Chapter 2
A Survey of Iris Biometrics Research: 2008–2010

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Abstract A recent survey of iris biometric research from its inception through 2007, roughly 15 years of research, lists approximately 180 publications. This new survey is intended to update the previous one, and covers iris biometrics research over the period of roughly 2008–2010. Research in iris biometrics has expanded so much that although covering only 3 years and intentionally being selective about coverage, this new survey lists a larger number of references than the inception through 2007 survey.

2.1 Introduction

Iris biometrics research is an exciting, broad, and rapidly expanding field. At the same time, there are successful practical applications that illustrate the power of iris biometrics; there are also many fundamental research issues to be solved on the way to larger scale and more complex applications.

A survey that appeared in 2008 covered the field from its inception in the early 1990s through roughly the end of 2007 [20]. This new survey is intended to update the previous one, covering roughly the period 2008 through 2010. However, as illustrated in Fig. 2.1, there has been tremendous growth in the literature in this area, Due to this growth, this new survey does not attempt as exhaustive a coverage of the field as the previous survey. We focus primarily on papers that appeared in SpringerLink or in IEEE Xplore, as these appear to currently be the two major sources of publications

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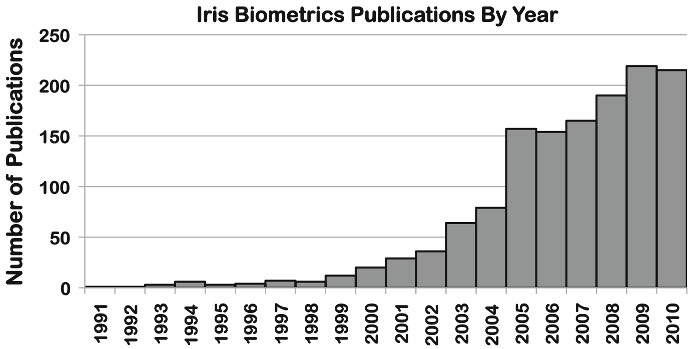

Fig. 2.1 Iris Biometrics Papers in Google Scholar from 1990 through 2010. This data was taken using Google Scholar's "advanced search" facility, searching for "iris biometrics pupil" appearing in articles, excluding patents, in the Engineering, Computer Science and Mathematics literature

in this field. We also omit coverage of some subareas of work judged to be of less importance. These omissions are explained at the appropriate points in the survey.

The main body of this survey is organized into the following sections:

Section 2.2—Iris Image Acquisition
Section 2.3—Iris Region Segmentation
Section 2.4—Texture Coding and Matching
Section 2.5—Multi-biometrics Involving the Iris
Section 2.6—Privacy and Security
Section 2.7—Datasets and Evaluations
Section 2.8—Performance Under Varying Conditions
Section 2.9—Applications
Section 2.10—Theoretical Analyses

Papers are grouped into a section according to their perceived main area of contribution. In some instances, a paper is mentioned in more than one section. The survey ends with a short discussion and a list of recommended readings.

There are several overview or introductory type articles that can be mentioned in this section. Gorodnichy [58] gives a good overview/introduction to biometrics, emphasizing evaluation of biometric system performance based on a dynamic, or life cycle view of operational systems. Bhattacharyya et al. [13] give a short, high-level overview of biometrics, primarily emphasizing iris biometrics. Phillips and Newton [143] present a short "point of view" type article on biometric evaluation, emphasizing issues such as the number of persons represented in the dataset and the longitudinal time over which biometric samples are collected. Each of these articles contains important elements for anyone new to the field of biometrics.

2.2 Iris Image Acquisition

There are still major research issues in the area of iris image acquisition. One issue involves imaging the iris with a sensor system that allows the person to be more “at a distance” and “on the move.” Matey and Kennell [118] present a comprehensive tutorial on the issues involved in acquiring iris images at a distance of greater than one meter. The tutorial includes a partial list of commercial iris recognition devices released between 1995 and 2008 and a description of several successful applications of iris biometrics. The authors describe acquisition issues including the wavelength of light used, the type of light source, the amount of light reflected by the iris back to the sensor, required characteristics of the lens, signal-to-noise ratio, eye safety, and image quality. Capture volume, residence time, and sensitivity to subject motion are also discussed.

Wheeler et al. [208] describe a prototype “stand-off” iris recognition system designed to work at sensor-to-subject distances of up to 1.5 m. The system uses two wide-field-of-view cameras to perform face location in the scene and an iris camera and illuminator to image the iris. Dong et al. [36] discuss the design of a system to image the iris “at a distance,” allowing a stand-off of 3 m. Although current commercial iris biometrics systems all use near-infrared (NIR) illumination, and most research assumes NIR imaging similar to that used in current commercial sensors, Proenca [152] argues for visible wavelength imaging as the more appropriate means to achieve “at a distance” and “on the move” imaging.

Boddeti and Kumar [17] investigate the use of wavefront-coded imagery for iris recognition. This topic has been discussed in the literature before, but Boddeti and Kumar use a larger data set and present experiments to evaluate how different parts of the recognition pipeline (e.g., segmentation, feature extraction) are affected by wavefront coding. They propose using unrestored image outputs from the wavefront-coded camera directly, and test this idea using two different recognition algorithms. They conclude that wavefront coding could help increase the depth of field of an iris recognition system by a factor of four, and that the recognition performance on unrestored images was only slightly worse than the performance on restored images.

There is little published work dealing with imaging the iris under different wavelength illumination. Ross et al. [170] look at imaging the iris with illumination in the 950–1650 nm range, as opposed to the 700–900 nm range typically used in commercial systems. They suggest that it is possible to image different iris structure with different wavelength illumination, raising the possibility of multispectral matching as a means to increased recognition accuracy.

Grabowski et al. [60] describe an approach to iris imaging that is meant to allow characterization of structures in the iris tissue over changes in pupil dilation. They use side-illumination, fixed to glasses frames worn by the subject, with imaging resolution that allows an 800-pixel iris diameter. This is many more “pixels on the iris” than in current commercial sensors.

Chou et al. [31] describe an iris image acquisition system meant to handle off-angle views of the iris and to make iris segmentation easier and more reliable. Their system uses a dual-CCD camera to acquire a color RGB image with one CCD and a near-infrared image with the other. The color image is exploited to improve the reliability of the segmentation. The non-orthogonal-view iris image is rectified to an orthogonal-view iris image using the pupillary boundary.

He et al. [70] design their own iris camera with the goal of being more economical than commercial alternatives, while still acquiring high-quality images. They use a CCD sensor with resolution of 0.48 M pixels, and add a custom glass lens with a fixed focus at 250 mm and NIR-pass filters that transmit wavelengths between 700 and 900 nm. The illumination unit consists of NIR LEDs of 800 nm wavelength, which they arrange to try to minimize specular reflections on the iris.

McCloskey et al. [120] explore a technique termed "flutter shutter" as a means to acquire sharply focused iris images from moving subjects. The idea is that the camera shutter "flutters" between open and closed while the sensor accumulates an image, from which an appropriately designed deblurring algorithm can then recover an in-focus image.

2.2.1 Nonideal Images and Quality Metrics

As mentioned earlier, one important current research emphasis is acquisition of images under less-constrained conditions. As iris images are acquired under less constrained conditions, the issue of image quality becomes more important and complex. Another element of this is the design of algorithms meant to handle "nonideal" or "noisy" images. For our purposes, "nonideal" means something more than just the presence of specular highlights or occlusion by eyelashes or eyelids.

While it is not part of the image acquisition step per se, iris biometric systems typically evaluate the focus quality, and possibly other factors, of each candidate image in order to select usable images. Ren and Xie [167, 168] proposed approaches to evaluating image focus quality that involve finding the iris region before computing the focus value. While iris biometric systems select images based in part on focus quality, there are few publications dealing with deblurring of iris images. Huang et al. [81] investigate image deblurring algorithms that exploit context specific to iris imagery. He et al. [73] estimate the user distance from the sensor in order to estimate the appropriate point spread function (PSF) for image restoration. They measure the distance between two specular highlights on the iris. Using this information, plus knowledge about the positions of the two infrared LEDs, they get the user's distance from the camera without using a special distance sensor. The knowledge of the distance from the sensor is used in estimating the PSF.

Belcher and Du [9] combine percent occlusion, percent dilation, and "feature information" to create an iris image quality metric. To compute "feature information," they calculate the relative entropy of the iris texture when compared with a uniform distribution. To fuse the three types of information into a single score, they first compute an exponential function of occlusion and an exponential function of dilation. The final quality score is the product of the three measures.

