Technical Note 2226

Forensic Iris: A Review, 2022

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Abstract

John Daugman correctly summarized the state of forensic iris recognition circa 2006 for the book *Forensic Human Identification: an Introduction* by Thompson (CRC Press, 2006).

> Iris recognition has limited forensic value, because (unlike fingerprints or DNA, for example) (1) iris patterns are not left behind at crime scenes; (2) and in death the pupil usually dilates significantly, the cornea clouds, and the iris tissue degrades relatively rapidly. (3) Moreover, currently available iris databases are quite small (only a few million digitized samples of iris patterns exist today); and because of the novelty of this biometric, (4) such data currently has no legal or established forensic status as admissible evidence. *[Numbers () added.]*

In the intervening ∼15 years, all of Daugman's observations, save one, have been overtaken by events: (1) The advent of ubiquitous high resolution video/photography has led to widespread collection/retention/dissemination of imagery of sufficient resolution for iris recognition. (2) Demonstrations of post-mortem iris recognition have been made. (3) Large iris databases have been constructed. The last issue (4) regarding admissible evidence remains to be resolved.

Forensic iris was a topic at the June 2018 Iris Experts Group Meeting[1]. Key issues discussed there were: measurements and analysis that need to be done to provide the underpinnings for a resolution of the forensic status of iris recognition and the development of documentation for such measurements and analysis that will enable explanation of iris collection and recognition to lay audiences, including those in a courtroom. An important point was that the perceptions of the public and the popular media with respect to biometrics and to iris recognition in particular are frequently inaccurate and must be considered in any development of materials designed to explain iris recognition to the lay public.

To help resolve the questions discussed at that meeting, this paper reviews the current state of the art in iris recognition, the perceptions of the public regarding iris recognition, and makes suggestions regarding measurements and analysis that will help enable use of forensic iris in appropriate settings going forward.

We welcome comments for the next revision of this document. Please send comments to james.matey@nist.gov.

[1]The Iris Experts Group (IEG), is an open forum for the exchange of technical information related to iris recognition and factors affecting its adoption and use as a means of identification/verification in civil and government applications. See IEG home page

Key words

biometric recognition; forensics; iris recognition; iris identification; iris verification.

Executive Summary

For the purpose of this paper *forensic iris* is the application of iris recognition technology to the investigation and prosecution of criminal acts[2]. Forensic iris typically involves comparison of pairs of iris images to determine if the images came from (1) the same person, (2) different persons, or (3) the images are of insufficient quality to make a determination; the comparison should also provide an estimate of the confidence level of the determination. The comparisons may be done by human examiners, by computer algorithms or a combination of the two.

Forensic iris is a new field. As discussed below, a little over 15 years ago, leaders in the field of iris recognition did not consider iris recognition useful in forensic applications. Though their observations at that time were correct, events have overtaken those observations. There are now demonstrations of iris recognition that can be plausibly applied to matters of forensic interest as discussed in recently published literature [1–4] and in sections 3.3 and 6 of this report.

It is an open question whether the science of forensic iris is sufficiently established to satisfy the criteria that the National Research Council(NRC)/National Academy of Sciences(NAS)[5] and the Presidential Council of Advisors on Science and Technology(PCAST) [6] put forth for forensic science in general – see section 1 of this report for details.

As described later in this document, iris recognition is already used for some types of investigative work. However, to the best of our knowledge, as of 2022, such applications have not required judicial review. Iris recognition has been rigorously tested in the NIST IREX program, e.g. [7] [8], and elsewhere [9]. Other sources of information that are arguably less rigorously tested than iris recognition are often accepted for the purpose of investigation. Eyewitness accounts are one example of evidence that is frequently accepted for investigatory purposes, but whose reliability has been questioned; recent reports include Albright's PNAS (Proceedings of the National Academy of Sciences) paper, "Why Eyewitnesses Fail" [10] and Newirths's paper "An Eye for the Science: Evolving Judicial Treatment of Eyewitness Identification Evidence" [11].

However for presentation of expert witness testimony, the bar is high. In US courts the key issue is satisfying the Daubert standard, the "standard used by a trial judge to assess whether an expert witness's testimony is based on scientifically valid reasoning that which can properly be applied to the facts at issue" [12] . The factors to be used under the Daubert standard are [12] :

1. Whether the theory or technique in question can be and has been tested;

[2]As this paper goes through publication review in 2022, there is no widely accepted definition of *forensic iris*.

2. whether it has been subjected to peer review and publication;
3. its known or potential error rate;
4. the existence and maintenance of standards controlling its operation; and
5. whether it has attracted widespread acceptance within a relevant scientific community.

Though iris recognition algorithms, as normally used in non-forensic settings, have been well tested[3] there are gaps in measurements, analysis, and understanding of forensic iris. Such gaps may prevent iris recognition evidence from being conclusive or dispositive as laid out by the NRC and PCAST reports. Section 6-6A of the PCAST report, "Use of feature comparison methods in Federal prosecutions", is particularly relevant in this context. Those gaps might be closed through additional measurements and analysis. We note that the PCAST report specifically recommends that NIST participate in determinations of foundational validity based on empirical studies and evaluations[4].

As discussed in the body of this paper, comparisons of iris images in a forensic iris setting can be done by computer programs and by people. In addressing the presentation of evidence based on forensic iris we need to address two major tasks:

1. Determine how an iris examiner can explain computer-based methods to a lay audience.
2. Conduct studies to determine the efficacy of human examiners, as recently done for face and finger.

This paper reviews the current state of forensic iris, with these primary observations and recommendations:

- It is generally recognized that iris recognition using images captured in the near infrared for the purpose of iris recognition is one of the most accurate biometric identification technologies; recent papers supporting this statement include [7, 13–15].
- There is confusion about iris recognition in popular media as discussed in section 2 of this report. Any explanation of iris recognition to persons who are not biometric experts needs to address points of common confusion including details of human

[3] See for example the reports from the long running NIST IREX program.
[4] See page 140 of reference [6]

anatomy[5], iris image capture, image processing, and the statistics of biometric identification.

- Images commonly found in the wild, which were not taken for the purpose of iris recognition, e.g., internet images, often display iris texture that can be matched using iris recognition at accuracies of forensic interest. A demonstration is presented in section 6 of this report.

- Computers and humans examine iris images differently; see section 3.1 of this report. Future practice of forensic iris will likely combine human examination and automated processes as is practiced in the examination of latent fingerprints.

- Within the context of current iris recognition algorithms, it is unlikely that we can make practical use of iris recognition for cases involving imagery from data collections where the stand-off distance[6] is as large as tens of meters. See section 3.6 of this report.

- Research to better characterize the human ability to adjudicate iris image pairs should be undertaken, analogous to work on face recognition and identification by White et al. [16, 17] and Phillips et al. [18] .

- Research to evaluate training effects for iris examiners, building on the face recognition work by Phillips et al. [18], should likely be part of any future efforts to improve forensic iris recognition.

- Further studies of the statistics of visible iris features should be conducted to provide the underpinnings for the science of human comparisons of iris images, as discussed for other modalities in the PCAST report[6]. Preliminary results have been reported by Quinn[19].

- Human iris examiners should be provided with training and tools that enable them to effectively employ computer based iris recognition algorithms in their work.

- If forensic iris is to be relied upon in criminal proceedings, training/education materials will be needed to provide appropriate training for people involved in its use and interpretation. These include: law enforcement officers, investigators, and iris image examiners/expert witnesses. The training materials should enable experts to explain forensic iris to non-experts participating in the proceedings, including judges, attorneys, and members of the lay public.

- Datasets appropriate for scenarios of interest, and reviewed by appropriate authorities, will be needed to enable further research into forensic applications of iris recognition and to provide material suitable for training and testing iris image examiners.

[5] For example, the iris and the retina are routinely confused in the popular literature.

[6] In this context, stand-off distance is the distance between the object/subject and the camera.

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Glossary

These definitions are for use in the context of this paper; they do not incorporate the full details of the standards on which they are based. For use outside the context of this paper, please refer directly to the full definitions in the standards rather than this glossary.

The definitions relating to biometrics are based on those recommended by ISO/IEC 2382-37:2017 and ISO/IEC 19795-1. ISO/IEC 2382-37:2017 is publicly available here. ISO/IEC 19795-1 is one of several key standards in the Registry of US Recommended Biometric Standards (2014). In general, those standards must be purchased, though there are other options for some researchers.[7]

At this time (2022), there remain differences in vocabulary usage between the biometric community and the forensic community. For example, in the biometric literature *recognition* encompasses *identification* and *verification*; whereas in the forensic fingerprint literature *identification* is used in place of *recognition* and the term *verification* is generally used in a different context; see Standard for Friction Ridge Examination Training Program. Our thanks to John Splain for bringing this issue to our attention during review of this paper.

Resolving the issues of vocabulary usage is beyond the scope of this paper. In this paper we generally use language based upon usage in the biometric community.

adjudication in this context, a determination by a human using methods acceptable within the judicial system, e.g. Daubert Standard, that a pair of iris images are

- from the same iris
- from different irides
- of insufficient quality to make a determination

The adjudication may include an estimate of strength of the determination.

ancestry in this context, the people from whom one has descended. Under discussion in the biometrics community as an alternative to race/ethnicity.

[7]The Federal Bureau of Investigation (FBI), the Department of Homeland Security (DHS), and the National Institute of Standards and Technology (NIST) have provided funds to purchase single use licenses for fifteen of the copyrighted standards cited in that registry. These licensed InterNational Committee for Information Technology Standards (INCITS) documents have been made available to United States Government (USG) workers (i.e., USG employees or USG contractors). Information on acquiring copies of these standards may be found here.

authentic pair a pair of biometric samples derived from the same source, e.g., subject/eye; deprecated in favor of mated pair.

bio-geographical origin in this context, the geographical region from which one's early ancestors came. Under discussion in the biometrics community as an alternative to race/ethnicity.

biometric identification searching a biometric database of enrolled subjects to find a previously enrolled subject.

biometric recognition automated recognition of individuals based on their physical, biological and behavioral characteristics; encompasses identification and verification.

biometric sample in this paper, an image of an iris; in a broader context, an image or other representation of a biometric characteristic, e.g., fingerprint, face image, DNA swab.

biometric verification comparing a biometric sample from a subject against a previously enrolled sample to verify the identity of the subject.

comparison score the numerical result from a comparison of two biometric samples; previous usage was match score; the value indicates the degree of similarity or dissimilarity of the two samples.

constriction see dilation.

Daubert Standard the "standard used by a trial judge to assess whether an expert witness's testimony is based on scientifically valid reasoning that which can properly be applied to the facts at issue" [12].

decision threshold the comparison score which is the boundary between a decision of match or no match. This varies with algorithm and scenario.

DET see detection error tradeoff.

detection error tradeoff (DET) graph a variant of the receiver operating characteristic; false match rate on the x-axis, false non-match rate on the y-axis; axes rescaled (typically log scale) to more clearly display low error rate regions of interest.

dilation in this context, an increase in the pupil diameter, normally in response to low light levels, but sometimes due to drugs. Ophthalmologists dilate the pupil with a topical drug to make examination of the eye interior easier. Constriction is the opposite of dilation, it is a reduction in pupil diameter normally in response to bright lights, but sometime due to drugs. Constriction and dilation can also be caused by illness or trauma including brain damage.

EER see equal error rate.

equal error rate the error rate at which the false match and false non-match rates are equal.

ethnicity categorization of people on the basis of social characteristics including customs, religion, nationality, language. Since these are social characteristics, they need not be related to DNA. Ethnicity has been used as a synonym for race; appropriate terminology is a matter of current discussion in the biometric community (2022). See also ancestry and bio-geographical origin.

false accept rate (FAR) a deprecated term, equivalent to false match rate.

false match rate (FMR) the fraction of comparisons of non-mated (e.g., from different subjects) biometric sample pairs that are erroneously reported as matches. FMR depends on the decision threshold. FMR is used to characterize 1-1 performance; see FPIR for 1-N.

false non-match rate (FNMR) the fraction of comparisons of mated (e.g., from same subject/eye) biometric sample pairs that are erroneously reported as not matched. FNMR depends on the decision threshold. FNMR is used to characterize 1-1 performance; see FPIR for 1-N.

false negative identification rate (FNIR) the fraction of comparisons of mated (e.g., from same subject/eye) biometric sample pairs that are erroneously reported as not matched. FNIR depends on the decision threshold and the gallery size. FNIR is used to characterize 1-N performance; see FNMR for 1-1.

false positive identification rate (FPIR) the fraction of comparisons of non-mated (e.g., from same subject/eye) biometric sample pairs that are erroneously reported as matched. FPIR depends on the decision threshold and the gallery size. FPIR is used to characterize 1-N performance; see FMR for 1-1.

FAR see false accept rate.

FMR see false match rate.

FNMR see false non-match rate.

FNIR see false negative identification rate.

FPIR see false positive identification rate.

forensic relating to or dealing with the application of scientific knowledge to legal problems[8], in particular to investigation and prosecution of criminal acts.

[8] From www.meriam-webster.com

forensic iris (recognition) application of iris recognition technology to legal problems, in particular to the investigation and prosecution of criminal acts.

GAR see genuine accept rate.

genuine accept rate (GAR) the fraction of mated pairs that are accepted; deprecated in favor of $1 - FNMR$.

Hamming distance in this context, a measure of the dissimilarity of two binary strings. The raw Hamming distance is the number of bits that are different in a bitwise comparison of two binary strings. The *fractional Hamming distance* is the fraction of bits which are different in a bitwise comparison of two binary strings. In much of the iris recognition literature, Hamming distance is used as a short hand for fractional Hamming distance. Example: given two binary strings, "1100" and "1010", the strings are the same at the first and fourth positions and differ at the second and third. There are two differences, so the Hamming distance is 2. The string length is 4, so the fractional Hamming distance is $2/4 = 0.50$. If a reported Hamming distance is a fraction between zero and one, it is a fractional Hamming distance.

illuminance a photometric measure of the amount of visible light impinging on a surface, units are $lumens/m^2$. See also irradiance. Not to be confused with luminance.

impostor pair a pair of biometric samples derived from different sources, e.g., different subjects or different eyes of one subject; deprecated in favor of non-mated pair.

iris, irides for this paper, the annular ring of colored tissue that surrounds the pupil of the eye; "irides" is the usual medical plural. The plural for the flower is irises, though that form is also used by some for the eye part in biometric literature.

iris identification biometric identification using iris images.

iris image examiner a person who adjudicates iris image pairs.

iris recognition biometric recognition using iris images.

irradiance a radiometric measure of the intensity of light/radiation impinging on a surface, units are power/unit area, e.g., $Watts/m^2$. See also illuminance. Not to be confused with radiance.

match (biometric) a decision that two biometric samples are derived from the same source; for iris, same subject, same eye.

mated pair a pair of biometric samples that are derived from the same source, e.g., subject/finger, subject/eye.

match score deprecated in favor of comparison score.

match threshold deprecated in favor of decision threshold.

modality the type of biometric, e.g., finger, face, iris, DNA.

non-match a decision that two biometric samples are derived from different sources, e.g., different subjects, different eyes of same subject.

non-mated pair a pair of biometric samples that are derived from different sources, e.g., different subjects or different eyes of one subject.

periocular the region surrounding the eyeball. In medical terminology, the region surrounding the eyeball but within the orbit – the cavity in the skull which contains the eye. In the biometrics literature some authors include the eyebrows as part of the periocular region.

photometric measurements measurements of *visible* electro-magnetic radiation; these measurements are based on the response of an average human eye.

radiometric measurements measurements of electro-magnetic radiation at any wavelength; these measurements are based on the physical characteristics of the radiation without regard to human perception of the radiation.

Receiver Operating Characteristic (ROC) Receiver Operating Characteristic, a plot of FNMR vs FMR (or FNIR vs FPIR) as the decision threshold is varied. This shows the unavoidable trade-off between FMR and FNMR – lower FMR is generally associated with higher FNMR and vice versa.

ROC see Receiver Operating Characteristic.

stand-off distance In the context of iris recognition, the distance between the subject and the camera.

