A NOVEL COGNITIVE-PSYCHOLOGY-BASED FACE-RECOGNITION SYSTEM FOR IMPROVED IDENTIFICATION RATES FOR THE PROBLEM OF AGE-PROGRESSION

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ABSTRACT
This paper discusses the novel application of an idea rooted in cognitive psychology to face recognition (FR). This cognitive-psychology method adapted for FR is evaluated against the difficult problem of age-progression. The age-progression problem occurs when enrolled images used by the FR algorithm are younger, typically more than one year in difference, than the test (probe) image. A model of a phenomenon in cognitive psychology known as "own-race bias" (ORB) is employed using Principle Components Analysis (PCA) as the face recognition engine. The ORB FR system has demonstrated performance gain of 200% over the baseline technique of Eigenfaces on the MORPH Album 2 face database. Where the baseline system Eigen face FR (which has been described in [1]) had a rank-based identification rate of 23%, the ORB-based FR achieved rates in the mid 50%.

KEY WORDS
Face Recognition, Principle Components Analysis, Cognitive Psychology, Own-Race Bias

1. Introduction

Face Recognition is part of a larger system of biological identification and verification systems known as biometrics. Biometrics as an industry is still relatively young, but projections in public and private outlays for biometric technology are in the billions of dollars; funding a large amount of research and development in attempts to produce effective biometric systems. There are many types of biometrics that are grouped into two broad categories: behavioural biometrics and physical biometrics. Behavioural biometrics is exemplified by voice verification and recognition, handwriting dynamics recognition, and keystroke dynamics recognition. Physical biometrics are exemplified by iris and retina scan, fingerprint, hand geometry, gait analysis, and face recognition, but there are many other techniques for uniquely identifying humans based on physical traits and characteristics.

In this work the authors focus on developing a face-based biometric system that improves the performance of identification against a specific problem that has only recently gained traction in the research community [2, 3, 4, 5]. Normal adult age-progression causes subtle, but significant, changes in a person's appearance that may even seem imperceptible to the human observer without direct comparison of images. Face recognition systems, though, have demonstrated significant problems with effectively handling the appearance changes that occur [2, 3, 4]. This work, which is inspired by an area of study in cognitive psychology concerning a person's ability to recognize members of his or her own racial or ethnic group versus those from other groups, uses this phenomenon as a model for a face-identification system that is demonstrated to achieve significant performance gains over the standard technique of Eigenfaces.

The following section discusses natural human aging and some of the effects shown in the face due to this process. Section 3 provides an overview of own-race bias. Section 4 presents the system developed in this work based on ORB. Section 5 discusses the results and conclusions of these experiments, and Section 6 provides suggestions for future work in this area.

2. Adult Age-Progression

The craniofacial region of a human is where effects of aging that would significantly impact human or computer recognition of individuals occurs. These changes include both the bony portion of the head as well as the overlying soft-tissue that produce the external appearance of one's face. There is a large body of literature concerning this facial morphology due to aging that may be referenced to learn aspects that should be considered for face recognition technologies [6, 7, 8, 9].

Degenerative soft-tissue changes and small shifts in skeletal form ultimately affect the appearance of the face during aging. The skeletal changes include cranial expansion, anterior face-height increase, and jaw shrinkage [8]. Soft-tissue appearance is affected by decreasing muscle tone or atrophy, diminishing collagen and elastin, and skin wrinkling and sagging. Along with these natural changes that occur with aging, there are other aspects that affect facial appearance over time. Of these, photoaging is one of the most significant – largely impacting fair-skinned individuals and those residing in sunny regions [7]. Other major factors include ancestry, gender, health and disease, tobacco and drug use, diet, stress-related sleep deprivation, biomechanical factors, gravity, and hyper-dynamic facial expressions [7, 8]. In addition, there are factors that can exacerbate the age-related changes such as weight loss due to illness, drug use, and/or some medications [7, 8].

These changes are not consistent but vary in rate over adulthood. As expected, changes occur less in the twenties, accelerating some in the thirties, and increasing even more in the forties and fifties – typically the period of greatest change. This period of greater morphology is fairly consistent across race and gender. Past the fifties, the changes that have begun increase significantly and other associated degenerative affects may appear.

Figure 1 illustrates the changes in an aged female with annotated points. Changes to note beginning in the twenties and thirties include horizontal creases in the forehead (areas 1 and 2), slight drooping of the eyelids (area 6 and 9), nasiolabial lines or "laugh lines" (areas 16 and 17), lateral orbital lines or "crow's feet" (area 7), circumoral striae (which are lines around the mouth) (areas 18 and 19), hollowing of the cheek (around area 15), decrease in upper-lip size (area 20), and retrusion (which is a backward movement of the upper lip that is more apparent in females) [6, 8, 9].

