Face Verification across Age Progression

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Abstract

Human faces undergo considerable amount of variations with aging. While studies have revealed the extent to which factors such as illumination variations, pose variations, facial expression and occlusions affect face recognition, the role of natural factors such as aging effects in affecting the same are yet to be studied. How does age progression affect the similarity between two images of an individual ? What is the confidence associated with establishing the identity between two age separated face images of an individual ? On a database of pairs of passport images, we study similarity of faces as a function time. We propose a Bayesian age-difference classifier that is built on a probabilistic eigenspaces framework. Since age separated face images invariably differ in illumination and have facial variations due to aging, we propose a method to overcome non uniform illumination across face images. The problem discussed in this paper has direct applications in passport renewal and homeland security.

1. Introduction

Perceiving human faces and modeling the distinctive features of human faces that contribute most towards face recognition have been some of the challenges faced by researchers in computer vision and psychophysics. Over the years, researchers have studied the role of illumination variations, pose variations, facial expressions, occlusions etc. in affecting the performance of face recognition systems. Zhao et al. [16] provide a critical review of still and video based face recognition systems that have been built over the years.

While studying the role played by these external factors in affecting face recognition is crucial, it is important to study the role played by natural phenomenon such as facial aging in affecting face recognition as well. Aging effects on human faces manifest in different forms in different ages. While aging effects are manifested more in terms of changes in the cranium's shape during one's younger years, they are manifested more in terms of wrinkles and other skin artifacts during one's older years. In the following subsection, we provide a brief overview of the literature on facial aging.

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1.1 Previous work on Age Progression

Pittenger and Shaw [9] characterized the growth of human faces as a viscal-elastic event and proposed shear & strain transformations to model the changes in the shape of face profiles due to growth. They studied the effects of shear and strain transformations on the perceived age. O'Toole et al. [8] applied a standard facial caricaturing algorithm to three dimensional models of faces and reported an increase in the perceived age of faces when facial creases were exaggerated into wrinkles and a decrease when such creases were deemphasized.

Lanitis et al. [4] proposed a method for simulating aging effects on face images. On a database of age progressive images of individuals each under 30 years of age, they used a combined shape-intensity model to represent faces. They modeled age as a quadratic function of the PCA coefficients extracted from the model parameters. They reported results on experiments such as estimating the age of an individual from his/her face image; simulating aging effects on face images etc. In [3], Lanitis et al. used a similar framework as defined in [4] on a similar data set and evaluated the performance of three age classifiers : the first was a quadratic function of the model parameters; the second was based on the distribution of model parameters; and the third was based on supervised and unsupervised neural networks trained on the model parameters.

Tiddeman et al. [11] developed a model for aging face images by transforming facial textures. Face images were represented in terms of 2D shape vectors and pixel intensities. They developed prototype faces by averaging the 2D shape vectors and pixel intensities across a set of face images under each age group. To age a face image, they superimposed the difference in 2D shape vectors and pixel intensities of the prototype faces on to the face image. Further, they simulated wrinkles in face images by employing locally weighted wavelet functions at different scales and orientations and thereby enhanced the edge amplitudes. Their experimental evaluation reported significant increase in the perceived age of subjects.

Wu et.al. [14] came up with a dynamic model to simulate wrinkles in 3D facial animation and skin aging. They represented skin deformations as plastic-visco-elastic processes and generated permanent wrinkles through a simulation of inelastic skin deformations. Givens et.al. [2] analyzed the role of various co-variates such as age, gender, expression, facial hair etc in affecting recognition and noted that older faces were easily recognized by three face recognition algorithms.

1.2 Problem Statement

How does age progression affect facial similarity across a pair of images of an individual ? Studying the above would have direct implications in passport renewal. Passports need to be renewed once in every 10 years and upon renewal, passports feature the individual's most recent image. Thus given a pair of age separated face images of an individual, what is the confidence measure in verifying his identity ?