TAR see true accept rate.

true accept rate (TAR) a deprecated term equivalent to $1 - FNMR$.

wavelength (optical) optical wavelength is the wavelength of the electromagnetic waves of which light is a subset. Blue light has a wavelength around 400 nm; red light has a wavelength around 700 nm, near-infra-red ranges from 750 nm to 1400 nm

wavelength (spatial) the distance over which any periodic phenomenon repeats. Examples include ripples on a pond, ocean waves, and acoustic waves. Optical wavelength is another example. In this paper, we need to draw distinctions between the optical wavelength of light used to illuminate the iris and the spatial wavelength of the structural details that are revealed by that illumination.

Caveats, Disclaimers, Licenses, and Human Subjects Protections

This paper reviews the current state of the art. Statements regarding that state are those of the authors and are accurate to the best of their knowledge at the time of writing. However, such statements do not necessarily reflect the position of the National Institute of Standards and Technology (NIST) or the US Government.

Certain commercial entities, equipment, software, or materials may be identified in this document to describe an experimental procedure or concept adequately. Such identification is not intended to imply recommendation or endorsement by NIST, nor is it intended to imply that the entities, materials, software, or equipment are necessarily the best available for the purpose.

Nothing in this paper should be taken as legal advice. When in need of legal advice, readers should consult their own legal counsel.

Some of the figures include content that is subject to copyright and/or other restriction. We have noted the licenses under which we have used that content and from where the content was obtained.

This paper uses biometric data from multiple sources. The NIST Research Protections Office reviewed the protocols for the data utilized in this work and determined that each of the protocols satisfied one of these criteria:

- it is not human subjects research as defined in Department of Commerce Regulations.
- it meets the criteria for exempt human subjects research as defined in Department of Commerce Regulations,
- the protocol was reviewed by the NIST Institutional Review Board, which approved the protocol.

1. Introduction

1.1 Scope: What is the definition of forensic?

Forensic is a term whose meaning has shifted over the years. We note that until 2013, the National Speech and Debate Association of the United States was called the National Forensic League[9] and the term forensic is still used in that context by some, e.g. Stanford National Forensic Institute.

The term forensic comes from the same Latin root as forum, the Roman place for public debates. Merriam-Webster[10] defines forensic as

1. belonging to, used in, or suitable to courts of judicature or to public discussion and debate.
2. relating to or dealing with the application of scientific knowledge to legal problems.

The Oxford dictionary[11], has a somewhat more restrictive definition: "Relating to or denoting the application of scientific methods and techniques to the investigation of crime".

For the purpose of this paper *forensic iris* is the application of iris recognition technology to legal problems, in particular to the investigation and prosecution of criminal acts; we will consider issues that are relevant to two somewhat different aspects of forensic iris:

1. Adjudication of iris image pairs by humans using visual inspection.
2. Adjudication of iris image pairs by humans using computer algorithms.

This paper will be incomplete when the reader reads it: forensic iris is a new discipline that is evolving as this paper is written.

[9] http://www.speechanddebate.org/history
[10] https://www.merriam-webster.com/
[11] http://www.oxforddictionaries.com

1.2 Rationale: Why now?

The reader may reasonably ask why we are reviewing forensic iris at this time.

The reason is that its use in criminal investigation and prosecution is foreseeable. The FBI conducted a pilot study on the use of iris recognition[12] As was the case with other technology innovations going back to the 1990s, e.g. digital cameras[20], the FBI solicited NIST expertise on standards and best practices. That expertise is illustrated in references listed on the pilot study web page, including IREX V[21] and a recent review of camera standards[22]. In September 2020 the iris pilot study transitioned to the Next Generation Identification (NGI) Iris Service[13].

If the Iris Service is to be used in the criminal justice system, it is important that we develop a firm foundation of understanding of the strengths and weaknesses of iris recognition in these applications. This review is a step in that direction.

The target audience for this paper is broad; it includes

- Iris image examiners: the experts who compare iris images and may be called upon to testify in court.
- Managers and supervisors of iris image examiners
- Law enforcement, including investigators, forensics staff, and legal staff
- Government, commercial and academic researchers and developers

Some members of the target audience may find the level of detail in explanations too great, others not great enough. For those who are in either category our apologies. We tried to strike a balance.

[12] See https://www.fbi.gov/file-repository/pia-fbi-ngi-iris-pilot.pdf and https://www.fbi.gov/news/stories/fbi-adds-iris-biometric-to-next-generation-identification-system-121120.

[13] See https://www.fbi.gov/services/cjis/fingerprints-and-other-biometrics/ngi and https://www.afcea.org/content/fbi-expands-next-generation-identification-system-iris-palm-prints

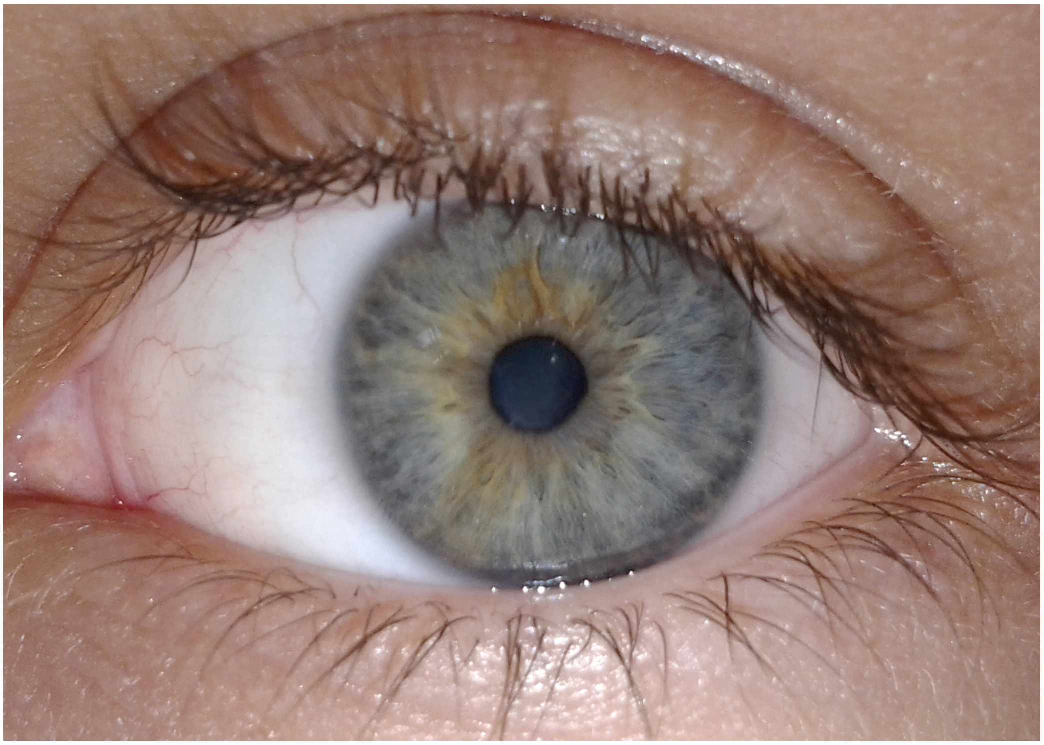

Fig. 1. Example of a human iris as seen with visible light [23]. The white of the eye (sclera) surrounds the iris, which in turn surrounds the pupil. The pupil is a transparent, near circular opening into the interior of the eye. It appears black because there is no light coming out of the eye – just as an unlit tunnel looks black. Pupils sometimes appear red in flash photographs because light from the bright flash enters the eye, reflects off the reddish colored retina inside the eye and then comes back out through the pupil towards the camera. License: Creative Commons Attribution-Share Alike 3.0 Unported.

1.3 Introduction to Iris Recognition

Iris recognition is based on analysis of the complex patterns seen in the iris – the colored part of the eye, as seen in figure 1. Although the basic notion of using the patterns of the iris for identification dates back to at least the late 1800's [24], it did not become practical until computer based algorithms were developed by John Daugman [25] in the 1990's. Daugman's algorithm and algorithms derived from it are commonly referred to as iris2pi[14].

Iris recognition is now one of the four most widely used biometric modalities: DNA,

[14]The operation of iris2pi is well documented in the literature; so well that Libor Masek was able to construct an iris2pi variant as part of a bachelors's thesis [26]. Other fully proprietary algorithms have been developed; the internals for these are not generally available.

face, finger, and iris. However, its impact on forensic science has thus far been limited, as demonstrated by the *Handbook of Biometrics for Forensic Science (2017)*[27] which does not have an entry for iris in its index and two major reports on forensic science from the NRC and PCAST. Neither the National Research Council (NRC)/National Academy of Science(NAS)[5] nor the Presidential Council of Advisors on Science and Technology (PCAST) [6] reports on forensic science discussed iris recognition in detail. A search of the documents reveal only a few mentions of iris recognition:

- NRC, page 74, NIJ award: "Selective Feature-Based Quality Measure Plug-In for Iris Recognition System, Indiana University"
- NRC, page 273, "In addition, systems will need to be designed with the flexibility to handle other kinds of biometric data in the future (e.g., iris and palm scans and possibly genomic data)."
- PCAST, page 15,"The President should request and Congress should provide increased appropriations to NIST of (a) 4 million to support the evaluation activities described above and (b) 10 million to support increased research activities in forensic science, including on complex DNA mixtures, latent fingerprints, voice/speaker recognition, and face/iris biometrics."
- PCAST, page 129, repeat of previous recommendation.
- PCAST, page 133, footnote 370, "NGI standards for Next Generation Identification and combines multiple biometric information systems, including IAFIS, iris and face recognition systems, and others."

Both reports covered face and finger, which were both already in use as forensic evidence in the courtroom, in much more detail: the NRC report mentions "finger" 282 times and "face" 43 times, and the PCAST report mentions "finger" 221 times and "face" 30 times[15].

The generic issues raised in the discussion of face and finger in those reports are, however, quite relevant to iris. Particularly relevant recommendations by PCAST on ensuring the scientific validity of forensic science include (extracted verbatim from the report):

Assessment of foundational validity, Section 6-1 It is important that scientific evaluations of the foundational validity be conducted, on an ongoing basis, to assess the foundational validity of current and newly developed

[15] Counts obtained by exporting pdf files as text and running a word search/count program, notepad++.

forensic feature-comparison technologies. To ensure the scientific judgments are unbiased and independent, such evaluations must be conducted by a science agency which has no stake in the outcome.

Development of objective methods, Section 6-5 C The FBI Laboratory should work with the National Institute of Standards and Technology to transform three important feature-comparison methods that are currently subjective – latent fingerprint analysis, firearm analysis, and, under some circumstances, DNA analysis of complex mixtures into objective methods. These efforts should include (i) the creation and dissemination of large datasets to support the development and testing of methods by both companies and academic researchers, (ii) grant and contract support, and (iii) sponsoring prize competitions to evaluate methods.

Use of feature-comparison methods in Federal prosecutions, Section 6-6 A, page 140 The Attorney General should direct attorneys appearing on behalf of the Department of Justice (DOJ) to ensure expert testimony in court about forensic feature-comparison methods meets the scientific standards for scientific validity. While pretrial investigations may draw on a wider range of methods, expert testimony in court about forensic feature-comparison methods in criminal cases which can be highly influential and has led to many wrongful convictions must meet a higher standard. In particular, attorneys appearing on behalf of the DOJ should ensure that:

i the forensic feature-comparison methods upon which testimony is based have been established to be foundationally valid, as shown by appropriate empirical studies and consistency with evaluations by the National Institute of Standards and Technology (NIST), where available; and

ii the testimony is scientifically valid, with the expert's statements concerning the accuracy of methods and the probative value of proposed identifications being constrained by the empirically supported evidence and not implying a higher degree of certainty.

One reason that iris has not enjoyed as much attention from the forensic community as finger and DNA is because latent iris images are seldom left behind at a crime scene, while DNA and fingerprints are often found at crime scenes. On the other hand people do not generally leave behind fingerprints or DNA online – though images are frequently posted publicly ('in the wild') that can be good enough for face and iris recognition. In 2012, Jain et al. surveyed forensic face recognition in scenarios including missing persons and human trafficking [28]. One of the challenges that Jain et al. pointed out for forensic face is aging – over time faces can change substantially. So far, iris recognition is much less affected by aging than face, as seen in the papers by Best-Rowden et al. [29], Das et al. [135], and Grother et al. [30, 31]. Hence, in some forensic applications the stability of iris patterns over time gives forensic iris an advantage over forensic face, though ongoing, active research and development in both modalities may erase or augment current advantages of either modality[16]

In summary, iris recognition is a widely used, and well tested biometric. Using iris recognition in the context of forensic iris for investigatory purposes is already possible. However, as of 2022, to the best of our knowledge, forensic iris evidence has not yet been presented in court. Such presentations will require an explanation of the image comparison by a human image examiner in terms that a typical juror, who has been subject to the confusion in the popular media about what iris recognition is and is not, as discussed below, can understand and accept. This paper is intended to help guide preparations of such presentations based on scientifically defensible explanations.

1.4 Organization of the paper

The remainder of this paper expands upon the material presented in the introduction.

1. Public perception of iris recognition and its implications for forensic iris.
2. A more detailed history of forensic iris.
3. Differences between the way algorithms and humans compare iris images.
4. Effects of optical wavelength on iris recognition.
5. Algorithm based comparisons of iris images from the wild.
6. Effects of image resolution on iris recognition.
7. Explanation of algorithm based comparisons for the lay person.
8. Statistics of features used by humans for visual comparisons.
9. Overview of effects of disease, illness and injury.

[16] As an example, the recent introduction of deep convolutional neural network techniques (DCNN) to face recognition has resulted in substantial improvements in face recognition performance. These improvements may close the various gaps between iris and face performance in some contexts. The NIST Face Recognition Vendor Test (FRVT) is an important source of information regarding face recognition algorithm performance. Appendix B of NIST IR 8271 [32] provides a summary; updates are underway.

Fig. 2. A scene illustrating "eye recognition" in the popular media, here the NCIS television series; other scenes show that the device bears resemblance to the LG-3000 iris camera. Such scenes can lead the public to incorrect perceptions about iris recognition. The blue laser-like light beams are special effects. Iris recognition uses LEDs similar to those in TV remote controls rather than lasers; the LEDs are nearly invisible near infrared light sources. This image is from WikiFoundry, http://image.wikifoundry.com/image/3/h1PlFea4X61krWopT2-hTA168962/GW350H197. License: Creative Commons' Attribution-NonCommercial-Share Alike 3.0 License, https://creativecommons.org/licenses/by-nc-sa/3.0/. A video of the special effect can be seen at https://www.youtube.com/watch?v=v0OUB-IFzGs.

2. Iris Recognition and Forensics: Confusion in the Public Forum

Forensics includes scientific tests or techniques used in connection with the detection and prosecution of crime. In recent years, we have seen many TV shows built around aspects of the practice of forensics in criminal investigations. Alldredge[33] recently pointed out a phenomenon that is linked to such shows and which contributes to confusion in the public domain: the so-called *CSI effect*; the lay public watching such shows can develop a distorted view of what can and cannot been done with forensic science. The problem was recognized years earlier by Butler[34] and Vallone [35] in connection with DNA evidence. One example is the "Enhance Button" [17] which is often used to enlarge a 4*x*4 pixel section of an image to provide a high resolution representation of a license plate. There are image enhancement techniques that can improve the visual perception of an image, but they cannot generate information that was not in the image to begin with. The Enhance Button is one illustration, among many, of plot elements that are more science fiction than science fact. The downside is that jurors who are exposed to such programs can have difficulty distinguishing science fiction from science fact and may have unrealistic expectations about

[17] See https://tvtropes.org/pmwiki/pmwiki.php/Main/EnhanceButton. The Enhance Button is a plot element often used to generate physically impossible enhancements of imagery – creating information out of thin air that was not available in the image and was not available to the investigator by other means.

what is possible. Recent papers [36] [37] [38] illustrate the complexity of the effect in a jury setting.

Iris recognition is a well known form of human identification and is technology that we see from time to time on such programs – often dressed up with special effects as in figure 2. It is commonly confused with retinal recognition in the press and popular culture. Iris recognition uses the features in the colored part of the eye surrounding the pupil that can be seen in a good photographic portrait. Iris recognition, as deployed using commercial hardware/software, ignores eye color. It uses gray-scale images produced using nearly invisible light from near infrared (NIR) LED's similar to those used in TV remote controls. Iris recognition has been deployed in a number of practical applications including the US-Canada NEXUS Border Crossing[18] [30, 39], the UAE Expellee Program [40, 41], and the Unique ID Authority India (UIDAI) [1, 42].

