HUMAN PERCEPTION OF AN ATTRACTIVE FACE

[1] Shubham Sanjay Mor, [2] Momidi Sai Deepak
[1] Dept. of CSE, Manipal Jaipur, [2] Dept. of IT, Manipal Jaipur
[1] shubhammor@outlook.com, [2] deepaksai395@gmail.com

***Abstract*— Attractiveness of a person is perceived differently by different individuals. Several experiments have been conducted before to find out which feature affects the attractiveness of a person the most. We have approached this problem in a completely quantitative manner using information obtained by having adults judge the attractiveness of a person. Females judged male attractiveness and vice versa. The results obtained were consistent with the evolutionary hypothesis of Koinophilia according to which faces with features close to mean of the population are considered most attractive. These results were used to calculate the feature whose averaging affected attractiveness in the most considerable manner. These findings suggest that facial Feature symmetry may have a direct correlation with psychological perception of attractiveness in humans.**

Index Terms— ***ARC – Average rating change, AFC – Average feature change, AFRC – Average feature rating change, PFC - Prominent feature change***

I. INTRODUCTION

A. Overview

Several studies have taken place before solely with the aim to find out what consists of beauty. Professional psychologists have conducted experiments in which they have had people rate photos of faces for attractiveness. This was done in order to find out the recurrent factors of a face which were rated as attractive. Some studies have found that, despite being of different ethnicities and cultures, people rate the same faces as attractive, proposing the presence of some universally intricate features that all humans find attractive. There has always been one very consistent finding related to this topic, people mostly find average of the faces present in a population to be more attractive. This phenomenon has been termed as Koinophilia. The word Koinophilia has derived from two Greek words, koinos meaning average and philia meaning love. [1]

This theory of Koinophilia: 'Love for the average' is a distinguished and respected one. It states that the closer your face is to the mean of all faces in a population, the more attractive you are.

B. Koinophilia and mate selection

This theory of averaging has evolved over the past few centuries as a strategy for mate selection. The two types of mating distribution theories are: Assortative mating – In this form of mating, individuals select mates which have features similar to their own. Koinophilic mating – In this form of mating, individuals choose the individuals who have features closer to the average of the population as their mating partner. The reason for Koinophilic mating theory having a higher plausibility is these common features are likely to be 'safer' than mutations because they would indicate well suitability of the feature in that particular surrounding, thereby likely to have higher fitness. [1] Koinophilia, thus, can be a strategy to stabilize traits in the kin while its counterpart, Assortative mating, can be a strategy to distribute varied traits to the kin.

II. LITERATURE SURVEY

J H Langlois et al. in his paper "Infant preferences for attractive faces: rudiments of a stereotype?" has stated that similar preferences for attractive faces exist in both, infants and adults. [2]. But the standards for attractiveness varies greatly for different populations [3]. D T Kenrick et al. feels that the media can highly influence a person's perception towards attractiveness [4]. Nevertheless, the theory of Koinophilia has been constant throughout the century. This theory was discovered in the 19th century by Francis Galton. It was an accidental discovery as he was trying to create a generalized prototype for a 'criminal face' [5]. He discovered that when several photos of people were overlaid on top of each other, the resultant photograph obtained looked more attractive compared to any original contributing faces. Later, Langlois and Roggman et al. generated average faces using computers and obtained similar results [1]. Let's look at a few possible reasons for this.

A. Symmetry

K Grammer et al. in his paper titled 'Human (Homo sapiens) facial attractiveness and sexual selection: The role of symmetry and averageness' believed that averaged faces were more symmetric than their original faces [6]. D I Perrett et al. in 1999 submitted a similar hypothesis [7]. While generating an average face, the lop-sidedness of the faces may cancel out thereby generating a symmetric face free of any kind of mutations. One theory as to why symmetry is preferred is that it points out progressive stability in a changing surrounding. This phenotype in a person indicates presence of high-quality genes. Progressive stability in an organism is its ability to buffer is developmental progress against environmental fluctuations and generate a specific biological feature. This wouldn't be possible if the individuals are not of high genetic quality. Hence, symmetry of a face can be considered an honest indicator of mate quality. M R Morris et al., J P Swaddle et al. and J T Manning et al. have discussed the possibility of not only humans, but also animals following this pattern [8-10]. This theory, although extremely plausible, is also ambiguous. Some studies show that perfectly symmetrical faces were not necessarily attractive [11] while some faces were considered attractive even in the absence of symmetry [12].