Kalka et al. [86] investigate a number of image quality factors, including percent occlusion, defocus, motion blur, gaze deviation, amount of specular reflection on the iris, lighting variation on the iris, and total pixel count on the iris. In evaluating various data sets, they found that the ICE data had more defocused images, the WVU data had more lighting variation, and the CASIA data had more occlusion than the other sets.

Schmid and Nicolo [181] evaluated iris image quality metrics in terms of how well they predict recognition performance. The quality metric is applied to each of a pair of images being matched, and the metrics mapped to a predicted matching score. The metric(s) can then be evaluated by how well the predicted matching score is correlated with the calculated matching score. Schmid and Nicolo experimented with both iris and face image data.

Zhou et al. [218, 219] propose adding four modules to the traditional iris biometrics system in order to handle nonideal images. A "Quality Filter Unit" eliminates images that are too poor quality to be useful. A "Segmentation Evaluation Unit" evaluates the quality of the segmentation. A "Quality Measure Unit" determines if there is sufficient iris area available to generate features. A "Score Fusion Unit" combines a segmentation score and a quality score. Experiments are shown using the MBGC dataset [180] and their own IUPUI near-field iris video dataset.

Zuo and Schmid [221] presented both a global quality metric for selecting individual frames from an iris video or image sequence, and multiple local quality metrics for the iris in a given frame. The global quality metric experiments use the Iris On the Move [119] videos distributed as part of the Multiple Biometric Grand Challenge [145]. The local quality metrics look at segmentation quality, interlacing, illumination contrast, illumination evenness, percent occlusion, pixel count, dilation, off-angle view and blur, and are evaluated using images from the ICE 2005 dataset [19, 146].

Breitenbach and Chawdhry [22] performed experiments looking at quality factors for an image and how they predict performance of face and iris recognition. They synthetically vary image factors such as defocus, contrast, and resolution. They find that the factors considered are better predictors of iris biometric performance than face recognition performance.

Proenca [153] presented an approach to quality assessment of iris images acquired in the visible-light domain. Factors considered in the quality assessment include focus, motion, angle, occlusions, area, pupillary dilation, and levels of iris pigmentation. The claim is that by using the output of the segmentation phase in each assessment, the method is able to handle severely degraded samples.

Phillips and Beveridge [141] presented a challenging view on the topic of using quality metrics in biometric matching. By analogy to AI-completeness in artificial intelligence and completeness in the theory of algorithms, they introduce the concept of biometric-completeness. The idea is that a problem in biometrics is biometric-complete if it can be shown to be equivalent to the biometric recognition problem and "the key result in this paper shows that finding the perfect quality measure for any algorithm is equivalent to finding the perfect verification algorithm."

2.2.2 Image Compression

Daugman and Downing [35] presented a detailed study of the effects of compression of the original iris image on the performance of iris biometrics. They present schemes that combine isolation of the iris region with JPEG and JPEG 2000 compression, evaluate their approach on images from the Iris Challenge Evaluation (ICE) 2005 dataset [19, 146] and conclude that it is "possible to compress iris images to as little as 2000 bytes with minimal impact on recognition performance."

Ives et al. [82] explore the effect of varying levels of JPEG 2000 compression, using the ICE 2005 dataset [19, 146], and find that the false reject rate increases with increasing level of compression, but that the false accept rate is stable.

Konrad et al. [93, 94] aim to compress iris data without degrading matching results. They use JPEG compression on unwrapped polar iris images. They design and compare different quantization tables to use with the JPEG compression. Two of their tested Q-tables are designed to preserve more angular iris texture than radial iris texture (i.e. the horizontal texture in the unwrapped image). The other two Q-tables are derived from the first two through genetic optimization. There is no clear winner among their tested Q-tables, and they conclude that custom Q-tables for iris recognition should be optimized to a specific target bitrate for best performance.

Kostmajer et al. [95] apply compression to the original, rectilinear iris images. They propose custom JPEG quantization tables for iris recognition. Their theory is that the highest and medium frequencies are not essential for iris recognition performance because of the coarse quantization used in template generation. Therefore, they test four custom compression tables, each one with an increasing number of high frequencies suppressed. In most of their tests, their proposed tables outperform the standard JPEG quantization table. Based on their experiments, they conclude that iris compression is not realistic at compression rates greater than 20. On the other hand, their experiments show that compression does not noticeably affect the impostor distribution.

Hämmerle-Uhl et al. [63] use JPEG 2000 compression on original iris images. They aim to improve compression performance using region of interest coding. They detect the iris using edge detection and a Hough transform, then set the ROI to the detected candidate circle with largest radius inside a certain allowed range. They compare compression with and without ROI coding and find that match scores improve and error rates decrease when using the ROI coding.

Carneiro et al. [25] examine the performance of different iris segmentation algorithms in the presence of varying degrees of fractal and JPEG 2000 image compression, using the UBIRIS dataset [154].

2.3 Iris Region Segmentation

Publications related to segmenting the iris region constitute a significant fraction of the published work in iris biometrics. Many of these publications can be grouped as tackling similar versions of the traditional iris segmentation problem; e.g., given one still image, find the pupillary and limbic boundaries. However, there are also a variety of approaches being explored to find occlusion by specular highlights and eyelashes, to segment the iris using less-constrained boundaries, and to refine initial segmentation boundaries.

Iris segmentation algorithms that assume circular boundaries for the iris region continue to appear in some conferences. We have chosen not to cover this subarea of work here, as the current frontier in iris segmentation is generally now focused on removing the assumption of circular boundaries [26, 74, 184] and on refining the segmentation to account for various occlusions and distortions of the iris texture.

Publications also continue to appear that propose iris segmentation techniques that are evaluated on the CASIA version 1 dataset. Again, we have chosen not to cover this subarea of work in this survey. The use of the CASIA v1 dataset to evaluate iris segmentation algorithms is inherently problematic. This is because the images have been edited to have a circular region of constant intensity value for the region of each iris [142]. Therefore, any segmentation algorithm built around the assumption of a circular region of constant dark intensity value should naturally meet with great success on this dataset, even though these conditions are generally not present in the iris region of real images.

A number of researchers have considered various approaches to segmenting the iris with boundaries not constrained to be circles. Wibowo and Maulana [209] evaluated an approach using the CASIA v1 data and their own dataset of 30 visible-light iris images. Labati et al. [99, 100] propose methods to find the pupil center and then to find the inner and outer iris boundaries, presenting experimental results on CASIA v3 and UBIRIS v2 images. Kheirolahy et al. [91] propose a method of finding the pupil in color images, with experiments on the UBIRIS dataset. Chen et al. [29, 30] consider an approach to segmenting the iris region under less-constrained conditions, experimenting with the UBIRIS v2 visible-light iris image dataset, and placing in the top six in the NICE competition. Broussard and Ives [23] trained a neural net to classify pixels in an iris image as either being on an iris boundary or not, selecting the most useful eight features from a pool of 322 possible features. Subjective visual evaluation of results indicates improvement over methods that assume circular boundaries. Zuo and Schmid [222] presented an approach to segmenting the iris using ellipses for the pupillary and the limbic boundaries, with experiments on CASIA, ICE and WVU datasets. Pan et al. [136] detected edge points using "phase congruency analysis" and fit ellipses to the detected edge points. They test their method on CASIA v2 and CASIA v3 twins data sets. Roy and Bhattacharya [173–175] suggested a segmentation method using geometric active contours. They apply opening operators to suppress interference from eyelashes [174]. Next, they approximate elliptical boundaries for the pupil and limbic boundaries. They refine the detected boundary using geometric active contours (i.e., active contours implemented via level set) to a narrow band over the estimated boundary. They fit parabolic curves to the upper and lower eyelids. To isolate the eyelashes, they use 1D Gabor filters and variance of intensity. Roy and Bhattacharya [177] also described a level set style active contour method for finding the pupil and iris boundaries in nonideal iris images, presenting results on the UBIRIS v2, ICE 2005 and WVU nonideal iris datasets.

Ryan et al. [179] present the "starburst method" for segmenting the iris. They preprocessed the image using smoothing and gradient detection, and then they find a pupil location as a starting point for the algorithm. To do so, they set the darkest 5 % of the image to black, and all other pixels to white. Then they create a Chamfer image: the darkest pixel in the Chamfer image is the pixel farthest from any white pixel in a thesholded image. They use the darkest point of the Chamfer image as a starting point. Next, they compute the gradient of the image along rays pointing radially away from the start point. The two highest gradient locations are assumed to be points on the pupillary and limbic boundaries and are used to fit several ellipses using randomly selected subsets of points. An average of the best ellipses was reported as the final boundary. The eyelids were detected using active contours.