Though often confused in the popular press, iris recognition and retinal recognition are not the same. The basic premise of retinal recognition was known at least as early as 1950, since it was a plot element in Issac Asimov's 1950 novel *Pebble in the Sky*; however, it took until the advent of modern image processing to became practical. In 2020, retinal recognition is a real form of biometric identification that images the interior back surface of the eye, the retina, a tissue that is normally only seen during a medical eye examination. The retina performs, for the eye, the same function as film or a silicon sensor does in a photographic camera. Because of the utility of retinal imaging in medicine [43], retinal recognition raises issues of health privacy that iris recognition does not[19]. A method for retinal recognition was patented by Hill in 1978 [45]; one of Hill's papers discusses the state of the art in 1996 [46]. The EyeDentify ICAM 2001 was a commercial product[20]. However, according to Frost and Sullivan, EyeDentify ceased production of the ICAM 2001 in 2001[21]. Though there remains academic interest in retinal recognition, as shown by papers as recently as 2014 [47], 2016 [48], and 2020 [49], retinal recognition is, at this time, not commercially available for human subjects and there are no active deployments to the best of our knowledge.

Optibrand, a company that makes retinal imaging devices for livestock identification suggested that their devices might also be used for human identification applications. As of February 2022, the Optibrand website stated that their medical retinal analysis software

[18] As of December 2020, https://usa.immigrationvisaforms.com/travel/nexus-iris-scan-locations remain listed online, though https://www.cbsa-asfc.gc.ca/prog/nexus/kiosk-eng.html.

[19] There is a branch of alternative medicine, iridology, that claims to be able diagnose disease from observations of the iris. Ernst [44] reviewed the iridology literature and conducted experiments to determine if iridologists could make correct diagnoses at better than random chance rates. He concluded that iridology does not provide useful diagnostic information. Interested readers may wish to review the papers cited by Ernst.

[20] The product name may be a cause of confusion since *iCAM* is a trade name used by a major iris recognition company, Iris ID (tm).

[21] https://www.frost.com/sublib/display-market-insight.do?id=RKUR-4ZMW3G

(RetCheck) "can be adapted to perform with a variety of devices to automatically capture, select and give the most precise and reliable biometric match" but did not provide any examples of active deployments for biometric identification.

Sclera vasculature, the veins in the white of the eye, is another biometric recognition technology [50] that is sometimes confused with iris recognition. At the time of this writing, we know of no commercially available implementations of this technology though there was academic interest as recently as 2017 [51] and 2020 [52].

Any explanation of iris recognition to people who are not experts in biometrics should address these points of common confusion.

3. Brief History of Forensic Iris

3.1 Background

John Daugman correctly summarized the state of forensic iris recognition circa 2006 for the book *Forensic Human Identification: an Introduction* [53]:

> Iris recognition has limited forensic value, because (1) (unlike fingerprints or DNA, for example) iris patterns are not left behind at crime scenes; and (2) in death the pupil usually dilates significantly, the cornea clouds, and the iris tissue degrades relatively rapidly. Moreover, (3) currently available iris databases are quite small (only a few million digitized samples of iris patterns exist today); and (4) because of the novelty of this biometric, such data currently has no legal or established forensic status as admissible evidence.
>
> Numbers in () added for this paper.

Over the past decade events have overtaken the first three of those observations:

1. The advent of ubiquitous high resolution videography/photography has led to widespread collection/retention/dissemination of facial imagery of high resolution and upon which iris recognition is possible, as demonstrated later in this paper.

2. Post-mortem iris recognition is now possible:

    - Trokielewicz et al. [2] demonstrated that iris recognition is possible on cadavers up to a day after death when the cadaver was protected from the elements.

- Bolme et al. [3] showed that on a fraction of cadavers (0.6%) irides could be verified after 60 days of exposure to the elements[22].
- Sauerwein et al. [4] demonstrated that iris recognition was viable for periods of 2-34 days post mortem, depending on environmental conditions.

3. Iris databases are now large; the most prominent is the UIDAI [42] which seeks to provide biometric identities for all of India's approximately 1.5 billion residents using both finger and iris. As of 2014, they had enrolled over a billion eyes [1] and at this writing the UIDAI website, https://uidai.gov.in/aadhaar_dashboard/india.php, reports over 1.25 billion persons enrolled.

Forensic image examination has traditionally been the province of skilled human examiners, though there has been significant progress in automating the examination of fingerprints and face images as exemplified by the FBI's IAFIS and NGI systems[23]. Iris recognition *started* as an automated process – Daugman's iris2pi algorithm [54] – without a human in the loop. There is now interest in incorporating human judgment into the loop so that evidence based on the comparison of iris images can be introduced into the court room via expert image examiners.

Iris texture, from the standpoint of a human examiner, has been evaluated in several quantitative studies, as discussed below. These show that there are aspects of iris texture, in addition to color, that appear to be genetically linked. Readers can demonstrate this for themselves by carefully examining the images in the CASIA [55] and Bath [56] iris datasets; they will note that the overall iris texture appears to differ between these datasets. In discussions within the IEG it is generally accepted that a practiced eye can distinguish between images from the two datasets based on iris texture and this is likely due to differences in the ethnicity[24] of the subjects in the two datasets – though differences in specularities and other image capture parameters may also contribute. The Notre Dame Computer Vision Research Laboratory (ND-CVRL) has quantified these observations by engaging in a series of experiments in which human examiners rated the similarity of pairs of iris images of varying degrees of genetic similarity taken using the same iris camera under similar conditions:

- same person, left-right eyes [57, 58]
- identical twins [59]

[22] Anthropology Research Facility (ARF) at the University of Tennessee at Knoxville, an outdoor research facility for the study of human decomposition.

[23] https://www.fbi.gov/services/cjis/fingerprints-and-other-biometrics/ngi

[24] We are using the term ethnicity because that is the term used in much of the prior literature. There is ongoing discussion in the biometrics community regarding the appropriate terminology. Ancestry and biogeographical origin have been suggested.

- siblings [60]

The performance of the examiners in these tasks ranged as high as 80-90% depending on task details.

On the other hand, Daugman [61] demonstrated that the distribution of match scores generated by iris2pi computer algorithms in comparisons of the left and right irides from the same person is statistically indistinguishable from the distribution of match scores in comparisons of different people. More recent work by Daugman [13, 62] and NIST [63] demonstrated essentially the same results when comparing iris images from twins.

In brief summary, the Notre Dame papers demonstrated that there are visible iris features that are genetically linked, while Daugman and NIST have demonstrated that unmated score distributions from iris2pi are not dependent on genetics. Together, these results make a compelling case for the existence of iris texture that is evident to a human examiner but which is not captured by iris recognition algorithms based on the iris2pi model. In short, they demonstrate that human examiners utilize different features than iris2pi recognition algorithms. Since human vision is strongly dependent on contrast (amplitude differences), while iris2pi is based on phase differences, this result is plausible from a theoretic standpoint.

These results suggest that the future practice of forensic iris will find it efficacious to combine human examination and automated processes as is currently practiced in the examination of latent fingerprints.

3.2 Brief History of Periocular Efforts

In the context of biometric recognition, periocular refers to the region of the face surrounding the eyes, including the iris, canthi, sclera, local skin texture, and eyebrows; see figure 9. Although the iris is contained within this region, iris recognition is considered a separate modality in the biometric literature.

In general, iris recognition algorithms ignore image features outside the iris. However, there are features in the periocular region that might be useful in comparing iris images, e.g., details of the canthi, details of the eyelashes, scars, and moles. Studies [64–69] have demonstrated that periocular features contain a fair amount of discriminating information in both the visible and near-IR spectrum, even when the iris texture is excluded. Additionally, the periocular region has shown promise as a means of identifying eye orientation (left or right) [70].

Deep learning and convolutional neural networks have enabled substantial improvements in face recognition algorithms. The same techniques are being applied to to periocular recognition [71, 72].

Proença [72]shows that, on their dataset, relying only on the periocular region gives better results than using all of the image. They report a true positive rate of 0.8 at a false positive rate of 0.001.

At the time of this writing (2022), a difficulty with nearly all *deep learning* approaches is that they do not necessarily represent *deep understanding*. Quoting Lopez-Rubio[73], ”Artificial neural networks have been regarded for decades as a typical example of a black box among machine learning methods“. Even experts often have little insight into the details of how any particular deep learning algorithm works. Rudin [74] discusses these issues at length in the context of high stakes decisions. However, explaining how deep learning algorithms work is an area of active research[75, 76] and one can hope that this difficulty will eventually be resolved.

It has also been demonstrated that minor tweaks to an image that would not be significant to a human observer can force a misclassification (a false match or false non-match) by a deep learning image analyzer [77] – again for reasons that are difficult to explain.

Hence, so long as one expert cannot explain the workings of a deep learning algorithm to another expert, it is unlikely that they can make an understandable explanation to a lay person on a jury. Of course, this is an issue that goes well beyond juries – explanation of the workings of deep learning algorithms is necessary other circumstances. In the literature this concept is known as *Explainable AI*; it is a topic of intense current (2022) research interest and was the theme of the recent (January, 2021) Explainable AI Workshop sponsored by NIST and attended virtually by more than 400 researchers from around the world.

Howard et al. [78] have pointed out that the insensitivity, to date, of iris recognition algorithms to ethnicity and gender is an attractive characteristic, particularly in light of the recent discussions of the sensitivity of face algorithms to those factors. Howard et al. suggest that developers should be careful not to lose that insensitivity through the incorporation of the deep learning methods that are used in face recognition

Fusing periocular recognition with limited-resolution or low-quality iris recognition may lead to improved accuracy over either one by itself, as was demonstrated in one study [79]. This is an operationally relevant problem since an image of the periocular region is often captured as a preliminary or ancillary step toward acquiring an iris sample.

At this time, to the best of our knowledge, there are no commercial implementations of periocular recognition per se. However, recent developments in face recognition, prompted by the widespread use of face masks, do rely upon the periocular region for cases where the rest of the face is covered. Recent papers by Damer [80] and by Ngan et al. [81, 82]

explore this domain.

3.3 Iris and Periocular Recognition by Human Examiners

Manual examination and comparison of iris images is not widely practiced. To our knowledge, the largest manual iris image examination effort is that carried out by the Defense Forensics and Biometrics Agency (DFBA)[25] in support of military operations. Iris examination is one part of a larger effort that examines a flow of face, finger, and iris imagery. Iris examinations are carried out by trained image examiners using conventional commercial and in-house image processing tools to resize/reorient images and to compare corresponding features of image pairs. The examiner makes a judgment of identification, non-identification, or no decision based on the number and quality of corresponding features and the lack of non-corresponding features. Since the examinations are used for intelligence purposes, statistical measures of evaluation quality (e.g., false match rate, false non-match rate, ROC/DET curves) have not been required and, to the best of our knowledge, have not been established. The operation examined over 16,000 iris image pairs in 2017. This operation might be a good candidate for a study based on the methods developed by the Phillips/O'Toole collaboration [18] to determine statistical measures of evaluation quality for face examiners. To get a larger context for the DFBA, the interested reader may consult a US Government Accountability Agency public report on Department of Defense Biometrics and Forensics efforts[26].

A similar method of comparing corresponding features of image pairs is used by human face image examiners [83, 84] and is referred to as morphological comparison in the forensic literature.

We note that examiners, in the process just described, normally examine images that include the periocular region and can make use of periocular details.

There have been several small scale academic explorations, independent of the DFBA efforts, that we describe below.

McGinn, et al., members of the ND-CVRL[27], applied a variant of their human examiner protocol to mated and non-mated pairs of iris images [85]. They used a group of 22 students to examine mated and non-mated pairs; the performance of the student examiners in correctly identifying mated/non-mated pairs ranged from 80% to 100% for mated pairs and from 75% to 98% for non-mated pairs. The student examiners got immediate feedback for each classified pair, so that a learning effect was possible. The researchers found a

[25] http://www.dfba.mil/about/faqs.html
[26] Available at https://www.hsdl.org/?view&did=802975.
[27] https://cvrl.nd.edu/

small improvement in performance between the beginning and end of their experiment that they interpreted as a learning effect. In this experiment, the entire periocular region was available to the student examiners – the decisions could be made on the basis of eyelashes, eyelids and other details. These efforts used high resolution (~200 pixels across the iris), near-infrared images collected using a commercial iris camera, an LG-4000.

Another variant of the protocol was used by Hollingsworth [86] in a comparison of human vs. machine performance on matching both iris texture and periocular features. For iris and periocular in the visible and NIR, human examiners had correct classification rates of the order of 80-90%.

Another publication from Notre Dame [87] explored how well humans can perform iris recognition including diseased eyes, post-mortem specimens and identical twins. Key results were that humans did better than the open source OSIRIS algorithm[88] on diseased and post-mortem samples but did worse for other cases. To date, the OSIRIS software has not been compared with high performing commercial iris recognition algorithms, so it is difficult to generalize these results to cases where the high performing algorithms are used. It would be useful to have a comparison of the performance of OSIRIS and other open source algorithms that are used in academic research with the commercial algorithms used in large scale applications such as UIDAI and the NGI Iris Service.

Shen [89] and Chen [90], both at Notre Dame, developed an automated iris matching system that relies upon matching of human understandable features of the iris (e.g.,crypts). One argument for such a system is that decisions can be more easily explained. NIST is evaluating, as part of IREX-10[7], the latest Notre Dame algorithms on sequestered datasets that have been used to evaluate other iris recognition algorithms. That work is ongoing; a report has not yet been issued as of 2022.

McGinn's paper reports average correct classification rates for mated pairs as 0.94 and for non-mated pairs as 0.89. From this we infer incorrect classification rates of 0.06 for mated, corresponding to false non-matches, and 0.11 for non-mated, corresponding to false matches. There is some ambiguity here because a fraction, 0.01, of the images were classified as ”uncertain”.

Figure 3 shows Detection Error Trade-off (DET) plots for commercial state of the practice face, fingerprint, and iris algorithms, circa 2016[28], based on data from the NIST ROC Baseline site [91]. The FM/FNM results from McGinn are overlaid on the plot in the lower right corner. Figures 7 and 10 in Hollingsworth [86] presented true accept rate (TAR) vs false accept rate (FAR) plots from which we extracted (FAR, TAR) pairs that we converted to (FMR, FNMR) pairs that are also plotted as the curves to the right of the McGinn point. Figure 6 in Chen [90] presented True Positive Rate (TPR) vs False Positive Rate (FPR)

[28]NIST is preparing an update to the ROC Baseline that will take into account improvements in the state of the practice, particularly for face recognition.

plots from which we extracted (TPR, FPR) pairs that we converted to (FMR, FNMR) pairs that are also plotted for the Shen-Flynn dataset described in the paper. The Chen results on the ICE-2005 dataset were not distinguishable from the human examiner results of Hollingsworth and are omitted to improve the overall clarity of the figure.

The crypt-matching method developed at Notre Dame by Chen [90] when employed on the Shen-Flynn dataset [89] is comparable to a good face recognition algorithm, circa 2016[29], but rather worse than the current best performing face algorithm and much worse than the fingerprint and iris algorithms. The crypts method is an automated method, not a method for human adjudication, though the features used are more easily interpreted by humans. Notre Dame has demonstrated a graphical markup tool for iris images based on the techniques used in their algorithm; markup of iris image features might be valuable for human examiners. Such tools might also be used to collect statistics that could be useful in establishing error rates for human examiner processes.