B. Familiarity

Another theory as to why averaged faces are considered attractive is that they are familiar looking [11]. A study by L a Zebrowitz has suggested that familiarity makes a face more attractive. The average face is a combination of facial features of many faces present in a population, and would be considered the prototype face of the whole population. What separates humans from other organisms is their ability to cognitively recognize faces and incorporate usage of visual cues in their daily life. Studies by D A Leopold and M K Unnikrishnan et al. suggest that humans only remember the average face of all similar faces they have seen in their life and then recognize a face by comparing the deviations in the face with the average face [13,14]. The presence of these deviations is important for the average faces to be considered familiar. Koinophilia would, therefore, make it easier to recognize individuals of same species during mate selection.

III. Methodology

The first and foremost step to perform facial averaging of two or more faces is to detect the facial landmarks present in an image. The boundary coordinates of the faces present in an image are found using a facial detector. Using these boundary coordinates obtained from the facial detection and joining them to form a rectangle, we crop the image to focus only on the face.

Then, for each face, 68 facial landmarks are detected using a facial pose detector. The reason why exactly 68 points are calculated is trivial. If less than 68 points are used then some facial features might go missing resulting in information loss. More than 68 points can be used but they do not contribute much to the detection efficiency. Therefore, the optimal number of points to consider is 68. The coordinates of these 68 points are further used for coordinate transformation. The images which are to be averaged need to be normalized in terms of size and scale of the image. For this, we set the size of the image such that the extremities of the eyes are at the following locations as they ensure that both the eyes are located on a straight horizontal line and the face was centered at 1/3rd of height from top of the image.

$$Left\ corner\ of\ left\ eye\ =\ (0.3 * width, height/3)$$
$$Right\ corner\ of\ right\ eye: (0.7 * width, height/3)$$

This process is generally used to remove the disfigurements and map the faces to same scale. We scale the images in such a way that the eyes, nose, lips and jawline come to a specific location in each image. The best way to do this is by using similarity transform. Similarity Transform consists of a matrix and is a combination of translation, rotation and scaling. It doesn't change the angle or shape of the original image. The matrix for similarity transform can be written as:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} s_x \cos(\theta) & \sin\theta \\ -\sin\theta & s_y \cos(\theta) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

where (x_t, y_t) are the coordinate points after performing the similarity transform and (s_x, s_y) are the scale factors for x and y coordinates respectively, θ is the angle by which the image needs to be rotated and (t_x, t_y) are the translation factors.

After this, we morph the faces into each other. The concept of face morphing is to create new image by blending two images. Let us assume two images A and B. We should have a pixel correlation between these two images. That is, if we have a pixel (x_a, y_a) in image A, then it should be correlated with the pixel (x_b, y_b) in image B. The location in the morphed image (x_m, y_m) will be:

$$x_m = (1-\alpha)x_a + \alpha x_b$$
$$y_m = (1-\alpha)y_a + \alpha y_b$$

The intensity of the morphed image can be produced by the following equation:

$$M(x,y) = (1-\alpha)A(x,y) + \alpha B(x,y)$$

Here, α (Alpha) is the transparency factor and its value ranges from 0 to 1. Before using the above-mentioned equation on images, it is a good idea to align the faces in consideration for

