Human Perceptual Categorization of Iris Texture Patterns

Louise Stark, Kevin W. Bowyer and Stephen Siena

Abstract— **We report on an experiment in which observers were asked to browse a set of 100 iris images and group them into categories based on similarity of overall texture appearance. Results indicate that there is a natural categorization of iris images into a small number of high-level categories, and then also into subcategories. Also, the categorization reflects the Caucasian / Asian ethnicity of the person. This iris texture categorization has potential application in, for example, creating an indexing algorithm to speed search of an iris database and / or determining soft biometric traits of a person.**

Index Terms— **Iris biometrics, texture analysis, texture categories.**

I. INTRODUCTION

In some applications, an unknown iris image may be matched against a potentially very large set of known iris images. (The country of India has embarked on a program called AADHAAR, that will result in a biometric ID card using iris and fingerprint for over one billion citizens. [8].) The search of the database could be faster if the iris images could be separated into categories of similar appearance.

This paper reports on the results of an experiment in which human observers were asked to group a set of 100 iris images into categories that reflect perceived similarity of overall texture appearance. Section II reviews related work. Section III describes the experiment and results. Section IV summarizes the conclusions and Section V outlines future work.

II. RELATED WORK

One area of related work deals with predicting demographic characteristics of the person, such as male/female or Asian/non-Asian, from analyzing iris texture. This area of work shows that there are potentially useful natural categories of iris texture. Another area of related work develops classifiers to categorize iris images into a small number of pre-determined categories. A third area of related work looks at methods of analyzing a dataset of iris images to learn a set of categories that could be used in an indexing scheme.

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Two research groups have looked at categorizing iris image texture with the goal of determining demographic attributes of the person. Thomas et al [18] have reported that iris images can be classified to detect the gender of the person, whereas Qiu et al [11], [12] have reported that iris texture is linked to Asian / non-Asian ethnicity.

Thomas et al [18] present results of experiments in classifying an iris image according to the gender of the person. They use features derived from the same log-Gabor filtering of the iris image that is used to derive the iris code for the IrisBEE implementation [3], and geometric features based on the relative size of the iris and pupil. Using ensembles of C4.5 decision trees, and 10-fold cross-validation on a set of images from the ND_Iris_0405 dataset [4], they report achieving nearly 80% accuracy in male / female classification of the image. Using texture features alone, without geometric features, they still achieve male / female classification accuracy significantly above random guessing.

Qiu et al [11], [12] develop methods to categorize iris images based on ethnicity classification of Asian / non-Asian. They argue that, "iris texture is race related, and its genetic information is illustrated in coarse scale texture features, rather than preserved in the minute local features of state-of-the-art iris recognition algorithms" [12]. They use Gabor filters for texture features and an Adaboost classifier algorithm to construct a classifier to distinguish between Asian and non-Asian iris textures, and get 86% correct classification on a dataset of 3,982 iris images [12]. They use the CASIA [6], UPOL [1] and UBIRIS [2] datasets, with Asian iris images coming from the CASIA dataset, and non-Asian iris images coming from the UPOL and UBIRIS datasets. The CASIA images are near-IR images. The UPOL and UBIRIS images are visible-light RGB color images. Thus there is the methodological problem of image acquisition factors being confounded with ethnicity. A small experiment was done with some subjects in the CASIA dataset to check that this was not a major factor in the results. Another paper from this group explores an approach using support vector machines and reports 91% correct classification rate using a dataset of 2,400 iris images, representing 60 persons, with all images acquired in near-IR illumination [11].

Other authors have experimented with developing classifiers to categorize iris images into one of a small number of pre-determined classes. Reddy and Babu [14] consider four intuitively named iris texture classes. Shirazi and Nasseri [16], [17] consider training a neural network to classify an iris image into one of five or six different basic classes.

