Silhouetted face profiles: A new methodology for face perception research

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We present a new methodology for constructing face stimuli for psychological experiments based on silhouetted face profiles. Face silhouettes carry a number of theoretical and methodological advantages compared to more complex face stimuli and lend themselves to a simple yet powerful parameterization. In five behavioral studies, we show that face silhouettes are processed like regular face stimuli: They provide enough information for accurate gender judgments (Study 1), age estimations (Study 2), and reliable and cross-valid attractiveness ratings (Study 3). Furthermore, face silhouettes elicit an inversion effect (Study 4) and allow for remarkably accurate cross-identification with front-view photographs (Study 5). We then describe a shape-based parameterization that relies on a small set of landmark points and show that face silhouettes can be effectively represented in a 20-dimensional "silhouette face space" (Study 6). We show that in this physical space, distance from the center of the space corresponds to perceived distinctiveness (Study 7), confirming a key axiom in the formulation of the face space model. Finally, we discuss straightforward applications of the face silhouette methodology and address some limitations.

Keywords: face perception, face silhouettes, silhouetted face profiles, face models

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Introduction

Humans have a remarkable capacity to perceive, to discriminate, and to remember faces. Our ability to recognize one another is critical to successful navigation in our social world, and faces—despite sharing the same basic features in the same basic configurations—serve as a primary source of individual recognition. Attempts to explain this ability have inspired the development of numerous empirical and methodological techniques in the fields of psychology, neuroscience, and computer science. Until recently, most experiments in face perception have used raw or manually altered photographs of faces as stimuli (e.g., Ellis, Burton, Young, & Flude, 1997; Tanaka & Sengco, 1997). Although this has allowed researchers to stay close to the phenomenon of interest, reliance on these stimuli has resulted in a number of important limitations. Photographed faces are largely uncontrolled stimuli; they are rarely matched for size, orientation, or lighting conditions. In addition, photographs 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.

Valentine's (1991) proposal of a face space, in which faces are represented as points in a high-dimensional space and distances between points represent perceptual dissimilarities between the corresponding faces, provided a theoretical framework in which relationships between face stimuli could be formalized. This general framework, along with a few axiomatic assumptions, produced elegant explanations of several well-known phenomena in the face perception literature, including the distinctiveness and other-race effects. Without direct control over the actual face stimuli used in experiments, however, it has been difficult to empirically test whether the assumptions behind the general model hold true.

For example, Valentine (1991) conjectured that typical faces occupy a dense, central region of face space, whereas distinctive faces lie in the sparser periphery of the space. This claim has been used as an explanation of the well-reported phenomenon that distinctive faces, being farther from each other and therefore less confusable, elicit better recognition performance than typical faces. However, the original claim regarding the spatial distributions of typical and distinctive faces cannot be tested without a method for assigning particular faces to particular points in face space. Another example involves the phenomenon of cross-race identification. Several studies have reported an asymmetric own-race bias in the recognition of faces (see Bothwell, Brigham, & Malpass, 1989; Meissner & Brigham, 2001; Sporer, 2001). In particular, Caucasian subjects often show better recognition performance with Caucasian faces compared to Asian or African American faces, whereas Asian or African American subjects perform just as well with both types of faces. Researchers debate the cause of this asymmetry, with some focusing on differences in exposure to cross-race faces between the two groups (e.g., Tanaka, Kiefer, & Bukach, 2004), others highlighting the role of differences in race homogeneity (see Lindsay, Jack, & Christian, 1991), and still others implicating social factors such as status and attitudes (e.g., Barden,

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Maddux, Petty, & Brewer, 2004). Having a concrete measure of the physical variability of faces within and between race and other demographic groups would help resolve this debate and contribute to our understanding of how individual faces and face categories might be encoded.

Since Valentine's (1991) proposition of the face space model, several different image-processing techniques have been developed to enable the measurement and manipulation of similarity between faces. The most popular methods have included the use of eigenfaces (e.g., Turk & Pentland, 1991), landmark-based morphing (Benson & Perrett, 1993) and 3D reconstructions based on laser scans or photographs (e.g., Blanz & Vetter, 1999; Bruce et al., 1993). Although these methods have contributed to our understanding of face representation, they have fallen short of providing a fully reconstructive face space model that would enable the controlled generation of parametrically defined stimuli.

The eigenface method decomposes images into a set of dimensions based on variations across pixel values. Because the processing is done on raw pixel values, even slight variations in lighting conditions among the original photographs can have massive effects on the eigenvalue decomposition, which can cause two faces that are perceptually similar to have vastly different eigenface representations. In addition, if face images are not precisely aligned and normalized before processing, the resulting dimensions in the eigenspace can be incoherent and averaging two or more face images together can result in "ghost" features. For example, averaging together a face with wide-set eyes and a face with narrow-set eyes will create a face with four semitransparent eyes. Because the relative locations of interior features vary substantially across faces, this correspondence problem cannot be avoided by simply centering and scaling face images. As a consequence of the correspondence problem, a large number of dimensions in the eigenface representation end up being uninformative, artificially boosting the dimensionality of the space to hundreds of dimensions (see Penev & Sirovich, 2000).

Landmark-based models provide a way to solve the correspondence problem. The method requires the manual placement of a few hundred points on identifiable face parts, such as the tip of the nose or the corners of the eyes, across a collection of face images. This spatial coding produces a high-dimensional space of landmark locations that allows for arbitrary averaging, or morphing, among the set of coded face images. However, the method does not provide a fully reconstructive parameterization; the location of landmark points alone, without accompanying color or texture information, is insufficient to reconstruct a face image. Therefore, reconstructions rely on detailed information from the original face images that is extremely high-dimensional and largely uncontrolled across images (see Beale & Keil, 1995).

Some researchers have also employed methods based on 3D laser scans as well as 3D reconstructions derived from photographs at multiple views (e.g., O'Toole, Vetter, Troje, & Bülthoff, 1997; Vetter, 1998). These methods involve automatic alignments of several thousand locations and textures across a collection of 3D face data and use specialized graphics software to display and manipulate the resulting images. Although this approach can produce rather realistic face reconstructions, the automatic alignment procedure—based on digitally derived image properties—does not guarantee true anatomical correspondence between points across different faces, again creating a correspondence problem and a large number of uninterpretable dimensions. In addition, its usefulness for face perception researchers is limited by the expensive equipment and software needed to build a database, to construct the model, and to display the 3D images.

To avoid some of these obstacles, there have been recent attempts at low-dimensional parameterizations of face space using simplified face stimuli. Synthetic faces (Wilson, Loffler, & Wilkinson, 2002) are one such method. These stimuli are computerized line drawings obtained from gray-scale face photographs by manually identifying a set of landmark points within each face and extracting local contrast information in specified regions. Synthetic faces are then reconstructed by smoothly interpolating between the landmark points, matching the contrast patterns of the original image, and placing face features in specified locations. Synthetic faces carry the main advantage of providing a relatively low-dimensional full parameterization of faces (using 37 dimensions) while preserving substantial individuating facial information. In their behavioral studies, Wilson et al. (2002) showed that synthetic faces allow for accurate matching to original photographs across various viewpoints and produce inversion effects, as originally reported with face photographs by Yin (1969). A main limitation to this method is its reliance on predefined, generic face features such as eyes and eyebrows to reconstruct each face. Recent research has shown that empirically derived "features" may be more useful in characterizing the perceptually salient information available in faces (see Schyns, Bonnar, & Gosselin, 2002).

Silhouetted face profiles

The method presented here (see also Davidenko, 2004) shares some qualities with the synthetic face algorithm but uses a purely shape-based approach to face representation. The stimuli are silhouetted face profiles obtained by reducing gray-scale photographs of face profiles to two-tone black and white images that are then cropped at the forehead, below the chin, and down the ear line (see Figure 1).

Methodological advantages

Silhouettes carry a number of advantages over the methods discussed above. First, because they rely only on

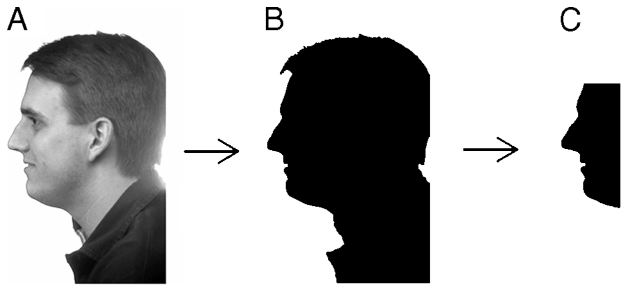

Figure 1. A profile view of a face (A), the two-tone reduction (B), and the cropped silhouette (C).

shape information from face profiles, there are minimal constraints on the viewing conditions in the photographs used and it is thus relatively easy and inexpensive to construct a large database of face silhouettes from a collection of profile-view photographs. Second, as we discuss below, face silhouettes lend themselves to a low-dimensional, landmark-based parameterization. Third, there is no need to predefine features to reconstruct silhouettes or even to define what a feature is; as we will see, psychologically salient "features" emerge naturally from the statistical analysis of the shape of the silhouettes. Of course, silhouettes, lacking texture information, also carry some limitations that are addressed in the general discussion.