Pundlik et al. [155] treat the image as a graph where pixels are nodes and neighboring pixels are joined with edges, Their first goal is to assign a label—either "eyelash" or "non-eyelash"—to each pixel. After removing specular reflections, they use the gradient covariance matrix to find intensity variation in different directions for each pixel. Then they create a probability map, P, that assigns the probability of each pixel having high texture in its neighborhood. The "energy" corresponding to a particular labeling of the images is written as a function of a smoothness term and a data term. The data term is based on a texture probability map. The second goal was to assign each pixel one of four labels: eyelash, pupil, iris, or background. They use a method similar to the initial eyelash segmentation; however, this time they use an alpha-beta swap graph-cut algorithm. Finally, they refine their labels using a geometric algorithm to approximate the iris with an ellipse.

Vatsa et al. [197] improve the speed of active contour segmentation by using a two-level hierarchical approach. First, they find an approximate initial pupil boundary, modeled as an ellipse with five parameters. The parameters are varied in a search for a boundary with maximum intensity change. For each possible parameter combination, the algorithm randomly selects 40 points on the elliptical boundary and calculated total intensity change across the boundary. Once the pupil boundary is found, the algorithm searched for the iris boundary in a similar manner, this time selecting 120 points on the boundary for computing intensity change. The approximate iris boundaries are refined using an active contour approach. The active contour is initialized to the approximate pupil boundary and allowed to vary in a narrow band of $\pm$ 5 pixels. In refining the limbic boundary, the contour is allowed to vary in a band of $\pm$ 10 pixels.

Although there are relatively few papers devoted specifically to this topic, better detection of specular highlights in the iris image is still an area of current research [183, 211]. He et al. [71] acknowledge the difficulty of detecting and removing specular highlights in the iris image and present an interesting multi-sample approach to this problem. They assume that multiple images of the same iris are available, with the specular highlights appearing in different places on the iris in different images. The segmentation of the iris region in the images is simple, and assumes concentric circular boundaries for the pupil and iris. The rectangular iris images from the multiple images are then registered, bright spots detected, and the bright spots replaced with values from a different image.

Liu et al. [110] propose a method for eyelid detection in UBIRIS v2 (visible-light) images. Their method uses a parabolic integro-differential operator similar to the operator described by Daugman for iris localization. They find that their proposed method has lower pixel error compared to algorithms involving the IDO alone, using detected edge pixels alone, or an algorithm using Canny edge detection and a Hough transform.

While most publications assume a single still image as the input to the segmentation stage, Du et al. [39] propose a method of using multiple thresholds on the intensity value in an image to achieve a rough segmentation of the iris in frames of a video sequence. Du et al. [40] also propose an approach to segmentation of iris images obtained in a context in which the subject is not explicitly cooperative. They filter to drop video frames in which the iris is not visible, fit ellipses for the iris boundaries, and develop a method to remove noise in the iris region.

Several researchers have considered the problem of evaluating the quality of an iris segmentation. Kalka et al. [85] tackle the problem of predicting or detecting when iris segmentation has failed, with experiments on the WVU and ICE datasets, and on two iris segmentation algorithms. Li and Savvides [106, 107] present work on taking an existing iris segmentation mask, in principle from any algorithm, and automatically refining it to produce a better segmentation.

Proenca [150, 151] observes that images acquired in the visible wavelength in less-constrained environments tend to have noise that results in severely degraded images. Whereas many iris biometric segmentation algorithms key on the pupil to anchor the segmentation, he proposes to anchor the segmentation on the sclera as much more naturally distinguishable than any other part of the eye. The sclera also provides a useful constraint, in that it must be immediately adjacent on both sides of the iris. One of the differences in iris biometrics processing for visible-light versus near-IR images, is that the pupillary boundary tends to be more distinct in near-IR whereas the limbic boundary appears to be more distinct in visible light.

Lee et al. [102] describe a way to locate and analyze eyes in the MBGC portal videos.They use the Viola-Jones detector that comes with OpenCV and is trained to detect eye pairs. They measure the edge density in an image to determine the focus level and select appropriate frames from the video. The IrisBEE algorithm [144] is used for segmentation and feature extraction. Eyes from the MBGC portal videos are compared to higher quality still iris images. The two-eye detection rate in the videos was 97.7 %. The segmentation rate was 81.5 %, and the matching rate was 56.1 %. This matching rate is low compared to typical iris recognition systems, likely reflecting the low level of iris image quality in the MBGC portal videos.

Munemoto et al. [133] suggest that "it is important to not only exclude the noise region, but also estimate the true texture patterns behind these occlusions. Even though masks are used for comparison of iris features, the features around masks are still affected by noise. This is because the response of filters near the boundary of the mask is affected by the noisy pixels." They used an image-filling algorithm to estimate the texture behind the occlusions. This algorithm iteratively fills 9×9 patches of the occluded region with 9×9 patches from unoccluded regions. It estimates textures at the boundary of the region first, selecting 9×9 source patches from the unoccluded iris that closely match the iris texture near the boundary of the area to be filled.

Thompson and Flynn [195] presented a method of improving the recognition performance of iris biometrics by perturbing parameters of the iris segmentation. The perturbations generate a set of alternate segmentations, and so also alternate iris codes, which effectively result in an improved authentic distribution.

2.4 Texture Coding and Matching

Performing texture analysis to produce a representation of the iris texture, and the matching of such representations, is at the core of any iris biometric system. A large fraction of the publications in iris biometrics deal with this area. It is not necessarily straightforward to organize these publications into well-defined and meaningful categories. Nevertheless, they are grouped here in a way intended to represent important common themes.

2.4.1 Experiments Using the CASIA V1 Dataset

One cluster of publications compares different texture filter formulations and presents experimental results on the CASIA v1 dataset. The issue with the CASIA v1 dataset that was mentioned earlier—artificial, circular, constant intensity pupil regions—does not necessarily compromise the use of this dataset in evaluating the performance of algorithms for texture analysis and matching. However, the small size of the dataset and the many papers in the literature that report near-perfect performance on this dataset make it nearly impossible to use it to document a measurable improvement over the state of the art. Therefore, for space considerations, we do not cover this subarea of publications in this survey. Fatt et al. [48, 49] implement a fairly typical 1D log-Gabor iris biometric system on a digital signal processor (DSP), and show results on CASIA v1 dataset. Showing the relative speed of software versus DSP implementations of an algorithm is an example of a context where using the CASIA v1 dataset may be reasonable.

2.4.2 "Eigen-Iris" Approaches

One group of papers might be characterized, by analogy to "eigen-faces" in face recognition, as using an "eigen-iris" approach. Chowhan and Sihinde [32] proposed using PCA for iris recognition, in an eigen-face style of approach. Moravec et al. [131] also use a PCA-based approach, with color images of 128 irises. Zhiping et al. [217] use a 2-D weighted PCA approach to extracting a feature vector, showing improvement over plain PCA. Chen et al. [28] use 2D PCA and LDA, on UBIRIS images, showing an improvement over PCA or LDA alone. Eskandari and Toygar [46] explored subpattern-based PCA and modular PCA, achieving performance up to 92 % rank-one recognition on the CASIA v3 dataset. Erbilek and Toygar [45] looked at recognition in the presence of occlusions, comparing holistic versus subpattern based approaches, using PCA and subspace LDA for iris matching, with experiments on the CASIA, UPOL, and UBIRIS datasets. Xu and Guo [213] propose to extract iris features from the normalized iris image using a method that they call Complete 2D PCA.

2.4.3 Alternative Texture Filter Formulations

Many researchers have looked at different mathematical formulations of filters to use in analyzing the iris texture. Patil and Patilkulkarni [139] used wavelet analysis to create a texture feature vector, with experiments on the CASIA v2 dataset. Velisavljevic [199] experiments with the use of oriented separable wavelet transforms, or directionlets, using the CASIA v3 dataset, and shows that they can give improved performance for a larger size binary iris code. Sun and Tan [188] propose using ordinal features, which represent the relative intensity relationship between regions of the iris image filtered by multi-lobe differential filters. Krichen et al. [96] explore using a normalized phase correlation approach to matching, as an alternative to the standard binary iris code. They compare results to the OSIRIS [14] and Masek [117] algorithms, on the ICE 2005 and the CASIA-BioSecure iris datasets.