Our database comprises of 465 pairs (younger and most recent) of face images retrieved from the passports of many individuals. Table 1 summarizes the database. The individuals in our database ranged from 20 years to 70 years in age. Since passport images are taken generally under controlled environments, the pose of most of the face images were frontal. But there were quite a few passport images where we observed an uneven distribution of illumination. Moreover, age separated face images of an individual invariably differed in the nature of illumination. Thus to study the aging effects on face recognition, it would be crucial to reduce variations due to illumination and pose.

Section II outlines a method to overcome non-uniformity in illumination across face images. In Section III, we present the age-difference classifier and discuss experimental results derived using the above formulation. Section IV highlights the interesting results obtained using the proposed similarity measure between age separated face images. We draw inferences and propose future direction of work in Section V. Figure 1 shows some examples of some age separated face images.

Table 1: Database of Passport Images

Age Difference	*1-2 yrs*	*3-4 yrs*	*5-7 yrs*	*8-9 yrs*
No:of pairs	*165*	*104*	*81*	*115*

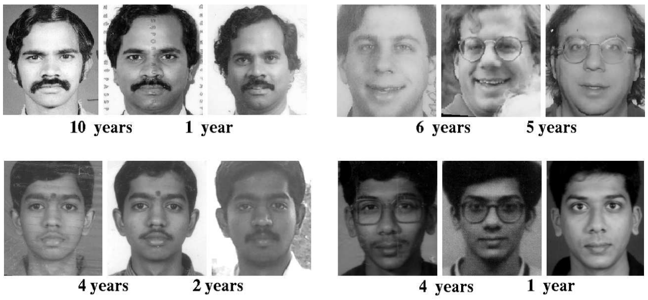

Figure 1: Age progressed images of individuals

2. Facial Symmetry

Psychophysical experiments devised by Troje et al. [12] study the role of bilateral symmetry of human faces in face recognition. Zhao et al. [15] assumed bilateral symmetry of faces and proposed a symmetric Shape from Shading approach for face recognition. On the contrary, Liu et.al [5] and Martinez [6] used the asymmetries introduced in faces due to facial expressions to improve recognition results. Are human faces perfectly symmetric in a bilateral sense ? Factors such as facial hair, scars or skin-blemishes might introduce minor asymmetries in human faces. But, how critical is the assumption of bilateral symmetry of human faces in terms of the performance of face recognition systems ? Can we circumvent non-uniform illumination across face images by assuming facial symmetry and representing the face by just one half of the face that is better illuminated ?

We introduce the notion of $PointFive\ Faces$ - the better illuminated half of a frontal face extracted assuming bilateral symmetry. In the following subsections we evaluate the significance of $PointFive\ Faces$ from a recognition framework and from a verification framework. We also define a criterion function that helps in the implementation of such a pre-processing step.

2.1 PointFive Faces : Evaluation

The performance of face recognition algorithms across non-uniform illumination can be significantly improved by incorporating $PointFive\ faces$. To substantiate the aforesaid, we perform a recognition experiment on the PIE dataset [10], with and without the incorporation of $PointFive\ faces$. From [10] we select frontal images of 68 individuals taken under 21 different illumination conditions. Following the same nomenclature as adopted in the PIE dataset, let : $(f_{02}, f_{03}, ..., f_{22})$ denote the set of images under the 21 different illumination conditions. We perform an eigenfaces [13] based face recognition experiment in a round robin fashion : f_i comprises the gallery and f_j comprises the probe, where $(i, j) \in (02, 03, ..., 22), i \neq j$.

