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A principal component analysis of facial expressions

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Abstract

Pictures of facial expressions from the Ekman and Friesen set (Ekman, P., Friesen, W. V., (1976). Pictures of facial affect. Palo Alto, California: Consulting Psychologists Press) were submitted to a principal component analysis (PCA) of their pixel intensities. The output of the PCA was submitted to a series of linear discriminant analyses which revealed three principal findings: (1) a PCA-based system can support facial expression recognition, (2) continuous two-dimensional models of emotion (e.g. Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*, 1161–1178) are reflected in the statistical structure of the Ekman and Friesen facial expressions, and (3) components for coding facial expression information are largely different to components for facial identity information. The implications for models of face processing are discussed.

Keywords: Facial perception; PCA; Face recognition; Image processing; Facial expression

1. Introduction

In spite of its longevity, Bruce & Young's (1986) functional model of face processing (Fig. 1) continues to provide the best overall account of current face research. Two aspects of this model are particularly relevant to the present study. One, is that facial identity recognition (far left-hand route) and facial expression recognition (far right-hand route) are conducted by parallel cognitive systems (Bruce, 1986; Young, McWeeny, Hay, & Ellis, 1986; Hasselmo, Rolls, & Baylis, 1989; Young, Newcombe, de Haan, Small, & Hay, 1993; Sergent, Ohta, MacDonald, & Zuck, 1994). The second, is that at the time of the model's publication, the mechanisms underlying facial identity recognition were considerably better understood than those for facial expression recognition. Fifteen years later, this imbalance still pertains, and there is no detailed cognitive account of how we recognise facial expressions.

Progress is being made, however, and cognitive researchers are beginning to address issues concerning mechanisms that underpin facial expression perception (Etcoff & Magee, 1992; Calder, Young, Perrett, Etcoff, & Rowland, 1996a; Calder et al., 1996b; Morris et al., 1996; Sprengelmeyer et al., 1996; Calder, Young, Rowland, & Perrett, 1997; Ellison & Massaro, 1997; Phillips et al., 1997; Young et al., 1997; Calder, Young, Keane, & Dean, 2000).

As far as we are aware, all researchers would agree that facial identity and facial expression recognition share some perceptual processes. Hence, given this link between these two facial characteristics, it is important that researchers interested in modelling facial expression recognition should consider research from two sources: (1) studies of facial expression recognition — of which the majority have investigated post-perceptual processing, and (2) cognitive investigations of facial identity processing, but especially computer-implemented models of facial identity recognition.

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1.1. Computer models of face recognition

Computer-implemented models of face recognition are of essentially two types: (1) image-based analysis systems that can map visual representations onto particular labels, and (2) psychological models of the cognitive processes involved in recognising a person's face as familiar, retrieving relevant semantic information about the person, and naming them. The image-based systems have been developed largely by computer scientists interested in the automated recognition of human faces. Their goal has been to develop a computer-based procedure that can extract the essential visual information in faces needed to match one picture of a person's face with another picture stored in memory. These researchers have applied a variety of statistical techniques to this problem, including principal component analysis (PCA) (Kirby & Sirovich, 1990; Turk & Pentland, 1991), Gabor wavelets (Lades et al., 1993), and linear discriminant analysis (Belhumeur, Hespnha, & Kriegman, 1997).

In contrast to the image-based analysis models, cognitive models of face recognition have been developed purely as implemented accounts of properties of human face processing (O'Reilly & Farah, 1999; Young & Burton, 1999). These models are connectionist networks in which person-relevant information (i.e. face representations, semantics for individual people, people's names, etc.) is represented by localist units (Burton, Bruce, & Johnston, 1990; Burton & Bruce, 1992; Brédart, Valentine, Calder, & Gassi, 1995; Young & Burton, 1999) or weights distributed across a number of connections (Farah, O'Reilly, & Vecera, 1993; O'Reilly & Farah, 1999).