In this paper, we first present a series of studies that demonstrate that face silhouettes are visually processed much like regular face stimuli, even providing enough information for individual face recognition. We then describe a simple parameterization of silhouettes that results in a low-dimensional silhouette face space. We present two further studies, the first of which seeks to determine the number of dimensions required to represent silhouette face space; in the second, we use the space to empirically test Valentine's (1991) conjecture that distinctive faces lie in sparse, peripheral regions of face space. Finally, we discuss the theoretical advantages of the face silhouettes compared to existing methodologies, propose straightforward applications for studying a variety of face perception phenomena, and consider limitations of the method.

Methods

Visual processing of silhouettes

Constructing face silhouettes

In the five studies described below, we used 48 face silhouettes to investigate how much face information is available in these simple stimuli. The first three studies were administered as questionnaires where participants made judgments of gender (Study 1), age (Study 2), or attractiveness (Study 3) on the 48 silhouettes. To keep the questionnaires brief, we randomly sorted and split the 48 silhouettes into three sets of 16, and each participant responded to only one of the three sets and to only one of the three measures. Silhouettes in each set were presented on a single sheet of paper, organized into four rows of four silhouettes. Following the questionnaire studies, we present evidence that silhouettes elicit an inversion effect (Study 4) and that they can be individually matched to their corresponding front-view images (Study 5).

Forty-eight face profile-view images were selected from the FERET database (Phillips, Moon, Rizvi, & Rauss, 2000; Phillips, Wechsler, Huang, & Rauss, 1998) to include various demographic groups. Of the 48 faces, 24 were male and 24 were female, and within each gender, approximately 16 were White, 4 were Black, 2 were Asian, and 2 were of other or mixed racial backgrounds. Ages of the people photographed ranged from 18 to 65 years, with a mean of 26 years. There were no correlations among gender, race, and age.

Silhouettes were generated by editing the 48 profile images using Adobe Photoshop. Images were passed through a threshold filter, resulting in black face profiles over white backgrounds (see Figures 1A and B). These two-toned images were then cropped horizontally at the forehead, below the chin, and down the ear line, removing any visible hair or clothing and obscuring head shape (see Figure 1C). The resulting silhouettes were flipped and rotated, if necessary, to face left and were magnified or shrunk to be of the same height.

Study 1: Gender judgments

Participants and procedure

The aim of this study was to determine how much gender information people could extract from face silhouettes. One hundred fifty-six Stanford undergraduates (ages 18–22) participated in the study for course credit. Participants were asked to determine the gender of 16 silhouettes and enter a confidence rating using a 1–7 scale. In this way, each of the 48 silhouettes was rated by 52 participants. A sample from this questionnaire is shown in Figure 2.

Results and discussion

There was a very high intersubject agreement on the gender of the silhouettes, as indicated by a Cronbach's α of .9716 on the gender judgments and .9754 on the signed confidence ratings. Overall, the proportion of correct classifications was 69.5%, significantly above chance, $\chi^2(1) = 598.8$, $p < .0001$. Performance was well predicted by subjects' confidence ratings, wherein higher confidence correlated with higher accuracy, $r = .927$, $p = .003$ (see Figure 3).

Male silhouettes were classified as male 83.3% of the time, $\chi^2(1) = 580.4$, $p < .0001$, and female silhouettes

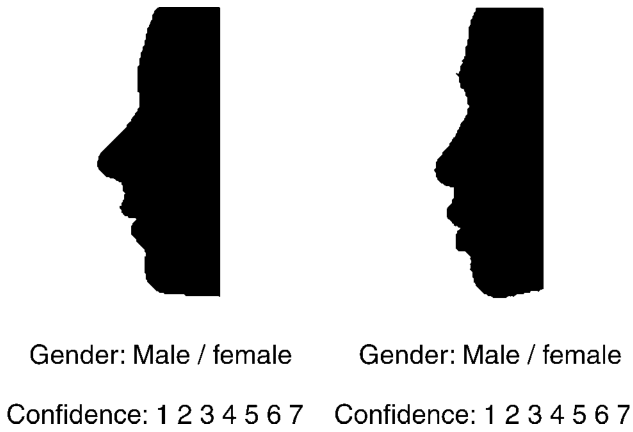

Figure 2. Gender judgments on face silhouettes in Study 1.

were classified as female 55.7% of the time, $\chi^2(1) = 17.3$, $p < .0001$. This male bias in the perceived gender of silhouettes is consistent with previous studies on gender classification from ambiguous or impoverished stimuli (e.g., Graf & Wichmann, 2002; Wild et al., 2000). We suggest two possible explanations for the male bias in our participants' responses. First, the lack of hair on the silhouettes could be perceived as a cue to baldness, which could in turn be a cue to maleness. Second, and more importantly, there is evidence from anthropological studies (e.g., Alley & Hildebrandt(-Karraker), 1988) that male faces are physically more variable than female faces (as we shall see below; when silhouettes are analyzed in a multidimensional space, the region occupied by male silhouettes is larger than that occupied by female silhouettes). A disproportionate overlap in the region of face space corresponding to both genders would make female faces more likely than male faces to fall into a gender-ambiguous region of the space (i.e., if the space of "clearly male" faces—and silhouettes—is larger than the space of "clearly female" faces, then probabilistically female silhouettes are more likely to be ambiguous than are male silhouettes). Overall, considering their lack of hair or texture information—two important cues for gender (see Wild et al., 2000; Wright & Sladden, 2003)—face silhouettes allowed for remarkably successful gender classification.

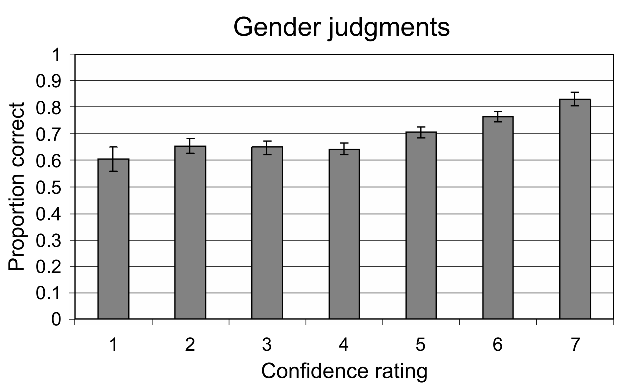

Figure 3. Proportion of correct gender judgments as a function of reported confidence ($r = .927$, $p = .003$).

Study 2: Age estimations

Participants and procedure

This study tested whether age information could be extracted from silhouettes. Fifty-one Stanford undergraduates (ages 18–20) participated for course credit. Participants were asked to estimate the approximate age of 16 silhouettes by selecting the appropriate age bracket, from a choice of "teens," "20s," "30s," "40s," "50s," and "60s." Each of the 48 test silhouettes was rated by 17 participants.

Results and discussion

There was high intersubject agreement as to the age of the silhouettes, as indicated by Cronbach's $\alpha = .9587$. We found a high correlation between the mean rated age and the actual age of the silhouettes, $r = .659$, $p < .0001$ (see Figure 4), confirming that information about age is indeed extractable from silhouetted face profiles. The percentage of classifications that fell within one bracket of the correct age was 68.3%, compared to a chance level of 38.8%, $\chi^2(1) = 298$, $p < .0001$. There was a tendency to overestimate the age of the silhouettes, especially on the younger faces, as shown in Figure 4. Again, silhouettes provide a substantial amount of age information, although they lack internal features that normally contribute to age perception (George & Hole, 1998).

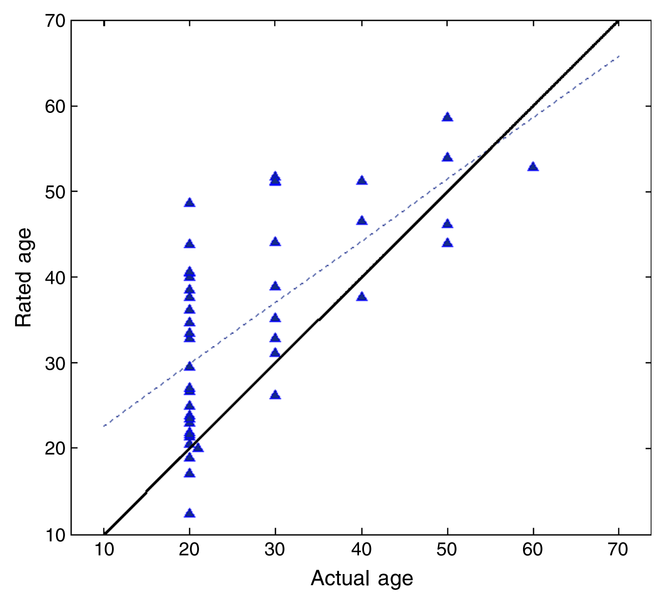

Figure 4. Actual and rated ages for the 48 silhouettes ($r = .659$, $p < .0001$). Regression line (dotted) and veridical line (solid) are shown for comparison.