PointFive Faces vs Full faces[1]: Rank 1 recognition scores (%)										
Gallery		f_{02}	f_{03}	f_{04}	f_{05}	f_{10}	f_{13}	f_{15}	f_{16}	f_{22}
Probes	f_{02}	-	100{97}	93{60}	38{29}	41{26}	29{4}	38{3}	35{3}	32{4}
	f_{03}	99{100}	-	100{100}	60{38}	62{41}	43{4}	41{3}	38{3}	46{3}
	f_{04}	72{44}	100{91}	-	100{84}	97{79}	56{4}	51{1}	40{1}	57{3}
	f_{05}	29{12}	47{21}	99{41}	-	100{100}	50{6}	37{4}	26{1}	51{6}
	f_{10}	26{10}	54{16}	97{49}	100{100}	-	56{6}	37{4}	18{4}	51{6}
	f_{13}	21{3}	41{3}	51{7}	53{6}	65{7}	-	97{68}	57{32}	100{100}
	f_{15}	44{3}	51{4}	51{4}	28{4}	26{4}	99{90}	-	97{82}	100{100}
	f_{16}	46{3}	46{4}	32{4}	18{4}	22{4}	82{49}	99{96}	-	90{65}
	f_{22}	29{3}	46{3}	54{4}	49{6}	37{7}	99{100}	100{100}	66{47}	-
Mean		46{22}	61{30}	72{54}	56{34}	56{34}	64{33}	63{35}	47{22}	66{36}

[1]Recognition scores using full-faces are enclosed within { }

Table 2: Evaluation of PointFive faces : Under a recognition framework

The training set is comprised of well illuminated frontal face images from the Yale Face Database B [1]. Across the 441 experiments under each setting the average $Rank\ 1$ recognition score improved by $27\ \%$ by the incorporation of $PointFive\ Faces$. In Table 2, we report the $Rank\ 1$ recognition scores from both the settings on face images from the 9 challenging illumination conditions illustrated in figure 2.

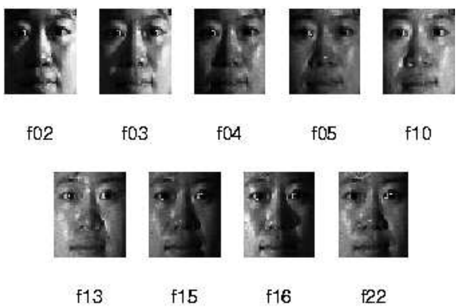

Figure 2: Image samples from PIE

On a verification framework, we illustrate the significance of $PointFive\ faces$ in computing a similarity measure on images of an individual taken under varying illumination conditions. Figure 3 displays 12 test images of an individual. The extracted $PointFive\ faces$ are displayed as well. We create two eigenspaces Φ and Ω from a set of well illuminated frontal faces and their respective $PointFive\ faces$. The full-faces and PointFive faces from the test set are projected on to their respective spaces. Defining a similarity measure between two images as the correlation between their projection coefficients, we compute the similarity between the first image and the rest of the 11 images. The similarity scores computed on full faces (Set I) and PointFive faces (Set II) are tabulated in Table 3. On the image samples where one half of the face was better illuminated, PointFive faces performed better.

Similarity Score(I_1, I_n)			
Image	Set I	Set II	Remark
I_{02}	-0.43	0.33	PointFive Faces in set II perform better
I_{03}	-0.13	0.79	
I_{04}	-0.44	0.81	
I_{05}	0.11	0.90	
I_{06}	-0.45	0.77	
I_{07}	0.14	0.95	
I_{08}	-0.16	0.84	
I_{09}	-0.32	0.22	
I_{10}	-0.34	0.16	
I_{11}	0.58	0.49	No Distinct Advantage
I_{12}	-0.48	-0.37	

Table 3: PointFive Faces : Under a verification framework

2.2 PointFive Faces : Criterion Function

Having illustrated how PointFive faces circumvent the non-uniformity in illumination across faces and improve the performance of face recognition systems, in the following subsection we define a criterion function towards the automatic selection of PointFive Faces from regular face images. The inherent simplicity in the implementation and the significant rise in performance are some of the primary reasons why we preferred PointFive Faces to other known methods that handle non uniform illumination across face images.