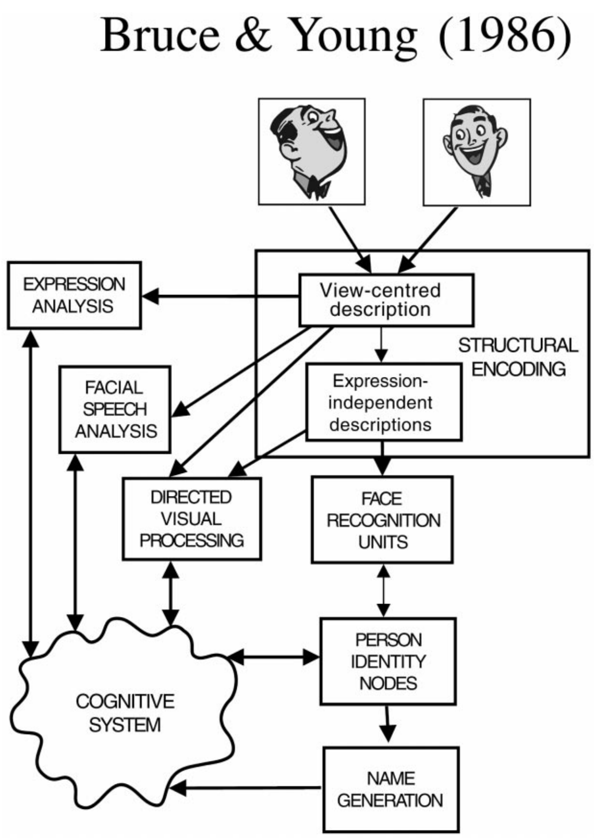


Fig. 1. Bruce and Young's (1986) functional model for face recognition.

Until recently, there has been very little communication between researchers interested in the image-based and cognitive approaches. In retrospect, this is unfortunate because in recent years, one image-based analysis technique in particular, principal component analysis (PCA), has been identified as a good psychological metaphor for the structural encoding and representation of faces (Valentin, Abdi, & O'Toole, 1994; Hancock, Burton, & Bruce, 1996; Hancock, Bruce, & Burton, 1998). For their recent model of face recognition, Burton, Bruce and Hancock (1999) have exploited this aspect of PCA to produce a single cognitive model that combines the image-based and cognitive approaches.

More explicitly, Burton and his colleagues have added the output of a PCA of faces (Hancock et al., 1996) to the front-end of an interactive activation and competition (IAC) model of face recognition and naming (Burton et al., 1990; Burton, Young, Bruce, Johnston, & Ellis, 1991; Burton & Bruce, 1992). At present, the Burton et al. (1999) architecture is only concerned with *facial identity* processing (i.e. recognising who a person is from their face): in fact, it can be considered an implemented model of the facial identity route in Bruce & Young's (1986) functional model of face recognition (Fig. 1, right-hand route). A potential long-term goal of this research, however, is to develop the Burton et al. model into a computer-based account of the entire Bruce and Young (1986) framework.

This is clearly dependent on at least two factors: (1) that we can develop a clearer understanding of the cognitive mechanisms involved in the remaining routes of the Bruce and Young model, in particular facial expression recognition, and (2) that the method of statistical analysis used to model the structural encoding of facial identity (currently PCA) can also be used to encode other types of facial information (e.g. facial expressions, lipspeech, sex, etc.). This latter condition is particularly important because, as illustrated in the Bruce and Young (1986) framework, some form of front-end analysis of faces ('structural encoding' in Bruce and Young's terminology) must be take place before information specific to each of facial identity, facial expression, lipspeech, etc. can be processed by the separate parallel routes. Interestingly, there is already evidence that PCA may be a suitable candidate because work has shown that this form of image-based analysis can represent other facial attributes besides facial iden-