Al-Qunaieer and Ghouti [156] used quaternion log-Gabor filters to analyze the texture of images in the UBIRIS color image dataset, and also [56] use a quaternion Fourier Transform and phase correlation to improve performance. Bodade and Talbar [16] used a rotated complex wavelet transform in matching iris textures, with experimental results on the UBIRIS dataset, but do not improve recognition performance over the Gabor wavelet. Tajbakhsh et al. [189] present a method of feature extraction based on Ma et al.'s earlier method of analyzing local intensity variation [114], and propose four improvements to the earlier method to make it work with the noisy images in the UBIRIS data set. Tajbakhsh et al. [190] use a 2-D Discrete Wavelet Transform applied to overlapping 32×32 pixel blocks, and achieve 0.66 % EER on the UBIRIS data.

The motivation behind Miyazawa's proposed method [127] is that Daugman-like, feature-based iris recognition algorithms require many parameters, and that their proposed algorithm should be easier to train. For each comparison using the proposed method, they take two images and select a region that is unoccluded in both images. They take the Discrete Fourier Transform of both valid regions, then apply a phase-only correlation (POC) function. The POC function involves a difference between the phase components from both images. They use band-limited POC to avoid information from high-frequency noise. The proposed algorithm requires only two parameters: one representing the effective horizontal bandwidth for recognition, and the other representing the effective vertical bandwidth. They achieve better results using Phase-Only Correlation than using Masek's 1D log-Gabor algorithm.

2.4.4 Alternative Methods of Texture Analysis

Another group of papers explores texture representation and matching approaches that do not map directly to the typical texture filter framework.

Gray-level cooccurrence matrices (GLCM) can be used to describe texture in an image [66]. A GLCM is formed by counting the cooccurrences of brightness values of pixel pairs in the image at a certain distance and direction. Chen et al. [27] propose a modified GLCM based on looking at triples of pixels instead of pairs. They call their modified method a "3D-GLCM," and use it to describe the texture of iris images in the UBIRIS data set. Using equal error rate, the 2D-GLCM method performs better, but for a FAR of 0 %, the 3D-GLCM performs better.

Kannavara and Bourbakis [90] explored using a local-global graph methodology to generate feature vectors, with experiments on color iris images. Sudha et al. [187] compute a local partial Hausdorff distance based on comparing the edge detected images of two irises, obtaining 98 % rank-one recognition on a UPOL dataset representing 128 irises. Kyaw [98] explores using simple statistical features such as mean, median, mode and variance within concentric bands of the iris, but presents no experimental results. Wu and Wang [210] use intensity surface difference between irises for matching and report relatively low performance on the CASIA v1 dataset. Mehrotra et al. [122] use a Harris corner detector to find interest points, which are paired across images for matching. Tests on Bath, CASIA and IITK datasets indicate that this method does not perform as well as traditional iris code approaches. To avoid aliasing problems from "unwrapping" an iris image, Mehrotra et al. [121] extract features from the annular iris image. They use the SURF algorithm (Speeded Up Robust Features) to identify rotation-invariant features, and report recognition accuracy above 97 % on BATH, CASIA3, and IITK databases. Radhika et al. [158] use continuous dynamic programming to extract iris texture information. They test their method on CASIA v2 and UBIRIS v1 data. Overall, it appears that none of the various different approaches in this category has yet demonstrated any clear performance improvement over the more traditional texture filtering approaches used in iris biometrics.

Patil and Patilkulkarni [137] described a comparison of different texture analysis methods for iris matching. The compare the use of statistical measures (mean, median, mode, variance), lifting wavelet transform, and gray-level cooccurrence matrices for deriving texture features. They perform experiments using the CASIA v2 dataset, and find that the lifting wavelet transform provides the best recognition accuracy. Patil and Patilkulkarni [138] also explored the use of SIFT features for iris biometrics.

Rathgeb and Uhl [162] developed an approach to iris biometrics that uses Contrast Limited Adaptive Histogram Equalization and traces pixel intensity variations along rows of the normalized image (concentric circles of the iris region). These are termed "pixel paths." They achieve an EER on experiments with the CASIA v3 dataset in the range of 1–2 %. They also show how this approach lends itself to cancelable biometrics.

2.4.5 Algorithms that Analyze the Iris in Parts

Several researchers have proposed approaches that analyze the iris region in multiple parts and combine the results. One motivation for this type of approach is to reduce the impact of segmentation errors and noise in the imaging process.

Adam et al. [1] analyze iris texture in eight subregions of the iris and fuse the distances from these local windows, with experiments on data from the CASIA v3 dataset. Bastys et al. [8] divide the iris into sectors and calculate a set number of local extrema in each sector at a number of scales. They achieve perfect separation between genuine and impostor scores for CASIA v1 and CASIA v3 interval, an EER of 0.13 % for the CASIA v2 data, and 0.25 % for the ICE 2005 data. Garg et al. [52] propose a method that uses a grid on the iris image and a vector of the average pixel values in the elements of the grid for representing and matching the iris texture. Eskandari and Toygar [46] explore subpattern-based PCA and modular PCA, achieving performance up to 92 % rank-one recognition on the CASIA v3 dataset. Erbilek and Toygar [45] looked at recognition in the presence of occlusions, comparing holistic versus subpattern based approaches, using PCA and subspace LDA for iris matching, with experiments on the CASIA, UPOL, and UBIRIS datasets. Lin et al. [108] divide the iris area into four local areas and the face into 16 local areas in their approach to iris and face multi-biometrics.

Campos et al. [24] propose an alternative method of feature extraction. They apply histogram equalization and binarization to the unwrapped iris image, and use a self-organizing Map neural network to divide the binary image into nodes. From the topological graph of the image, they compute corresponding Voronoi polygons. Next they calculate the mean, variance, and skewness of the image in each polygonal region. They achieve 99.87 % correct recognition on the Bath University iris data.

Rachubinski [157] presented a method of feature extraction using wavelet coefficients based on a wedgelet dictionary. A wedgelet is a division of a square region into two sections. The wedgelet is parameterized by the distance of the segment from the center of the square, and the angle of the segment dividing the two regions. Rachubinski divided the unwrapped iris image into overlapping local regions of 8×8 pixels, and determines a wedgelet dictionary for each region. The wedgelet angles are quantized to create a binary iris code, and codes are compared using Hamming distances. Rachubinski achieved 100 % rank-one recognition rate (0.15 % EER) on the relatively non-challenging CASIA v1 dataset.

Don et al. [37] present what is termed a "personalized iris matching strategy". A weight map is learned for the features in the image of each given iris, based on training images of that iris. This is conceptually similar to the "fragile bits" work of Hollingsworth. This approach is said to be especially useful in the case of poor quality iris images.

2.4.6 Approaches to Speed Iris Matching

Hao et al. [65] present a technique to speed up the search of a large database of iris codes, with experiments that use over 600,000 iris codes from the ongoing application for border control in the United Arab Emirates. They use a "beacon-guided search" to achieve a "substantial improvement in search speed with a negligible loss of accuracy" in comparison to an exhaustive search.

Gentile et al. [55] experiment with generating a shorter iris code that maintains recognition power, and conclude that it is best to focus on the middle radial bands of the iris, and to sample every n-th band. Gentile et al. [54] also use a short length iris code to index into a large iris dataset to reduce the total number of iris code comparisons to search the dataset, with a small degradation in recognition rate.

Roy and Bhattacharya [172–176] reduced matching time by applying feature selection to choose the most discriminating features. They explore the use of genetic algorithms to select a subset of most useful features for iris matching [172, 176]. In [174] they use Support Vector Machine–Recursive Feature Elimination (SVM-RFE). In [173] they apply a genetic algorithm to select important features, and use an iterative algorithm, called the Contribution-Selection Algorithm, from the field of coalitional game theory, to reduce the feature vector dimension.

Mehrotra et al. [123] propose an indexing algorithm to reduce the search time. They divide each unwrapped iris image into subbands using a multiresolution Discrete Cosine Transform. They create a histogram of transform coefficients for each subband using all the images in the database. They use histograms containing about ten bins each. The algorithm forms a key for each image from noting the bin numbers associated with the subbands of the image. The keys are organized into a search tree. To search for a match to a new image, the algorithm computes the key for the new image, retrieves all irises with matching keys from the database, and compares iris templates from the retrieved set. They achieve a bin miss rate of 1.5 % with a penetration rate of 41 %.

Rathgeb et al. [165] present an approach to "incremental" iris code matching, with the aim of reducing the number of bit comparisons used per recognition result. It is claimed that "the proposed technique offers significant advantages over conventional bit-masking, which would represent binary reliability masks."