[29] Current face recognition algorithms have improved significantly

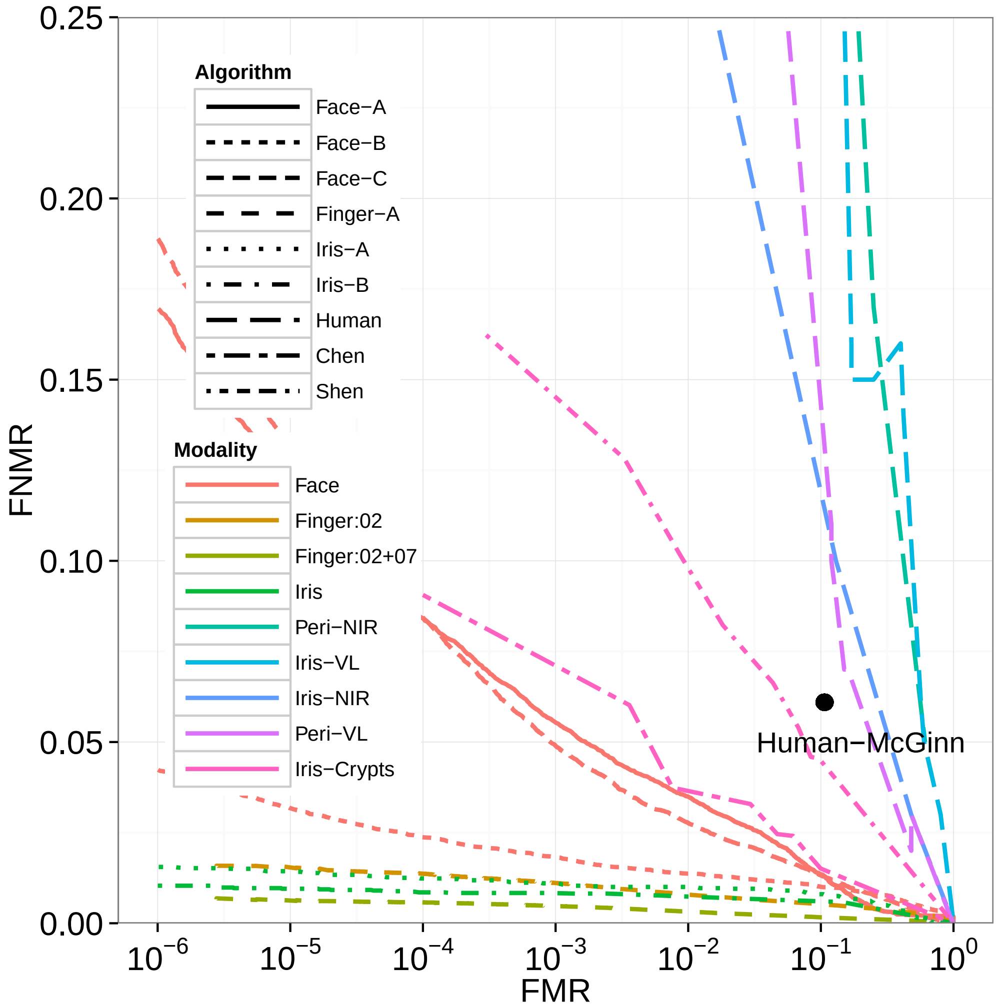

Fig. 3. Receiver Operating Characteristic (ROC) plots for best commercial face, fingerprint and iris algorithms based on data from the NIST ROC Baseline site [91]. Face algorithms have improved significantly since then; this plot should be updated once the ROC Baseline is updated with recent (2020) results. The single point in the lower right is the operating point inferred for human examiners in the McGinn paper [85]. The curves to the right of McGinn are extracted from Hollingsworth [86]. We also show data from the automated crypts based method presented in figure 6 of Chen [90] – on the Shen-Flynn dataset [89, 90]. At an FMR of 0.01, starting from the x-axis and working along a clock-wise arc, the curves are: Finger-A (two index fingers), Iris-B, Iris-A, Finger-A (one index finger) Face-B, Face-C, Face-A, Crypts-Chen, Crypts-Shen, four Human variants(Iris/Peri, Visible/NIR). The best human result is the McGinn result for which we only have a single point.

3.4 Human Examiner Learning

Though there is widespread belief that training can improve the pattern recognition capability of humans, the literature on training effects on the performance of human biometrics examiners has been, until recently, scant.

Our human examiner learning literature search can be summarized as follows:

Face The 2014 review by Phillips and O'Toole notes that the published reports are scant and the results mixed [92]. In the intervening four years White et al. [17], and Phillips et al. [18] have shown clear evidence for the existence of specialized expertise in facial analysis. There is evidence that there is a broad distribution of innate face recognition ability [93]. This result may not generalize to other recognition tasks since, as discussed in Chellapa's review [94], there is evidence that face recognition tasks have dedicated support in the human brain that may not generalize to other tasks. On the other hand, process-based face analysis of the form used in forensics does not rely heavily on that dedicated support. Of particular note are results that suggest that a fusion of computer algorithms and human examination is better than either alone[18].

Finger Thompson [53] demonstrates that there is a wide disparity in false acceptance rates between expert, 0.0068, and novice, 0.55, fingerprint examiners. This demonstrates that training and experience are important in fingerprint examinations by humans.

Iris Our literature search found only the previously mentioned studies at Notre Dame [85, 86]. Since the methods used by iris examiners overlap with those used by fingerprint and face examiners, properly designed studies could be used to help determine the utility of iris examiner training.

In summary, (1) recent studies [18] on training face examiners shows the existence of specialized expertise in facial analysis, though the existence of brain ”firmware” for face recognition complicates the interpretation. (2) There is good evidence that fingerprint examiners can be trained [53]. (3) There are no published studies that make a strong case that iris examiners can, or cannot, be trained. However, since there is overlap in the methodology of face/finger and iris examination, we have reason to hope that a properly designed study on iris examiners will show similar effects to those seen with face/fingerprint examiners.

Studies of training effects for iris examiners, building on the face work by Phillips et al. [18], are needed to firmly establish the efficacy of examiner training in the context of forensic iris recognition.

3.5 Spectral Issues: Visible and Near Infrared

There are compelling reasons for routine iris recognition to be carried out in the near infrared (NIR): (1) melanin is much less absorptive in the NIR, so the stromal structures in dark colored irides are much less obscured in the NIR; (2) for all eye colors, the irradiance at the eye that is required to make a high quality iris image can be uncomfortably high at visible wavelengths – but in the nearly invisible NIR, the irradiance can be high[30] without making the subject uncomfortable.

However, many images of forensic interest will likely be taken in the visible. In recent years, there has been interest in exploring iris recognition in the visible and cross-wavelength between visible and NIR.

Some of the first multi-spectral studies were reported by Boyce [96, 97]. This work was followed up at West Virginia University (WVU) and Noblis by Monaco and Burge [98, 99], at WVU by Ross [100] and at Indian Institute of Information Technology (IIT) by Vatsa and colleagues [101].

An independent collection was carried out by Etter's group at Southern Methodist University (SMU) [102–104]; the SMU collection was a follow-on to earlier work by Ive's group at the US Naval Academy [105]. It resulted in the Combined Multi-Spectral Iris Database (CMID) that was used in NIST's IREX-IX studies [7, 8].

These efforts have shown that it is possible to carry out iris recognition in the visible, though it is likely not practical for subjects with very dark eyes. It is important to note that brown eyes comprise more than 70% of eyes world wide with a distribution that varies substantially by location [106, 107].

In addition, the ROC performance curves developed for data collected in the NIR, e.g., the IREX studies [7, 108–110], may not apply in other wavelength regimes. We will discuss this in more detail in section 5.

3.6 Iris at a Distance

Several papers have discussed the possibility of acquisition of matchable iris images at a distance and from possibly unaware or non-cooperating individuals [111–113]. At a distance, one issue is providing sufficient on target irradiance. Scott Rudder of Innovative Photonic Solutions presented some otherwise unpublished work at the 2010 Biometric Consortium Conference on the use of super luminescent diodes (SLD's) to provide high irradiance, low coherence illumination at a distance of 30 meters.

[30] While staying within safety limits[95].

To understand the issues with long range iris recognition, it is important to consider the mathematical and physical constraints on iris at a distance which are discussed in detail by Matey, Ackerman and colleagues [114–116]. We direct the interested reader to those references. One of the most important messages from the Matey/Ackermann papers is that diffraction sets a constraint relating the on-target-resolution, Δx, the diameter of the collection optics, D; the wavelength of the illumination, λ; and the range to the target, R:

$$D = \frac{\lambda R}{\Delta x} \tag{1}$$

For illumination of approximately 0.8 micron and a desired on-target-resolution of 100 microns we find $D = 0.008R$, so for a standoff of 30 meters, our lens needs to be at least 0.24 meters in diameter for an on-target resolution of 100 microns (about 100 pixels/cm). Two hundred pixels/cm is the recommendation for enrollment quality iris images. From this calculation, it is clear that iris recognition by a cell phone like device at tens of meters is not feasible.

In the realm of published implementations, Fancourt [117] presented what may be the first demonstration, at 10 m. Another important demonstration of iris at a smaller (2-3 m) distance was Iris On The Move$^{\text{TM}}$ [111]. In Ives' group at the US Naval Academy, de Villar demonstrated iris recognition at 30 meters [113] using a telescope with a 200 mm aperture, obtaining a resolution a bit worse than 100 pixels/cm. de Villar's results are, to the best of our knowledge, the longest distance reported in the literature. The Savvides group at CMU developed a 12 m system [118] .

The papers by Matey, Ackerman and their colleagues, noted above, have been repeatedly cited, but so far we are not aware of any practical solutions (as opposed to laboratory demonstrations) to the difficulties they pointed out for long distance iris recognition. The sticking points remain: (1) size of the lenses needed, (2) the pointing stability required for the camera package, and (3) at the longest distances, the atmospheric stability requirements. Application of adaptive optics might help on the last two, but there are fundamental physical constraints on the size of the lenses for a given resolution and standoff. Since it would be impossible to bypass this constraint without violating fundamental physical laws, any attempt to do long range iris acquisition with small lenses will require development of algorithms that can provide acceptable performance at lower resolution.

Within the context of current commercial iris recognition algorithms, it is unlikely that iris recognition in forensic applications will be useful where the stand off distance is tens of meters and the capture device is hand-held.

4. Demonstration that Humans see different features than machines

The Notre Dame papers on human adjudicated similarity between twins, siblings, and left/right eyes of the same person [57–60] suggest that there are aspects of iris texture that humans recognize, but are not captured by current iris recognition algorithms.

Here we present an example that supports that conjecture. Figure 4 presents three images of the same eye. Two of the images were taken 10 years apart – 2003 and 2013 – with different cameras; the third image was created by extracting the iris texture of the 2003 image as a pseudo-polar normalized image at 320x240. The pseudo-polar image was filtered with a Gaussian filter of radius 4 and then re-inserted into the original 2003 image. The blurring essentially removes the finer details of the iris texture.

Using a commercial implementation of iris2pi to generate templates, the fractional Hamming distance of the 2013 image from the original 2003 images is 0.130, a very solid match. The fractional Hamming distance between the original 2003 image and its filtered version is 0.066, again a very solid match – and better than the 2003 to 2013 pair. However, visual inspection of the 2003 to 2013 pair and the 2003 to 2003-filtered pairs would suggest that the visual match between the 2003 to 2003-filtered pairs is much worse than the 2003 to 2013 pairs. If we ignore the periocular features (eyebrows, eyelids, eyelashes), it would be difficult to make a strong argument on the basis of visual appearance that the original and filtered image have the same iris structure. However, the iris2pi algorithm gives a solid match at 0.066, rather better than the match between the 2003 and 2013 images that are more similar visually. This supports the conjecture that the iris2pi algorithm and the human eye are looking at different image characteristics.

Assuming the conjecture is correct, providing forensic human examiners with access to iris recognition algorithms may lead to better results than can be achieved by examiners or algorithms alone, as has been recently (2018) demonstrated for face recognition [18] .

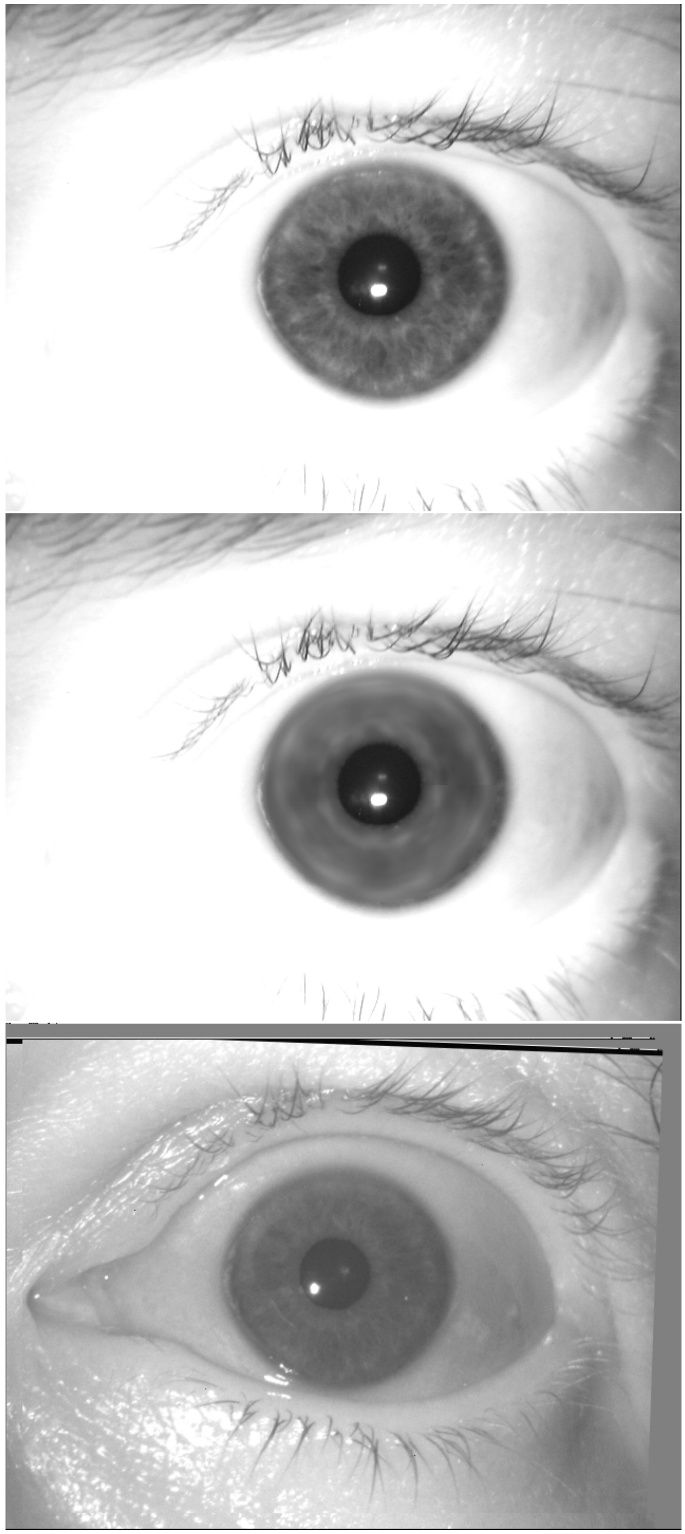

Fig. 4. As discussed in section 4, three images of the same eye: from the top 2003, 2003 with filtered iris texture, 2013. From NIST subject who signed a model release.

