A New Method for Synthetic Face Generation Using Spline Curves

Ali Borji

School of Cognitive Sciences,
Institute for Research in Fundamental Sciences, Tehran, Iran
borji@ipm.ir

Abstract. Faces are complex and important visual stimuli for humans and are subject to many psychophysical and computational studies. A new parametric method for generating synthetic faces is proposed in this study. Two separate programs, one in Delphi 2005 programming environment and another in MATLAB is developed to sample real faces and generating synthetic faces respectively. The user can choose to utilize default configurations or to customize specific configurations to generate a set of synthetic faces. Head-shape and inner-hairline is sampled in a polar coordinate frame, located at the center of line connecting two eyes at 16 and 9 equ-angular positions. Three separate frames are placed at the left eyes center, nose tip and lips to sample them with 20, 30 and 44 angular points respectively. Eyebrows are sampled with 8 points in eye coordinate systems. Augmenting vectors representing these features and their distance from the origin generates a vector of size 95. For synthesized face, intermediate points are generated using spline curves and the whole image is then band pass filtered. Two experiments are designed to show that the set of generated synthetic faces match very well with their equivalent real faces.

Keywords: Synthetic faces, Face recognition, Face perception, Face space, Spline curves, Pattern recognition, Pattern discrimination, Psychophysics.

1 Introduction

Faces are among the most important visual stimuli we perceive, informing us not only about a person's identity, but also about their mood, sex, age and direction of gaze. Humans have a notable ability to discriminate, to recognize, and to memorize faces. Our ability to identify one another is vital to successful navigation in the community, and faces regardless of sharing the same basic features in the same basic configurations provide as a key source of person recognition. Attempts to elucidate this capability have motivated the development of numerous empirical and methodological techniques in the fields of psychology, neuroscience, and computer science. Neuroscientists and psychologists are concerned with the mechanisms underlying human face recognition. Computer scientists' goal is to automate the process for applied reasons. Face recognition systems are progressively becoming

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popular as means of extracting biometric information. Face images are the only biometric information available in some legacy databases like international terrorist watch-lists and can be acquired even without subject's cooperation.

Although automatic face-recognition systems need not be forced to mimic human brain's processes, advances in brain's technique for face recognition have proved to be useful.

Several formal models of the representation, classification and recognition of artificial stimuli have been developed, which assume that the relevant stimuli are represented within a multidimensional space. The central assumptions of many of the models are closely related. This formal approach has been highly successful in accounting for human performance in laboratory experiments. In order to develop and test a formal model it is necessary to identify and control the relevant features or dimensions. The approach has, therefore, concerned the processing of sets of highly artificial and relatively simple stimuli [1]. Also Schematic faces have been used in the experiments. In [2], Brunswik and Reiter were the first to employ simplified face stimuli in a psychological study, and a recent neurophysiological study of inferotemporal neurons in macaques employed Brunswik faces to study categorization [3]. These faces are extreme face schematics (single horizontal line for mouth, single vertical line for nose within an ellipse, etc.) and are far too abstract to capture significant information about individual faces. Synthetic faces combine simplicity and low dimensional description with sufficient realism to permit individual identification [4].

Other studies of face perception have used photographs, computer averages of several photographs, or reconstructions from laser scanned faces [5]. While this has provided researchers to investigate different aspects of the topic, reliance on these stimuli has resulted in a number of important limitations.

Photographs are basically uncontrolled stimuli, which rarely match for color, size, orientation, texture, or lighting conditions. Additionally, they do not provide a systematic way of modifying face-specific image properties, which severely limits the extent to which similarities between stimuli can be measured, controlled, or manipulated. However the complexity of these stimuli has made it difficult to relate perception to the responses of underlying neural mechanisms.

It has been proposed that faces are represented as undifferentiated whole shapes, with little or no explicit representation of face parts. However, humans can also recognize a face on the basis of isolated features presented independently of the facial context or within a different context (e.g. scrambled faces), albeit with some loss of accuracy [6]. It appears then that both feature based and holistic representations can be used in face discrimination and their dependence or independence has been a matter of debate [7], [8].

To avoid some of these obstacles, we attempted to complete and optimize Wilson's method [4]. Here we added the facial features instead of generic features used by Wilson and designed a new 95 dimensional face stimulus set. It is also possible to sample a specific feature with more detail by inhomogeneous sampling in different locations. This new stimulus set provides face space components such as mean face, identity levels, and caricatures. It is also possible to morph two different faces to each other.