2.4.7 Exploiting "fragile" Bits in the Iris Code

Hollingsworth et al. [77] describe the concept of "fragile bits" in the traditional Daugman-style iris code. Bits in the iris code can be fragile due essentially to random variation in the texture filter result, causing them to "flip" between 0 and 1. Recognition performance can be improved by masking an appropriate fraction of the most fragile bits. Dozier et al. [38] use a genetic algorithm to evolve a mask for the iris code that best masks out the "fragile" iris code bits. Hollingsworth et al. [80] describe an approach to averaging the iris image through multiple frames of video, prior to generating the iris code, to improve recognition performance. This approach is effectively reducing the fragility of the bits in the iris code. Hollingsworth et al. [78] also describe an approach to using the spatial coincidence of the fragile bits in the iris code to improve recognition performance.

2.4.8 Use of "Sparse Representation" Techniques

Pillai et al. [147] explore the use of sparse representation techniques for iris biometrics. This approach involves having a number of training images per iris, where the images span the range of different appearances that the iris might have. An unknown iris is then recognized by solving a minimization problem that finds a representation of the unknown image in terms of the training images.

2.5 Multi-biometrics Involving the Iris

The term "multi-biometric" is used to refer to techniques that use more than one biometric sample in making a decision. Often the samples are from different sites on the body; for example, iris and fingerprint. Also they might be from different sensing modalities; for example, 3D and 2D. Or they might be repeated samples from the same sensor and site on the body. The motivation for multi-biometrics is to (a) increase the fraction of the population for which some usable sample can be obtained, and/or (b) increase recognition accuracy, and/or (c) make it more difficult to spoof a biometric system. In India's Unique ID program [169], in many ways the most ambitious biometrics application in the world to date, iris and fingerprint are used primarily, it seems, to increase coverage of the population.

Most multi-biometric work involving the iris has looked at combining iris with some other biometric site, rather than multiple sensing modalities for iris, or repeated iris samples. Papers have been published looking at almost any combination of iris and some other modality that one can imagine. Often the practical motivation for the particular pairing is not clear. The vast majority of this work has used *chimera* subjects; that is, virtual subjects created by pairing together biometric samples from already existing uni-modal datasets. For example, several papers use iris images from a CASIA dataset and face images from the ORL [101] dataset. In general, there is a need for research in this area to progress to using true multi-biometric datasets, to use datasets representing a much larger number of subjects and images than in the ORL face dataset or the CASIA v1 iris dataset, and to compare performance of the multi-biometric approach to performance of state-of-the art algorithms for the individual biometrics. In the summaries below, we have tried to explicitly note the few instances where the dataset used was not chimeric.

Perhaps naturally, the largest cluster of papers in this area deals with the combination of face and iris. This group of publications is multi-biometric both in the sense of combining iris and face, and often also in the sense of using near infrared illumination (for iris) and visible light (for face). Lin et al. [108] generalize the posterior union model (PUM) to perform face and iris multi-biometrics, constructing chimera subjects from the XM2VTS or AR face datasets and the CASIA iris dataset, and dividing the normalized face images into sixteen local areas and the iris area into four local areas. Gan and Liu [51] apply a discrete wavelet transform to face and iris images, and use a kernel Fischer Discriminant analysis, with chimera subjects created from the ORL [101] face database and (apparently) the CASIA v1 iris database. Wang et al. [204, 206] use a complex common vector approach to face and iris, using the ORL and Yale face datasets and the CASIA v1 iris dataset. Liu et al. [109] experiment with a 40-person chimera dataset made from ORL face images and CASIA iris images, with relatively low performance. Wang et al. [205] fuse face and iris information at the feature level. They create a complex feature vector from the real-valued iris feature vector and the real-valued face feature vector. Next, they use complex Fisher discriminate analysis (CFDA) to maximize the between-class scatter with respect to the within-class scatter. They test their algorithm on CASIA v1 iris images and ORL and Yale face images. Wang and Han [201] fuse information from face and iris at the score level. The scores from the two different algorithms are normalized using two sigmoid functions, and then they employ a SVM-based fusion rule to obtain a final score. They test their method using faces from the ORL data set and irises from UBIRIS data set. Breitenbach and Chawdhry [22] perform experiments looking at image quality factors for an image and how they predict performance of face and iris recognition. Rattani and Tistarelli [166] fuse information from face and iris at the feature level. They divide the images into windows, and extract one SIFT feature from each window. They obtain feature vectors of length 128 each from the face, right eye, and left eye images, and find that a fusion of face, right iris and left iris gets better performance than any one or any fusing of two. Morizet and Gilles [132] use data from the FERET face dataset and a CASIA iris dataset in presenting a method that develops a user-specific fusion of scores from the two modalities.

Vatsa et al. [198] consider approaches based on multiple iris samples. They use elements of belief function theory for iris-based multi-biometrics and look at two scenarios: combining results from enrolling one iris with two images and combining results from the left and right iris each enrolled with one image.

A broad variety of other multi-biometric combinations involving the iris have been studied. Several researchers have looked at fingerprint and iris. Baig et al. [5] investigate iris and fingerprint fusion using the Masek algorithm and a SUNY-Buffalo algorithm, respectively, experimenting on a West Virginia University dataset. It is noted that performance is relatively low, due to design for a "small memory footprint realtime system." Ross et al. [171] explore multi-biometric iris and fingerprint where fusion is used only in certain cases within the Doddington Zoo framework, experimenting with a chimera dataset of fingerprints from a WVU dataset and irises from a CASIA dataset. Elmadani [44] presents the "fingerIris" algorithm for combination of iris and fingerprint. The approach is evaluated on a true multi-biometric dataset representing 200 individuals. The system gets 4–5 false reject and/or false accept results on this dataset, depending on the setting of the decision threshold.

Wang et al. [202] explore score-level fusion of iris matching and palmprint matching using an apparently chimera dataset representing 100 persons. Tayal et al. [12, 193, 194] use a wavelets approach to analyze iris texture and speech samples for multi-biometrics. Sheela et al. [185] experiment with iris and signature, using CASIA v2 and MYCT datasets, respectively, but do not focus on multi-biometric combination. Mishra and Pathak [126] explore wavelet analysis of iris and ear images for multi-biometrics on a chimera dataset representing 128 persons.

Poh et al. [149] report on multi-biometric research involving face, iris and fingerprint, carried out as part of the BioSecure project. This project particularly looks at quality-dependent fusion at the score-level and cost-sensitive fusion at the score level. A total of 22 fusion systems were evaluated in this project.

Maltoni et al. [116] discuss pros and cons of fusing multiple biometrics. Generally, fusing more classifiers improves performance if the classifiers are not highly correlated. However, extra classifiers can increase cost and throughput time of the system. Maltoni et al. discuss performing fusion at the image, feature, score, rank, or decision level.

Hollingsworth et al. [79] present an approach that uses multiple iris samples taken using the same sensor, taking advantage of temporal continuity in an iris video to improve matching performance. They select multiple frames from an iris video, unwrap the iris into polar form, and then average multiple frames together. They find that this image-level fusion yield better matching performance than previous multi-gallery score fusion methods.

Conti et al. [33] give an overview of concepts and terminology in multi-biometric systems. They also present an approach to using fuzzy logic methods for score fusion in a multi-biometric system.

Zuo et al. [220] investigate the possibility of matching between a visible-light image and a NIR image of the iris. They formulate a method to estimate the NIR iris image from a color image. It is claimed that this approach "achieves significantly high performance compared to the case when the same NIR image is matched against R (red) channel alone."

2.5.1 Ocular Biometrics

The papers covered in this section deal with "ocular" biometrics as a possible multi-biometric complement to iris. An ocular biometric is one based on features of the region of the face around the eye. Much of this research uses ocular regions cropped from visible-light images, often from the Face Recognition Grand Challenge (FRGC) face image dataset. Xu et al. [212] use local binary pattern (LBP) texture features computed over the ocular region. In experiments with images from the FRGC dataset, they achieve 61 % verification rate at 0.1 % false accept rate. Miller et al. [125] also propose a method using LBP texture features, again using images cropped from the FRGC database. They investigate the effects of image blur, resolution of the periocular region, illumination effects and different color bands. Lyle et al. [113] present an approach to predicting the gender and ethnicity of a person using LBP features and an SVM classifier. In experiments with images from the FRGC dataset, they obtain 93 % accuracy on gender classification and 91 % on Asian/non-Asian ethnicity classification. Bharadwaj et al. [10] present a method of ocular recognition with experiments using the UBIRIS iris images. Their method uses the GIST global descriptor and LBP texture features. Merkow et al. [124] predict the gender of the subject based on features computed from he ocular region, and obtain 85 % correct gender prediction using frontal-view color face images taken from the web.