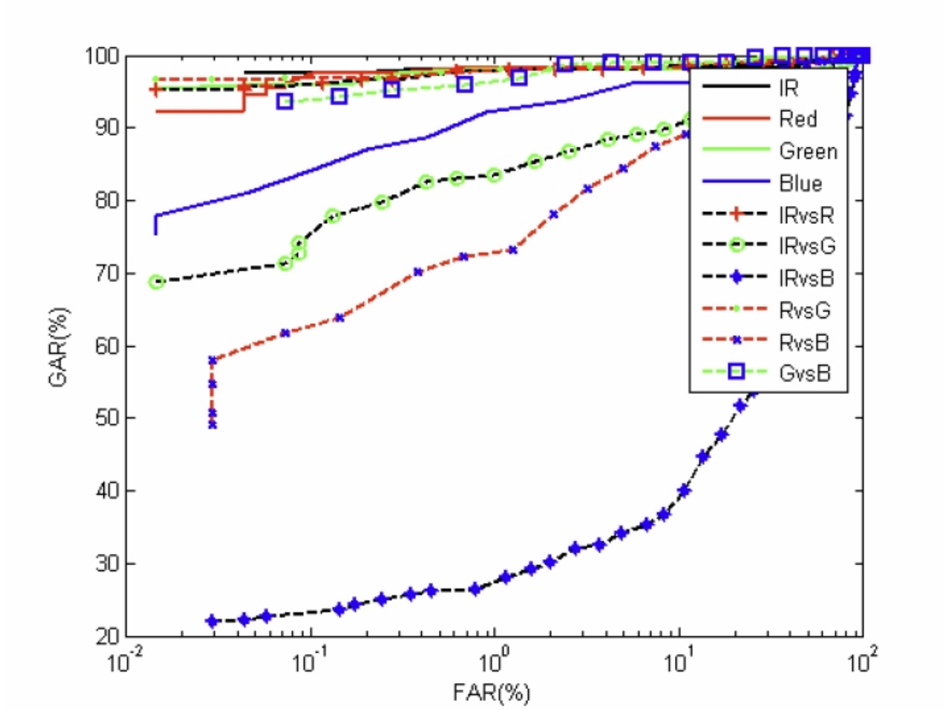

Fig. 5. Reproduction of figure 9 from Boyce [97]. Note that the scales are per cent. Also note that nomenclature has changed since this figure was published. False match rate (FMR) is now used in place of false acceptance rate (FAR). In the text, we use the current nomenclature[119]. Permission for reuse obtained from IEEE through Rightslink/Copyright Clearance Center.

5. Optical Wavelength Effects in Iris Recognition

In sub-section 3.5, we briefly discussed the importance of illumination wavelength. In this section, we cover it in more detail and discuss results from IREX-IX [7, 8].

5.1 History of Optical Wavelength Effects

Iris recognition for image pairs captured using visible wavelength (VIS) illumination, rather than near-infrared (NIR), and between images captured with different wavelength illumination has been a topic of interest since the beginning of iris recognition efforts. The paper by Boyce and colleagues at West Virginia University [97] in 2006 is likely the earliest published discussion of the issues. A key result of the paper is the ROC plot for cross channel matching shown in figure 5.

In that work, at an FMR of 0.001 the GAR's (genuine accept rate, or ~1-FNMR) are well in excess of 0.9 for all except blue-blue (~0.82), NIR-green (~0.74), red-blue (~0.62) and NIR-blue(~0.21).

More recent results have been produced by Proenca's group at the University of Beira Interior [120, 121], the West Virginia University group [100], Jain's group at the University of Michigan [65, 66], and by Ive's group at the US Naval Academy [105]. The work at the US Naval Academy led to data acquisition efforts by the Etter group at Southern Methodist University (SMU) [102, 103, 122, 123]. As mentioned earlier, the SMU dataset is denoted the Consolidated Multispectral Iris Dataset (CMID) [103].

All of these results are in basic agreement – (1) there is information in the iris that is useful for recognition over a range of illumination wavelengths that includes the visible; (2) recognition can be carried out cross wavelength for some fraction of the population; (3) performance is dependent on eye color, the illumination wavelength(s), and the difference between illumination wavelengths.

5.2 Summary of Latest Results from NIST

All currently deployed iris recognition systems operate on images of the iris illuminated in the near-infrared (NIR) band of the electromagnetic spectrum. The ISO/IEC 19794-6:2011 and 29794-6:2015 standards require the eye to be illuminated between ”approximately 700 and 900 nanometers (nm)” [124, 125]. NIR illumination is specified because melanin, the pigment that makes dark eyes dark[31], is nearly transparent in the NIR. This makes the stromal structure of dark brown irides easier to resolve. Operation at still longer wavelengths becomes problematic because fluids bathing the iris are strongly absorbing at wavelengths beyond 1000 nm and silicon-based image sensors lose essentially all sensitivity beyond 1000 nm.

Southern Methodist University provided NIST with the Consolidated Multi-Spectral Iris Dataset (CMID). This data was collected in well-controlled laboratory settings and is ideal for multispectral analysis. It contains iris samples from over 400 subjects, an order of magnitude larger than any dataset used in previous studies. During each capture session, multiple samples of the iris were acquired across a range of wavelengths spanning from the short end of the visible (405 nm) to well into the near infrared (1550 nm). A comprehensive description of the dataset can be found in the IREX-IX reports [7, 8]. NIST tested the accuracy of twelve commercial matchers on the CMID as part of IREX-IX. Previous studies on multispectral iris recognition used only a single iris2pi matcher. In addition, the effects of image resolution were explored.

[31] 70-90% of the world's population have dark brown eyes.

Near-IR Matching: The latest results from NIST show that matching accuracy is dependent on illumination wavelength, even within the standard 700 - 900 nm band. For some iris matchers, error rates (FNMR) vary by more than an order of magnitude depending on whether matching is performed at 700 nm or 910 nm. Nearly every matcher evaluated in IREX-IX performs better on the CMID at 910 nm than at 800 or 700 nm. That said, matching accuracy was only measured at these three discrete wavelengths, which is not enough to precisely locate the ”optimal wavelength” or to determine if this wavelength is consistent across matching algorithms. There may also be some, as yet unexplored, co-variate in the data collection that contributes to the variation.

Visible Wavelength Matching: The visible (VIS) band spans from about 400 (violet) to 700 nm (red) with 620 nm corresponding to an orange-red color. Matching iris samples acquired at visible wavelengths is possible, although the error rates are higher compared to NIR matching. One matcher from Neurotechnology performs significantly better than the others at visible wavelengths. At an FMR of 10^{-4} this matcher produces an FNMR of 0.045 (corresponding to a ”true match rate” of 0.955) at 620 nm when both eyes are used for matching. Matching accuracy tends to be much better at longer wavelengths (700 nm, corresponding to red and near the infrared) end of the visible band. At the shorter end (405 nm, corresponding to a violet color) matching does not appear viable at all.

Effect of Eye Color: Lighter irides – *i.e.* blue, grey, green – generally match better than darker irides – *i.e.* brown, black – at visible wavelengths. However, at standard NIR wavelengths darker irides tend to match better than lighter irides. The reason for the former result is that the melanin pigments in darker irides are obscuring the iris texture. As for the latter result, it is unclear whether this is due to more rigorous algorithm tuning over darker irides (since brown is by far the most common eye color), or whether there is something intrinsic in the features of dark irides that makes them easier to recognize in the NIR. Although lighter irides match better than darker irides at visible wavelengths, overall accuracy for both light and dark eyes is still better in the NIR.

Cross-Wavelength Matching: Matching accuracy tends to be better when both compared iris samples were acquired at the same (or similar) wavelengths. Accuracy is best for most IREX-IX matchers when both samples were acquired at 910 nm. Neurotechnology’s matcher, which performs well on VIS iris samples, can compare VIS samples to each other about as well as it can compare VIS samples to NIR samples. False matches are more common when both samples were acquired at visible wavelengths.

Impact of Wavelength on FMR: Generally, matching accuracy is assessed by quantifying two properties: 1) the ability to recognize that two iris samples represent the same eye, and 2) the ability of the matcher to distinguish when two iris samples represent different eyes. Previous research on multi-spectral iris recognition has focused on the former. IREX-IX investigates both. As Daugman has often noted, a strength of iris recognition over other biometric modalities is its ability to distinguish samples that come from different sources [61, 126, 127]. This is evidenced by the extremely low False Match Rates (FMRs) that iris matchers are able to achieve [108, 128]. Although this is true for conventional (NIR) matching, FMR tends to be much less predictable when comparing visible-wavelength samples. FMR can vary by orders of magnitude depending on the wavelength at which the samples were acquired. Moreover, the variation in FMR is highly matcher-specific. Hence, calibration of systems used for examination and comparison of iris images taken with cameras that do not comply with the ISO/IEC standard 29794-6 [125] may require additional effort.

Comparison to Earlier Research: The results from IREX-IX do not perfectly align with existing literature. Ngo et al. [105] found that the mean SQRT-normalized Hamming distance for mated comparisons [32] is minimized when both compared iris samples were acquired at 800 nm rather than 910 nm. The dataset used by Ngo et al. was small, containing only 6 subjects, and no manual markup of the iris boundaries was provided to the feature extractors. Ives et al. [129] expanded on Ngo et al.'s work and found that when boundary coordinates were not provided, the lowest mean SQRT-normalized Hamming distance was achieved at 910 nm with slightly increased distances at the neighboring wavelengths 810 nm and 970 nm. When boundary coordinates were provided, the mean distance score varied little between 500 and 900 nm with the lowest mean score at 590 nm. This contrasts with the current report which indicates accuracy is highly sensitive to the wavelength at which the samples were acquired. A possible explanation for this apparent discrepancy is that previous studies used the mean SQRT-normalized Hamming Distance while the current study uses FNMR (at a fixed decision threshold or FMR) to assess accuracy. The former statistic is more robust but the latter places greater emphasis on the behavior of the crucial right-tail of the mated distribution. For this reason, FNMR at a fixed FMR for assessing accuracy is used in this analysis.

[32] Daugman [127] recommended a correction factor to take into account the change in the width of the non-mated distribution as the fraction of the iris useful for iris recognition varies due to factors such as specularities and occlusion. This is an important correction for operational systems. It can confuse results in laboratory experiments. Some implementations of iris2pi have an option to turn this off; some do not. For algorithms used in IREX-IX, the use of such normalization is an unknown.

6. Demonstration of Iris Recognition on Images from the Wild

In section 1, we noted that there are images ”in the wild” that might have value in a forensic analysis. In this section we provide an example of such analysis. We note that Daugman's work on the identification of the "Afghan girl" in 2002[33] is an early example of confirming an identity using iris recognition on images that were not taken for the purpose of iris recognition. In that case, the analysis was performed on high quality, high resolution, original images provided by the photographer, Steve McCurry.

Figure 6 shows a pair of head shots of a popular child actor taken some years apart. The periocular regions of both images were extracted, interpolated to 640x480 images and converted to gray scale using a conventional RGB to luma conversion formula $(0.11B + 0.59G + 0.3R)$. The resulting iris images were compared using a commercial implementation of iris2pi. The right iris images match score was 0.268, with 675 of a possible 2048 bits used[34] in the hamming distance calculation. This corresponds to a match score of 0.300 if Daugman SQRT-normalization [127] is applied. Using match score vs. false match rate data from Daugman [9], the probability of a non-mated score being this low is about $1:10^7$ – assuming no systematic errors as the result of capture or processing of the images. The possibility of systematic errors needs to be explored in more detail; an example of systematic error are Purkinji images, or specular reflections of the scene in front of the subject at the instant of capture. The characteristics of such reflections can be much less random than the structure of the iris – e.g., reflections caused by light streaming through a venetian blind.

These results should be regarded as an anecdotal examples rather than research conclusions – but suggest that research on this type of imagery exploring both face and iris recognition is warranted. Issues to consider include:

- Images from the wild have varying pose, illumination, expression and resolution.
- The richness of facial detail varies across demographics including age and ancestry/bio-geographical origin.
- Facial details change with time.

As another example of iris recognition on "in the wild" images, Matey et al. [130] recently demonstrated iris recognition on iris images extracted from the gray scale pho-

[33] See https://www.cl.cam.ac.uk/~jgd1000/afghan.html for details. See https://www.nationalgeographic.com/magazine/2002/04/afghan-girl-revealed/ for the National Geographic article.

[34] The bits used are those which are deemed good by the algorithm in both the templates derived from the two images.

Fig. 6. Example of two images (left, right) from the Internet on which iris recognition is successful. The images are of the same person captured some years apart. The dates for the images are not certain. The best available information is 2004 and 2011; from on-line biographies of the subject, the subject would be approximately 6 years of age in the early image and 13 in the later image. The image sizes in pixels are 600x797 and 1200x1680 respectively. The interpupillary distances are approximately 180 and 410 pixels respectively. Using a commercial iris2pi algorithm the right eyes match score (fractional Hamming distance, a dissimilarity score) is 0.268 with 675 of 2048 bits set in the mask. As explained in the text, a value this low in unlikely for a non-mated pair. These particular images were used because the licensing for the images permitted inclusion in this report. These images were found at
left: https://www.listal.com/viewimage/1753385.
right: https://commons.wikimedia.org/wiki/File:2011_Chandler_008_5x7.jpg
Licenses: https://www.listal.com/help/tos and https://creativecommons.org/licenses/by/3.0/deed.en.

tographs taken over a period of 40 years by Nicholas Nixon for his Brown Sisters project [131].

In a related vein, Schuckers' research team at Clarkson University published the first (to our knowledge) longitudinal study of iris recognition in children [132] and expanded on that work in 2020 [133, 134] and 2021 [135]. Their results suggest that the iris is stable from at least the age of four, supporting the work reported here on figure 6. Schuckers' work is ongoing and is worth continued attention, though the images used in those studies were collected under near laboratory rather than under the "in the wild" conditions of interest for many forensic applications.

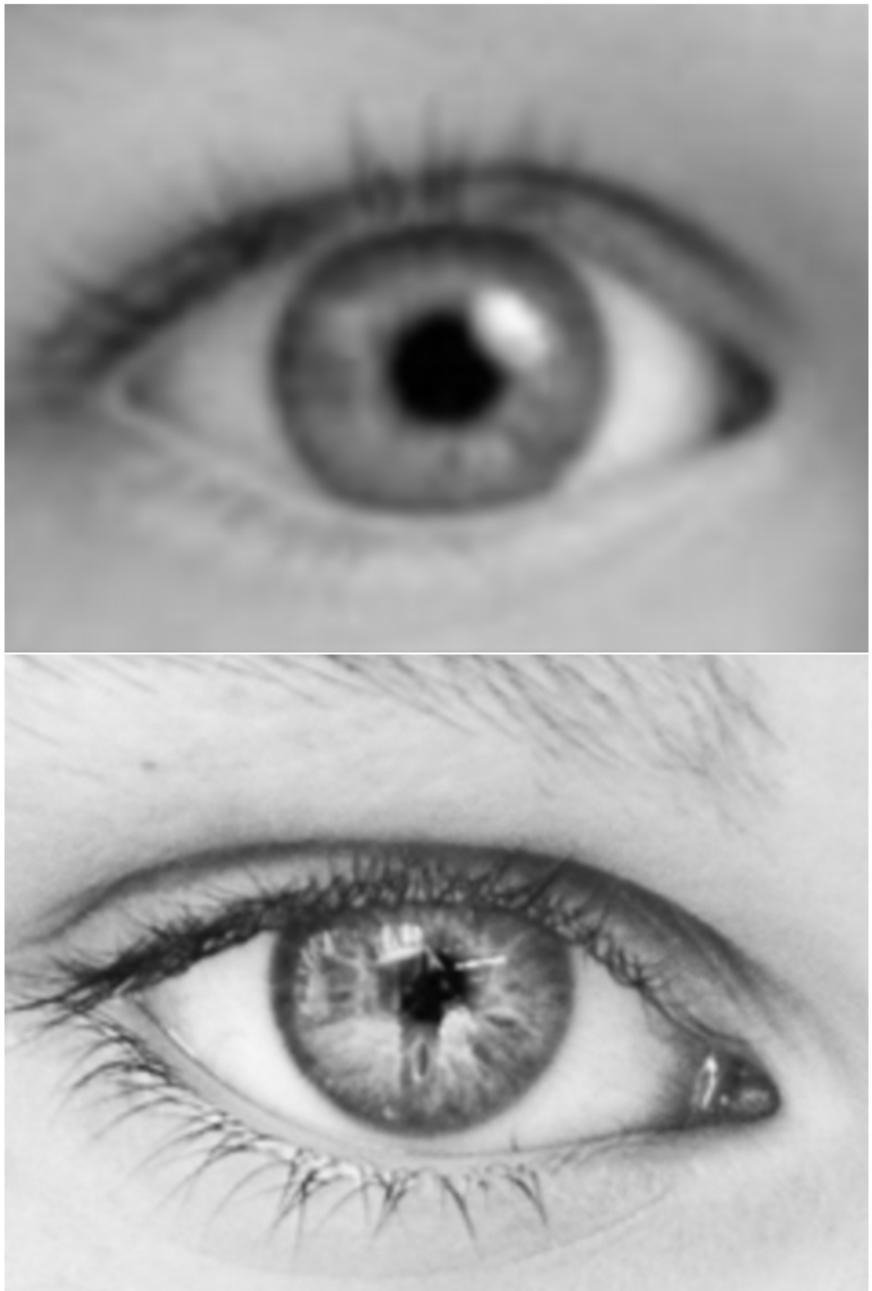

Fig. 7. Extracted right iris images from figure 6 The extraction locations were upper image(0158,0341,0104,0078), lower image (0233,0305,0237,0178); (ul-x, ul-y, w, h). The iris width in pixels in the original images were approximately 40 and 80 pixels respectively.