2 Face Sampling

We first describe how we prepared a set of digital photos. In next section, the way we generate synthetic faces from these real faces will be presented. A data set comprising photos of 110 people, half from each gender was created. Each person was photographed at a distance of 1 m in frontal view. Each Person's eyes remained straight ahead within their head in the course of photographing. People were required to have a neutral expression and emotional state. We only considered male persons without facial hairs. Everybody wearing glasses was required to remove it before photographing. Color, luminance, and contrast of all images then were adjusted using Adobe PhotoShop Me 7.0. Extra parts of all images (e.g., neck, collar, etc.) were cropped. An example of such a face after pre-processing is illustrated in Figure 1.

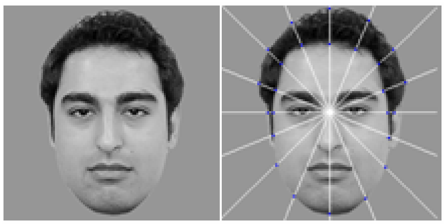

Fig. 1. A real and sampled face in outer head shape

A program was developed in Delphi 2005 programming environment (Figure 3) for sampling faces. A polar coordinate system was manually positioned to be on the middle of a line connecting the pupils of eyes. As it is shown by radial lines in Figure 1, the outer shape of the head was sampled at 16 radial axes equally spaced at polar angles of 22.5 (degree). Likewise, the inner hair was sampled by 9 further radii on and above horizontal line of the central polar coordinate system. A parameter (Degree) which controls the number of radial axes is available by changing the degree between them. For each facial feature, a separate polar coordinate system was positioned in the center of that feature.

For the left eye, center of the pupil was considered as the center of its coordinate system. It was then sampled at twenty radial axes with 18 degrees apart. Because eyes contain more spatial information along 0 and 180 axes compared with other axes we devised a mechanism for sampling around those points with more resolution. For that angles was multiplied by a scale factor greater than 1, which controls the density of angles around 0 and 180 degrees. The inverse coding mechanism was used when generating synthetic faces. Figure 2 shows a scaled coordinate frame placed at the center of the left eye.

The diameter of the iris and the thickness of the eyebrow were coded by the user subjectively in a range between 1 and 5.

The left eyebrow was sampled in the same coordinate frame located at the left eye's center. This feature was sampled in 15 degrees starting from 30 to 135.

We assumed for simplicity that the right eye and eyebrow are the mirror image of their left counterparts, so, their information were calculated as the mirror and translated code of the left eye and eyebrow.

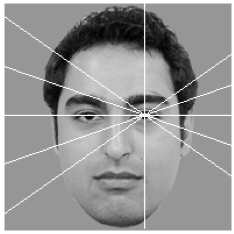

Fig. 2. Left eye coordinate frame

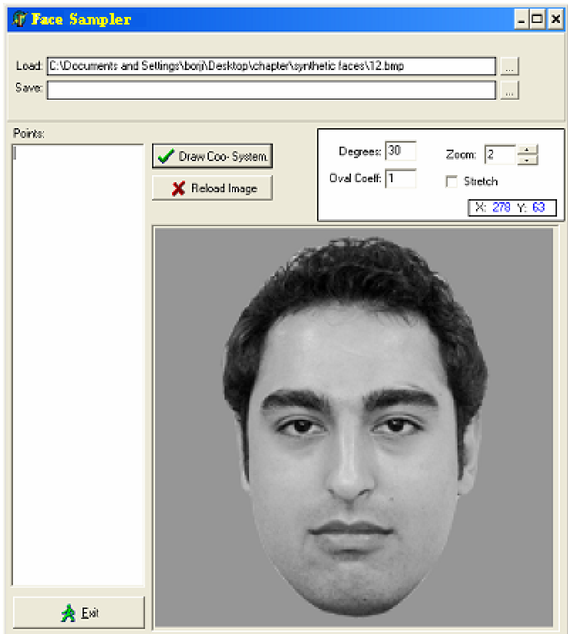

Fig. 3. Delphi program for face sampling

Another coordinate frame was positioned at the tip of the nose and was then sampled in 22.5 degrees starting from -45 to 67.5 degree. The right side of the nose was then generated by a mirror and translation operation on the information of the left side. To code the nose opening, its position was determined on 22.5, -45, or -67.5 degree.

A coordinate frame was placed in the middle of the line separating top and bottom lips. It was then sampled at 15 degrees. Finally, combination of vectors generated in each feature coordinate frame resulted in a 95 dimensional vector for each face. Figure 3 shows a snapshot of face sampling program.