Study 3: Attractiveness ratings

Participants and procedure

A recent study by Valenzano, Mennucci, Tartarelli, and Cellerino (2006) suggests that simplified face profiles with minimal information about internal features can provide reliable attractiveness information. The goal of this study was to determine whether face silhouettes—which carry no internal features—could elicit reliable and cross-valid ratings of attractiveness. Three groups of Stanford undergraduates ($N_1 = 84$, $N_2 = 48$, $N_3 = 30$; ages 18–23) participated in the study for course credit. Each participant in Group 1 rated the attractiveness of 16 silhouettes on a 0–10 scale. Participants in Group 2 rated the attractiveness of gray-scale profile-view images of the same faces as in Group 1. Participants in Group 3 rated the attractiveness of gray-scale front-view images of the same faces. Figure 5 shows a sample row from each of the three questionnaires. Each face in each view was rated by at least 10 participants.

Results and discussion

Silhouettes elicited highly reliable attractiveness ratings across participants (Cronbach's $\alpha = .9430$). This reliability was comparable to that obtained with profile images (Cronbach's $\alpha = .9464$) and surprisingly even higher than that obtained with front-view images (Cronbach's $\alpha = .8834$). Attractiveness ratings were significantly correlated across view types (see Figure 6). Ratings on the silhouettes were highly correlated with ratings on the profile-view images, $r = .78$, $p < .0001$. This value was as high as the correlation between ratings on profile-view images and front-view images, $r = .77$, $p < .0001$. There was a lower but still highly significant correlation between ratings on silhouettes and front-view images, $r = .49$, $p = .0004$. One might expect a lower correlation in this case because silhouettes lack texture information and present a vastly different view than front-view images. Still, attractiveness ratings on silhouettes were highly predictive of those ratings on front-view and profile-view faces, indicating that silhouettes contain much of the information necessary to determine the attractiveness of a face.

Consistent with previous findings using front-view images (e.g., Little & Hancock, 2002), we found a negative correlation between rated masculinity (Study 1) and rated attractiveness among the silhouettes, $r = -.76$, $p < .0001$. Also consistent with previous work (e.g., Ishi & Gyoba, 2001), this correlation was driven by ratings on male faces; that is, among female faces, there was no significant correlation between rated gender and rated attractiveness. Interestingly, male and female participants did not differ systematically in the way they rated the

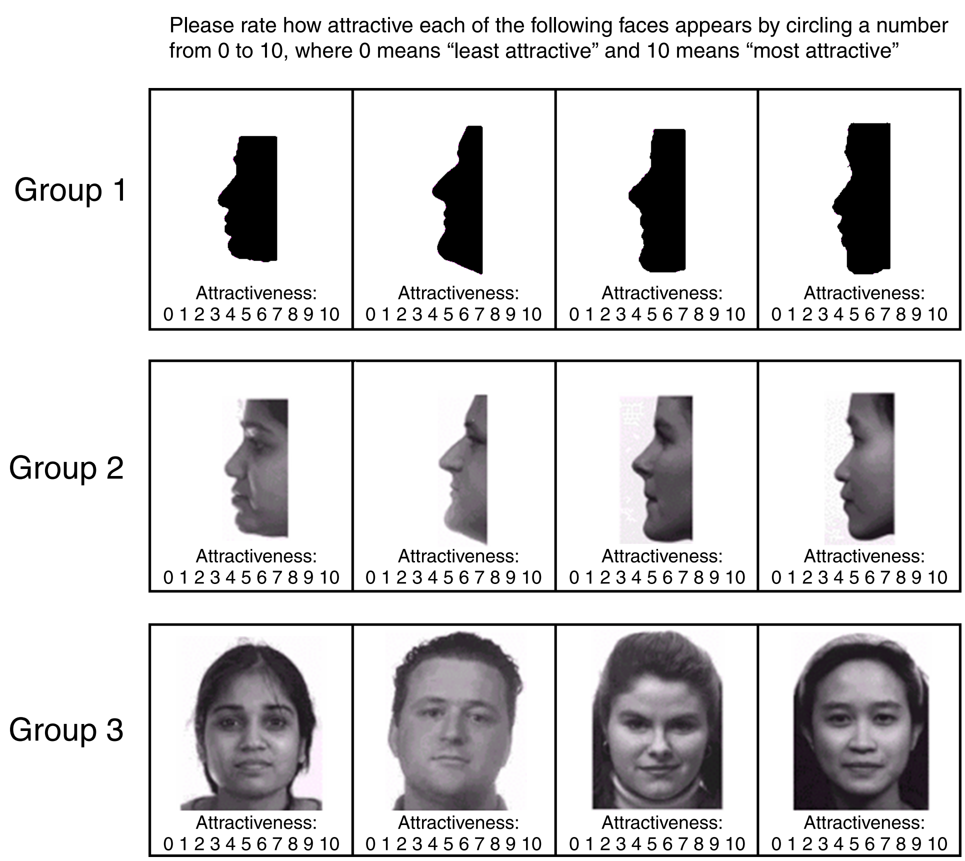

Figure 5. Sample stimuli for attractiveness ratings (Study 3).

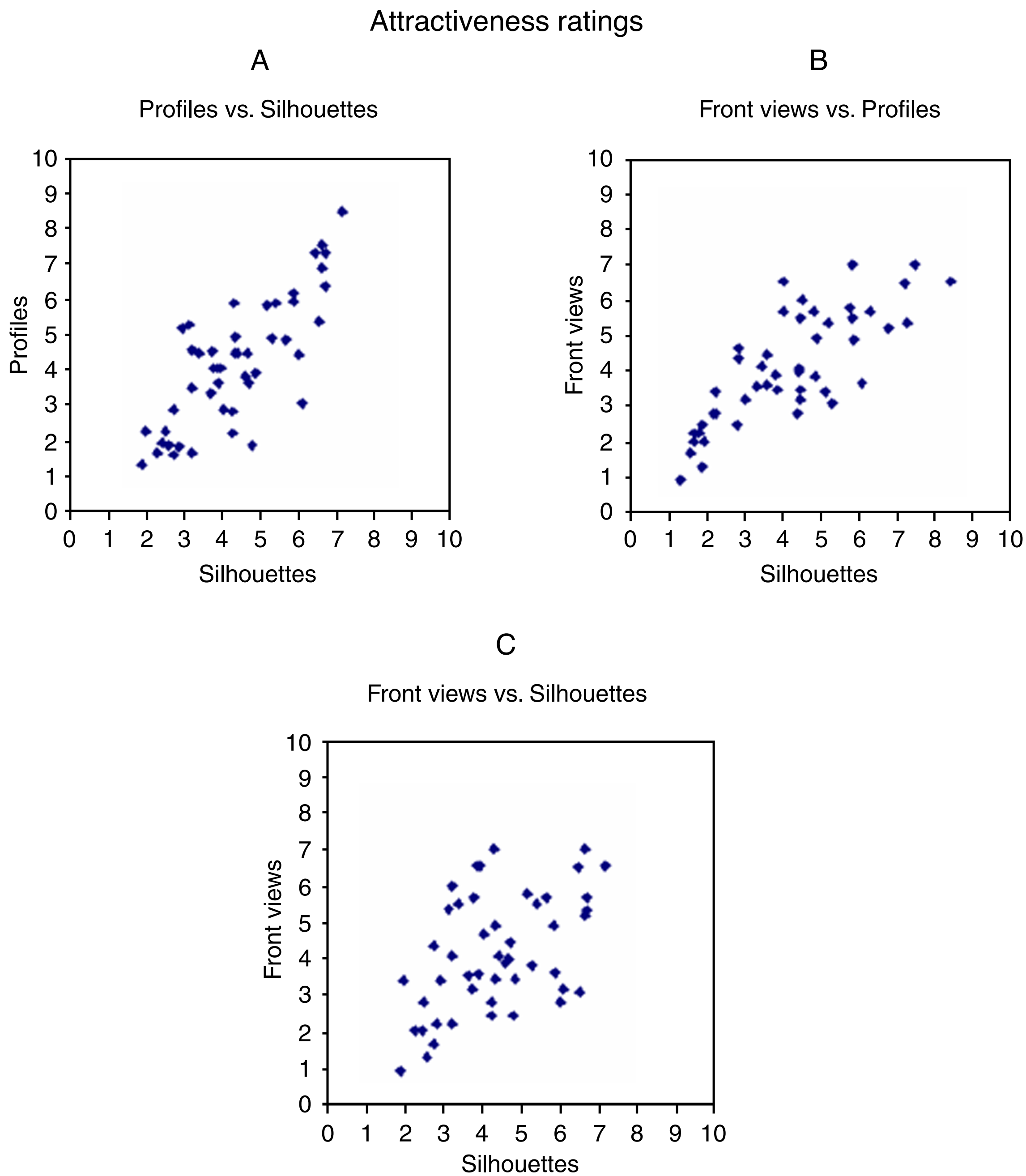

Figure 6. Correlations of attractiveness ratings of profile-view images versus silhouettes (A; $r = .78$, $p < .0001$); front-view images versus profiles (B; $r = .77$, $p < .0001$); and front-view images versus silhouettes (C; $r = .49$, $p = .0004$).