7. Effect of Image Resolution on Matching

Forensic iris is expected to sometimes involve images acquired in unconstrained environments where the resolution of the image could not be controlled. The images pulled from the internet in Section 6 are good examples. For optimal performance ISO/IEC 19794-6:2011 recommends a spatial sampling rate of no less than 10 pixels/mm and a Modulation Transfer Function (MTF) resolution of no less than 0.6 at 2 cycles/mm. An earlier version of the standard recommended 20 pixels/mm and a Modulation Transfer Function (MTF) resolution of no less than 0.6 at 4 cycles/mm [136]. Matey et al. [111, 115, 137] and Ackerman [116, 138] demonstrated that the Iris on the Move® applications could operate successfully at 10 pixels/mm. Typical commercial iris cameras such as the IrisAccess 4000 series [139] produce images with ≈200 pixels across the nominally 10 mm wide iris in accord with the earlier recommendations of 20 pixels/mm. The examples from Section 6 have iris radii of 20 and 40 pixels corresponding to approximately 2 and 4 pixels/mm respectively.

To date there has been little published research on the impact of image resolution on the accuracy of iris recognition. As of this writing, NIST is actively studying the problem as part of its IREX program; initial results were published in part two of the IREX-IX report [8]. What follows is a summary of those results.

A sufficiently large database of low-resolution iris samples was not available to NIST. Hence, images from the previously mentioned CMID dataset were decimated to simulate low-resolution acquisitions. Analysis was further limited to VIS iris samples because it is expected to be the most common use-case. NIST found that the ability of matchers to recognize that two samples represent the *same* iris remains stable until the radius of the iris is reduced to about 20 pixels (≈ 2 pixels/mm). However, the ability of matchers to distinguish that two samples represent *different* irides begins to deteriorate much earlier, at radii of 64 pixels (≈ 6.4 pixels/mm). No single matcher yields the best accuracy across all resolutions. Neurotechnology's IREX-IX submission achieves the best accuracy at higher resolutions while Tafirt's and IrisID's submissions achieve the best accuracy at lower resolutions. The latter two matchers are capable of correctly matching the iris more than half the time when the radius of the iris is only 8 pixels (≈ 0.8 pixels/mm). When low-resolution iris samples are compared, it appears to be the lower resolution of the two that dictates matching accuracy.

8. Technical Background for Explanation of Machine-Based Iris Recognition to the Lay Public

The intent of this section is to outline an explanation of machine-based iris recognition that could be used by an iris image examiner in preparing an explanation of matching decisions that would be understandable by a member of the lay public.

8.1 Background

In biometric identification, physical, biological, or behavioral[35] characteristics of a person are used to identify an individual. DNA, face images, fingerprint images, and iris images are all currently employed for biometric identification. According to Jain [140] the key requirements for a biometric are, ideally:

1. Universality: each person should have the characteristic.
2. Distinctiveness: any two persons should be sufficiently different in terms of the characteristic to distinguish them.
3. Permanence: the characteristic should be sufficiently invariant/stable over relevant periods of time.
4. Collectability: the characteristic can be measured/collected quantitatively.

Biometrics vary in the degree to which they fulfill these requirements. For example, (1) people lacking hands also lack fingerprints, (2) identical twins start life with identical DNA, (3) the face portrait of a newborn may have little resemblance to a portrait of the same person at age 50, and (4) iris images can, in some circumstances, be difficult to collect. The issue is whether a particular biometric fulfills the requirements sufficiently to be useful in particular use cases. There is general consensus [140] that DNA, fingerprint, face, and iris recognition fulfill the requirements well enough to be useful in many use cases.

8.2 What is the iris?

The human iris is the colored, donut shaped tissue surrounding the pupil of the human eye, illustrated in the following figures.

[35] Behavioral examples include gait, keystroke dynamics, voice and signature.

- Figure 1, a front/anterior view of an iris under normal visible light.
- Figure 8, an artist's sketch showing the interior of the eye and the relationship of the iris to other components.
- Figure 9, an annotated front/anterior image of an iris.
- Figure 10, an artist's sketch of the iris in cross-section.

The purpose of the iris and pupil is to control the amount of light reaching the interior of the eye. In brightly lit conditions, the pupil constricts, becoming smaller in diameter which decreases the amount of light going into the eye. In dark conditions, the pupil dilates, becoming larger in diameter which increases the amount of light going into the eye. The iris on a camera takes its name from the iris of the eye and performs a similar function.

The iris can be divided into 4 layers [36]: (1)the anterior (front) border layer, (2) the stroma, (3) the dilator muscle layer, and (4)the posterior (rear) epithelium. The anterior border layer is a layer of cells that separates the iris from the front-most region of the eye; it may or may not have pigmented cells that contribute to the eye color. The stroma consists largely of radial tissue structures that include fiber, blood vessels, and nerves. The dilator muscle is the muscle responsible for enlarging the pupil by pulling radially on the edge of the pupil. There is also a circular sphincter muscle at the pupil-iris border that are responsible for closing the iris. The posterior epithelium is a layer of highly pigmented tissue that is like a piece of black paper – it blocks any light that gets through the stroma from reaching the interior of the eye.

The primary pigments in the iris are melanins, the same pigments that give rise to differences in skin color and to suntan; the color of the iris depends on the quantity, type and distribution of cells pigmented with melanins. When there is little pigmentation, the eye color is pale blue, with the blue color being generated by scattering effects similar to those that make the sky blue.

[36] There are alternative divisions.

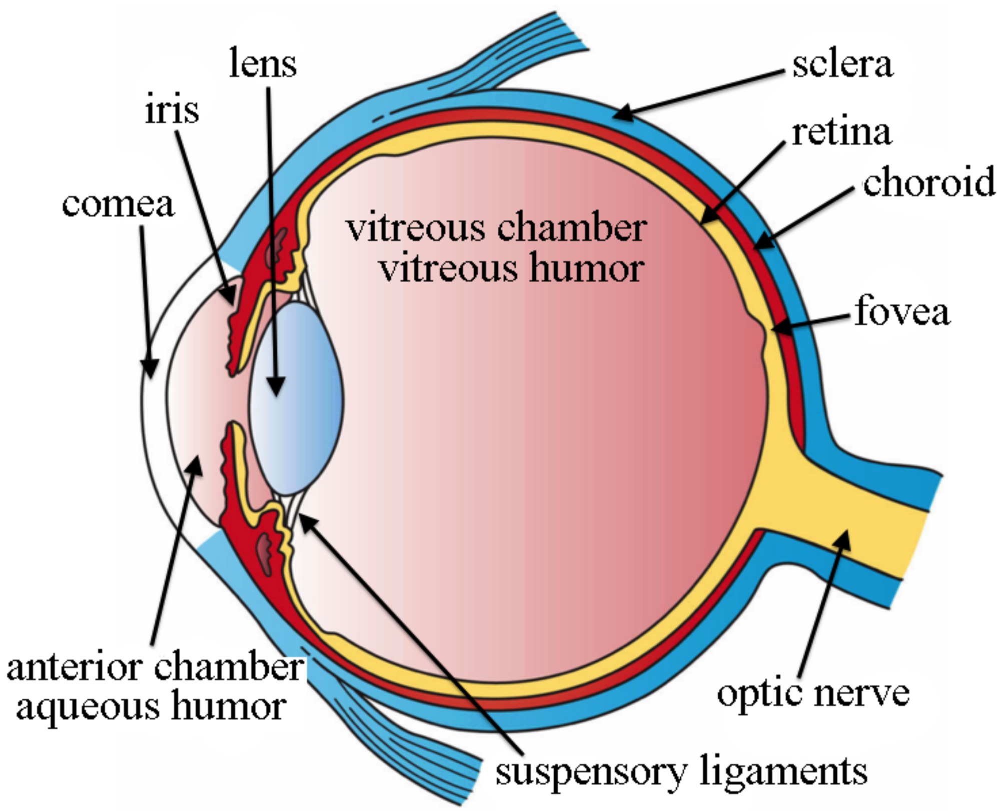

Fig. 8. Schematic view of human eye. Note: the iris is just below the cornea surface on the left and visible through the cornea; the retina is on an internal surface that is only visible by looking through the pupil [141]. License: urlhttps://creativecommons.org/licenses/by/3.0

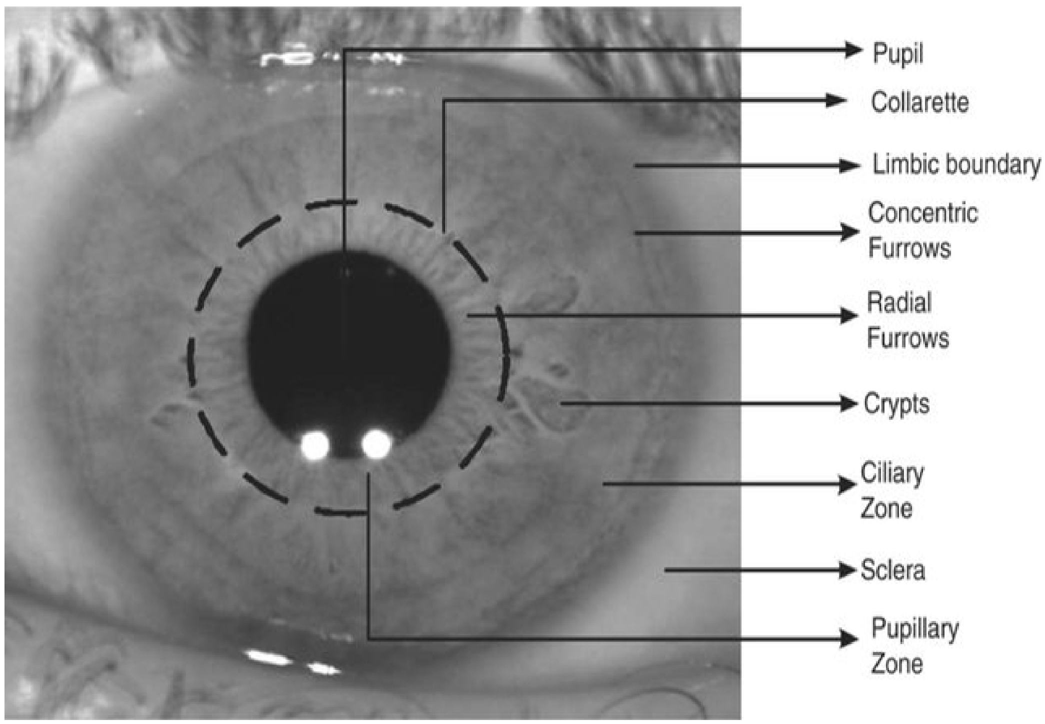

Fig. 9. Anterior view of human eye with annotations relevant to iris recognition; reproduction of figure 2 from Shah [142]. Permission for reuse obtained from IEEE through Rightslink/Copyright Clearance Center.

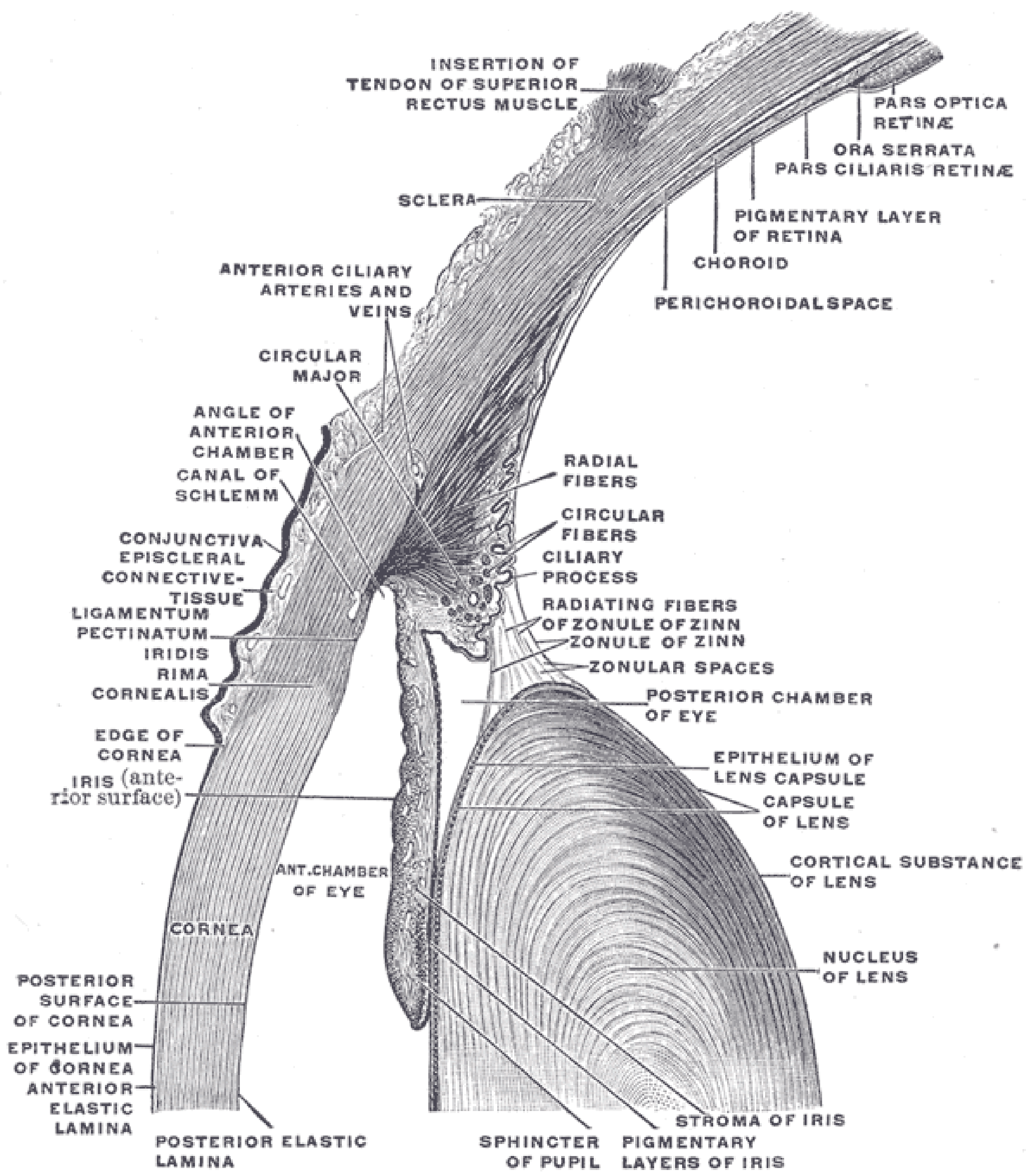

Fig. 10. Cross section sketch of human iris from Gray's Anatomy, figure 883 [143]. This shows the relationship of the iris to the cornea and lens. Copyright expired on original 1918 book. An online version of the book may be found at https://www.bartleby.com/107/226.html.

8.3 What makes the iris useful as a biometric?

Figure 11 is an image of two irides from the same person, making them genetically identical. In figure 12 the two irides are magnified to reveal details of the iris structure. The gross structure of the two irides are similar – these similarities are genetic[144] :

1. Both images have an approximately circular pupil.
2. The pupils are approximately the same diameter under similar lighting conditions.
3. Both images have an approximately circular iris.
4. The irides are approximately the same diameter.
5. The irides are similarly colored.
6. The overall texture of the irides are similar: radial structures, existence of crypts, furrows, etc.