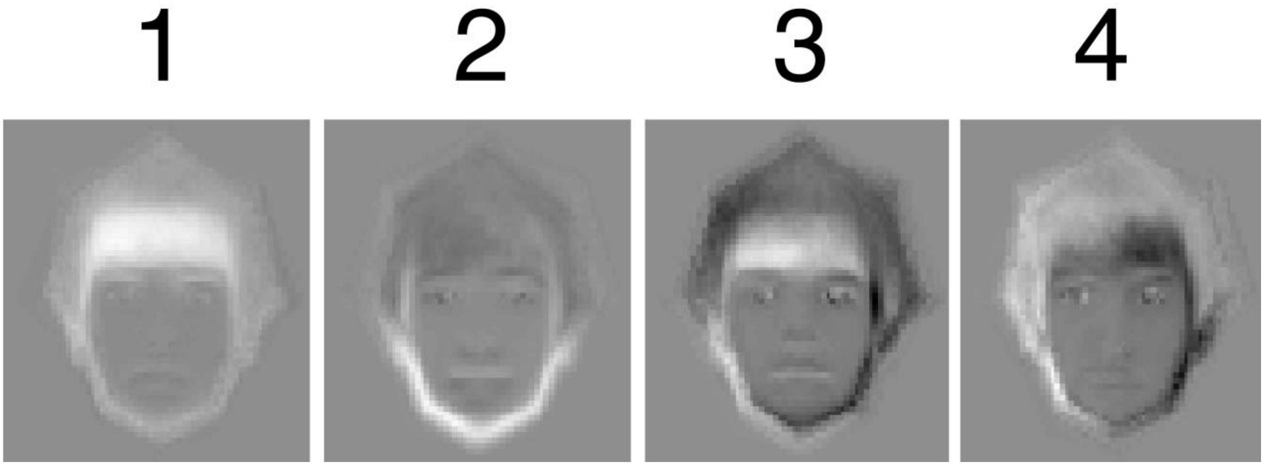


Fig. 2. The first four eigenfaces abstracted from a PCA of faces (Hancock et al., 1996).

tity. For example, O'Toole and colleagues have demonstrated that PCA can also code the sex and race of people's faces (O'Toole, Deffenbacher, Valentin, & Abdi, 1994; O'Toole, Abdi, Deffenbacher, & Valentin, 1993; O'Toole et al., 1998). One of the remaining critical tests for PCA, then, is whether it can code facial expressions. In this present study we investigate this issue.

1.2. Principal component analysis (PCA) of faces

1.2.1. Modelling facial identity recognition

Many readers will be familiar with PCA as a standard statistical technique that is used to identify a relatively small number of factors that represent the relationships among many inter-correlated variables. As applied to the image-based analysis of faces, PCA serves a similar function: it identifies a limited number of factors that can represent the complex visual information in faces in a suitable form for face recognition. Studies in this area have taken the same basic approach. Greyscale pictures of faces containing a set number of pixels, for example 190×285, are standardised for their inter-ocular distance. Pre-analysis, each image is considered as an array of pixel values, 54 150 for the example given, so one way we can think of each face as a vector in a 54 150-dimensional space. For the purposes of the PCA, however, each face is treated as a separate one-dimensional array of pixel values (comprising 54 150 grey levels). The PCA looks for correlations among the faces (one-dimensional arrays), and where these exist, their coefficients (eigenvectors or eigenfaces, Turk & Pentland, 1991) are extracted.

The eigenfaces have the same dimensionality as the original pictures, and hence, can be displayed as visual images. Fig. 2 shows the first four eigenfaces extracted from a PCA of faces conducted by Hancock et al. (1996). The homogeneous structure of human faces (two eyes above a central nose, above a central mouth) means that the values of corresponding pixels in different faces are not random. Consequently, the eigenfaces have a face-like quality; although from their murky appearance it is not immediately apparent what characteristics each eigenface is coding. All that we can derive from a visual inspection of these images is that areas of light and dark (areas that deviate from the uniform grey level), indicate features that differ across subsets of faces; although, the actual sign (light/dark) of these areas is essentially arbitrary. On the basis of these guidelines, we can see why Hancock et al. (1996) suggested that one of the features coded by eigenfaces 1 and 3 (Fig. 2) is fringe length.

The number of components extracted by a PCA is specified in advance, so if say 50 components are produced from a set of 100 faces, then each face, originally coded in a high dimensional pixel space (e.g. 54 150 dimensions), is recoded as 50 component values. These 50 values are referred to as the face's 'signature', and from each signature, it is possible to reconstruct a version of the original face. This is done by weighting each of the eigenfaces with the appropriate component value for the face, and then summing the results. Another feature of PCA is that the eigenfaces extracted from one set of faces can be used to code any number of new additional faces.

There is accumulating evidence that PCA is an effective analogue of the perceptual encoding of a face's identity (Kirby & Sirovich, 1990; Turk & Pentland, 1991; Costen, Craw, & Akamatsu, 1995; Hancock et al., 1996; Hancock et al., 1998; Burton et al., 1999); for example, PCA produces good recognition rates and it is relatively invariant to changes in lighting or facial expression (Kirby & Sirovich, 1990; Turk & Pentland, 1991; Costen et al., 1995; Burton et al., 1999). More recent work has shown that PCA can also model psychological effects in face recognition. These include distinctiveness effects (the finding that distinctive faces are more readily recognised than typical faces, O'Toole et al., 1994; Hancock et al., 1996; Burton et al., 1999), the caricature effect (caricaturing or exaggerating a face's features can facilitate its recognition, Costen et al., 1995; Deffenbacher, Vetter, Johanson, & O'Toole, 1998), and the 'other-race' effect (the fact that people find it easier to discriminate between faces of their own race than of another race; O'Toole et al., 1994).