attractiveness of the silhouettes. Overall, silhouettes provide information for reliable ratings of attractiveness that are highly predictive of ratings of their profile- and front-view counterparts.

Judgments on face silhouettes

Studies 1, 2, and 3 demonstrate that despite being relatively simple stimuli, silhouetted face profiles carry rich information about their front-view counterparts. People can extract gender and age from the silhouettes, and they can make reliable judgments of attractiveness on silhouettes that correspond well to those judgments on profile- and front-view images of the same faces. The negative correlation between attractiveness and masculinity of silhouettes is consistent with previous studies using front-view images of faces, suggesting a clear correspondence in the information carried by front-view faces and silhouetted face profiles. Face silhouettes seem to isolate consistent factors pertaining to these judgments, as they produce extremely reliable ratings (Cronbach's $\alpha > .94$ for all three types of judgments).

In the next study, we test whether a well-known phenomenon associated with face processing, the face inversion effect, also holds with face silhouettes.

Study 4: Silhouette inversion effect

In the face inversion effect, first reported by Yin (1969), people demonstrate superior processing for upright faces that does not transfer to upside-down faces. Not only are upside-down faces processed more poorly than upright faces, but this decreased performance is disproportionate compared to other object categories. This study tested whether upright face silhouettes are recognized more accurately than upside-down face silhouettes. If so, it would suggest that people's expertise with upright front-view faces generalizes to the silhouette view.

Stimuli

One hundred different target face silhouettes were constructed by smoothly interpolating among the 48 silhouettes used in Studies 1, 2, and 3 (the next section in this paper describes this procedure in more detail). Based on the distribution of variations across silhouettes, we created small distortions of the target silhouettes to create two distractors for each target silhouette. An example of a target and its two distractor silhouettes is shown in Figure 7.

Participants and procedure

Eighteen Stanford undergraduates (ages 18–20) participated in the study for course credit. Participants completed 100 short-delay 3-alternative-forced choice (3AFC) recognition trials. In each trial, participants observed one of the target silhouettes for 2 s, followed by a masked delay of 3 s (see Figure 8). They were then presented with three alternative test silhouettes—the target and two distractors—positioned randomly on the screen, from which they were instructed to choose the silhouette they had just seen. There were two between-subject conditions: nine participants were assigned to the "upright condition" and nine to the "upside-down condition" in which all target and test silhouettes were flipped vertically (see Figure 8).

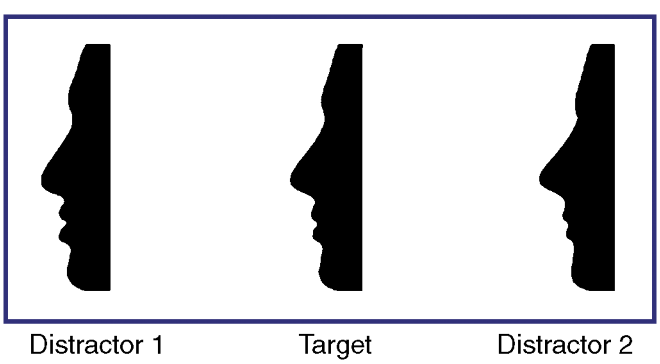

Figure 7. Example of a target and two distractor silhouettes.

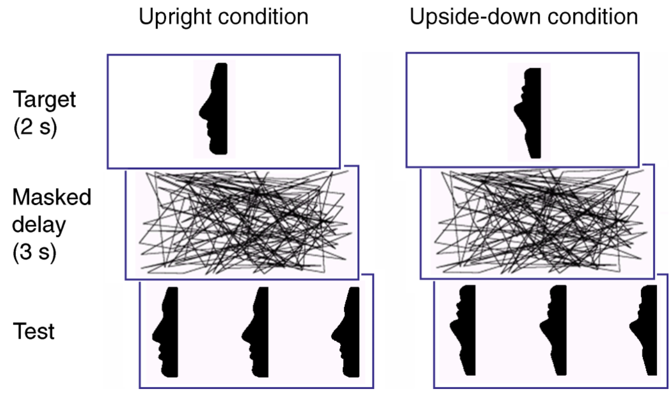

Figure 8. Example upright and upside-down trials from Study 4.

Results and discussion

Performance on the 3AFC task was significantly above the chance level of 33% correct in both conditions: 59% correct in the upright condition, $\chi^2(1) = 267$, $p < .0001$, and 48% correct in the upside-down condition, $\chi^2(1) = 147$, $p < .0001$. Once again, we found that silhouettes exhibited the same processing characteristics as front-view faces: participants showed a significant performance advantage for upright silhouettes over upside-down silhouettes, unpaired $t(16) = 2.15$, $p = .024$. Further, the advantage found in this study (roughly 10% difference between upright and inverted silhouettes on a 3AFC task) is comparable to that found in previous studies using front-view faces (e.g., Aylward et al., 2005).

That silhouettes provide sufficient information for generic categorical and qualitative judgments and elicit an inversion effect clearly suggests that they are processed much like regular face stimuli. It remains to be seen, however, whether the information correspondence between silhouettes and their front-view counterparts allows for individual recognition. To test whether this is the case, we measured people's ability to match a silhouette to its front-view counterpart in Study 5.

Study 5: Matching silhouettes and front-view images

Participants and procedure

Seventeen Stanford students (ages 19–29) volunteered to participate in the study. A set of 20 male and 20 female silhouettes were randomly selected from the database of 48 silhouettes. The study consisted of four pages, each page containing six rows of 4AFC items. On the first page, each row contained a male front-view image (target) followed by four silhouettes from which participants were asked to circle the appropriate match to the target. In the second page, participants matched female front-view images to silhouettes. The third and fourth pages were like the first and second, except participants matched silhouettes to front-view images. An example row from each of the four pages is shown in Figure 9. As a first

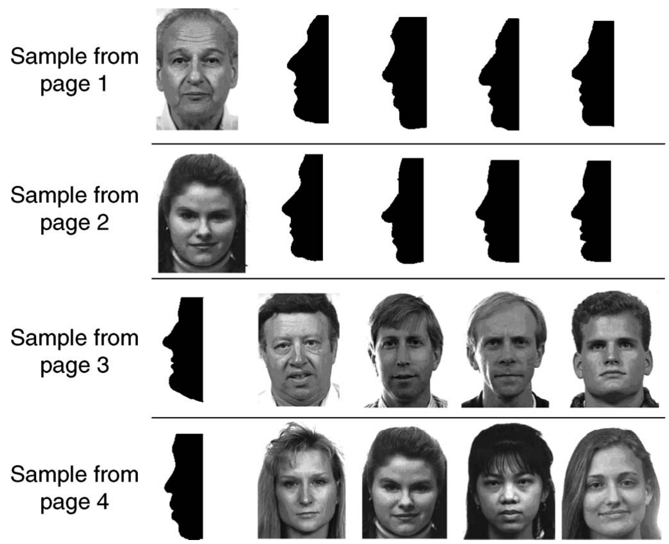

Figure 9. Example row from each page of the matching study (Study 5).

study in novel face identification with silhouettes, this task presented targets and tests simultaneously and imposed no time constraints for participants' responses.

Results and discussion

Overall performance in the 4AFC task was 70.1% correct, significantly above the 25% level expected from chance performance, $\chi^2(1) = 443$, $p < .0001$. Performance on male faces was substantially better than performance on female faces (80.9% correct vs. 59.3% correct). This advantage for male faces again may be due to the greater variance generally found among male faces, as compared to female faces (Alley & Hildebrandt(-Karraker), 1988), which would make them more distinguishable from each other. Indeed, the male and female silhouettes used in this study had a variance of 1.67 and 1.27, respectively (arbitrary face space units), which may have contributed to the behavioral performance differences. There were no effects of participants' gender on performance. There were also no performance differences between matching a front-view image to the correct silhouette and matching a silhouette to the correct front-view image.