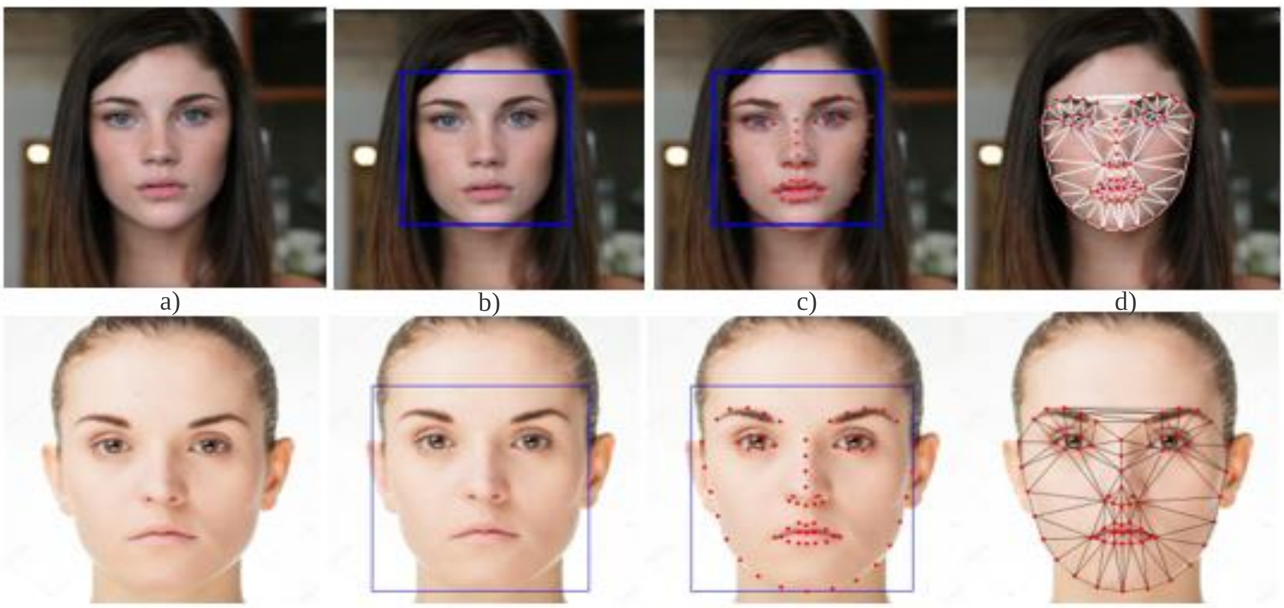

Fig. 1. a) Original Image b) Detected Face c) Face with 68 Landmark points d) Delaunay Triangulation

averaging as using this equation without alignment will result in a disfigured output.

Therefore, the steps for face morphing include performing facial landmark detection, coordination transformation and then creating Delaunay Triangles. Given there are points in the space, Delaunay triangulation divides the plane into triangles with points as the vertices. These triangles are created in such a way that no vertex comes in the circumcircle of other triangle. To calculate the Delaunay triangles, we start with any triangulation, and check if the circumcircle of any triangle contains another point. In case it does, the edges are flipped. This process is repeated until there are no triangles with their circumcircle containing a point. Delaunay triangulation results in an array which contains a list of triangles represented by their indices of the 68 detected facial points. We then warp the face in consideration to the average landmarks. This is achieved using affine transformation. Affine transform can be calculated by considering the three vertices of the corresponding triangles in both the faces. This transform can be used to convert all the pixels that come under the triangle to the corresponding pixels in the average landmarks image. The next step is to actually average the faces. We calculate an average image by taking the sum of the intensities of the corresponding pixels in all the images and divide it by number of images.

The images for creating the dataset have been randomly picked from Google Image search. The dataset includes faces of people of different ethnicities. None of the faces contained glasses or jewellery. The dataset was created keeping in mind that no part of the face is hidden. The averaged images were modified and their background and hair were masked with only their faces being visible in order to remove any kind of individual perception bias. Facial averaging has been applied to several images in our dataset and we have created many different combinations (Example: Average of 3 faces, 4 faces etc). These images were made part of a crowdsourcing experiment where people have rated each image for attractiveness on a scale of 1 to 5. The experiment resulted in around 284 people rating 20 images each, thereby generating a dataset of 5,680 ratings.

Fig. 2. Two original images which are to be averaged

Let's recap the whole procedure by averaging the above illustrated two faces. Firstly, the 2 faces would be detected using a facial detector. Then, 68 landmark points on both faces will be found out. A new subdivision will be created and the Delaunay triangles for 68 points will be calculated. These triangles will then be warped to form a new averaged face. All of these steps are represented via figures in Figure 1

Fig. 3. Averaged Face (also including background)

Now This image could have been used directly for the crowdsourcing experiment. But when it is placed beside a single face, this image looks a litlle less natural. To prevent user bias, we mask the background and ears.

Fig. 4. Background and ears masked from the resultant average face

First crowdsourcing experiment: Every person was asked to rate 20 images in groups of 2 (that is, a total of 10 bundled images). These images were created by averaging various combinations of faces. For instance, one bundled image (2 images: one placed left and another, right) had one face which was an average of two faces, while the other face was an average of 6 faces also including those two faces displayed on the left. This allowed users to rate the faces comparatively. The order of the images in a bundled image was jumbled up and the user wasn't informed which image was highly averaged.