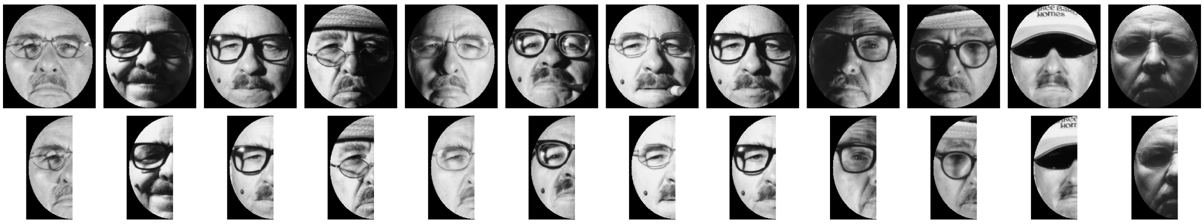

Figure 3: Evaluation of PointFive faces : 12 test images and their respective PointFive faces

2.2.1 Mean Intensity Curve

Given I, a frontal face image of size m x n we extract I_1 and I_2, the right half and the mirror reflected left half of I. Let $X_c^i = [x_1, x_2, ..., x_{n/2}]$ denote the column-wise mean intensity of I_i. The mean intensity curve of I_i, $\bar{X}_{MIC}^{(i)}$ is defined as :

$$\bar{X}_{MIC}^{(i)} = \frac{(X_c^i - \bar{X}_c^i)}{\| X_c^i - \bar{X}_c^i \|} \quad (1)$$

where $\bar{X}_c^i$ denotes the mean of X_c^i and $\| \ . \ \|$ denotes Euclidean norm. If $\bar{X^{(1)}}_{MIC}$ and $\bar{X^{(2)}}_{MIC}$ denote the mean intensity curves of I_1 and I_2,

$$MIC_d = \| \bar{X^{(1)}}_{MIC} - \bar{X^{(2)}}_{MIC} \| \quad (2)$$

is a measure that quantifies the disparity in the spread of illumination between the two halves of the face. A lower MIC_d denotes better uniformity in the spread of illumination across the face.

Next, using the above measure we compute the *optimal mean intensity curve* for frontal face images. For an image from a large gallery of faces, we compute the MIC_d as defined above. If $MIC_d \ < \ \alpha$, where α is a pre-defined threshold, then the face image is classified as optimally illuminated. From N such optimally illuminated face images, we compute the *optimal mean intensity curve* as

$$\bar{X}_{OptimalMIC} \triangleq \frac{1}{2N} \sum_{i=1}^{N} (\bar{X^{(1)}}_{MIC_i} + \bar{X^{(2)}}_{MIC_i}) \quad (3)$$

The criterion function for the selection of the better half face is defined as follows :

$$j = \min_{i=1,2} \quad \| \bar{X}_{OptimalMIC} - \bar{X^{(i)}}_{MIC} \| \quad (4)$$

$$I_{opt} = I_j \quad (5)$$

Figure 4 illustrates the criterion proposed towards the automatic selection of PointFive faces. Self-shadows due to non-uniform illumination and specularities due to illumination saturation are some of the most common effects of uncontrolled illumination on face images. Loss of facial features due to either of the above irregularities affect the performance of face recognition systems. The robustness of the method to overcome the same is evident from figure 4. An added feature of mean intensity curves is that they provide localized information on the irregularities in illumination across face images which could be a cue to feature based face recognition systems.

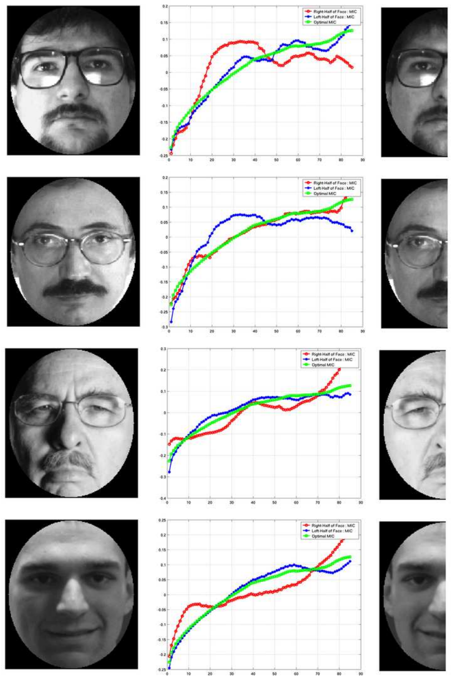

Figure 4: Criterion to select PointFive Faces : Green - Optimal Mean Intensity Curve; Red - Mean Intensity Curve from the mirror-reflected left half face; Blue - Mean Intensity curve from the right half face