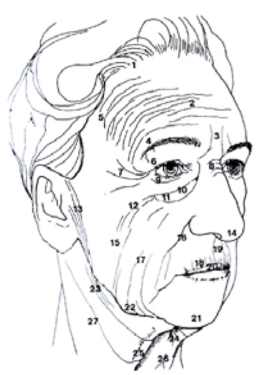

Figure 1: Annotated diagram of craniofacial morphology.

Through the adult aging process these changes become more noticeable, and by or around fifty years, there are other changes that have begun including the appearance of fine lines and thinning and sagging of skin as shown in Figure 2. Skin also becomes rougher, drier, and shows loss of tone and elasticity. This combined with atrophy in corrugator and orbicularis muscles can greatly affect facial appearance. Wrinkles appear on the neck, and discolorations in skin may begin to appear. Loss of hair and de-pigmentation may occur. Hair may also grow in areas that previously had little or no growth [8, 9].

In general, trends occur that affect facial size as well. Small skeletal changes in height and width affect the outer appearance of the soft tissue. Nose height and length increase, and ear length increases. Mouth width also increases. In very aged people, faces may appear smaller due to overall degeneration of the boney substructure (craniofacial complex) and tissue degeneration.

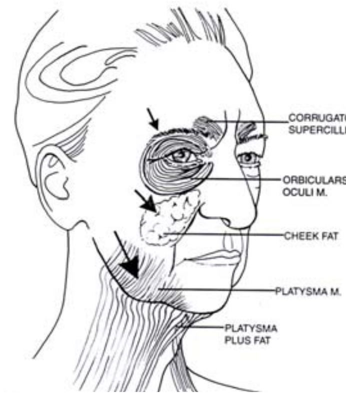

Figure 2: Illustration of Aging: Impacts on soft-tissue (musculature and skin) demonstrating wrinkling and muscle sagging.

3. Own-Race Bias

This work models the psycho-cognitive process of own-race bias and cross-race effect[1] to build a FR system that mimics aspects of the human-recognition process.

The idea of own-race bias is built on the notion of differential experience [10]. In general, differential experience, which begins at birth, consists of the learning/discrimination of visual stimuli as it is repeatedly encountered. These stimuli continue to gain effect as a child grows older and continues to experience social contact through daily life. It has been reported [11] that Caucasian-Americans living in integrated communities exhibited greater recognition ability for African-American faces than did those living in segregated communities. Also, Feinman et al. [12] examined adults who claimed to have close friends of another race against adults without, and found that ones with close, other-race friends exhibited less of a cross-race bias than those without. In general, research in cognitive psychology has shown that adults who grew up in integrated communities had a better ability to recognize other-race faces.

Schema hypothesis states that an age-related memory schema develops over time for own-race faces which

[1] A synonym in context for own-race bias is the cross-race effect which demonstrates that other-race faces are more difficult to accurately recognize than same-race faces [10].

increases FR accuracy in human studies [11]. At young ages human brains are experiencing the most growth; hence, the more visual contact children have with other-races forces the brain to encode face features and configurations which are needed to facilitate recognition at later ages. Although human face recognition rates grew with age, own-race effect was still evident: Caucasian-American children were more accurate in recognizing Caucasian-American faces, and African-American children would more accurately recognize African-American faces.

Recent research has supported cross-race effect suggesting that the information people perceive when looking at a face of and individual of another race is information that allows them to classify the person as Caucasian-American or African-American. The face information people mainly use when looking at a face of another racial group is information that is optimal for race classification rather than identification [13, 14].

A variety of research supports the idea that people recognize faces from their own-race more effectively than other-races [10, 11, 12, 13, 14]. This work exploits the literature by building a system that is modeled on the phenomenon by creating a race-specific face-space using principle components analysis (PCA). The use of PCA to model the human face perception and recognition mechanisms has its foundations in work by Bruce [15, 16]. PCA analysis is used to develop a race-biased space by "training" the space only on faces of that race. In order to implement an ORB FR system, each target face must be classified by race prior to identification. See Figure 1 for an illustration of the system operation.

It is further demonstrated in the following sections that this approach to automated face recognition increases the performance of identification on the MORPH data corpus (a database created specifically to test aspects of longitudinal face samples in face recognition technologies).