Reddy and Babu [14] consider iris texture patterns to have four basic groups - Stream, Jewel, Shaker and Flower - along with the different combinations of these. The "Stream" texture pattern "is determined by the arrangement of the white fibers radiating from the center of the iris (or pupil)." The "Jewel" texture pattern "... can be recognized by the presence of pigmentation or colored dots on top of the fibers ... the dots (or jewels) can vary in color from light orange through black. They can also vary in size from tiny (invisible to the naked eye) to quite large." The "Shaker" texture pattern "... is identified by the presence of both flower like petals in the fiber arrangement and pigment dots or jewels ... The presence of even one jewel in an otherwise Flower iris is sufficient to cause the ... shaker characteristics." The "Flower" texture pattern "... contains distinctly curved or rounded openings in the iris. ... they are neither regular nor uniform. A flower iris may have only one significant petal with the remainder of the iris looking like a stream." They use gray-level co-occurrence matrix features, with the gray-level range of the image reduced to 8 levels, to classify the iris texture pattern. They use a 756-image CASIA dataset and a 450-image MMU iris image datasets in experiments, and categorize irises into six texture categories. The accuracy for categorizing an iris image into one of the six categories does not appear to be stated.

Shirazi and Nasseri [17] define six iris classes. Using 716 images from the CASIA dataset, the six categories of images range in size from 9% to 29% of the total. They compute entropy-related texture features from sixteen subregions of the iris image, eight subregions in the outer band and eight in the inner band. Using a two-hidden-layer neural network, they are able to obtain a 94% correct classification rate. There is not a train-test division of the data reported. In a related paper [16], differential of fractal dimension is used as a texture feature in classifying images into five categories rather than six, and a neural network is trained to 96% correct classification rate. Again, there is not a train-test division of the data reported.

Still other authors have considered creating indexing schemes that can be adjusted to have a range of number of bins for similar iris textures. The performance of these schemes is generally stated in terms of a miss rate and penetration rate for a given indexing parameterization. The miss rate is the fraction of probes that do not get matched to the correct enrolled image. The penetration rate is the fraction of the database that is searched to find a match to the probe. Better performance is achieved through a lower miss rate and / or lower penetration rate.

Mukherjee and Ross [10] compare two approaches to indexing a large iris database: "post-encoding indexing", which operates on the iris codes, with "pre-encoding indexing", which operates on texture features. Indexing based on the iris codes uses an initial step to reduce the dimensionality of the codes, and then a k-means algorithm to cluster the codes. Dimensionality reduction is explored using (a) the average along rows, (b) the average along columns, average of MxN blocks, and (c) principal components analysis of the codes. The indexing based on iris texture uses the Signed Pixel Level Difference Histogram (SPLDH) of the raw pixel intensities in multiple blocks of the segmented iris region. The subset of the CASIA v3 dataset that contains at least six images per iris is used for experiments. Indexing based on statistics from 8x8 blocks of the iris codes had a performance of about 80% hit rate and 8% penetration rate, whereas indexing based on texture features had performance of a hit rate of about 84% at a penetration rate of about 30%.

Mehrotra et al [7] divide the iris image into non-overlapping 8x8 blocks, compute DCT coefficients from the blocks, and create an energy histogram for the image. This results in a 10-element key to index to a group of iris images with similar texture. They experiment with the CASIA, Bath and IITK iris image datasets. On the CASIA dataset, they are able to obtain a bin miss rate of 1.6% and a penetration rate of 36% with five classes, and a miss rate of 3.6% and penetration rate of 22.7% with 16 classes. On the Bath dataset, they obtain a miss rate of 4% and a penetration rate of 26% with five classes. On the IITK dataset, they obtain a miss rate of 1.5% and a penetration rate of 41% with five classes.

Mehrotra et al [9] develop an approach to indexing a dataset of iris images based on geometric hashing applied to a set of SIFT keypoints detected on the iris image. SIFT keypoint detection is applied on the annular iris image. Geometric hashing is applied to the set of keypoints. The CASIA v3, Bath, IITK and UBIRIS v1 datasets are used in experiments. Results indicate that this recognition using this approach to indexing may be able to achieve a combined low miss rate and low penetration rate - "The accuracy at EER is obtained within each bin and system is performing with an average accuracy of 98.5%."

Qiu et al [13] use a K-means clustering algorithm applied to iris texton texture descriptions of images to learn a set of iris texture pattern categories. A set of 400 images is used for learning, 200 from a CASIA dataset and 200 from a Bath dataset. A 40-dimensional feature vector of Gabor filter results is computed for each pixel of an iris image. Then a K-means algorithm is used to find 64 clusters for the feature vectors. The cluster centers are then the learned iris textons. A given iris image generates a histogram of these iris texton values. A K-means algorithm is then used to find five clusters in the iris texton histogram space. The different categories represent from 12% to 31% of the irises. Using additional images of the same irises used in the learning, they are able to achieve a 95% correct classification rate into the five categories. They estimate that an iris image database larger than 1,579 can be searched more quickly using this category structure for indexing.