These results can be compared to those reported by Wilson et al. (2002) using synthetic faces. In their study, five participants performed a similar task, matching synthetic faces to their real counterparts, and vice versa. Performance was 90% correct on a 4AFC when views between targets and alternatives were mismatched by a 20° rotation in depth. Although this performance exceeds that obtained here with silhouettes, it should be noted that silhouettes have three additional constraints over synthetic faces that should be expected to limit performance. First, silhouettes are two-toned, so any gray-scale information, including texture, skin color, or eye position, is unavailable. Second, the cropping at the forehead eliminates the possibility of using hair cues for matching. Third, silhouettes are entirely in profile view, which provides shape information that is not directly observable in their front-view counterparts. This is a far more drastic angle difference than the 20° difference used Wilson et al.'s (2002) study. Given these constraints, it is impressive that performance on face silhouettes is as high as it is, even surpassing performance on a similar task with 3D models (Bruce et al., 1991).

The results of this last study show that not only do silhouettes carry a substantial amount of generic, face-relevant information and elicit face-specific processing, but they also contain sufficient information about individualistic features that allow them to be successfully matched to their gray-scale front-view counterparts. In the next section, we develop a simple parameterization that allows us to fully represent face silhouettes in a low-dimensional metric space. We first describe a shape-based parameterization of silhouettes. We then show that silhouettes can be effectively represented in a 20-dimensional subspace of the original parameterization (Study 6). Finally, we use this silhouette parameterization to test Valentine's (1991) conjecture regarding the relationship between eccentricity in face space and perceived distinctiveness (Study 7).

Parameterization of silhouettes

To construct a parameterized silhouette face space, we selected 384 profile images from the FERET database to include 192 males and 192 females, 256 Caucasian, 41 Asian, 32 African American, and 76 other or mixed race faces. Using Matlab, two independent coders recorded the positions of 18 key points on the contour of each profile image (see Figure 10A). The 18 points were chosen to be easily identifiable landmarks that clearly corresponded across faces (e.g., the tip of the nose, the cusp between the lips, etc.; for a similar approach, see Valenzano et al., 2006). The precise correspondence of key points across face images ensures that the dimensions of the resulting face space will represent actual face variations and not encoding noise.

Using Matlab, a normalization procedure was used to translate, to rotate, and to dilate each set of 18 points to make the first and last points coincide at (0, 0) and (0, 1) across all 384 images (see Figure 10B). This was done for two reasons. First, because the profile images from the FERET database were not taken under the same viewing conditions for each person, the actual size of each image was not informative about the physical size of the person's face. A flat normalization was the simplest way to make a canonical size for the silhouettes. Second, by having the first and last points coincide for all images, the position of these points becomes uninformative, which reduces the number of informative points from 18 to 16 coordinate points, or 32 scalar x and y values.

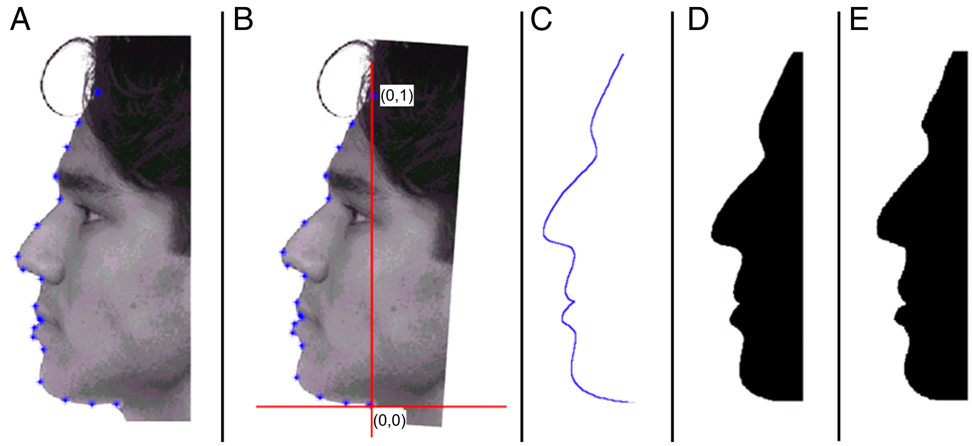

Figure 10. Steps in the parameterization of a silhouette. The original gray-scale profile image with 18 key points (A); normalized image (B); splines between adjacent points to create a smooth contour (C); filled in contour (D); and original silhouetted face profile (E).

The power of a full parameterization lies in the ability to reconstruct a stimulus given only the relevant parameter values. In the case of face silhouettes, the 32-dimensional vectors (representing the 16 informative *x*–*y* coordinates) contain the necessary information for reconstruction but are not themselves the reconstructed stimuli. To display a reconstructed silhouette given the 32 parameters, we first used Matlab to generate bi-cubic splines that smoothly interpolated between adjacent *x*–*y* points, forcing a single cusp between the lips (see Figure 10C). We then added a fixed-width rectangle along the height of the face and shaded the interior of the silhouette black (see Figure 10D). Neither of these transformations increased the number of parameters needed to define each silhouette. The resulting reconstructions are subjectively very similar to the two-toned, cropped versions of the original profile images for all 384 silhouettes (for an example, see Figures 10D and E).

Creating a silhouette face space

The most direct way of obtaining a vector space to represent the set of possible silhouettes would be to consider each of the 16 informative *x*–*y* coordinates, or 32 parameters, as a separate dimension. Each silhouette would correspond to a point in this space, and all possible silhouettes would correspond to a complex region in the space. A major disadvantage of this direct approach is that there are many intercorrelations among the 32 parameters. For instance, the *x* value for the point corresponding to the tip of the nose is highly correlated with the *x* value of the point below it (see Figure 10A). This type of interdependence results in complex constraints among the dimensions of the space, making it difficult to describe properties of the space and to sample from it to construct novel silhouettes.

To capture the intercorrelations among parameters, we conducted a principal components analysis (PCA) on the 32 parameters to produce 32 linearly independent principal components (PCs). There are several advantages of using a PC representation. First, each PC is linearly independent from every other PC. This means that whatever value a silhouette has on PC_1 does not in any way constrain its value on PC_2, PC_3, and so forth. In addition to being independent, we used a test of normality to show that the 32 PCs are distributed normally across the 384 silhouettes (see Figure 11). The normal distribution of silhouettes in this space provides concrete support of Valentine's (1991) original conjecture about the centrally dense distribution of faces in face space.

A second advantage of using PCA is that the resulting PCs are listed in order of how much physical variance they account for. Figure 12 shows that the first PC alone accounts for roughly 42% of the physical variance of the 384 silhouettes, the first 5 PCs together account for almost 90% of the physical variance, and the first 20 PCs together account for over 99% of the variance. This suggests that fewer than 32 parameters may actually be necessary to accurately represent the 384 silhouettes from our database, and conceivably most silhouettes in general. In Study 6, described below, we examine how many PCs can be pruned from the representation of a silhouette before the physical consequences become noticeable.

Finally, the PC representation provides practical advantages for constructing novel face stimuli. Because the PCs are independent and normally distributed about zero, one can easily sample from a multinormal space to construct artificial yet realistic-looking face silhouettes (a procedure we employ in Studies 6 and 7). This also simplifies the process of averaging and caricaturing faces. For example, the 32-element zero vector represents the average of all 384 silhouettes. To obtain a morph between two silhouettes, simply compute the arithmetic average of the two corresponding vectors of PC coefficients. To create caricatures, "anticaricatures," or "antifaces" of a particular silhouette, simply multiply the original vector of coefficients by a scalar greater than one, between zero and one, or less than zero, respectively. One can create

