patients in radiology and the identification of

320 unknown bodies or human remains in forensic pathology.



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



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



329 Figure 3. Histograms for correlation values obtained with two chest radiographs for the

- 330 same patients and for different patients. The threshold value was set at the lowest
- 331 correlation value for the same patient. However, it can be changed to control the valance
- 332 of true positives and false negatives.



333

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

the right.



339

340 Figure 5. Example of a novel BF technique for biometric verification in CT scout 341 images of the chest, abdomen, and pelvis under a clinical setting. Scout views of follow-342 up (center) and baseline (right) scans of the same patient are shown. A follow-up 343 (center) and baseline (left) scans corresponding to different patients are shown. Yellow 344 circles indicate the local feature points. Lines connecting pairs of yellow circles in the 345 pairs of images are valid corresponding feature points of the same-patient pair (cyan 346 lines) and different-patients pair (magenta lines). The number of such lines indicates the 347 similarity score. The more the number of lines connecting the feature points, the more

- 348 likely they are to be the same patient.
- 349 Note: Original figure adapted from data from Ueda et al. [37].



- 351 Figure 6. Examples of nine BF images reconstructed from a 3D MR image of the brain.
- 352 Each 2D BF image was determined comparing each right or left 2D image. The
- 353 resemblance between the 2D BF images of each identical section was used for biometric
- 354 verification.
- 355 Note: Images were adapted from data from Ueda [38].



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



361 **Figure 8.** Examples of forensic skeletal identification for sex determination using

- 362 thoracic vertebra (a, b), 3D and 2D skeletal images (c, d), head PMCT images before
- 363 and after semiautomated position readjustment (e, f, g, h), and an example of three
- 364 automatically roughly classified body parts for PMCT scout view, including an artificial



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377 Ethics declarations

378 Conflict of interest

379 All authors declare that they have no conflict of interest.

380

381 Ethical statement

382 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

- 384 Board at each authors' affiliated institutions and with the 1964 Helsinki Declaration and
- its later amendments or comparable ethical standards.

386

387 Informed consent

388 Written informed consent of the studies, which involved human participants of 389 introducing in this paper, were not required owing to the retrospective design.

390

391 Animal rights

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

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