Ross and Sunder [15] propose the use of iris texture to classify irides into categories to help reduce search space. They segment the inner iris region into overlapping blocks used for extraction of 68 statistical features associated with structures found in the iris such as crypts, furrows and pigment spots. The experimental database consisted of 384 images from the UPOL database, using three images of each of the left and right iris of 64 individuals. Feature vectors from each iris was partitioned into three clusters and five clusters based on the measure of cohesiveness determined by the magnitude of the eigenvalues within a cluster. Experiments showed that classification accuracies are affected by block width and resolution of the iris. Experiments were also conducted using feature level fusion and decision level fusion using two different iris blocks. 100% classification accuracy was achieved using smaller block width for iris texture with higher discriminating characteristics. They note that their classification method does not perform well on images with low texture clarity.

Our work differs fundamentally from these in that we hope to discover a category structure for iris image texture classes that is motivated by human perception of similarity in iris texture. However, we share the goal of arriving at a number of iris image texture categories that allow a large dataset to be searched with low miss rate and low penetration rate.

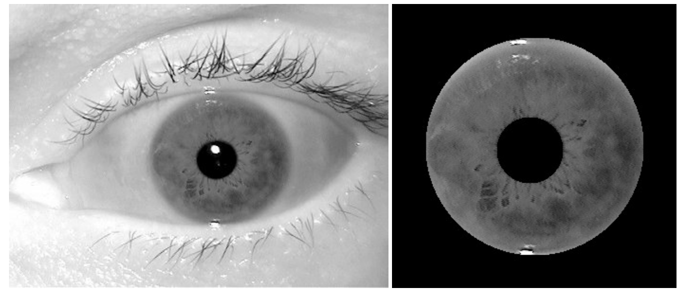
III. PURPOSE OF THE STUDY

The purpose of this study is to determine if humans define consistent categories when they are given a set of iris images and asked to place them into groups of similar texture appearance. If there is substantial agreement across subjects in terms of how to group the images by similarity of appearance, this result could potentially be used to guide the creation of a computerized image analysis system to categorize by iris appearance. Such an image analysis system could be used to speed up search of large iris image datasets. Because some previous related work has reported success at determining gender and ethnicity from iris images, we also select our dataset to allow us to explore these issues. Iris texture categories that are closely correlated with soft biometrics such as gender and ethnicity may be of value independent of database search issues.

A. Experimental Setup

Human subjects were asked to categorize a set of iris images purely by their texture pattern, creating sub-groups that they perceive to represent similar general appearances of the iris. A set of 100 iris images from 100 different individuals was chosen by hand from the ND-IRIS-0405 dataset of iris images [4]. Since the experiment depended on human subjects making their decision upon the visible iris texture, only well focused images were chosen. The 100 images were selected to represent 26 Asian male, 24 Asian female, 26 Caucasian male and 24 Caucasian female persons. This distribution of images was motivated by works referenced in Section II ([18], [11], [12]) that indicated gender and ethnicity could be determined from iris texture.

The images from the ND-IRIS-0405 Iris Image Dataset were captured using the LG 2200 system, which automatically processes the images to stretch the contrast range values from 0-255. [4] This processing is performed on the full eye image (see Fig. 1a). Since it was important in this study to have subjects use only the iris texture in forming categories, each image was further processed to mask out all but the iris, as shown in Fig. 1b. Also, to standardize the size of the



(a) Original image (b) Iris only

Fig. 1: (a) Sample original iris image extracted from ND-IRIS-0405 Iris Image Data (b)Masked iris. Subjects in our experiment viewed iris-only images such as those in (b).

images for the experiment, each iris-only image was resized to 300x300. The resulting image can be seen in Fig. 1b.

Subjects were given a brief verbal description of the study along with the following set of instructions:

1) Your task for this experiment is to categorize a set of 100 iris images using their iris texture pattern. You can create as many categories as you see fit, however, each category must have at least two members.
2) Disregard things like pupil size, specularities, shape of iris and eyelashes. Use only the iris texture pattern to categorize the images.
3) You can create a miscellaneous category whose members do not fit into any other category. The miscellaneous category should have no more than five images.
4) When you are finished categorizing all the images, you will be prompted to provide a descriptive word or short phrase that represents the iris texture similarity of the images in that category.