1.2.2. Modelling facial expression recognition

Few studies have applied PCA to facial expression recognition, and those that have tended to take a computer-science approach — by which we mean that their aim has been to achieve optimal performance from their system rather than a psychologically plausible model (Padgett & Cottrell, 1995; Donato, Bartlett, Hager, Ekman, & Sejnowski, 1999). For example, Padgett and Cottrell (1995) explored three approaches to PCA of facial expressions. For the first, they analysed the pixel information in whole-face images, for the second they conducted separate analyses of the faces' eye and the mouth regions, and for the third method they analysed 'randomly located' overlapping areas in the eye and mouth regions. Padgett and Cottrell's results showed that the third method produced the best identification rates (followed by the second method, and then the first) and they have gone on to use this third, 'part-based', approach in additional interesting work (Padgett, Cottrell, & Adolphs, 1996). It is worth noting, however, that recent research with human subjects has shown that it is unlikely that facial expressions are processed in a purely part-based manner. Rather, it seems that the configural relationship between facial features plays an important role in their recognition (Calder et al., 2000). Hence, although Padgett and Cottrell's model produces a good hit rate, and may therefore have useful practical applications, the manner in which it achieves this does not concur with recent psychological data.

More recently, Donato et al. (1999) have compared the performance of a number of image-based analysis techniques, including PCA, in their quest to develop an automated facial action coding system (FACS) to underpin a method of identifying facial expressions from muscle positions (Ekman & Friesen, 1978). Again, however, it is difficult to draw direct comparisons with human data because Donato et al. (1999) analysed the upper and lower parts of the face separately. In the present study we have attempted to adopt a more psychologically plausible approach to the image-based analysis of facial expressions; hence, we have only used whole facial images in the principal component analyses reported.

In adopting this design, it was important to remember that Padgett and Cottrell found *poorer* performance for their PCA of whole faces than for the two PCAs in which the eye and mouth regions alone were analysed (part-based analyses). One possible explanation for this finding, however, is that Padgett and Cottrell used faces that were pre-processed to have the same eye and mouth positions. This would have produced significantly greater correspondence among the features of the images submitted to the part-based analyses (where only the eye and mouth regions were analysed), than those of whole face analysis (for which nose, face outline, etc., may have shown less good correspondence). Hence, one reason why Padgett and Cottrell's part-based PCAs may have produced better classification rates than their whole face PCA is because the former method would have reduced the level of noise in the analysis.

1.2.3. Pre-processing faces for PCA

Poor correspondence between feature positions is a problem for PCA, and although pre-processing the images to have the same eye locations and mouth locations can help alleviate its effects, it does not eliminate them completely. To help get round this problem, Craw and Cameron (1991) introduced an ingenious method of pre-processing the facial images. This involved 'morphing' (or warping) each face to the same average face shape before conducting the PCA. Essentially, this meant that the facial features in a given set of faces were shifted to the same standard positions: for this reason, these images were referred to as 'shape-free' faces. Craw and colleagues showed that the shape-free faces produced better hit rates for models of facial identity recognition than faces standardised for their eye position alone, and that both produced better hit rates than a PCA of shape vectors alone (i.e. data describing the positions of facial features, Costen, Craw, & Akamatsu, 1996; see also Hancock et al., 1996; Hancock et al., 1998). Hence, the advantage for the shape-free faces results from an improved correspondence among the features of the different faces, and consequently, a reduction in noise.

One reason for the improved performance in extracting identity from shape-free images may be that aligning the facial features to an average-face shape minimises the contribution of other *irrelevant* facial information such as emotional expressions. If this is the case, then the shape-free method is likely to be of little use to PCA-based models of facial expression recognition. However, it is not clear to us that the average-morphing process removes all cues to facial expressions. Fig. 3 (see Section 2.1.2.2) shows examples of six facial expressions from our stimulus set (pictures of facial affect; Ekman & Friesen 1976) and their shape-free (average-morphed) equivalents. As can be seen, although morphing the faces does indeed change their shape, its effect on their texture information is less dramatic (note, we use the term 'texture' as a shorthand for skin tone, shading, hair colour, etc.). For example, the white 'toothy smile' in the original picture of the happy expression in Fig. 3 is still evident in its shape-free version, albeit in a distorted form. Similarly, wrinkles at the corners of the eyes, brow, and below the cheeks of the faces are also present in the shape-free images. Hence, it is possible that the facial expressions remain identifiable in their shape-free form because texture cues that are important for facial expression recognition are preserved in the shape-free faces. Consequently, we were interested to compare two different approaches to the PCA of Ekman and Friesen (1976) faces in which the facial images were: (1) pre-processed to have the same inter-ocular distance and eye position (full-images), or (2) pre-processed to have the same average face shape (shape-free images). Moreover, we reasoned that if a PCA of shape-free faces can support better facial expression recognition than a PCA of the full-images, then this would suggest that texture information contributes more to facial expression recognition than has previously been assumed. On the other hand, the opposite pattern would confirm the view that cues to facial expressions are contained largely within a face's shape.