Hollingsworth et al. [75] study how human observers rate the value of different features of the ocular region for recognition. This study was done with NIR images from the LG 2200 iris sensor. Thus this investigation is more directly relevant to ocular as a complement to iris, and less directly relevant to ocular as a subset of face recognition using visible-light images.

2.6 Privacy and Security

This section includes several somewhat different areas of work. The development of privacy-enhancing techniques generally involves rigorous conceptual or mathematical approaches. More general security techniques look at integrating biometrics into encryption schemes in some way. The study of liveness detection, or spoofing and anti-spoofing, often involves clever exploitation of sensor capabilities.

Ratha [161] gives a broad perspective on security and privacy issues in large-scale biometric systems. Taking a system-level view of biometric authentication, he considers the various possible attack points. He also summarizes the concept of cancelable biometrics as a means to enhance privacy and security. This is a good general article for someone who is not already familiar with basic concepts in this area.

2.6.1 Privacy-Enhancing Techniques

The area of privacy-enhancing techniques for biometrics is challenging and fast-moving. Its importance is perhaps not yet fully understood and appreciated by the field as a whole. One can see the importance of this area by considering what would happen in a biometric-enabled application when a person's biometric template is stolen. The application needs some way to protect each individual's biometric template and/or to be able to revoke an enrollment in the application and reenroll a person.

Several authors have proposed encryption methods to protect the privacy of a biometric template. Luo et al. [112] propose to perform anonymous biometric matching, using encryption to protect the probe biometric. Alghamdi et al. [4] propose using the iris code to generate a key for encryption of the iris image or other data. Moi et al. [129] propose using AES encryption of an enrolled iris code to store the key to encrypted documents.

Li and Du [104, 105] propose watermarking the iris image at the time that it is acquired by the sensor, as a means to later determine the authenticity of the image. This would in principle allow detection of an image that did not originate with the particular sensor.

Tan et al. [192] propose an "image hashing" technique, which converts the iris biometric into a short bit string in a manner that is irreversible. That is, given the short bit string, it is not possible to generate the iris biometric.

Agrawal and Savvides [3] describe an approach to hiding an iris biometric template in a host image. Their steganographic approach is designed to cause imperceptible change in the host image, and to be robust to JPEG artifacts.

Adjedj et al. [2] describe a way to create a biometric identification scheme while storing only encrypted data. Their method uses Symmetric Searchable Encryption which is a technique allowing a server to return all documents containing a particular keyword without learning anything about the keyword. They also use a family of locality sensitive hashes.

Hämmerle-Uhl et al. [62] propose a cancelable biometrics technique for irises. Cancelable biometrics are transformations of the original biometric that can be used for authentication without revealing the original, unaltered biometric, thus improving privacy for the user. In a cancelable biometric system, if a user's biometric is stolen, it can be canceled and reissued. They suggest two types of transformations. One proposed transformation is to randomly re-map blocks of iris texture to create a new signal. A second proposed transformation is to warp the texture along a grid with randomly offset vertices. Färberböck et al. [47] present an approach to transforming rectangular and polar iris images to enable cancelable iris biometrics. They experiment with block re-mapping and texture warping techniques for this purposes, using images from the CASIA v3 iris image dataset. Kanade et al. [87, 88] propose a two-factor approach to cancelable biometrics. Their proposed system uses an iris biometric and a password. In addition, their system uses an error-correcting-code technique and a user-specific shuffling key to increase the separation between the genuine and impostor distributions.

2.6.2 Security

Zhang et al. [215] propose a method to bind cryptographic keys to biometric data. During enrollment, they use Reed-Solomon coding and convolutional coding to add error-correcting data to a random key. They XOR the random key with the iris code, and produce helper data that hides the biometric and the key. During verification, the new iris code is XORed with the helper data, and then Reed-Solomon and Convolutional coding is used to decode the bit string and correct errors, thus unlocking the original cryptographic key. This method is similar to the method proposed by Hao et al. [64].

Rathgeb and Uhl [163] describe how to construct an iris-based fuzzy committment scheme to hide and retrieve a cryptographic key. Like [64], they use Reed-Solomon and Hadamard error-correcting codes. However, they show how to extend this scheme to an arbitrary iris biometrics algorithm.

Rathgeb and Uhl [162] discuss the problem of generating cryptographic keys from iris biometric samples. Their proposed approach uses an interval mapping technique and does not store biometric data in either raw or encrypted form. On experiments with the CASIA v3 dataset they are able to obtain key generation rates as high as 95 % using 5 enrollment samples.

Mahmud et al. [115] present a stream-cipher method that uses an iriscode as an initial input to seed a linear feedback shift register (LFSR). The LFSR is used to implement a stream-cipher. Since biometric templates are not identically repeatable, their system stores the intial biometric key on a smart card, which is programmed to release the key only when a similar biometric template is presented to unlock the smart card. The authors claim that their method is stronger than other ciphers like A5/1 and RC6.

Plaga [148] computes the theoretical maximal achievable information content of biometric keys. A biometric template, such as the iriscode proposed by Daugman, may have a length of 2048 bits. However, there are correlations in the bits, so in actuality, the information content in the template is smaller; for this example, 249 bits. Even so, a cryptographic key must necessarily be even shorter, because some number of bits are required for error correction. The number of bits required for error correction is a function of the number of bit errors between two templates from the same biometric feature. Using numbers provided by Daugman, Plaga determines that the maximum error-free and correlation-free biometric key has length 25 bits. Using numbers from a performance study conducted in the Frankfurt International Airport, Plaga determines that even fewer bits are available for biometric keys derived from face, fingerprint, and iris systems under airport-type operating conditions. Plaga concludes that “current commercial state-of-the-art biometric systems based on a single biometric feature like one finger or iris create templates from which no more than about 30 bits can be derived.” Therefore, in order to use biometrics to create keys, either the performance of the systems must be substantially improved, or the systems must employ multi-modal or multi-instance biometrics (e.g., ten-print fingerprints).

Rathgeb and Uhl [164] consider the operation of two-factor authentication systems in which one of the factors is iris biometrics. They illustrate empirically how this helps to increase the separation of the authentic and impostor distributions relative to iris biometrics alone. They point out that the increased recognition accuracy in the two-factor system is based on the assumption “that additional factors are considered to never be stolen, lost, shared or duplicated where in practice the opposite is true” and discuss requirements for performance analysis of two-factor systems where one of the factors is a biometric.

2.6.3 Liveness Detection (anti-Spoofing)

Ruiz-Albacete et al. [178] explore “direct attacks” on an iris biometric system, in which a printed image of an iris is presented to an iris biometric system in an attempt to enroll an iris and/or to match an enrolled iris. They find that with appropriate choice of commercial printer, printer paper, and image processing algorithm, they are able to generate printed iris images that are enrolled and/or matched by the iris biometric system with substantial rates of success. The particular iris biometric system used in the experiments is the LG Iris Access 3000, a model that is no longer marketed. It is not clear that the experience with this system could easily be replicated with current commercial iris biometric systems, as current commercial systems may incorporate some sort of liveness detection that should defeat simple spoof attempts using paper-printed iris images.

Bodade and Talbar [15] propose an approach using multiple images of the same eye to look at variation in pupil dilation in order to detect iris spoofing. Takano and Nakamura [191] describe a neural network approach to iris recognition and to detecting “live” iris versus iris patterns printed on paper with experiments on a limited dataset representing 19 persons.

He et al. [72] aim to detect certain types of spoofs by detecting printed contact lenses. They consider three subregions on the right side of the iris, and three on the left. They analyze texture in each subregion using local binary patterns (LBPs) at multiple scales. Gaussian kernel density estimation is applied to complement the insufficiency of counterfeit iris images. They train an Adaboost classifier and select 85 LBP bins to use in testing. The proposed method achieves lower error rates than previous methods [68, 207].

He et al. [69] research detection of blurry, spoofed images. They note that Daugman’s method of computing the FFT [34] can only detect printed contacts with high frequency, but it would fail if the spoofed pattern were partially blurred. He et al. use wavelet packet decomposition to perform wavelet packet decomposition, and then employ a support vector machine to classify irises as live or spoofed. Their method correctly detects 98.6 % of the spoofed images in their data set.

2.7 Datasets and Evaluations

Datasets and evaluations play a large role in biometrics research. The widespread availability of common datasets has enabled many researchers to enter the field and demonstrate results whose relevance can be more easily understood due to the use of a known dataset. Evaluation programs have given researchers an idea about the current state of the art, and helped to focus and shape research to address the interests of sponsoring agencies.