The study interface was developed to display the original set of 100 images in a scrollable area on the left side of the display (Fig. 2). All images are always displayed in their 300x300 size. Subjects click on images from this unclassified group and assign them into scrollable subgroups on the right side of the display, with the capability to create as many subgroups as they feel necessary. Subjects could move images out of categories and re-assign them to other categories if they wanted. On average, it took subjects about 30 minutes to complete the categorization of the 100 images.

B. Discovering Categories

Twenty-one subjects categorized the set of 100 images. The subjects did not have a medical background, nor was it likely that they discussed the experiment prior to their participation. The different subjects categorized the images into as few as three to as many as thirteen categories. Table I shows the distribution of the 100 images into categories by each of the twenty-one subjects. By not specifying a minimum or maximum number of categories the subject should create, other than stating that each category must have

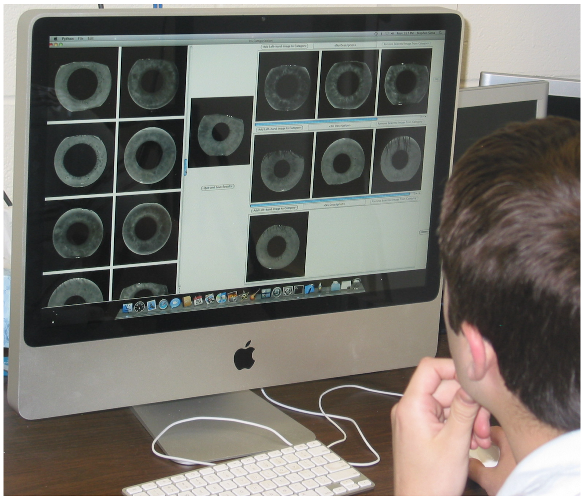


Fig. 2: Program interface divided into three regions: (1) left two columns are a scrollable area of images yet to be classified; (2) single center image displayed is the image selected by the subject to be classified; (3) Three rows to the right of the image to be classified are categories created by the subject. Images can be added to an existing category or start a new category.

TABLE I: Distribution of images by subjects.

Subj.	# of cat.	# images in each category
1	5	14, 17, 19, 20, 30
2	5	4, 14, 23, 29, 30
3	6	6, 8, 11, 12, 30, 33
4	13	4, 5, 5, 5, 5, 6, 6, 7, 7, 7, 8, 9, 26
5	5	10, 13, 19, 20, 38
6	6	8, 9, 12, 16, 23, 32
7	7	3, 8, 12, 13, 16, 17, 31
8	4	8, 10, 26, 56
9	9	2, 6, 6, 9, 10, 10, 11, 13, 33
10	7	6, 7, 9, 14, 16, 24, 24
11	7	4, 6, 11, 15, 16, 23, 25
12	6	6, 6, 9, 19, 21, 39
13	7	2, 6, 9, 9, 13, 26, 35
14	10	3, 5, 6, 7, 10, 11, 11, 12, 14, 21
15	9	4, 6, 7, 8, 19, 12, 17, 17, 20
16	4	9, 10, 37, 44
17	9	2, 6, 6, 9, 11, 12, 13, 15, 26
18	6	9, 10, 10, 19, 20, 32
19	6	4, 11, 12, 13, 15, 45
20	12	2, 3, 5, 6, 6, 6, 7, 8, 10, 15, 13, 19
21	3	27, 30, 43

at least two members, the wide range of results relates to the level of texture detail that different individuals used in differentiating their subcategories. Since the subjects were allowed to use any naming scheme they chose, in the initial analysis of the results, the category names provided by the subjects were not used.

An NxS Category Membership (CM) matrix (with N=number of images and S=number of subjects) was generated where each $CM_{i,j}$ $(1 \leq i \leq N; 1 \leq j \leq S)$ is the category number into which $Image_i$ was placed by $Subject_j$. For example, the first column of the Category Membership matrix denotes the distribution of the images for subject 1. As seen in Table I, subject 1 created a total of five categories with 14, 17, 19, 20 and 30 elements. This means $CM_{i,1}$ $(1 \leq i \leq N)$ can take on the values 1 to 5, corresponding to which of the five categories that $Image_i$ was assigned to by subject 1. Table II provides a portion of the Category Membership matrix for the twenty-one subjects categorizing the set of 100 images. For example, it can be seen that Subject 3 placed image 2 into their category number 4.