3. Age Difference Classifier

We develop a Bayesian age-difference classifier that is built on a probabilistic eigenspaces framework [7]. The classification based on age-differences, comprises of two stages. The first stage of classification deals with establishing the identity between a pair of age separated face images. In the second stage, the pairs of age separated face images across which identity has been established, are further classified based on their age differences. Since the dataset comprises of pairs of face images retrieved from passports, the age difference across each pair ranged from a year to 9 years. We consider the following four age difference categories in our formulation : $1-2\ yrs$, $3-4\ yrs$, $5-7\ yrs$, $8-9\ yrs$.

Reducing the variations in face images due to factors such as illumination and pose is crucial in studying aging effects in faces. Since passport images are frontal face images, pose variations across images were minimal in our dataset. An elliptic mask is overlaid on face images to suppress the background information in the image. Some of the passport images have non uniform illumination and are affected by self shadows specularities. As explained in the previous section, to minimize the non uniformity of illumination within face, we convert each face image into PointFive faces. Further, the mean intensity is normalized across every pair of PointFive faces.

3.1 Bayesian Framework

Let $I_{11}, I_{12}, I_{21}, I_{22}, ..., I_{M1}, I_{M2}$ be the set of N x 1 vectors formed by the lexicographic ordering of pixels in each of the M pairs of PointFive faces. The intra-personal image differences $\{\mathbf{x}_i\}_{i=1}^{M}$ are obtained by the difference of two PointFive faces of the same individual.

$$\mathbf{x}_i = I_{i1} - I_{i2} \tag{6}$$

Given the training data $\{\mathbf{x}_i\}_{i=1}^{M}$, its KLT basis vectors span the intra personal space Ω_I which in turn can be decomposed into two mutually exclusive and complementary subspaces F, the feature space (spanned by k basis vectors $\{\Phi_i\}_{i=1}^{k}$ the variance along each of which is maximum, extracted by principle component analysis) and $\bar{F}$, the orthogonal complement space (spanned by the basis vectors $\{\Phi\}_{i=k+1}^{N}$).

We assume that the intra-personal image difference samples are Gaussian distributed.The likelihood function for the data is estimated as :

$$\begin{aligned}
P(\mathbf{x}|\Omega_I) &= \frac{\exp(-\frac{1}{2}(\mathbf{x}-\bar{\mathbf{x}})^T\Sigma^{-1}(\mathbf{x}-\bar{\mathbf{x}}))}{(2\pi)^{N/2}|\Sigma|^{1/2}} \\
&= \frac{\exp(-\frac{1}{2}\sum_{i=1}^{N}\frac{y_i^2}{\lambda_i})}{(2\pi)^{N/2}\prod_{i=1}^{N}\lambda_i^{1/2}} \\
&\simeq \left[\frac{\exp(-\frac{1}{2}\sum_{i=1}^{k}\frac{y_i^2}{\lambda_i})}{(2\pi)^{k/2}\prod_{i=1}^{k}\lambda_i^{1/2}}\right] \cdot \left[\frac{\exp\left(-\frac{\epsilon^2(\mathbf{x})}{2\rho}\right)}{(2\pi\rho)^{(N-M)/2}}\right] \\
&= P_F(\mathbf{x}|\Omega_I)\ .\ \hat{P}_{\bar{F}}(\mathbf{x}|\Omega_I)
\end{aligned} \tag{7}$$

where $y_i = \Phi_i^T(x-\bar{x})$ are the principal components,λ_i are the eigenvalues, $\epsilon^2(\mathbf{x}) = \sum_{i=k+1}^{N} y_i^2 = \|\tilde{\mathbf{x}}^2\| - \sum_{i=1}^{k} y_i^2$ is the PCA reconstruction error and ρ, the estimated variance along each dimension in the orthogonal subspace is $\rho = \frac{1}{N-k}\sum_{i=k+1}^{N}\lambda_i$. The sum $\sum_{i=k+1}^{N}\lambda_i$ is estimated by means of extrapolation of the cubic spline fit on the computed eigenvalues $\{\lambda_i\}_{i=1}^{k}$.