Second crowdsourcing experiment: This experiment was performed on a smaller scale compared to the first experiment. A few people were shown the same 20 bundled images (with 2 images in each bundled image) used in the previous experiment and were asked to provide the percentage changes (approx.) in each facial feature. The features that were a part of this survey are: Eyes, Lips, Nose, Face Shape and Facial Texture. People had an option to choose from one of the following percentages which would then be averaged and used for finding the most prominent feature change in each bundled photo: 0%, 25%, 50%, 75% and 100%.

The data collected from the first experiment was used to find the average ratings for less averaged and highly averaged image. The facial feature who averaging results in the highest rating increase was also calculated using the combination of the data collected from the first and second experiment.

IV. RESULTS

Using the results of this crowdsourcing experiment, we can visualize how the average rating of a less averaged face and that of a highly averaged face compare:

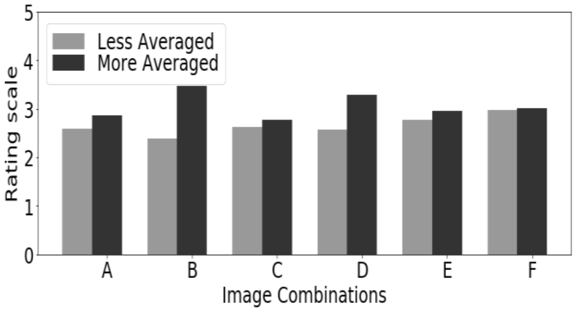

Fig. 5. A) 1 Face against 3 Faces B) 1 Face against 4 Faces C) 1 Face against 5 Faces A) 2 Faces against 5 Faces A) 2 Faces against 6 Faces A) 3 Faces against 6 Faces

It can be clearly seen that averaging a face further increases its average rating. The increase might not be considerable, but there is always an increase.

Our next aim is to find out the feature that yields the highest change in attractiveness when averaged. For this, the first step is to calculate the prominent feature change in each image which is averaged in our data.

A. Calculation of Prominent Feature Changes

Each bundled image in the dataset contains 2 images, one which is less averaged and another which is highly averaged.

To calculate the prominent feature changes, we begin by calculating the average feature change for each feature of a bundled image. Average feature change is the percentage change in appearance present between the same feature of two different images. Later we can select the maximum value from these average feature changes and that will serve as the prominent feature change for those two particular images. The data collected from crowdsourcing was used for this purpose. Each person was required to choose from a set of available options that represented a percentage change. The options were: Exactly same (0% change), Somewhat different (25% change), Average difference (50 % change), Highly different (75% change), Completely changed and unrecognizable feature (100% change). The first five rows of this data for a single image are shown in Table 1 along with the image. (Note: The remaining paper displays only the first five of several rows in each table)

Fig. 6. Example of a dataset image (Right - Average of 2 Faces. Left - Average of 6 Faces)

The average feature change for each feature (eyes, nose, lips, face shape and texture) can be calculated using the following equation:

$$\text{AFCi, feature} = \frac{\sum_{i=1}^{n} \text{(PC)i,feature}}{n}$$

for feature = eyes, nose, lips, face shape and texture

where $(PC)_{i,feature}$ is the percentage change given by a person for a particular feature as in the table illustrated above and n is the total number of people.

Now using data in table 2, we can find out the most prominent feature change in each image:

$$(\text{PFC})_{\text{i}} = Max\ (AFC\text{i, eyes}, AFC\text{i, nose}, AFC\text{i, lips}, AFC\text{i, faceshape}, AFC\text{i, texture})$$
$$\text{for i = 1 to n}$$

where PFC is the prominent feature change for each image, n is the total number of images and $AFC_{i,eyes}$ is the Average feature change (in %) in eyes for that image.