TABLE II: Portion of Category Membership Matrix denoting placement of images into categories by subject.

	Subject									
Image	**1**	**2**	**3**	**4**	**5**	…	**18**	**19**	**20**	**21**
1	3	1	3	10	1	…	1	3	1	2
2	1	4	4	4	2	…	3	5	3	1
3	1	1	2	3	2	…	3	4	2	1
4	2	2	1	11	3	…	2	2	4	2
…	…	…	…	…	…	…	…	…	…	…
98	5	2	1	13	3	…	2	2	12	2
99	4	4	4	9	4	…	6	1	7	2
100	2	4	6	9	4	…	5	5	1	2

The goal of this project is to discover agreement across subjects that certain images have similar texture pattern and should be placed in the same category. The number of subjects that categorized the same images together measures strength of agreement. If two (or more) images were placed into the same category by all twenty-one subjects, this would mean that the rows of the Category Membership matrix associated with those images would be equal. We intentionally gave subjects minimal guidance on the number of categories to use or the level of granularity to use in the categorization. For this reason we expect that some subjects will form a small number of coarse-grain categories and others will form a larger number of categories based on finer distinctions. We then recover a category-subcategory structure by analyzing results across a set of subjects.

Through an iterative process, the Category Membership matrix was scanned, identifying agreement among the subjects where images should be grouped into the same category according to their texture pattern. The Category Membership matrix was processed by first looking for images that all twenty-one subjects agreed have similar texture pattern and should be placed into the same category. Three subjects created miscellaneous categories, which were not used in this process. The strongest possible level of grouping a pair of images together, all twenty-one subjects agreeing, was found with one pair of images (Fig. 3a), image 3 and 15.

This process was continued, looking at the agreement of 20 subjects, 19 subjects, etc., clustering images together when there was strong support by the subjects. Each time there was agreement, either a new category was formed or images were merged into existing categories. For example, the next strongest level of agreement found was on another pair of images that nineteen of twenty-one subjects placed together in a category (Fig. 3b), images 82 and 84.

As the process continued with fewer subjects in agreement, there were times when some or all of two existing categories were placed into the same category by a number of subjects. When there was a majority agreement, these two existing categories were merged into a single category. Table III represents the discovery of implied (sub)-categories of the 100 images. The left column represents the number of subjects that are in agreement regarding the grouping of images, showing twenty-one down to eight.

If we think of the table as a subcategory tree, the leaves of the tree will be the shaded cells of the tables. The branches of the tree are the columns. Some categories (branches) are made up of a single column (e.g., A and Q).

Column A (Tab. III) shows that twenty-one subjects (all subjects) agreed that two of the images should be categorized together. Eighteen subjects agree that two more images should be in the same category as the first two. There is agreement by fifteen of the twenty-one subjects that five (summing down the column) images of the 100 should be in the same category. Moving down the column, the set of images grouped into category A grows to 10.

Columns B through I represent subcategories that are created independently, but eventually merge into one larger category of 50 images. Look, for example, at the merging of existing categories that took place at thirteen Subjects in Agreement. The following groups were merged into a single category at level 13 (to find the number of images in the subcategory add the numbers down the column through 14 Subjects in Agreement):

- 4 images from subcategory B
- 5 images from subcategory C
- 15 images from subcategory D
- 2 images from subcategory E
- 5 new images merged into the subcategory from agreement by thirteen subjects

Therefore, at level 13 there are 31 images that have been merged into a single subcategory (subcategories B, C, D, E and 5 new images). The result of this process produced a hierarchy of clusters.

This hierarchy of image groupings provides evidence that some subjects used more detail in their partition scheme, yet merging some of their smaller category groups brought them into agreement with other subjects that did not use as much detail.

The process continued until all 100 images were categorized in this way. There were instances during the process where there was disagreement between subjects on images that had already been categorized. For example, two images that were merged into the tree in the same category may later have evidence that some smaller number of subjects disagreed. The process always kept the majority level of agreement. When there was conflict within the same level, the image(s) was not merged until there was a majority consensus.

C. Analyzing the Results

The result of this process generated five major iris texture categories with refinements into a total of seventeen subcategories (see shaded cells Table III). An ideal partitioning would have an evenly distributed partitioning of the images into categories across the entire population, resulting in optimal search cues. The level of merging could be set such that subcategories B-E are merged and subcategories F-I are merged, producing a total of six final subcategories.