3 Synthetic Face Generation

Ninety-five dimensional vector of each face was feed to a separate MATLAB file (Face Synthesizer) to generate the final synthetic faces. Main strategy here was interpolation of middle point using spline curves. Figure 4 illustrates an example of the interpolation of points of outer head shape. The same procedure was carried out for all facial features. Code snippet for interpolating outer head shape is shown below:

```
% head shape ----------------------------------------
res = 0.01;   % 2*pi/360;
y1 = 0:0.3927:2*pi+0.3927; % outer head shape
D1 = Data (5:20);  % outer head shape sampled points
cs = spline (y1, D1);
yy = 0: res: 2*pi+res;
h=polar (yy, ppval (cs,yy),'k-')
cs = spline (y1, [D2(2:11)  D1(11:16)  D2(2)]);
```

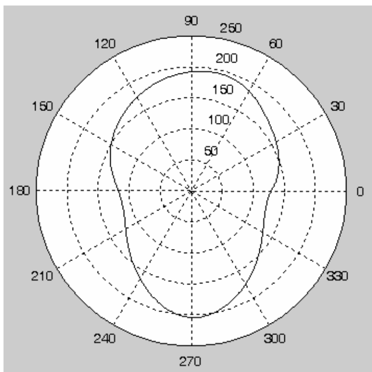

Fig. 4. Spline interpolation of outer head shape

Synthetic faces derived up to now, still lack similarity with real faces. Particularly, face parts do not have relative contrast as it could be seen in real faces. Almost in every real face, hairs and lips are usually darker than the skin, the sclera and iris of the eye are respectively lighter and darker than the skin. So, each part was filled with appropriate color to have real face-like contrast.

As face discrimination is optimal within a 2.0 octave (at half amplitude), a bandpass filtering was done with a bandwidth filter centered upon 8-13 cycles per face width [9], [10], [11], [12], [13]. Particularly, a radial asymmetric filter with a peak frequency of 10.0 cycles per face with a 2.0 octave bandwidth described by a difference of Gaussian (DOG):

$$DOG(R) = 1.26\exp(-\frac{R^2}{\sigma^2}) - 0.26\exp(-\frac{R^2}{(2.2\sigma)^2}) \tag{1}$$

where R is radius and σ was chosen so that the peak spatial frequency would be 10.0 cycles per face width on average [4]. Output of the bandpass filtering on the mid-level synthesized face is shown in Figure 5.

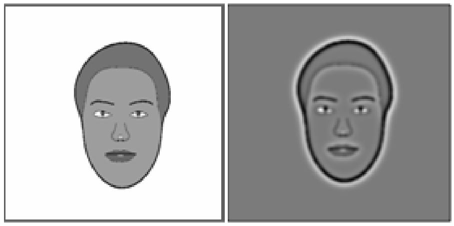

Fig. 5. Mid-level and final bandpass filtered synthetic face

Representation of faces in vector form allows algebraic operations such as morphing faces to each other, generating caricature faces, etc. Figure 6 shows a linear interpolation between two sample faces in 10 percent increments as follows:

$$C = (1 - \frac{x}{100})A + (\frac{x}{100})B \tag{2}$$

where C is the morphed face, A and B are two faces to be morphed to each other and x is the percent of morphing.

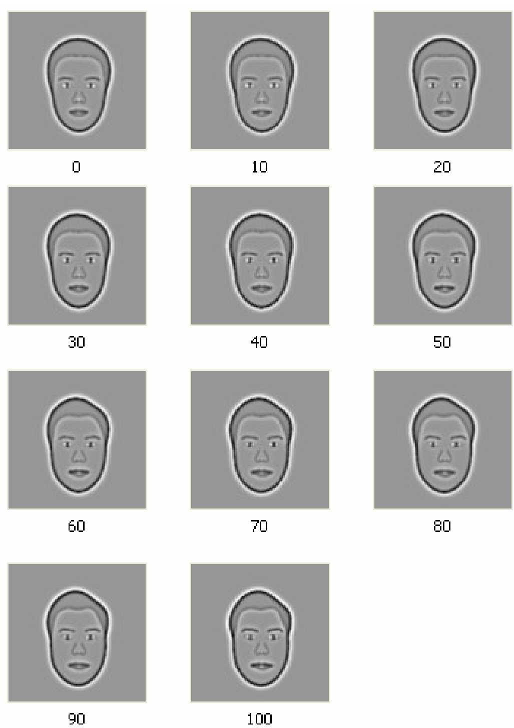

Fig. 6. Morphing two faces to each other

Some other examples of generated synthetic faces are shown in figure below:

Fig. 7. Three sample synthetic male (top-row) and female faces (bottom-row)

4 Experiments

To show that our generated synthetic faces carry the major geometric information to discriminate faces, we designed two experiments:

4.1 Face Similarity Tasks

The first experiment consists of two parts. In the first part, in all trials a forced choice procedure was used with no limitation on viewing time. Each experimental run, consisted of a total number of 800 trials, and was initiated by a button press. Target image was shown in the center of the screen, and 4 alternative options were shown simultaneously besides the target and the subject's task was to match the target with its relevant option.