However, the detailed structure is quite different. For example (using clock face measures of angle):

1. The lower eye has a small dark spot just outside the pupil at about 0830[37] that is not seen in the upper eye.
2. The upper eye has a white arc at the edge of the iris at about 0300 that is not seen in the lower eye.
3. The lower eye has a group of crypts (pot hole like details) about halfway between the pupil and the sclera (white of eye) at about 0100 to 0230 that are not seen in the upper eye.
4. The upper eye has a pair of darker colored crypts about halfway between the pupil and the sclera at about 0530.

Careful examination of the images shows other features that are different between the two eyes.

The detailed structure seen in the iris is due to the same types of random influences during fetal development [145–147] that result in the detailed structure of friction ridges (fingerprints, palmprints, ...) [148].

[37] We use this notation to indicate angle as would be indicated by the hour hand of a clock. 1200 is pointing up vertically; 0300 is pointing horizontally to the right. Similarly for 0600 and other “times”.

Figure 13 shows two images of the same eye taken 6 months apart. Careful examination shows that essentially all of the fine detail in the structure of the iris reproduces between these two images. This is consistent with the results of IREX-VI, Temporal Stability of Iris Recognition Accuracy [30, 31], which found that the features of the iris remain relatively stable over a period of years (barring injury or disease).

The key points here are that

1. there is a lot of fine, detailed structure in the iris.
2. that detailed structure is stable over time.
3. that detailed structure is distinctive – varying from eye to eye, even when the eyes are genetically identical, similar to the way different fingers from the same individual have different friction ridge structures.

The reader can examine their own eyes in a mirror or the eyes of someone else to see these effects, albeit in visible light only.

Referring back to the work by Hollingsworth and others at Notre Dame cited in section 3.1, it is important to remember that there is evidence for larger scale visible features that are genetically linked [57–60]

Fig. 11. Binocular color image. Note that the iris details of the two eyes are different, though the eyes have identical DNA. [This image provided by NIST staff member who has signed a model release.]

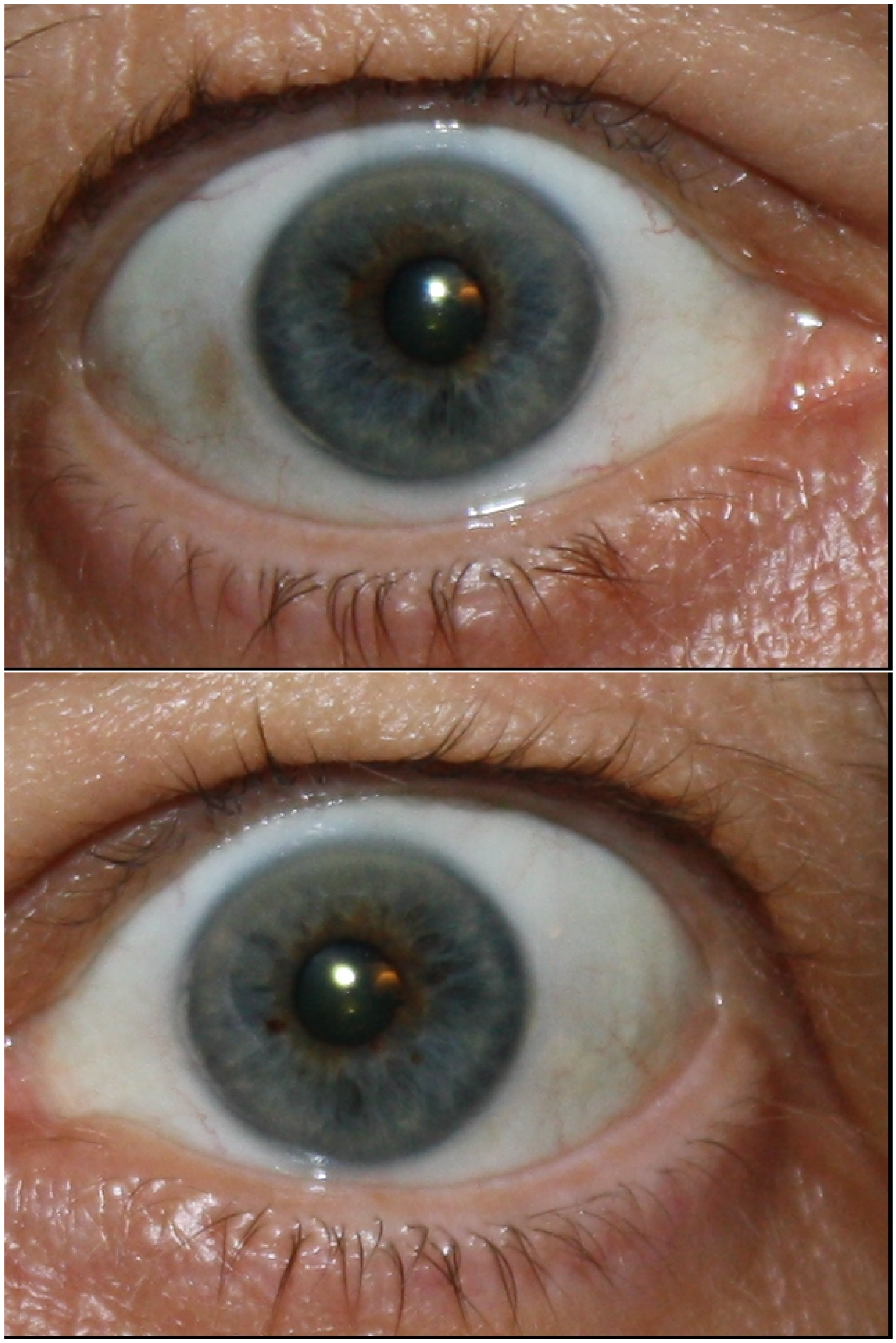

Fig. 12. Left and right iris extracted from figure 11 and shown zoomed in. Note that the detailed structure of these two irides are different, though the eyes are genetically identical.

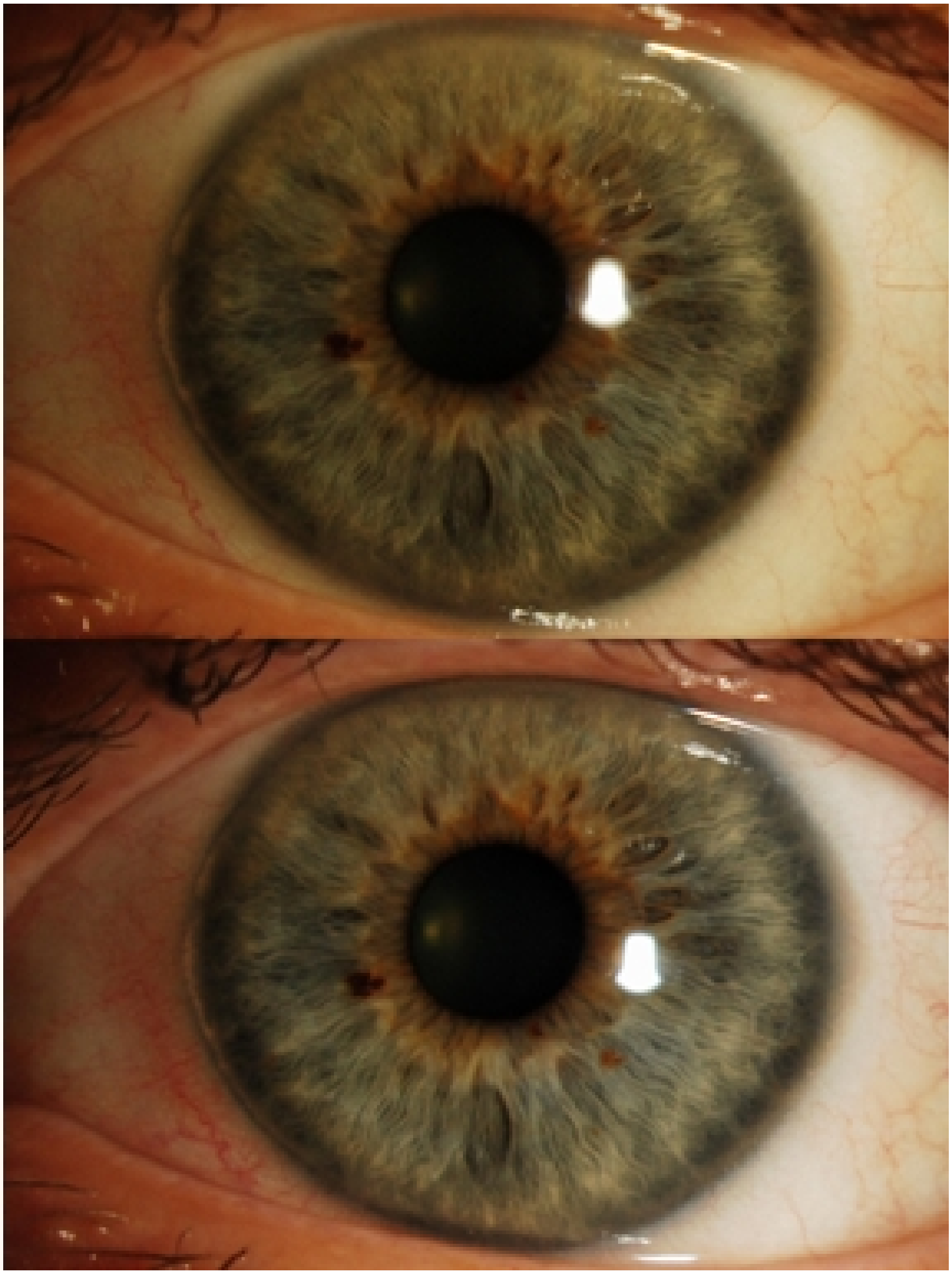

Fig. 13. Two images of one eye taken six months apart. This is the left eye from figure 11 at higher zoom, taken with a different camera. The difference in apparent color is due to the difference in illumination – color temperature.

8.4 Explanation of Matching

To the best of our knowledge, as of June 2022 iris recognition evidence has yet to be utilized in the court room. Iris recognition evidence, in this respect, is approximately where DNA evidence was prior to the 1987 court cases of Colin Pitchfork in England [149] and Tommie Lee Andrews in Florida [150]. The history of the use of DNA in judicial proceedings may provide guidance for adoption of forensic iris. Jain and Ross began a discussion of of these issues for multiple biometric modalities in their 2015 paper [151], but much remains to be done.

The dominant iris recognition algorithm family is iris2pi, based on the seminal work of Daugman [25, 126]. Though the internals of the algorithm require advanced mathematics for their efficient implementation, iris2pi can be explained to members of the public; we offer an example explanation below.

8.5 Iris2pi Explanation

This section contains an explanation of iris2pi that one of the authors has presented with good effect to lay audiences. It draws heavily on the papers of John Daugman [14, 15, 61, 127, 152, 153], the iris recognition patent literature [154] and papers by others [155–158].

As we look carefully at the textures of the left and right irides in figures 11 and 12, we note that although the DNA for the two eyes is identical (they are, after all, from the same person), the details of the iris structures are different. There are similarities on a large scale: both eyes have pupils, irides, and sclera; both eyes are the same color. These traits are all expressions of the person's DNA. The circular to oval "openings" in the iris structure are called crypts. The density (number of crypts per eye) and the crypt size distribution are genetically related as are some other large scale features [57], though the details are not [126] . The fine, largely radial structures and the detailed placement of crypts are the result of random processes that occur during gestation [61]; the same type of processes give rise to the unique ridge patterns on our finger-tips. In the same sense that fingerprints are unique, irides are also unique.

You can easily repeat these observations on a small scale on your own eyes in a mirror or on a person standing in front of you, albeit only in visible light and with lighter colored irides; seeing the details in dark irides requires use of NIR illumination and a camera that is sensitive to NIR.

These observations date back to the 1880's – Alphonse Bertillon [24] suggested that the details of the iris could be a means for identification. Others, e.g., Frank Burch (1936) [61], made the same suggestion over the years, but a satisfactory means for collecting iris images and comparing the images was not developed until the 1990's – the iris2pi algorithm mentioned above. This was in large part because the comparisons of a large number of fine details were difficult to implement before the advent of computers and image processing programs.

Though the detailed technical description of the internal workings of iris2pi makes use of advanced math concepts such as complex exponentials, dot products, transforms, kernels and binomial distributions, the basic workings of the algorithm can be understood in terms of the behavior of donuts, rubber bands, ripples on a pond, and coin tosses.

The first step in preparing an iris image for iris recognition is called segmentation – a fancy word for marking (1) the boundary between the pupil (the dark region at the center of the eye) and the iris (the colored part of the eye that we have been talking about and (2) the boundary between the iris and the sclera (the white of the eye). An example is shown in figure 14. Note that the image has been converted from color to grayscale.

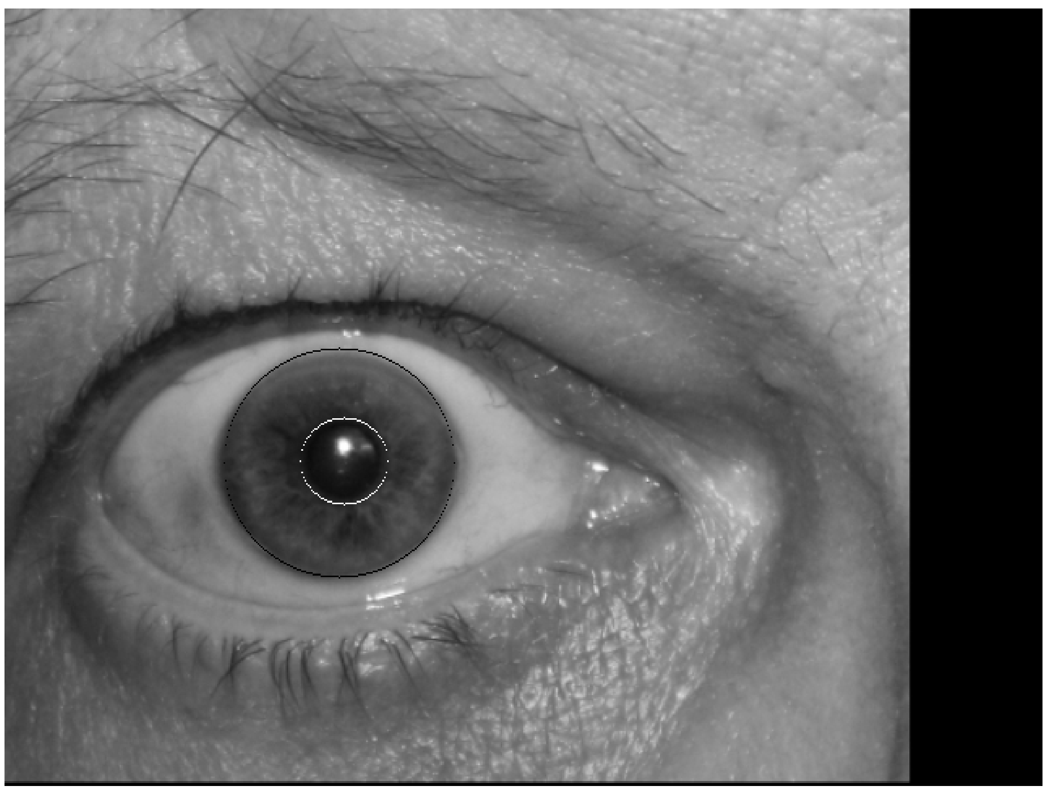

Fig. 14. The image from the right eye in figure 11, converted to gray scale, with the pupil/iris and iris/sclera boundaries marked.

We all know that the pupil can constrict (contract) and dilate (expand). When the pupil does this, the tissue of the iris expands and contracts much like rubber bands stretched between two concentric hoops as with the spokes of a bicycle wheel. If the inner hoop changes diameter, the bands will stretch or contract. We can also think of it as similar to the surface of a balloon as it is blown up. If we drew a pattern on the rubber bands or on the balloon surface, when the bands or balloon are stretched, the pattern would also stretch. We see such stretching of the patterns in the iris as the pupil constricts and contracts. The science of elastic materials gives us a model for how such patterns will change, commonly called the rubber sheet model. While not a perfect model[38] of how the patterns stretch, it is a very good model for modest amounts of stretch. We can use the rubber sheet model to adjust iris images at different levels of pupil dilation to a common dilation to make comparisons easier.