The extra-personal image differences $\{\mathbf{z}_i\}_{i=1}^{M}$ are obtained by the difference of two PointFive faces of different individuals.

$$\mathbf{z}_i = I_{i1} - I_{j2}\ ,\ j \neq i,\ 1 \leq j \leq M \tag{8}$$

Again, the KLT basis on training data $\{\mathbf{z}_i\}_{i=1}^{M}$ spans the extra-personal space Ω_E which can be decomposed into two complementary spaces : the feature space and the orthogonal space. The density in the feature space is modeled using a mixture of gaussians. We estimate the likelihood for the data as

$$\hat{P}(\mathbf{z}|\Omega_E) = P(\mathbf{y}|\Theta^*)\ .\ \hat{P}_{\bar{F}}(\mathbf{z}|\Omega_E)$$

where

$$P(\mathbf{y}|\Theta) = \sum_{i=1}^{N_c} w_i N(\mathbf{y};\mu_i,\Sigma_i) \tag{9}$$

$$\Theta^* = argmax\left[\prod_{i=1}^{M} P(\mathbf{y}_i|\Theta)\right] \tag{10}$$

$N(\mathbf{y};\mu_i,\Sigma_i)$ is Gaussian with parameters (μ_i,Σ_i) and w_i correspond to the mixing parameters such that $\sum_{i=1}^{N_c} w_i = 1$. We solve the estimation problem using the Expectation-Maximization algorithm.

During the first stage of the classification, we use the above formulation in building a classifier that establishes the identity between a pair of face images. Given a pair of age separated face images, we extract the PointFive faces I_1 and I_2 and compute the difference image $\mathbf{x} = I_1 - I_2$. The *a posteriori* probability $P(\Omega_I|\mathbf{x})$ is computed using the Bayes rule.

$$P(\Omega_I|\mathbf{x}) = \frac{P(\mathbf{x}|\Omega_I)P(\Omega_I)}{P(\mathbf{x}|\Omega_I)P(\Omega_I) + P(\mathbf{x}|\Omega_E)P(\Omega_E)} \tag{11}$$

The classification of the image difference as intra-personal or extra-personal is based on a maximum *a posteriori* (MAP) rule. For operational conditions, $P(\Omega_I)$ and $P(\Omega_E)$ are set equal and the difference image $\mathbf{x}$ is classified as intra personal if $P(\Omega_I|\mathbf{x}) > \frac{1}{2}$.

During the second stage of classification, those pairs of face images that were classified as intra-personal, are further classified based on their intra age differences using the underlying formulation. Let Ω_1 ,Ω_2 ,Ω_3 ,Ω_4 be the space of intra personal difference images for age difference categories $1-2\ yrs$, $3-4\ yrs$, $5-7\ yrs$ and $8-9\ yrs$ respectively. We assume the underlying distribution of samples from each of the intra-personal spaces to be Gaussian.

Given a difference image **x** that has been classified as one belonging to the intrapersonal space Ω, we compute the *a posteriori* probability $P(\Omega_i|\mathbf{x})$ with $i = 1, 2, 3, 4$ as :

$$P(\Omega_i|\mathbf{x}) = \frac{P(\mathbf{x}|\Omega_i)P(\Omega_i)}{\sum_{j=1}^{4} P(\mathbf{x}|\Omega_j)P(\Omega_j)} \tag{12}$$

For operational conditions, $P(\Omega_i)$ were set equal. Thus if $P(\Omega_i|\mathbf{x}) > P(\Omega_j|\mathbf{x})$ for all $i \neq j$, $i, j = 1, 2, 3, 4$, then Ω_i is identified to be the class to which the difference image **x** belongs. Figure 5 illustrates the classifier.