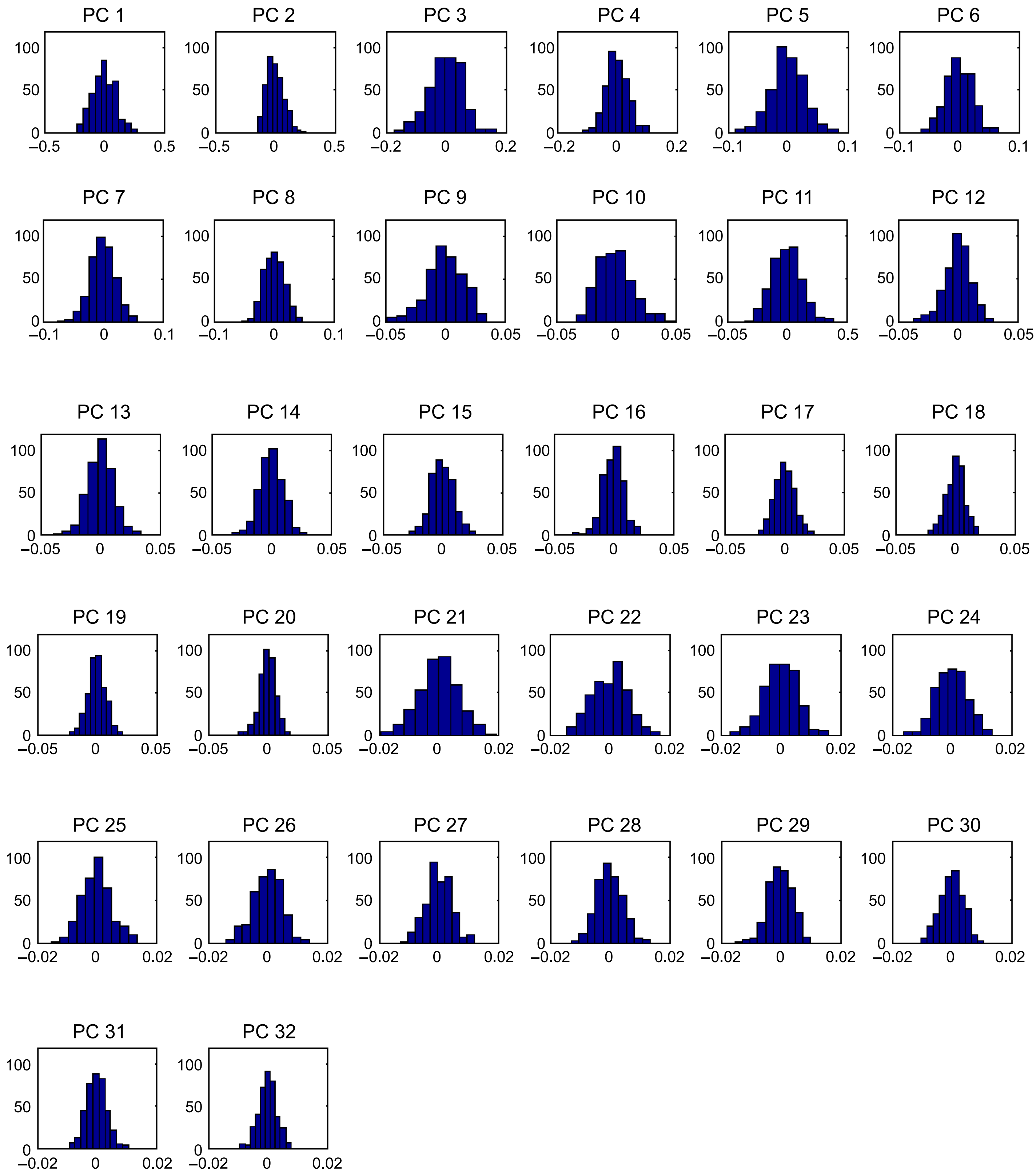

Figure 11. Distribution of PC coefficients across all 384 silhouettes. The range of coefficients (shown on the *x* axes) decreases by a factor of about 30 from PC_1 to PC_{32}.

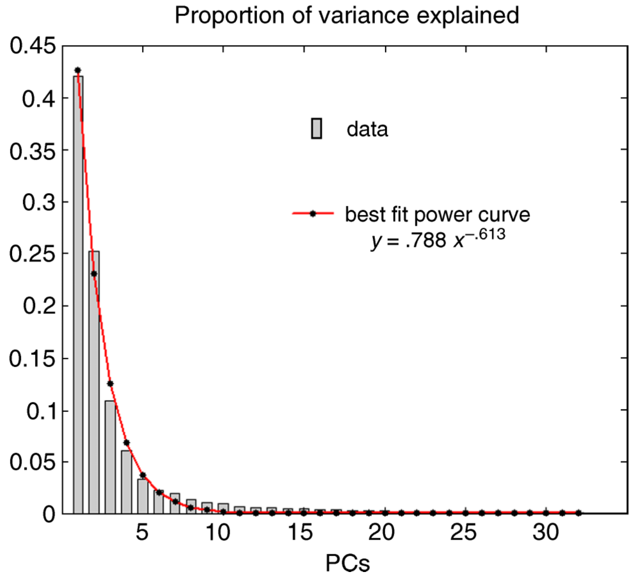

Figure 12. Proportion of physical variance explained by each of the 32 PCs. The data are well fitted by a power curve with coefficients .778 and −.613.

intermediate morph levels between two or more silhouettes by computing linear combinations of the corresponding vectors. Figure 13 shows the effect of varying the coefficients of PC_1, PC_2, and PC_3 from negative to positive values.

Study 6: Effective dimensionality of silhouette face space

Although a PCA tells us how much physical variance each PC accounts for, this information does not directly predict the magnitude of the perceptual effect of varying each PC coefficient. In this study, we examined the perceptual effects of pruning a silhouette representation down from its original 32 PCs. Specifically, we measured performance on a same/different task comparing fully represented silhouettes (sampled from the multinormal silhouette face space, using all 32 PCs) to "reduced" silhouettes (setting the last *n* PCs to zero).

Participants and procedure

Twenty-eight Stanford undergraduates (ages 18–21) participated in the study for course credit. The task required participants to observe two parameterized silhouettes (a "target" and a "test" silhouette), side by side, on a computer monitor and enter "s" if the silhouettes were the same or "d" if they were different. The two silhouettes remained on the screen until participants entered their response, after which a blank screen was presented for 500 ms preceding the next trial. Each participant completed 360 same/different trials, 120 of which were "catch" trials where the target and test silhouettes were identical. For each trial, a target silhouette was generated from silhouette face space by sampling randomly from the multinormal distribution of PC coefficients described earlier (see Figure 11). The corresponding test silhouette was either identical to the target (catch trial) or matched the target on the first *n* PC coefficients, with all subsequent PC coefficients set to zero. For example, the two vectors below could represent the set of normalized PC coefficients describing a target silhouette and a test silhouette with 12 matching PC values (n = 12):

V_{target} = [0.8 0.7 1.3 0.7 1.2 −1.2 −0.0 −0.2 −1.6 0.3 −1.1 1.4 −0.8 0.5 0.2 −0.9 −2.2 −0.1 −1.0 0.6 0.5 1.7 0.6 −0.6 0.4 −1.0 −0.0 −0.0 0.0 −0.3 1.1 −1.9]; and

V_{test} = [0.8 0.7 1.3 0.7 1.2 −1.2 −0.0 −0.2 −1.6 0.3 −1.1 1.4 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0].

The number of matching PC values varied from trial to trial. For the 240 noncatch trials, the number of matching PC values was sampled uniformly from the set {0, 1, 2, 3, 4, 6, 8, 10, 12, 15, 18, 21, 24, 27, 30}. Participants completed five practice trials before beginning the experiment to become familiar with the task.

Results and discussion

As expected, participants' ability to detect a difference between the target and test silhouettes decreased as a function of the number of matching PCs. Figure 14 shows

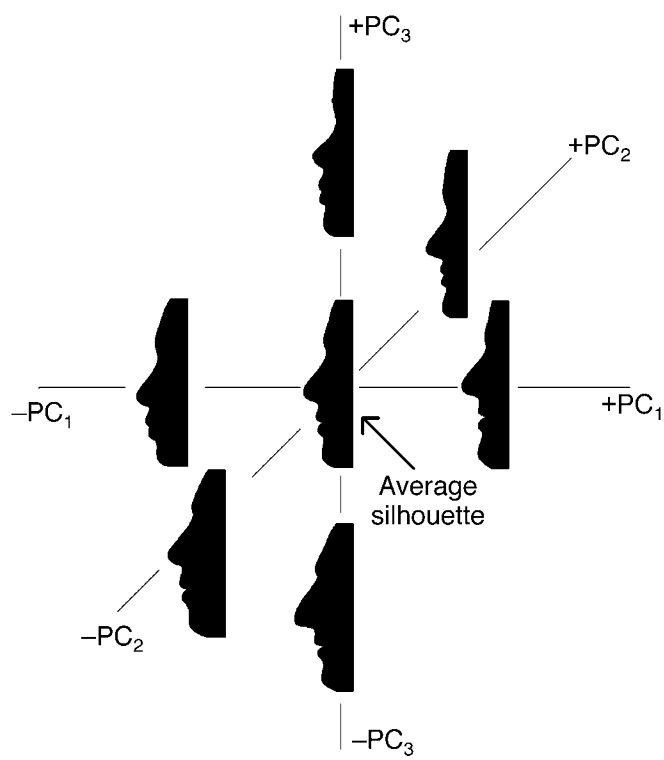

Figure 13. The effects of varying the coefficients of PC_1, PC_2, and PC_3. The middle silhouette is the center of silhouette face space (i.e., the average of all 384 silhouettes from our database).