Image No.	Eyes	Nose
Image 1	62.5	33.3
Image 2	37.5	20.8
Image 3	45.8	20.8
Image 4	54.2	58.3
Image 5	8.3	8.3

Table 2. Average feature change for the first two feature of the first 5 images

Person	Eyes	Nose	Lips	Face shape	Texture
Person 1	50%	75%	75%	75%	50%
Person 2	50%	25%	100%	100%	25%
Person 3	100%	25%	50%	100%	25%
Person 4	50%	25%	75%	50%	25%
Person 5	75%	25%	75%	75%	25%

Table 1. Data collected from crowdsourcing for find prominent change

Image No.	Prominent feature change
Image 1	Lips (75%)
Image 2	Lips (45.8%)
Image 3	Texture (50%)
Image 4	Lips (70.8%)
Image 5	Face Shape (29.2%)

Table 3. Prominent feature change for the first 5 images

A table (Table 4) containing the set of images for each feature change needs to be created. This table will be used later to calculate the average rating change for a particular feature.

Prominent Feature	Images
Eyes	Image 7, Image 8, Image12, and so on…
Nose	Image 6, Image 14, Image 19 and so on...
Lips	Image 1, Image 2, Image 4, and so on...
Face Shape	Image 5, Image 10, Image 11, and so on…
Texture	Image 3, Image 17, Image 18, and so on…

Table 4. List of images having a particular Prominent feature change

B. Calculation of Average Rating changes

After the calculation of most prominent features for each image, we calculated the average rating change for each image. The data obtained from crowdsourcing which contains over 5600 ratings is used and a separate table for each image is made. These tables contain the ratings varying from the values between 0 and 5 for both images: one less averaged and another highly averaged. An example of this table for the first 5 ratings of the same image discussed above is presented below:

Less averaged	Highly Averaged
2	4
4	2
1	1
3	2
3	4

Table 5. Crowdsourcing result for Image 1 (First 5 rows)

To calculate the average Rating change for this image, we use the following equation:

$$\frac{\sum_{i=1}^{n}\left(\frac{R_2 - R_1}{R_1}\right) \times 100}{n}$$

Where R_2 is the rating of highly averaged image, R_1 is the rating of less averaged image and n is the total number of ratings. This equation yields an average rating change of 0.24 % for this image. Note that if highly averaged image was considered less attractive by people, this percentage change would have been negative. The same equation is applied to each image and the result is a table with average rating change for each image:

Image number	Avg. Rating change (%)
Image 1	0.24%
Image 2	-32.1%
Image 3	73.71%
Image 4	42.18%
Image 5	-37.73%

Table 6. Calculation of Average Rating change for each image (First 5 images)

C. Calculation of Average Feature Rating changes

Post calculating the average rating change for each and every image, we refer back to Table 4.4 to calculate the average feature rating change. The following equation is used:

$$\mathrm{AFRC_i} = \frac{\sum_{i=1}^{n}((ARC\mathrm{eyes})\mathrm{i},(\mathrm{rating}))}{n}$$

where ARC_{eyes} refers to the Average rating change for images with eyes as their prominent feature change (prominent feature for each image was calculated in Table 4.3) and n refers to the total number of images with eyes as their prominent feature change. Similar equation is used to calculate the average prominent feature rating change for nose, lips, face shape and facial texture (Table 4.7)

Male	
Prominent feature change	Average Feature rating change (%)
Eyes	16.39%
Nose	96.08%
Lips	21.08%
Face Shape	57.13%
Texture	25.85%

Table 7. Final results for average feature rating change for each feature of men

Female	
Prominent feature change	Average Feature rating change (%)
Eyes	20.06%
Nose	6.12%
Lips	14.48%
Face Shape	2.37%
Texture	73.71%

Table 8. Final results for average feature rating change for each feature of women

Collective	
Prominent feature change	Average Feature rating change (%)
Eyes	18.22%
Nose	55.35%
Lips	15.8%
Face Shape	33.63%
Texture	41.8%

Table 9. Collective final results for average feature rating change for each feature

It is clearly evident from Table 4.8 that the feature which causes the most average rating change in case of females is facial texture followed by eyes. A change in nose and face shape have the average rating changes in negative. This means that the highly averaged image was mostly rated lower compared to a less averaged image. In case of males, a prominent change in nose results in a huge bump in facial attractiveness. Face shape can be considered another factor that increases attractiveness among men as the experiment results in an average rating increase of 57.1% when the face shape is changed. Eyes and lips of men on the other hand do not result in a very considerable average rating increase.