The images with the strongest agreement of grouping for the five main categories are shown in Fig. 3. These images represent the leaf nodes of the Category Discovery Tree depicted in Tab. III. Each of these categories will henceforth be referenced by their initial subcategory (categories A, B, J, N and Q). A measure of dissimilarity was evaluated between each category. This was accomplished by finding how many of the twenty-one subjects grouped core images from different discovered categories (see Table 3). From this analysis it can be seen that there is strong agreement that Category A is very dissimilar to members of Category B, J and Q. However, around level 6 or 7, Categories A and N would have been merged into a single category. This is information that can be used to order the search of the categories, from the category most likely to contain a match, if one exists, to the category least likely to contain a match.

In the same way the categories identified by the subjects provided evidence of similarity, it also provided evidence of strong dissimilarity. There were pairs of images that none of the subjects put into the same category. This disjoint category condition would be necessary to be able to use the categories discovered through this process as a way to eliminate parts of the search space. All category lists were compared between subjects to identify agreement in both combining and also not combining images.

The question is raised, how similar or dissimilar are the discovered subcategories? Measures of similarity can be used to identify bordering subcategories (see Table IV). From this evaluation it can been seen that Categories A and B-I are very dissimilar. However, Category A and N-P have some similarities. This knowledge can be used to order a hierarchical search strategy. If an iris is expected to be in Category A, but is not found, search can continue in category N-P.

D. Ethnicity and Gender Effect on Categorization

The 100 image dataset was chosen specifically to include irises of 26 male Caucasian, 24 female Caucasian, 26 male Asian and 24 female Asian. This was done to see if there were any trends in categorization that suggested iris texture differs for gender or ethnicity at a level that could possibly be used to help to define categories.

All subcategories defined by all subjects which had 15 or more members were used in the analysis. Table I shows there were 52 out of 146 subcategories with 15 or more members. A percentage of male/female and Asian/Caucasian was calculated for each of the 52 subcategories. The absolute value of the difference of the percentage of male/female and

TABLE III: Subcategory Discovery Tree

# Subj in Agreement	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
21	2					Subcategories B-I											
19		2				merged				3		J-M merged				N-P merged	
18	+2		2											2			
17				3							2				2		
16		+2		+6	2	2				+1	+1	2		+2		2	
15	+1		+2	+3		+1	2	2	2	+1				+2			2
14	+1		+1	+3		+1		+1					2	+1		+2	+1
13	+2		+5			+1			+2		+1				+4		+1
12	+1				+5												+1
11	+1										+3						
10																	
9																	+1
8											+1						
Totals	**10**	**50**								**17**				**17**			**6**

TABLE IV: Similarity across subcategories - the value represents the average number of subjects that placed core images from different subcategories into the same category (see Fig. 3).

Category	A	B-I	J-M	N-P
B-I	0			
J-M	0	1		
N-P	7	0	5	
Q	1	4	1	0

Asian/Caucasian should give us information as to whether either gender or ethnicity in some way affect the texture pattern and therefore affect the categorization. The average difference in percentage for male/female was 15.5%. This means the categories were split, on average, 42.5% to 57.5%. This does not seem to be significant difference, being only 7.5% away from an even split for male and female. The average difference in percentage for Asian/Caucasian, however, was 62.1%. This does seem significant. Since the study only looked at a total of 100 images, larger studies are needed to further explore this aspect of the results.

IV. CONCLUSION

This is, to the best of our knowledge, the first study to systematically identify consistent iris texture categories by using input from a set of human subjects. This work suggests that there are categories and subcategories of iris texture patterns that are consistently identified by humans. Five major iris texture categories were identified. Measures of similarity and dissimilarity could be used to guide a search on next best category or categories that could be eliminated from the search path.

V. FUTURE RESEARCH

Future work in this area will include determining the texture analysis routine(s) that partition images into the same (sub)-categories identified through this study.

Despite the strong agreement found across the twenty-one subjects, it would have been good to be able to measure the reliability of each subject. A future study will be conducted which includes pairs of images of the same eye for some subset of the images, taken at different time frames and a disjoint set of image pairs made up of images of the left and right eyes of the same individual. This will allow us to calculate a reliability measure of the subjects. There is an expectation that iris images of the same eye of an individual, even if taken at different time frames, should have the same general iris texture pattern and should therefore be placed into the same category. From studies conducted on the appearance of left/right iris image texture [5], there was also an expectation that images of left and right eyes of the same individual should have texture pattern similar enough to always be categorized into the same set. A reliability measure can be calculated by looking at the consistency of placing each of the pairs of images into the same category.