3.2 Experimental Results

We selected pairs of PointFive faces of 200 individuals from our database. We computed the intra personal difference images from the selected pairs and created the intra-personal subspace Ω. We computed the extra personal difference images (by randomly selecting two images of different individuals from the 200 pairs of images) and created the extra-personal subspace Ψ. Thus having created the two spaces, we created two sets of image differences : Set I comprised of intra-personal difference images computed from the 465 image pairs from our database and Set II comprised of 465 extra-personal difference images computed by the random selection of PointFive faces of different individuals from our database. The results of the first stage of classification are as below :

- During the first stage of classification, $99\ \%$ of the difference images from Set I were correctly classified as intra-personal.
- $83\ \%$ of the difference images from Set II were correctly classified as extra-personal.
- It was observed that the image pairs from Set I that were misclassified as extra-personal differed from each other significantly either in facial hair or glasses. Moreover, their average age difference was 7.4 years.

During the second stage of classification, 50 pairs of PointFive face images from each of the following age-difference categories $1-2\ yrs$, $3-4\ yrs$, $5-7\ yrs$ and $8-9\ yrs$ were randomly selected and their corresponding difference image subspaces namely Ω_1, Ω_2, Ω_3, Ω_4 were created. The image pairs from Set I that were classified as intra-personal were further classified into one of the above four age-difference categories using the formulation discussed in the previous subsection. The classification results are tabulated in Table 4. The bold entries in the table correspond to the percentage of image pairs that were correctly classified to their age-difference category.

Table 4: Age-Difference Classifier

Age-Difference Classifier				
	Ω_1	Ω_2	Ω_3	Ω_4
Ω_1	**51 %**	2 %	9 %	38 %
Ω_2	17 %	**37 %**	11	35 %
Ω_3	6 %	1 %	**61 %**	32 %
Ω_4	1 %	1 %	12 %	**86 %**

- When the image pairs from Set I that were correctly classified as intra-personal were classified further based on age-differences, it was observed that image pairs with little variations due to factors such as facial expressions, glasses and facial hair were more often classified correctly to their respective age-difference category.
- Image pairs belonging to age difference categories $1-2\ yrs$ or $3-4\ yrs$ or $5-7\ yrs$ with significant differences in facial hair or expressions or glasses, were misclassified under the category $8-9\ yrs$. The above trend is likely since Ω_4, the subspace of difference images from the age difference category $8-9\ yrs$, spans more intra pair variations than compared with other three age difference categories.

Thus, in applications such as passport renewal where the age difference between the pair of images is known *apriori*, if a pair of images are classified as intra-personal and further classified to their corresponding age-difference category, the identity across the image pair could be verified with low probability of error.

4. Similarity Measure

We adopt the similarity measure defined in $Section\ 2.1$. The face images in our database are processed as discussed in $Section\ 3.1$ and PointFive faces are extracted. We designed the following experiment to study how age progression on affects the measure of facial similarity.

We created an eigenspace using 200 PointFive faces retrieved from the database of passport images. The 465 pairs of PointFive faces were projected onto the space of eigenfaces and were represented by the projections along the eigenfaces that correspond to 95% of the variance. Since illumination variations and pose variations across each pair of PointFive faces is minimal, the similarity score between