V. CONCLUSION AND FUTURE WORKS

The results obtained in this paper were consistent with the theory of Koinophilia. Feature that affects attractiveness the most in women is change in the facial texture, while for men, averaging of the nose considerably increases the average attractiveness rating. This research needs to be conducted on a larger scale in the future with even more images present in the dataset and a normalized surrounding for people who judge the attractiveness in an image. The concept of facial averaging has several real-world applications. It can be extremely useful in Biological and medical field of plastic surgery. An average face would help pumping up the confidence in case of face disfigurement. This technique can also be used for security purposes. A paper by A.k Jain [15] suggests that this technique might be used extensively in the future for encoding the facial data of several people in a fingerprint image of a person. A similar application is suggested by Ralph Gross [16] in which, facial averaging of faces is performed to protect the identity of people by removal of identifying information from images. This is known as Face De-identification. The results obtained in this paper can be used by Beauticians and smartphone camera companies. They can find the perfect balance of facial feature modification on a person's face to yield the highest attractiveness. Another application is to symmetrize faces by morphing one side of the face to the other. Movies and TV shows can make use of the results to efficiently create morphing animations without losing the naturalness of the face. A reversible method for facial averaging can be developed to prevent misuse of this technology by unethical organisations.

REFERENCES

[1] J H Koeslag, "Koinophilia: Groups sexual creatures into species, promotes stasis, and stabilizes social behaviour", Journal of Theoretical Biology, Vol.144, No.1, pp.15–35, 1990

[2] J H Langlois, L A Roggman, R J Casey, J M Ritter, L A Rieser–Danner, V Y Jenkins, Infant preferences for attractive faces: rudiments of a stereotype?", Developmental Psychology, Vol.23, No.3, pp.363–369, 1987.

[3] D Jones and K Hill, Criteria of facial attractiveness in five populations, Human Nature, Vol.4, No.3, pp.271–296, 1993.

[4] D T Kenrick and S E Gutierres, "Contrast effects and judgments of physical attractiveness: when beauty becomes a social problem", Journal of Personality and Social Psychology, Vol.38, No.1, pp.131—140, 1980.

[5] F Galton, "Composite portraits", Nature, Vol.18, pp.97–100, 1878.

[6] K Grammer and R Thornhill, "Human (Homo sapiens) facial attractiveness and sexual selection: The role of symmetry and averageness", Journal of Comparative Psychology, Vol.108, No.3, pp.233–242, 1994.

[7] D I Perrett, D M Burt, I S Penton–Voak, K J Lee, D A Rowland and R Edwards, "Symmetry and human facial attractiveness", Evolution and Human Behavior, Vol.20, No.5, pp.295–307, 1999.

[8] M R Morris and K Casey, "Female swordtail fish prefer symmetrical sexual signal, Animal Behaviour", Vol.55, No.1, pp.33–39, 1998.

[9] J P Swaddle and I C Cuthill, "Female zebra finches prefer males with symmetric chest plumage", Proceedings of the Royal Society, Vol.258, No.1353, pp.267–271, 1994.

[10] J T Manning and M A Hartley, "Symmetry and ornamentation are correlated in the peacock's train, Animal Behaviour", Vol.42, No.6, pp.1020–1021, 1991.

[11] J H Langlois, L A Roggman and L Musselman, "What is average and not average about attractive faces?", Psychological Science, Vol.5, No.4, pp.214–220, 1994.

[12] T I M Valentine, S Darling and M Donnelly, "Why are average faces attractive? The effect of view and averageness on the attractiveness of female faces", Psychonomic Bulletin and Review, Vol.11, No.3, pp.482–487, 2004.

[13] D A Leopold, I V Bondar and M A Giese, "Norm-based face encoding by single neurons in the monkey inferotemporal cortex", Nature, Vol.442, No.7102, pp.572–575, 2006.

[14] M K Unnikrishnan, "How is the individuality of a face recognized?", Journal of Theoretical Biology, Vol. 261, No.3, pp.469–474, 2009.

[15] A.K. Jain; U. Uludag; Rein-Lien Hsu, "Hiding a face in a fingerprint image" Proc. IEEE, no. 10, Dec. 2002, pp. 1051-4651.

[16] Ralph Gross, Latanya Sweeney, Jeffrey Cohn, Fernando de la Torre and Simon Baker "Face De-identification"