Experiment one, part one evaluated the similarity of synthetic facial features with their original image. As shown in Figure 8, the target was always a photograph. In half of the trails, inner facial features, and in the other half, the outer facial features were used as answer options, randomly. The subject's task was to match the most similar option with the target image.

Results showed that subjects could match both inner and outer facial features precisely with their real images. Mean performance were 75% and 86% correct for

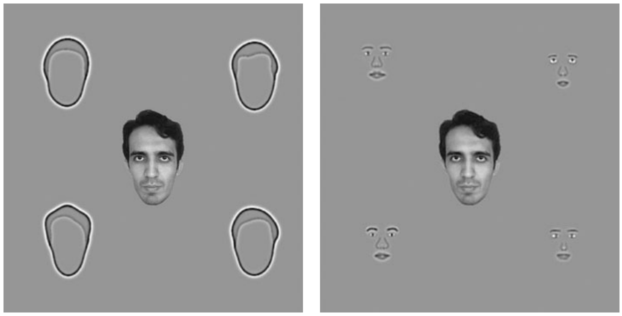

Fig. 8. Experiment one, part one test screen

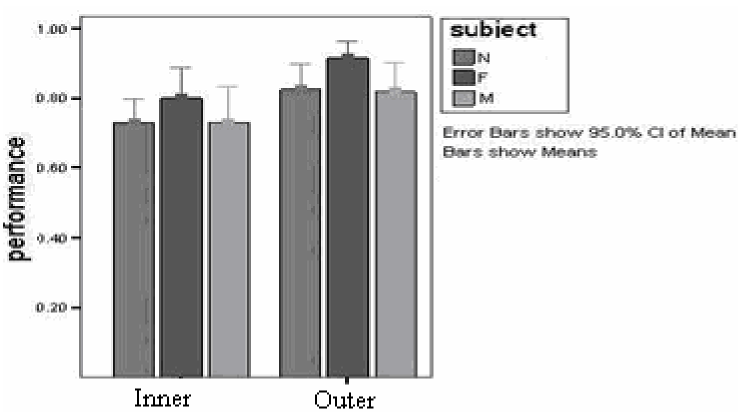

Fig. 9. Mean subject performance in first experiment

inner and outer facial features, respectively. There was no significant different between 3 subjects performing these tasks (P>0.05). Results are shown in Figure 9.

Results showed that subjects could match both inner and outer facial features precisely with their real counterpart image.

In the second part, expectedly, performance was much better when the task was matching real faces to their complete synthetic images (with both inner features and outer head shape), as shown in previous studies [4].

4.2 Gender Discrimination Task

We designed a gender discrimination task to see whether our faces carry information needed for gender categorization. In each trial, subjects were asked to determine the face gender by pressing a button indicating male or female gender.

As shown in Figure 10, mean subjects performance in this task was 0.92 and differences between female and male targets was not significant. The subjects had no significant difference as well (P>0.05).

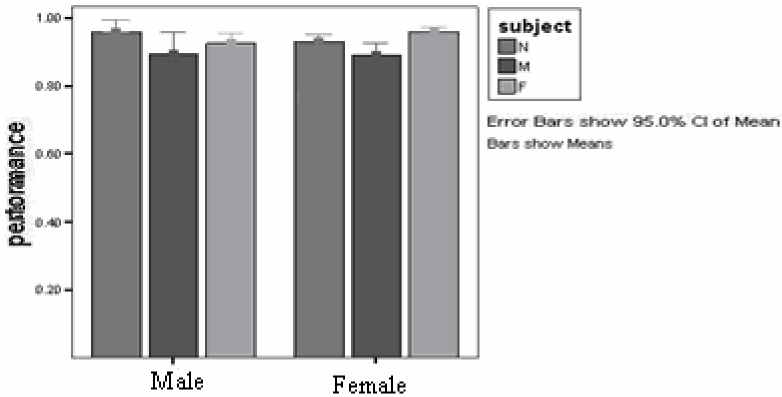

Fig. 10. Mean subject performance in gender discrimination task

5 Conclusions

A Toolbox for generating synthetic faces was introduced in this paper. It could be used for verifying both face recognition algorithms as well as conducting psychophysics tasks to understand face perception and recognition in humans and monkeys. Sampling is done with an executable program developed in Delphi 2005 and a vector of size 95 is generated which codes much detail of a real face. It is then fed to a MATLAB file, which generates a synthetic face. A set of real faces and their corresponding synthetics faces is also available and could be asked from authors. In our experiments, for the present, synthetic faces defined in a 95-dimensional face space catch very much of the information in real faces and are useful for research on face perception, memory, and recognition based upon salient geometric information in the most significant spatial frequency band.

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