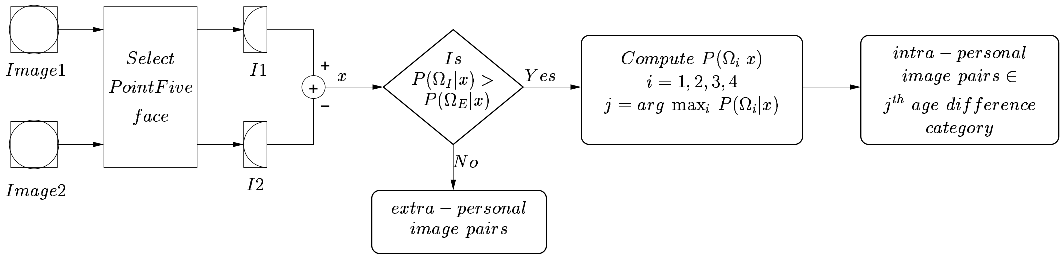

Figure 5: Age Difference Classifier

each pair would be affected by factors such as age progression, facial expression variations and occlusions due to facial hair and glasses. We divided our database into two sets : the first set comprised of those images where each pair of passport images had similar facial expressions and similar occlusions if any, due to glasses and facial hair. The second set comprised of those pairs of passport images where differences due to facial expressions or occlusions due to glasses and facial hair were significant.

The distribution of similarity scores across the age-difference categories namely $1-2\ yrs$, $3-4\ yrs$, $5-7\ yrs$ and $8-9\ yrs$ is plotted in Figure 6. The statistical variations in the similarity scores across each age-difference category and across each set of passport images are tabulated in Table 5.

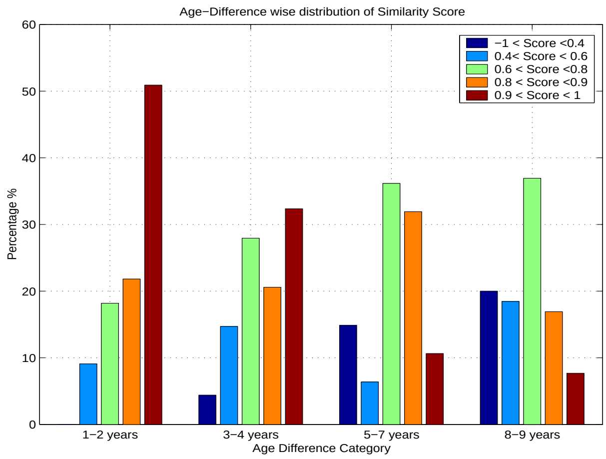

Figure 6: Age Difference Category

- From Figure 6 we note that as the age difference between the pairs of images increases, the proportion of images with high similarity scores decreases.
- While the distribution of similarity scores has a strong peak for category $1-2yrs$, it flattens out gradually as the age difference increases.
- From Table 5 we note that as the age difference increases, across both the sets of images and across all the variations such as expression, glasses and facial hair, the mean similarity score drops gradually and the variance of the similarity scores increases.
- Within each age-difference category, we see a notable drop in similarity scores when variations due expressions and facial hair are more pronounced.

5. Conclusions & Future Work

We had formulated two approaches to studying facial similarity across time. The method proposed in this paper, is very relevant to applications such as renewal of passports. During renewal of passports, the age difference between the image pairs in known *apriori*. Given a pair of age-separated face images of an individual, the age difference classifier establishes the identity between the image pairs and further classifies them to their corresponding age difference category. Moreover, the similarity scores computed between two images of an individual when compared with the scores tabulated in table 5 help in identifying outliers, if any. All through the paper, the methods proposed need very little manual intervention and are computationally simple.

Understanding aging of faces is crucial to the success of face recognition systems. In future, our primary pursuit would be to derive a robust model for facial aging across all age categories. In this paper, we had considered the ages 20 years and above. In future, we wish to perform a similar analysis on ages less than 20 years. Modeling facial aging effects for ages less than 20 years poses a lot of interesting challenges.

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Table 5: Similarity Measure

Age Based Similarity Measure								
Age Difference	First Set		Second Set					
			Expression		Glasses		Facial Hair	
	μ	σ^2	μ	σ^2	μ	σ^2	μ	σ^2
1-2 yrs	0.85	0.02	0.70	0.021	0.83	0.01	0.67	0.04
3-4 yrs	0.77	0.03	0.65	0.07	0.75	0.02	0.63	0.01
5-7 yrs	0.70	0.06	0.59	0.01	0.72	0.02	0.59	0.10
8-9 yrs	0.60	0.08	0.55	0.10	0.68	0.18	0.55	0.10

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