To use the rubber sheet model, we pop the annular (donut shaped) iris out of the image. We then slit the donut from pupil edge to scleral edge at 0300[39]; the exact position is not important so long as we are consistent. We then grab the two edges of the slit and stretch the annulus into a rectangle with the slit edges on the sides – the pupil boundary on the top and the limbus boundary on the bottom – as seen in figure 15. Top to bottom is now pupil to sclera and left to right is clockwise around the iris. After this treatment, every iris will have its pupil boundary on the top edge of the image and its limbus boundary along the bottom of the image.

If we take figure 15 and render it in three-dimensions with the height corresponding to the brightness of each pixel we get the result in figure 16. The result resembles a snapshot of the ripples on a pond due to a handful of pebbles thrown into the water. Note that much of the texture runs pupil to sclera – as expected from the radial nature of the structure in the original image. We note that the pixel brightness is not a direct measure of height – pixel brightness depends on illumination angle and multiple scattering of the incoming light. We represent the brightness as height to aid in visualization of the data.

These ripples may be thought of as a two-dimensional bar code for the iris. There are many ways to characterize/summarize/compare the ripples. One, which is equivalent to that used in iris2pi, is to ask these questions at each of a number of specific locations on the snapshot:

- The nearest peak is to the left, True/False?
- The nearest trough is closer than the nearest peak, True/False?

Experimentally, if we make a table of the results of the peak/trough questions at multiple positions for many irides, we find that half of the results are True and half are False –

[38] At large dilations the iris tissue can fold over; the rubber sheet model does not take such folding into account.

[39] We use this notation to indicate angle as would be indicated by the hour hand of a clock. 1200 is pointing up vertically; 0300 is pointing horizontally to the right. Similarly for 0600 and other “times”.

Fig. 15. The iris from figure 14, extracted from the image, cut along 03:00 and stretched to a rectangle. The upper edge is the pupil/iris boundary; the lower edge is the iris/sclera boundary; horizontal lines (left to right) correspond to circles (clockwise) around the pupil. This image is 640x480; it has been intentionally oversampled.

as we would expect for textures generated from random processes. This is the same type of randomness we find in the flips of a fair coin, tossed many times – half the flips are heads, half are tails.

Here is a thought experiment. Take two quarters, give one to friend A and one to friend B, then have them play this game: A flips their coin, then B flips theirs. If the coins match (heads/tails), B wins; if not, B loses. If they play this game multiple times, we expect that B will win 50% of the time. If B wins 90% of the time, we suspect that something is wrong. Using statistics, we can show that if they play the game 10 times and B wins 9 times, the likelihood of that happening by chance are about 1%. If they play the game 20 times and B wins 18 times, the likelihood of that happening by chance are down to about 0.02%. If the likelihood of the outcome is low, we can infer that B is not really flipping the coin every time – B is just matching whatever A flipped.

This thought experiment is the basis for a critical insight by Daugman. If we make tables of the peak/trough questions for two different iris images (A and B) and use the

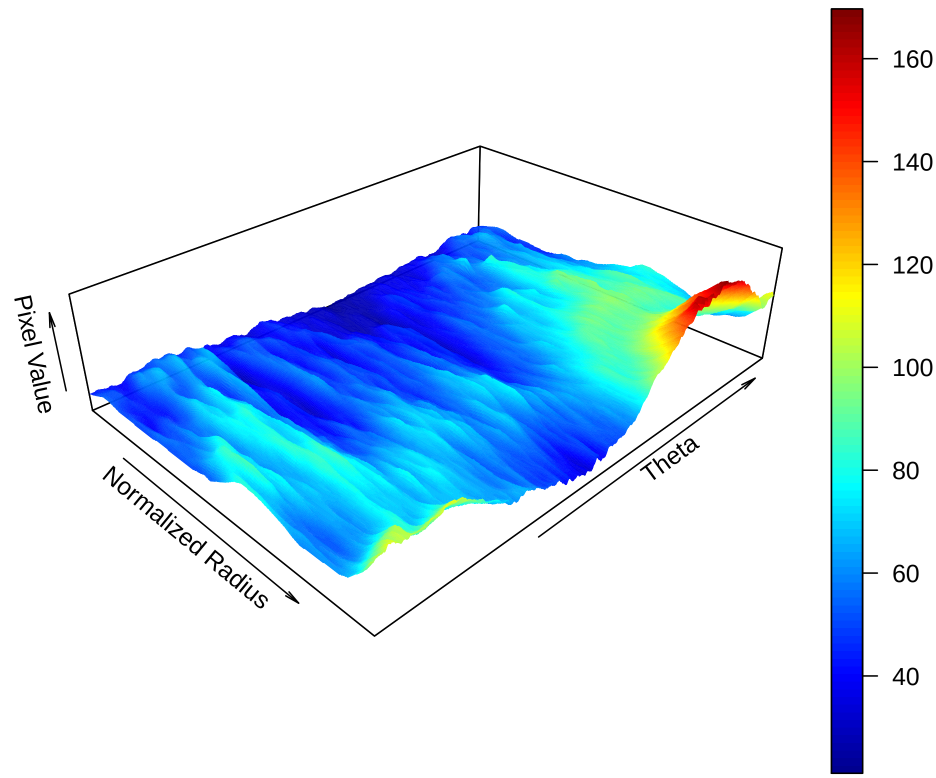

Fig. 16. Figure 15 replotted in 3D with the height and color corresponding to pixel value. We can imagine this as a snapshot of ripples on pond that were caused by tossing a handful of pebbles in the water. Note that pixel value does not correspond to the "height" of any iris feature. The bump in the lower right corner is due to uneven illumination of the eye and to a small departure from iris circularity – the sclera intrudes – as can be seen in figure 14 around 1200.

answers True/False rather than heads/tails to play the game between the two iris images, we would expect that the B iris should "win" 50% of the time. Daugman's great insight was that if B's answers match A's significantly more often than chance would dictate, the B image is not an image of a random iris, it is another image of iris A. The likelihood that we make a mistake in identifying A and B as coming from the same iris is just the likelihood that the B answers would match the A answers by chance.

In working iris2pi systems, on the basis of measurements on large numbers of iris images, we have the equivalent of about 250 coin flips. Using statistics, we can compute that getting 65% agreement (or equivalently 35% disagreement) between the answers will occur about 1 time in a million, by chance.

This description/discussion has some simplifications built in. In practice some steps are combined using advanced math methods. We've left out dealing with parts of the iris being obscured by eyelids, eyelashes, or bright reflections off the eye (e.g., the bump in figure 16) and we've not taken into account the possibility that the image was acquired with the head tilted or even upside down. Those can all be dealt with using the sort of image processing techniques that are commonly available in the software that commonly comes with a digital camera.

In deployed systems, iris recognition works very well. Three examples, of many, are (1) NEXUS: a US-Canadian border control system [39]; the UAE expellee program [41] (another border control application) which is one of the longest running deployments; and (3) Unique ID Authority India [42], which is the largest application in the world. UIDAI has enrolled over 1 billion people (iris and fingerprint) and is using iris recognition for financial transactions and distribution of social services.

NIST IREX-IX [7] assessed the performance of several state-of-the-art iris recognition algorithms over field-collected iris data. The most accurate matcher was able to achieve an FNIR (False Negative Identification Rate) of 0.0067 (about 1 in 150) at an FPIR (False Positive Identification Rate) of 10^{-3} (1 in 1000) when searching against an enrolled population of $160,000$ people.

8.6 Interpreting Comparison (Match) Scores

In the latest version of the ISO/IEC 2382-37 standard, Information Technology Vocabulary, Biometrics [119][40] the term *match score* is deprecated in favor of the term *comparison score*. Comparison score is defined as the numerical value resulting from a comparison of two images; the score may be a measure of similarity or dissimilarity.

The scale for comparison scores for a biometric algorithm can be arbitrary. The only constraint is that for similarity scores, higher values mean higher similarity and for dissimilarity scores higher values mean lower similarity between the compared images. Direct interpretation of comparison scores is not intuitive. For a given algorithm the interpretation can be made more intuitive by calibrating the match scores using results from a large, sequestered evaluation of the algorithm that generates a plot of false match rate (FMR) vs comparison score. This requires a large number of distinct subjects in the evaluation to get good statistics at low false match rates. Use of sequestered data ensures that the algorithm developer has not "tuned" the algorithm to the data. For iris algorithms, the NIST IREX program[41] provides FMR vs match score results on sequestered data [7, 108]; some algorithm vendors provide FMR vs match score tables as part of their documentation.

Using such results, an FMR corresponding to a match score can be looked up and used as a calibrated match score. The calibrated match score indicates the probability that a comparison score could occur by chance for two images that are not from the same iris and that have not been subject to some systematic error. An example of systematic error, noted earlier, would be the presence of a patterned specular reflection in both images.

Using a comparison score that is calibrated to FMR enables comparisons across algorithms and provides an intuitive interpretation of the score.

9. Statistics of Visible Iris Features

The NAS and PCAST reports[5, 6] suggest that to firmly ground human examination/comparison of image pairs, it is necessary to understand the statistics of the type of features that are used for correspondences between the images. In 2016, Edwards et al. [159] published an analysis of iris features that is the most comprehensive analysis that we are aware of.

In their introduction they state:

> Considerable research has been devoted to iris pigmentation variation. How-

[40] Available without charge at https://www.iso.org/standard/66693.html
[41] https://www.nist.gov/programs-projects/iris-exchange-irex-overview

> ever, very few studies have attempted to look at global variation in iris surface features. Although the functional consequences of these features remain largely unknown, they have become a topic of significant forensic, biomedical and ophthalmological interest.

Figures 17 and 18 summarize their results. These results could be used to construct a statistical model that provides an estimate of the probability that two iris images would have equivalent features in corresponding quadrants by random chance. If data were available on a finer scale, perhaps octants rather than quadrants, and included feature size, the model would have more power.

It would be useful to construct a model based on the available data and test it with datasets available to the NIST IREX program. The results of such a study could guide collection of additional data.

In designing the model, its tests, and collection of additional data, we would need to consider whether we are interested in color images, NIR images, or some combination.

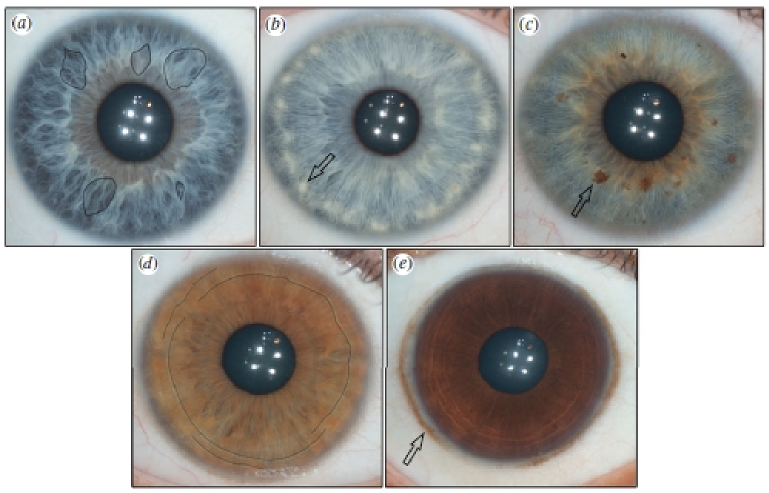

Figure 1. The five features found most commonly in the human iris. The arrows are pointing to the features in images b, c and e. Fuchs' crypts (*a*) are lacunae in the anterior border of the iris which arise during resorption of the pupillary membrane. They may be either large or small and closely resemble windows. Four sample crypts are outlined in the image above. Wolfflin nodules (*b*) are small bundles of collagen that are the consequence of atrophy in the stromal layer of the iris. Pigment spots (*c*) are discrete areas of pigmentation that can be observed on the surface of the iris. Spots that distort the stromal layer are referred to as nevi and spots that do not distort the stromal layer are referred to as freckles. Contraction furrows (*d*) are rings that extend around the outer border of the iris. They closely resemble wrinkles and are the product of the contraction and dilation of the pupil. Furrows are typically discontinuous and staggered across the iris. In the above image, the black line follows the path of the furrows around the eye. Conjunctival melanosis (*e*) is spotting that can be observed on the scleral region surrounding the iris. It is usually benign, and is found more commonly in some ancestries than in others.

Fig. 17. Reproduction of figure 1 from Edwards et al. [159]. The figure shows the 5 most common features of the human iris. The paper was published under the terms of the Creative Commons Attribution License http://creativecommons.org/licenses/by/4.0/, which permits unrestricted use, provided the original author and source are credited.)

Table 4. The percentage (and number) of irises with large crypts, contraction furrows, pigment spots and Wolfflin nodules in each of the four quadrants of the iris.

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trait	population	quadrant 1	quadrant 2	quadrant 3	quadrant 4
large crypts	East Asian	10.9% (51)	15.8% (74)	14.3% (67)	18.4% (86)
	European	31.5% (195)	35.5% (220)	25.8% (160)	29.2% (181)
	South Asian	23.6% (86)	29.9% (109)	22.5% (82)	22.3% (81)
furrows	East Asian	26.8% (125)	70.4% (329)	82.4% (385)	61.0% (285)
	European	82.1% (508)	84.8% (525)	89.2% (552)	84.3% (522)
	South Asian	70.6% (257)	91.2% (332)	95.1% (346)	84.1% (306)
pigment spots	East Asian	2.8% (13)	5.1% (24)	10.3% (48)	8.1% (38)
	European	17.3% (107)	18.6% (115)	31.7% (196)	31.2% (193)
	South Asian	2.7% (10)	4.9% (18)	6.3% (23)	6.6% (24)
nodules	East Asian	0% (0)	0% (0)	0% (0)	0% (0)
	European	23.7% (147)	28.6% (177)	34.9% (216)	31.2% (193)
	South Asian	0.8% (3)	1.1% (4)	1.4% (5)	1.4% (5)

Fig. 18. Reproduction of table 4 from Edwards et al. [159]. The table shows the statistics of four iris features as a function of ethnicity and quadrant within the eye. The paper was published under the terms of the Creative Commons Attribution License http://creativecommons.org/licenses/by/4.0/, which permits unrestricted use, provided the original author and source are credited.)

10. Disease, Illness and Injury

Going back to Bertillon [24] and persisting through Daugman's papers, anecdotal evidence suggested that in the absence of disease, illness or injury, the structure visible in the human iris persists over time. In the past decade, that conjecture was put to the test. Despite some preliminary findings to the contrary [160–162] , there is strong evidence that the details of the iris that are used in current iris recognition algorithms persist over time [30, 31, 132–134, 163].

The caveat here is *in the absence of disease, illness, or injury*. Disease, illness, or injury can make temporary or permanent changes to the appearance of the human iris. The degree of change can range from nil, in some cases of allergy induced red-eye[42], to destruction of large extents of the iris, in the case of progressive essential iris atrophy [43].

The published literature on this topic is not extensive, as noted in the selected references listed below.

- In 2009 Borgen et al. [164] conducted one of the first investigations into the effect of disease, illness, and injury on iris (and retina) recognition using simulations of the pathologies.
- In 2014,Trokielewicz et al. [165] examined the impact of cataract surgery on iris recognition.
- In 2017,Trokielewicz et al. [166] expanded on their previous efforts, presenting, in their words, "the most comprehensive study of what we can expect when iris recognition is employed for diseased eyes."

All three of these studies showed that, as expected, disease, illness, or injury, including surgical trauma, can adversely affect iris recognition.

At this time (2022), the literature does not provide us with the tools to quantify the impact of disease, illness, and injury on forensic iris recognition. Exploration of the ocular pathologies that have been identified by the ophthalmological community, e.g., Clinical Eye Atlas [167] or the online Atlas of Opthalmology[44] is warranted. That exploration should include examination of the prevalence of the various pathologies and how the prevalence varies with age, sex, ethnicity, and occupation.

[42] https://www.emedicinehealth.com/image-gallery/eye_allergies_picture/images.htm

[43] https://www.atlasophthalmology.net/photo.jsf;jsessionid=466667A9EFDC77DF6588EB6C4B1FFEF2?node=2773&locale=en

[44] https://www.atlasophthalmology.net/search.jsf

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[45] https://www.nist.gov/programs-projects/iris-experts-group-ii-homepage

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