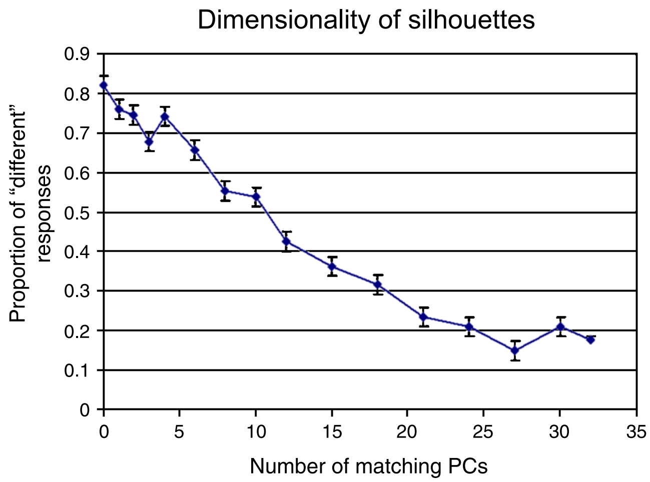

Figure 14. Performance on a same/different trial where the test silhouette matches the target on the first *n* PCs, and all other PCs are set to zero. When the number of matching PCs is 21 or greater, performance is indistinguishable from catch trials (i.e., 32 matching PCs).

the proportion of "different" responses as a function of the number of matching PCs, including catch trials with 32 matching PCs. The proportion of "different" responses when the test silhouette matches the target in more than the first 20 PC coefficients was statistically indistinguishable from when the test and target silhouette were identical. That is, the information present in PCs 21 through 32 seems to be perceptually unnoticeable. We therefore suggest that silhouettes can be effectively and veridically represented in a 20-dimensional space.[1]

Having constructed a fully parameterized, 20-dimensional silhouette face space, we can exploit it to test any number of predictions about face perception and representation. In our final study, we test one of Valentine's (1991) basic conjectures about face space: the relationship between the distinctiveness of a face and its eccentricity in the space.

Study 7: Distinctiveness and silhouette face space

Spatial models of face representation carry the assumption, explicit or implicit, that the space is centrally distributed with typical faces packed densely near the center of the space and that distinctive faces spread sparsely in the periphery. We have already shown that silhouette face space is centrally distributed; specifically, silhouettes are distributed normally along each PC dimension. With our fully parameterized face space, we can now test whether distance from the center of the space corresponds to perceived distinctiveness.

Participants and procedure

Sixty Stanford undergraduates (ages 18–22) were instructed to rate the distinctiveness of 16 of the 48 real face silhouettes used in Studies 1, 2, 3, and 4, on a 1–10 scale, from least distinctive to most distinctive. Following previous convention (e.g., Valentine, 2001; Wickham, Morris, & Fritz, 2000), participants were instructed that "distinctive faces are those that would be easy to spot in a crowd." Each of the 48 face silhouettes was rated by 20 participants.

Results and discussion

There was a reasonably high intersubject reliability in the distinctiveness ratings of the silhouettes (Cronbach's α = .8869). More importantly, these ratings were well predicted by the position of the silhouettes in silhouette face space. We first defined an unweighted Euclidean distance between each of the 48 silhouettes and the overall mean; that is, we computed the root sum of squares of the raw PC coefficients that define each silhouette. The correlation between these distances and the mean distinctiveness ratings was highly significant, r = .583, $p < .0001$ (see Figure 15), providing empirical evidence of Valentine's (1991) conjecture.

Because of the disparity in the amount of variance explained by each subsequent PC, a statistically large coefficient on an early PC has a much larger physical effect on the shape of a silhouette than an equivalently large coefficient on a later PC. For instance, suppose Silhouette A has a value of +3 standard deviation (*SD*) on PC_1 and 0 on all other PCs, whereas Silhouette B has a value of +3 *SD* on PC_{10} and 0 on all other PCs. When converting to x–y units,[2] Silhouette A will have a Euclidean distance of 0.09365 units from the center of the space, whereas Silhouette B will have a Euclidean distance of 0.00124 units from the center. This means that Silhouette A lies roughly 75 times farther than Silhouette B from the center of space. However, it is unlikely that

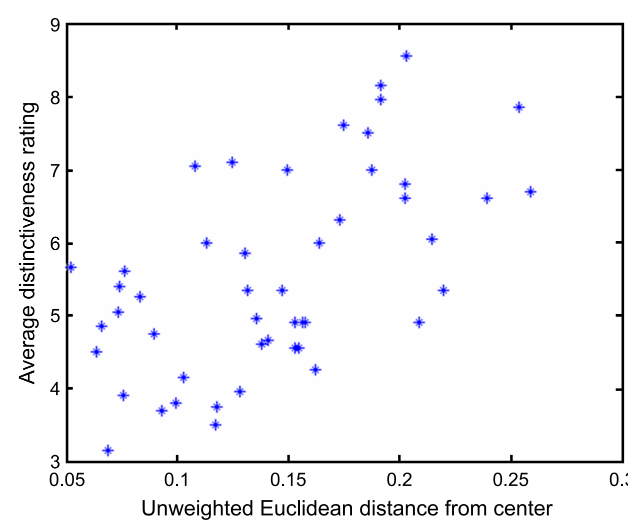

Figure 15. The correlation between unweighted Euclidean distances and distinctiveness ratings on the 48 silhouettes (r = .583, $p < .0001$).

Silhouette A is 75 times as distinctive as Silhouette B (see Figure 16). At the same time, the physical variance accounted by each subsequent PC should not be ignored; that is, we would not predict that Silhouette A and Silhouette B, both 3 *SD* away from the average silhouette, should be equally distinctive.

We reasoned that although the variance accounted for by each PC should influence its role in determining perceptual distinctiveness, the contribution of the 20 PCs might be more evenly distributed than is suggested by the power function derived earlier (see Figure 12). We therefore considered a family of Euclidean metrics with a single parameter w that determined how much to normalize the distribution of standard deviations of the PCs. Specifically, for w ranging from 0 to 1, we defined a set of weighted PC coefficients C_{weighted} (PC, w) for each silhouette, as follows:

$$C_{\mathrm{weighted}}(\mathrm{PC}, w) = C_{\mathrm{unweighted}}(\mathrm{PC})*(\mathrm{SD}(\mathrm{PC}))^{-w}. \quad (1)$$

When $w = 0$, the coefficients are unchanged; when $w = 1$, the standard deviations of the PCs are nullified and every PC is weighted equally; for values of w between 0 and 1, there is an intermediate weighting of PCs. Figure 17A shows the effect of the parameter w on the correlation between Euclidean distance and average distinctiveness ratings. We find that the highest correlation, $r = .668$, $p < .0001$, is achieved when $w = 0.68$ (see Figure 17B). This suggests that although the magnitude of physical change in silhouettes decreases considerably with subsequent PCs, the perceptual effects of statistically large PC values remain large. This raises a number of intriguing questions about the relationship between physical and psychological face space that are beyond the scope of the present project and remain work in progress.

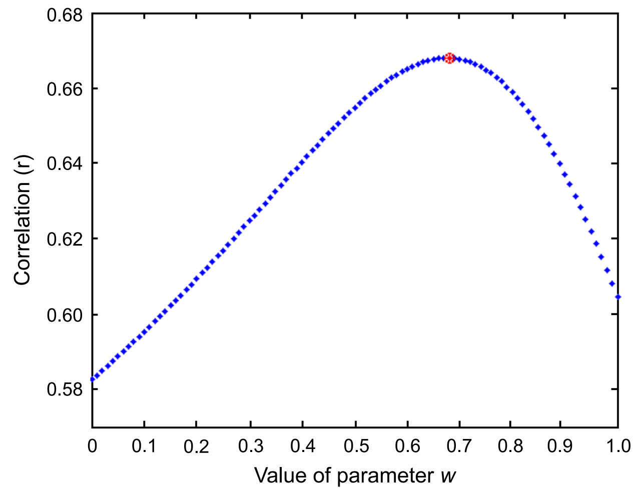

Figure 17. The effect of varying parameter w from 0 to 1 on the correlation between Euclidean distance and distinctiveness ratings.