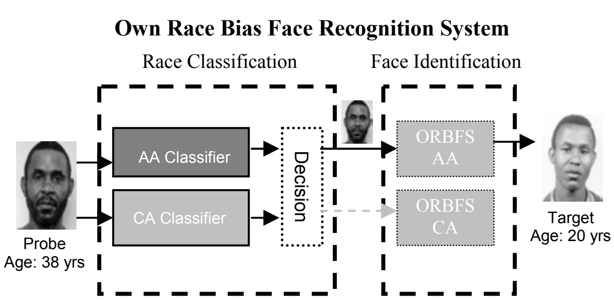

Figure 3. Own-race biased face identification system

4. Own-Race Bias Face Recognition (ORBFR) System

4.1. Craniofacial Morphological (MORPH) Face Data Corpus

The MORPH data corpus is a longitudinal face database developed for researchers investigating all facets of adult age-progression. Only a few of the many face and gesture data corpora that are publicly available for researchers contain longitudinal images of ethnically diverse adults. The MORPH database includes meta-data on the face images within the database: subject's ethnicity, height, weight, gender, and age. Figure 4 is a sample of two subjects from the database highlighting appearance changes of adult faces.

Figure 4. Photographs of two age progressed individuals from Album 1 of the MORPH data corpus

The database is divided into two sets named Album 1 and Album 2. This work used images taken solely from Album 2. Album 2 has over 15,000 images made up of males and females of the Caucasian, Asian, Hispanic, and African ethnic heritages, although there are fewer Asian and Hispanic samples. Additional information on the MORPH data corpus is found in [5].

This research used a sample of 100 male images from Album 2 for African-Americans and Caucasian-Americans only. Images were selected on the following criteria: forward facing, neutral expression, minimal facial hair with no beard, and initial longitudinal (target) image ranging between 20 and 35 years old.

4.2. ORB-FR Image Pre-processing

Offline pre-processing was used to located eyes, convert images to greyscale, perform contrast stretching to reduce lighting irregularities, scale images to 100 x 110 pixels, and mask the background and head hair with an oval. Image samples after pre-processing are shown in figure 5.

Figure 5. Preprocessing: row 1 original image and row 2 pre-processed.

4.3. Race-Classifier for ORB-FR System

The PCA algorithm was used to create a race-classifier that used a race-based face space created by selecting exemplars from the set of AA and CA faces processed as stated above. Thirty total exemplars, fifteen from each race class, were randomly selected from the pool of 100 CA and AA subjects for each experiment. Two decision metrics were evaluated: 1) Euclidean distance using thresholding and a standard deviation criterion and 2) Mahalanobis distance with nearest neighbor. Results for the Mahalanobis distance are reported in table 1. (A Euclidean metric demonstrated poor performance).

The nearest-neighbor scheme uses the Mahalanobis distance defined in equation 1:

$$d(\vec{x},\vec{y}) = \sqrt{(\vec{x}-\vec{y})^T \Sigma^{-1} (\vec{x}-\vec{y})} \qquad (1)$$

where $\vec{x},\vec{y}$ are projected coefficients into the race-classifier space such that $\boldsymbol{x}$ is the probe (test) face, $\boldsymbol{y}$ is a target (enrolled) face, and Σ is the covariance matrix. Fifty experiments were performed to evaluate the effectiveness of the race classifier, and the average percentage correct scores using three nearest-neighbor schemes are reported in Table 1. If the probe was closest in Mahalanobis distance to AA then it was classified as AA for the simple nearest-neighbor measure. For the second scheme, nearest three with single vote, the probe was classified by the closest two neighbors. And, for the third scheme, nearest five with one vote, the probe was classified by the closest three out of five target neighbors. The results in Table 1 demonstrate better classification performance for CA images than for AA images and also show that the five-neighbor method resulted in the best rates. Lighting, in particular, hot spots in the photos of the AAs were likely a factor in the lower performance of the AA results. Histogram analysis of the probes that were misclassified demonstrated the effects of significant specular highlights in those images.

Table 1. Accuracy of Mahalanobis Race-Classifier for ORBFS.

Average Results Probe	Simple	3-Neighbor	5-Neighbor
CA	93.3%	94.4%	95.5%
AA	90.0%	90.0%	92.2%

4.4. ORB-FR Identifier

Identification tests are evaluated in three face spaces: CA, AA, and blended (BL). In the Caucasian and African-American face spaces, a probe is first racially classified then projected into race-specific face space for identification, which is illustrated in Figure 6. However, if the face is incorrectly race classified then it fails identification; hence, face identification rates include the error rates for race classification. The identification metric uses Euclidean distance where a probe is projected into either Caucasian or African-American face space and distances are ranked in ascending order. A face is identified when its rank falls in the top 10% of a test set of N faces. Under the current configurations of the system, this means that a probe has to be ranked either 1, 2, or 3 (10% of 30 test faces) for correct identification.