The topic of iris texture classes associated with demographic attributes of the subject needs further investigation. On one hand, the texture categories found through our study strongly reflect the Asian / Caucasian classification of the subject. This is consistent with the results in the work of Qiu et al [11], [12]. On the other hand, the texture categories found in our work do not consistently reflect the male / female classification of the subject. This suggests that the classifier developed by Thomas et al [18] uses texture features that are not used by humans in constructing the texture categories in our results. Further study needs to be conducted on gender as well as looking at a broader range of ethnicities.

The goal of speeding up the search of an iris database is made difficult by the need for maintaining very high accuracy. A pure indexing scheme, in which only a subset of the database is searched, only seems feasible if the indexing scheme is near perfect. However, if the indexing scheme is viewed as a way of ordering a search that stops when it finds a close match, and that begins with the indexed subset of the database but that might eventually search the whole database, then the scheme is more generally viable.

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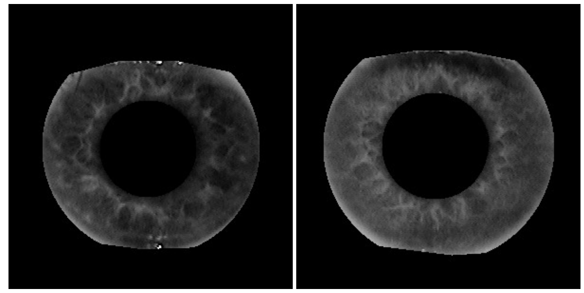
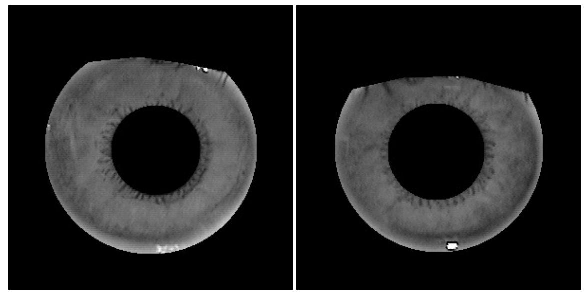
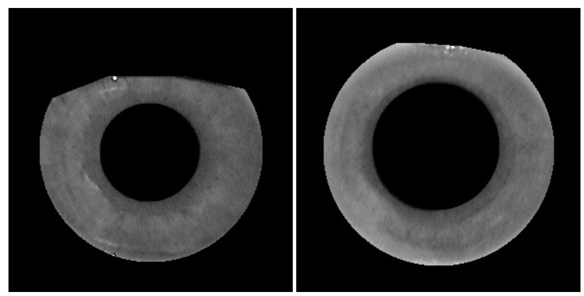


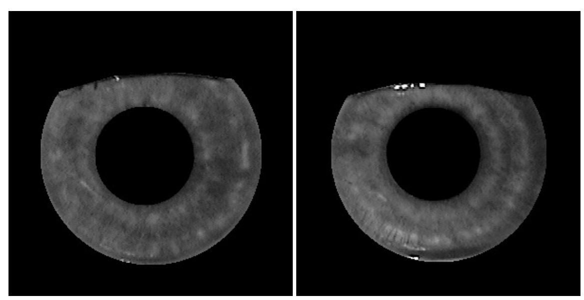
(a) Category A: Images 3 and 15



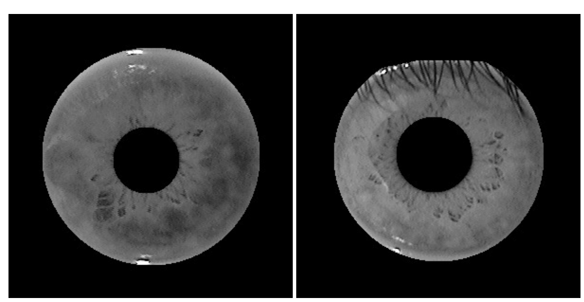
(b) Category B-I: Images 82 and 84



(c) Category J-M: Images 12 and 24



(d) Category N-P: Images 17 and 47



(e) Category Q: Images 1 and 40

Fig. 3: Core images for the five main categories discovered.