Proenca et al. [154] describe the UBIRIS v2 dataset of visible-light, color iris images, acquired with four to eight meters distance between subject and sensor, and with subjects in motion. The dataset represents 261 subjects, with over 11,000 iris images. The purpose of the dataset is to support research on visible-light iris images acquired under far from ideal imaging conditions [154].

Johnson et al. [84] describe the “Q-FIRE” dataset of face and iris videos. These videos represent variations in focus blur, off-angle gaze and motion blurb, and are acquired at a range of 5 to 25 ft. This dataset is potentially useful for research in iris, face and multi-biometric face + iris.

Fierrez et al. [50] describe a multi-biometrics dataset acquired as part of the BioSecurID project. The dataset represents 400 persons, with biometric samples for speech, iris, face, handwriting, fingerprints, palmprint, hand contour geometry, and keystroking. The iris images are acquired with an LG Iris Access EOU 3000, and include four samples per eye with subjects not wearing eyeglasses and the presence of contact lenses recorded.

Ortega-Garcia et al. [135] describe a larger and more varied version of the multi-biometrics dataset resulting from the BioSecure Network of Excellence. This version contains biometric data representing more than 600 individuals. The data represents three different scenarios: “(i) over the Internet, (ii) in an office environment with desktop PC, and (iii) in indoor/outdoor environments with mobile portable hardware.” Again, the iris part of the dataset was acquired using an LG Iris Access EOU 3000. The total dataset involved the efforts of eleven institutions. The iris portion of the dataset represents 667 persons, with two acquisitions per person, and two images of each iris in each session.

Schmid and Nicolo [182] suggest a method of analyzing the quality of an entire database. They compare the capacity of a recognition system to the capacity of a communication channel. Recognition channel capacity can be thought of as the maximum number of classes that can be successfully recognized. This capacity can also be used as a measure of overall quality of data in a database. The authors evaluate the empirical recognition capacity of biometrics systems that use PCA and ICA. They apply their method to four iris databases and two face databases. They find that the

BATH iris database has a relatively high sample signal-to-noise ratio, followed by CASIA-III, then ICE 2005. WVU had the lowest signal-to-noise ratio.

Krichen et al. [97] gives a brief introduction to the open-source iris recognition system, OSIRIS. They also describe their BioSecure Iris Database, which they combine with the CASIA v2 data to create a database with equal numbers of Asian and European subjects. They test the OSIRIS system on the CASIA-BioSecure data and also on the ICE 2005 data, and show that the OSIRIS system outperforms the Masek open-source system.

Phillips et al. [144] describe the results of the Face Recognition Vendor Test 2006 and the Iris Challenge Evaluation 2006. These evaluations follow on the Face Recognition Grand Challenge and the Iris Challenge Evaluation 2005. The ICE programs resulted in a dataset of over 64,000 iris images from over 350 subjects, acquired using an LG 2200 iris sensor in 2004 and 2005, being made available to the research community [19]. The dataset contains both "ideal" images, and "poor quality" images. The ICE programs also resulted in the source code of a baseline Daugman-like system being made available to the research community.

Petrovska et al. [140] describe the BioSecure benchmarking methodology for evaluating performance of biometric algorithms. The BioSecure reference system provides open-source software, publicly available biometric databases, and evaluation protocols that allow researchers to conduct reproducible research experiments. The book chapter explains the need for a common benchmarking methodology, and summarizes the frameworks. Frameworks for eight different biometric modalities are available: iris, fingerprint, signature, hand geometry, speech, 2D face, 3D face, and talking face.

The U.S. Government has organized a number of biometrics challenge problems and evaluations to motivate advancements in biometric technology. Phillips et al. [180] describe the data available in the Multiple Biometrics Grand Challenge (MBGC). The MBGC includes three different challenge problems, one of which involves iris recognition: the Portal Challenge Problem. The goal of the Portal Challenge Problem is to recognize people from near-infrared and visible-light video as they walk through a portal. Five different types of data are provided as part of the Portal Challenge: (1) still iris images from an LG2200 sensor, (2) video iris images from an LG2200 sensor, (3) medium-resolution, still, frontal face images, (4) high-resolution NIR video acquired from a Sarnoff Iris on the Move (IoM) system, and (5) high-definition, visible-light video acquired at the same time as the IoM videos. MBGC version 1 data was released in May 2008. MBGC version 2 data was released in February 2009.

Newton and Phillips [134] present a meta-analysis of three iris biometric evaluations: the Independent Testing of Iris Recognition Technology performed by the International Biometric Group, the Iris Recognition Study 2006 conducted by AuthentiCorp, and the Iris Challenge Evaluation 2006 conducted by the National Institute of Standards and Technology. The meta-analysis looks at the variation across the three studies in the false non-match rates reported for a false match rate of 1 in 1,000.

2.8 Performance Under Varying Conditions

Some early folklore of the iris biometrics field held that pupil dilation, contact lenses, and template aging do not negatively impact iris biometrics. Bowyer et al. [21] test these assertions. They show that iris biometric performance can be degraded by varying pupil dilation, by wearing non-cosmetic or cosmetic contact lenses, and by time lapse between enrollment and verification. They also show that using a different sensor between enrollment and verification can degrade performance. These factors primarily affect the match distribution, while the non-match distribution remains stable. Thus, for a verification scenario, the false accept rates are unaffected by these factors. For a watchlist scenario however, operators should be aware that suspects may attempt to fool the system by, for example, artificially dilating their eyes or wearing contacts.

Baker et al. [7] look at how contact lenses affect iris recognition, with the conclusion that even normal prescription contacts can cause an increase in the false rejection rate. The size of the increase in the false reject rate varies greatly across different matching algorithms and different types of contact lenses. In general, the effects of contact lenses on iris biometrics accuracy seem not yet fully understood.

Rankin et al. [160] explore effects of pupil dilation using images from three subjects taken over a period of up to 24 weeks under varying pupil dilation conditions, using a biometric slit lamp. Some unusual results are obtained on applying a version of an early Daugman algorithm and Masek's algorithm to these images. However, results generally agree with those of previous researchers that found that pupil dilation increases the false reject rate [61, 76].

Gonzaga and da Costa [57] propose a method to exploit the "consensual reflex" between a person's irises to illuminate one eye with visible light to control the dilation of both pupils, and image the other eye with NIR illumination. In this way, they can compute features of the iris over dilation.

Baker et al. [6] explore the effects of time lapse on iris biometrics. They compare the average Hamming distance between images taken 4 years apart with the average Hamming distance between images taken within a single semester. They find statistically significant evidence that the distance scores between images taken years apart are greater than the distance scores from images taken within a few months of each other. Using the IrisBEE iris matcher, they observe an approximate 0.018 increase in Hamming distance for matches with a 4-year time lapse. The increased false reject rate for the long-time-lapse matches relative to the short-time-lapse matches indicates that a template aging effect exists for iris biometrics. This was the first study to make any rigorous experimental evaluation of the issue of template aging for iris biometrics.

Borgen et al. [18] investigate the effects of common ocular diseases on iris recognition. They use the UBIRISv1 data set and simulate different pathologies. All simulated pathologies were validated by opthalmology and optometry specialists. Changes in iris color, scars from glaucoma surgery, and vessel growths caused only small increases in the false reject rate. Corneal bleaching and scarring caused a false reject rate of 86.8 %. The corneal bleaching caused segmentation of the outer iris boundary to fail in many cases. Central keratitis increased the false reject rate of bright-eyed subjects more than dark-eyed subjects. High-density infiltrates caused more problems with dark-eyed subjects. The authors conclude that iris recognition is robust for some pathologies, but that others—such as corneal bleaching—can unacceptably damage the false reject rate in just three months of disease progression.

2.9 Applications

A small number of publications have appeared which envision the use of iris biometrics in particular application scenarios. One interesting aspect of this group of papers is the very broad range of uses envisioned for biometrics, almost none of which involve national security.

Kadhum et al. propose using iris biometrics to authorize entry through doors to secure areas, an application for which commercial iris biometric systems already exist (e.g., LG Iris). Mondal et al. [130] propose using biometrics for secure access to home appliances over the network. Iris biometrics is used in this paper, but the approach can potential be extended to other biometrics. Garg et al. [53] propose a vision system that will recognize a set of hand gestures to control devices and use iris biometrics to authenticate the user identity. Leonard et al. [103] propose using fingerprint, iris, retina and DNA (“FIRD”) to distinctively identify a patient to his or her complete electronic health care record. Mohammadi and Jahanshahi [128] propose an architecture for a secure e-tendering (offering and entering into a contract) system, with iris as the example biometric for identity verification. Wang et al. [203] propose using Daugman-like iris biometrics “to make the large animals be recognizable and traceable from the farm to the slaughterhouse,” furthering the goal of food chain safety. Wang et al. [200] propose to use face and iris multi-biometrics as part of a scheme to enforce digital rights management, which would allow only authorized remote users to access content. Hassanien et al. [67] show how an iris template can be embedded in a digital image to prove ownership of the image.