Identification rates are calculated by the number of faces identified out of a test set. The identification rates are compared to those of the blended face space that acts as the baseline for comparison against the racially tuned identification system. Table 2 shows the results of all identification systems. The average rank is calculated by dividing the sum of all ranked values for a specific face space over the number of ranked images which is the total number of subjects of that race classification. In this case, one hundred images were used for both CA and AA tests. It should be noted that the identification data for the baseline Eigenface method in Table 2 was created by running identification tests only. The baseline system is a simple face identification system that does not require classifying the race of the face before identification.

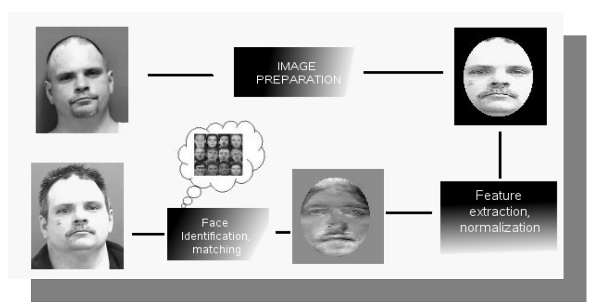

Figure 6. Own-Race Biased Face Identification System

5. Results and Conclusion

Face recognition tests were evaluated in the three spaces, CA, AA, and BL as well. As discussed in the previous section, test images were first classified then projected into race-specific face space for identification. However, if a face was falsely classified then its misclassification result impacted the identification rate for the ORBFS. Therefore, it was important to have a robust race classification system.

Table 2. ORBFR Identification Rates and Average Rank: AA (African-American) and CA (Caucasian-American) identification rates includes performance results of the race classification system (RCS). BL (Blended) is an implementation of Turk's Eigenface FR.

Tests	Rates	Avg. Rank
AA	53.3%	7.1
CA	55.6%	6.2
BL	*23.2%*	10.1

The results of the BL experiments are in line with previous published results for like techniques. The results for the PCA-based face recognizer which used the Mahalanobis Cosine distance, one of the best decision metrics from FR literature, demonstrates the poor response of the technique on the age-progression face data corpus. The graph in Figure 7 shows that using the FERET FAFB data set (blue line) has a rank-N performance above 80% while using the same technique against the MORPH Album 1 performance was limited to less than 30% correct identification no matter what rank was chosen [4, 5].

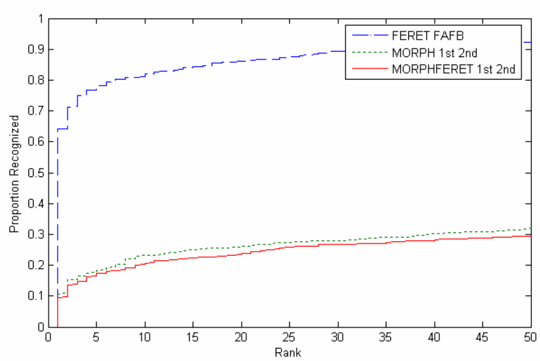

Figure 7. Chart of from previous experiments on the impacts of adult aging on PCA based FR [5].

In this project a proposed method to increase the efficacy of a FR system using the neurocognitive model known as own-race bias has been presented. Principal Component Analysis has been shown to be a very simple yet powerful tool for this purpose. The PCA algorithm reduces the dimensionality of image space to feature space, which helps to model the hypotheses of many psychologists that state that human face recognition is done using only a few exemplars. To further support the own-race effect, a face classifier is designed and tested which provides a relatively high classification rate. While there is not a single measure that is best for all cases, in general the Mahalanobis distance metric using nearest neighbors outperforms the Euclidean. While it was critical to have the meta-data associated with the MORPH data corpus, the project face sample provides a real-world challenge.

6. Future Work

We will extend this research by evaluating against a larger set of longitudinal images to determine whether the efficacy rates continue to hold at double the baseline. Also, some analysis has begun on determining PCA components that may directly correlate to race.

Online pre-processing is under development that automatically marks the location of eye centers. Currently, it takes approximately 45 seconds per image to load, manually locate eyes, and process the images for the system to use. The automatic pre-processing will make it easier and faster to perform experiments.

Overall, this research suggests that future work is important in individualized rather than generalized models for face recognition, particularly when the important problem of age-progression is considered.

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