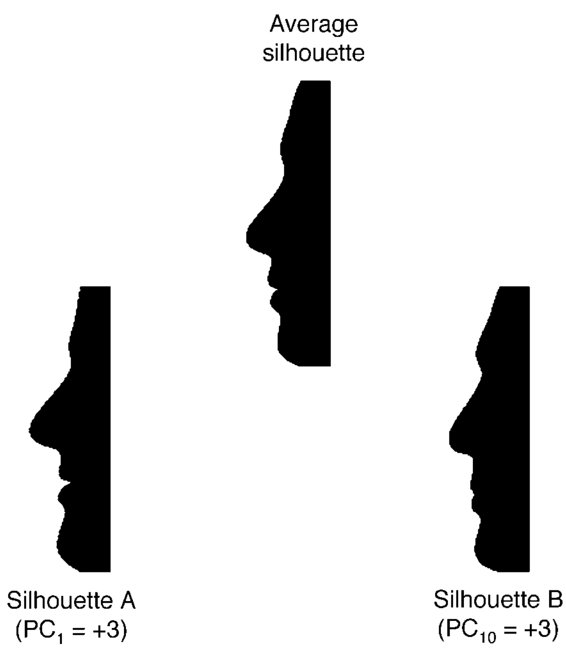

Figure 16. The perceptual effects of varying PC_1 and PC_4. Although +3 *SD* on PC_1 causes a physical change 75 times larger than +3 *SD* on PC_{10}, the perceptual effects seem much less disproportionate.

Discussion

In the studies reported above, we have shown that silhouetted face profiles provide a simple yet powerful methodology for studying face perception. In Studies 1, 2, 3, and 4, we showed that silhouettes carry a rich amount of information pertinent to face perception, including information about the gender, age, and attractiveness of faces, as well as orientation-dependent processing that elicits an inversion effect. In Study 5, we showed that silhouettes contain enough identifying information to allow for accurate matching to front-view images. In Studies 6 and 7, we showed how a simple parameterization of face silhouettes yields a useful model to address questions in the face perception literature. Specifically, we showed that face silhouettes can be fully specified by their position in a 20-dimensional, multinormal vector space, where distinctive silhouettes lie in the sparse periphery. This is an empirical confirmation of a key assumption in the face space framework (Valentine, 1991)—one that may generalize to front-view representations of faces.

Theoretical contributions

In evaluating a novel methodology, it is necessary to compare it to existing methodologies. Silhouetted face profiles carry a number of theoretical advantages compared to existing methods reviewed earlier, and we argue that these advantages make silhouettes especially well suited to experimenters studying face perception.

First, like the 3D face models (e.g., Blanz & Vetter, 1999), face silhouettes provide a shape-based approach for deriving face dimensions. This has the advantage of introducing minimal bias in the representation of face stimuli. The method measures variability across faces along various dimensions without specifying a priori what those dimensions, or features, are. This featureless representation can allow experimenters to study what the perceptually salient aspects of a face are, without presupposing "classical" features. Much research in face perception is concerned with determining whether we perceive faces as a sum of their features or whether we pay more attention to the configurations of features (for a review, see Rakover, 2002). Surprisingly, little work has focused on determining what exactly a face feature is (for an exception, see Schyns et al., 2002). It is not clear whether face parts for which we have names (the nose, the mouth, the chin, etc.) contribute to face perception in a qualitatively different way than other less well-defined, perhaps unconnected, face parts. Indeed, the PCs of silhouette face space provide a set of empirically testable candidate dimensions of representation based on intrinsic variations across face stimuli. Future studies can compare these candidate dimensions to classical features as well as arbitrary configurations, such as the distance between the eyes or the space between the nose and the mouth, that have been used in many perceptual paradigms (e.g., Yovel & Kanwisher, 2004).

Second, like synthetic faces (Wilson et al., 2002), face silhouettes provide a low-dimensional parameterization of face space. In contrast to high-dimensional models in which a large number of uninterpretable dimensions make the space difficult to characterize, silhouette face space is efficient and substantially more manageable. Because face silhouettes exclude texture or internal feature information, the space of face silhouettes is inherently low dimensional. In Study 6, we showed that silhouettes can be effectively represented in a 20-dimensional PC space without any perceptually noticeable loss of information. This allows for a fuller exploration of face space than can be done with more complex models.

These two key advantages, which are individually present in other methods, are rarely encountered in conjunction. Face silhouettes thus provide a featureless, shape-based representation with minimal biases that has an empirically derived low-dimensional solution.

Third, the face silhouette methodology suggests straightforward extensions for the parameterization of nonface stimuli, such as objects and nonsense shapes. The abstract structure of the parameterized face space can be transformed to create a fully equivalent nonface object space. This arbitrary object space would share all the statistics of the face space (including normal distributions on all PCs, a "prototype" shape, etc.), enabling one to quantitatively test the generality of theories derived to explain face perception in a well-controlled, comparable set of nonface stimuli.

Practical advantages and applications

The simplicity of the encoding of face silhouettes, along with the minimal constraints placed on profile face images that can be included in a parameterization, allows researchers to compile very large databases (e.g., including thousands of different faces). Once profile images are obtained, constructing parameterized silhouettes is a relatively quick procedure. The method requires recording the positions of 18 landmark points along the contour of each profile image, which can achieved with Matlab or comparable software. It takes less than a minute to code each profile, providing a huge savings over other methods such as morph-based models (e.g., Benson & Perrett, 1993). In addition, no sophisticated software is required to generate and display the parameterized silhouettes. This complements existing methodologies by allowing statistical analyses of face space that are not currently feasible with more complex models.

For instance, a simple analysis of the 384 database silhouettes shows that the "hyper-volume" occupied by male silhouettes in 20-dimensional silhouette face space exceeds the hypervolume occupied by female silhouettes roughly by a ratio of 1.7:1. This could be a key factor in explaining the male bias found in the identification of gender-ambiguous faces as well as the performance difference between male and female faces in the matching task from Study 5. Specifically, based on the different sized regions, one would predict that the region of face space that contains both male and female faces makes up a larger proportion of the female region than of the male region; that is, female faces are more likely than male faces to look gender ambiguous. As another example, a preliminary study (Davidenko & Ramscar, 2007) shows that people can identify race from face silhouettes substantially more accurately than they can identify gender. A cluster analysis shows that Black, White, and Asian face silhouettes occupy more distinct regions of face space than do male and female face silhouettes, explaining the differences in classification performance. These and many other statistical analyses are possible because of the sheer quantity of faces that can be included in the parameterization.

A fully parameterized face space allows us to create face stimuli at specified locations in the space to make, for instance, equally similar pairs of faces. A problematic issue in face perception research is that the face stimuli are rarely controlled for similarity, and this can bias the results of behavioral measures such as recognition memory performance. For example, if recognition performance is shown to be better on a set "A" of faces compared to a set "B," this may be due to a proposed experimental manipulation, but it could also be due to faces in Set A being more variable, and thus more distinguishable from each other, than faces in Set B. Being able to measure, to control, and to manipulate face similarity gives experimenters the ability to overcome these potential confounds in studies examining the role of distinctiveness or race in face recognition.

Limitations

There are some clear limitations to the face silhouette methodology. We know from previous research that certain parts of a face, like the eyes, are important for face perception, recognition, and categorization (e.g., Brown & Perrett, 1993; Bruce et al., 1993; McKelvie, 1976), and these parts are not available in the silhouette representation. Furthermore, silhouettes lack texture and color information which are also known to contribute to recognition and perception of gender, age, and race (Alley & Schultheis, 2001; O'Toole, Vetter, & Blanz, 1999; Yip & Sinha, 2002).

We certainly do not claim that face silhouettes contain all of the information used in face perception. However, as the studies presented here demonstrate, processing face silhouettes involves some of the critical mechanisms present in standard face perception and recognition, and insights from our silhouette face space model may generalize to other forms of face representation. We hope that, as a first parametric model of faces in profile view, the face silhouette methodology will provide a complementary approach to existing models based on front-view images.

Finally, it is worth noting that what we have constructed with the parameterized silhouettes is a physical face space and not necessarily a psychological face space (for a distinction, see Busey, 1998). We have not fully determined whether pairs of points that bear the same spatial relationship in silhouette face space will necessarily correspond to face silhouettes that bear the same perceptual similarity to each other. Preliminary psychophysical analyses (Davidenko, Ramscar, & Yarlett, 2007) show that values along the first four PCs indeed predict similarity ratings as well as confusability rates across face silhouettes. Although we reserve a stronger claim until this work is complete, the fact that the parameterization of silhouettes is based on their physical shape alone gives us good reason to believe that the physical space of silhouettes will bear a close relationship to psychological face space.

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Footnote

[1]It remains to be shown whether silhouettes can be represented in an even lower dimensional space. Here we merely claim that 20 dimensions are sufficient.

[2]Units are defined with respect to the normalized silhouettes that span (0, 0) to (0, 1) on the x–y plane.

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