Dutta et al. [41–43] propose embedding the iris code of a person in an audio file as a watermark to prove ownership of the audio file. They apply Haar wavelets at four levels of decomposition to create a feature vector from an iris image. Next, they binarize the feature vector by comparing each element of the vector to the median value in the vector. This process creates a biokey with power evenly distributed throughout the audio spectrum, thus allowing the key to be embedded in the audio signal without affecting listeners. They test their method by embedding biokeys in five different musical samples, then comparing the embedded keys with all iris keys in their database. A high correlation between the embedded key and the stored key is evidence of a match. Their method is robust to various types of attack on the audio signal.

2.9.1 *Hardware Implementations*

Liu-Jimenez et al. [111] and Rakvic et al. [159] describe the implementation of iris biometric algorithms on FPGAs. Zhao and Xie [216] describe an implementation of an iris biometric system on a DSP. Vandal and Savvides [196] present results of iris matching parallelized for execution on graphics processing units, and report a 14-times speedup relative to state-of-the-art single-core CPUs.

Jang et al. [83] describe the design and implementation of a "portable" or hand-held iris biometric sensor. The heart of the system is an "ultra-mobile personal computer," the Sony model VGN-UX17LP. The system uses a near-infrared illuminator and a CCD camera with a fixed-focus zoom lens. An image restoration algorithm is used to increase the effective capture volume, which is claimed to exceed that of the PIER 2.4 and the HIDE systems.

Kang and Park [89] describe an iris biometrics system implemented to operate on a mobile phone. The system repeatedly takes images of both eyes and performs a quality assessment until at least one image passes the quality assessment check. Then it performs authentication either with one image, or with score-level fusion of two images.

2.10 Theoretical Analyses

There are relatively few studies that might be considered theoretical analyses of fundamental issues in the field. Bhatnagar et al. [11] develop a theoretical model for estimating the probability of random correspondence of two iris codes, and compare this with the analogous value for a pair of palmprints. Kong et al. [92] undertake a theoretical analysis of the Daugman-style iris code representation of iris texture. One interesting element of this is a discussion of the impostor distribution as an instance of the binomial distribution.

Gorodnichy and Hoshino [59] develop a score calibration function that can convert match scores into probability-based confidence scores. They present a theoretical argument and also supporting experimental results to show that this approach results in the best possible detection error tradeoff curves. The calibration that is effected is meant to ensure that "... the statement 'I am 60 % sure that this person is Alice' is correct exactly 60 % of the time."

Yager and Dunstone [214] tested for the existence of "Doddington Zoo" animals in a number of different biometric databases, using a number of biometric algorithms. Each of the animal types was present in some of the experiments and absent in others. The authors note that "The reasons that a particular animal group exist are complex and varied. They depend on a number of factors, including enrollment procedures, feature extraction and matching algorithms, data quality, and intrinsic properties of the user population" [214]. Their analysis also leads the authors to assert that people are rarely “inherently hard to match.” Instead, they suggest that matching errors are more likely due to enrollment issues and algorithmic weaknesses rather than intrinsic properties of the users.

Stark et al. [186] conduct experiments in which human observers view iris images and categorized them into groups of similar-appearing texture pattern. The results suggest that there are a small number of generally agreed-upon texture categories. The results also suggest that texture categories may be correlated with ethnicity, although the iris textures in the experiment all represent either Asian or Caucasian ethnicity and so greater variation in ethnicity remains to be examined.

2.11 Discussion

In this section we give eight “recommended reading” suggestions. This is not meant as a best papers list, but rather as a list of papers representing interesting and/or unusual viewpoints and directions in iris biometrics.

Gorodnichy’s paper “Evolution and evaluation of biometric systems” [58] is a worthwhile read for those who want to get a sense of how biometric technology is evolving, how the performance of biometric technology is evaluated, and an introduction to much basic biometric terminology. Gorodnichy is Senior Research Scientist with the Canadian Border Services Agency, and so he brings a systems and application-oriented viewpoint to the task of evaluating biometric technology. He particularly makes that point that biometric systems are not fielded in a static context, but that the mix of data and challenges that they must handle naturally evolve over time, and so the biometric technology must evolve as well.

Current commercial iris biometric systems all, to our knowledge, use near-infrared illumination in the 700–900 nm wavelength range. There is also a body of iris biometric research based on visible wavelength images. But there is almost no published work on imaging the iris outside of the 700–900 nm range. For this reason, the paper by Ross et al. [170], “Exploring multispectral iris recognition beyond 900 nm,” is unique. It remains to be seen whether or not it will be technically and economically viable to image the iris at multiple wavelengths and/or to match iris texture across wavelengths. For those who are intrigued by the topic, this paper is a good introduction. This is likely an area that will see increased attention in the future.

To our knowledge, the paper by Chou et al. [31], “Non-Orthogonal View Iris Recognition System,” is the only system proposed to simultaneously acquire both a visible-light image and a near-infrared image of the iris. They exploit the two images in a complementary manner in the segmentation stage, using the color image to aid in finding the limbic boundary. For anyone interested in multi-biometrics, the relative simplicity of the sensor design and the method of exploiting the two images should be interesting and suggest additional possibilities.

Proenca’s paper, “On the Feasibility of the Visible Wavelength, At-a-Distance and On-the-Move Iris Recognition” [152], is interesting because it argues that visible-light imaging is the way to go, especially for imaging “at a distance” and “on the move." This argument runs counter to the approach used by all commercial systems that we are aware of, and also counter to the majority of academic research. However, because it does represent a "contrarian" sort of approach, those interested in the illumination issue for iris biometrics should find this paper worthwhile.

The paper by Pillai et al., "Sparsity inspired selection and recognition of iris images" [147], is the first that we know of to try to transfer the excitement about sparse representation techniques in the face recognition community over to iris recognition. Extraordinary recognition performance has been claimed for face recognition systems using sparse representation techniques. A potential weakness of using a sparse representations approach is the requirement for a large number of training images per iris, and that the images should span the range of different possible appearances. It remains to be seen whether or not sparse representation techniques will revolutionize either face or iris recognition in practice, but this paper is a good starting point for how the concepts could be applied in iris recognition.

The paper by Vatsa et al. [198], "Belief Function Theory Based Biometric Match Score Fusion: Case Studies In Multi-instance and Multi-unit Iris Verification," is interesting as an example for what it terms "multi-instance" and "multi-unit" iris biometrics. Multi-instance refers to using multiple images of the same iris, either to enroll a person in the system, and/or as a probe to be matched for recognition. Multi-unit refers to using an image of both irises rather than a single iris. Early iris biometric systems seem to have all enrolled a person using a single iris biometric template formed from a single image. This paper shows that there are simple ways of increasing recognition performance by using multiple images.

For anyone not already familiar with the concept of cancelable biometrics, the paper by Kanade et al., "Cancelable Iris Biometrics and Using Error-Correcting Codes to Reduce Variability in Biometric Data" [87], should be worth reading. In this particular instance, they propose a two-factor approach to cancelable biometrics. The two factors are the biometric and the password. If needed, a person's current enrollment in a biometric system using this scheme can be canceled, and then the person reenrolled with a new password. This particular proposed system also uses the password to effectively increase the separation between the genuine and impostor distributions.

Zuo and Schmid's paper, "Global and Local Quality Measures for NIR Iris Video" [221], provides a good introduction to the complexity of the problem of evaluating the quality of an iris image. For a single iris image, they compute nine different quality metrics, for segmentation quality, interlacing, illumination contrast, illumination evenness, percent occlusion, pixel count, dilation, off-angle view and blur. Quality metrics concerned with interlacing will presumably not be important in the future, as iris images will be acquired digital rather than digitized from analog video. But the problem is actually even more complex than it appears here. For example, the focus quality of an image is not necessarily even over the entire iris. Also, it is not only the dilation of a single image that is important, but the difference in dilation between two images that are being matched [76].

This group of eight papers that touch on very different topics in the field of iris biometrics research should convey a sense of the breadth of the field. It should also help to convey a sense of the excitement in the field, in that there are many directions being explored that could serve to increase accuracy of, and/or increase the breadth of application of, iris biometrics.

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