For comparison, the role of shape cues in facial expression recognition was assessed in a separate PCA of shape vectors derived from the original full-images (i.e. the positions of a specified set of anatomical features such as the corners of the mouth, the tip of the nose, etc.). Previous studies have shown that PCA of shape information alone is a relatively poor method of coding facial identity. Hence, we were interested to determine whether a different pattern might be observed for facial expressions, where the effect of many of the muscle movements involved is to change the shape of prominent facial features (e.g. the upturned or downturned corners of the mouth, or the wrinkling of the nose). Given the success of Ekman and colleagues facial action coding system (FACS) (Ekman & Friesen, 1978; Ekman & Rosenberg, 1997) — a method of categorising facial expressions from 2D facial measurements — we predicted that a PCA of shape information would be a better method of coding facial expressions than facial identities.

In summary, separate PCAs were conducted on three data sets acquired from Ekman and Friesen (1976) pictures of facial affect: (1) the greyscale pixel values of the faces pre-processed to have the same eye positions (full-images), (2) the greyscale pixel values of the faces pre-processed to the same average face shape (shape-free images), and (3) the physical positions of a set number of anatomical feature points on the faces (shape only).

1.3. PCA of facial expressions

1.3.1. Questions addressed by this study

Our study addressed two main questions:

1. Can PCA support facial expression recognition?
2. Can PCA code facial expressions in a psychologically plausible form?

Question 1 was addressed by submitting the output of each PCA (full-image, shape-free, and shape only) to a stepwise linear discriminant analysis (LDA) with the faces' expressions (happy, sad, anger, fear, disgust, surprise, and neutral) as the dependent variable. An additional LDA was also conducted on the outputs of the shape-free PCA and shape information PCA *combined*: this was done to determine the effect of adding back shape information to 'shape-free' data. Each LDA assessed the number of correct expression categorisations that could be made from the component values associated with the first 50 components from each

Fig. 3. Examples of six facial expressions (happy, sad, anger, fear, disgust and surprise) in their original format (full-image, top row) and morphed to average face shape (shape-free, bottom row).

PCA. Finally, each of the same four data sets (full-image, shape-free, shape only, and shape-free + shape) were also submitted to two additional LDAs, with faces' identities and the faces' sex as the respective dependent variables. These examined the extent to which the same PCAs could code the identity and sex of the Ekman and Friesen faces.

The psychological plausibility of PCA for facial expression recognition (Question 2) was addressed in two ways. The first examined the relationship between PCA and psychological models of facial expression developed by social psychologists. The second investigated Bruce and Young's (1986) suggestion that separate cognitive routes are used to process facial identity, facial expression, and facial cues to a person's sex. The theoretical backgrounds to these two issues, are briefly outlined below.

1.3.2. Category-based accounts and dimensional accounts of facial expression identification

As we discussed earlier, there is currently no detailed cognitive account of how we recognise facial expressions. However, two theoretical frameworks have been developed by social psychologists; a category-based account, and a dimensional model. Exponents of the category-based account propose that a limited number of emotions have a 'basic' status, and that signals of these basic emotions are identified by activating discrete category representations (one for each emotion). Taxonomists generally agree on five basic emotions (happiness, sadness, anger, fear, and disgust), although other putative basic emotions such as surprise and contempt have also been suggested. One of the main reasons for these emotions having this status is that their corresponding facial expressions are recognised by a number of cultures throughout the world (Ekman, 1982, 1992a).

The alternative to the category-based viewpoint is the dimensional account. This was born out of the observation that human errors in recognising facial expressions are not random, as would be expected from a purely category-based account, but instead form consistent, replicable patterns. For example, disgust is occasionally confused with anger, but rarely with fear, whereas fear is sometimes confused with surprise, but not with happiness. Schlosberg (1941, 1952) and Woodworth and Schlosberg (1954) suggested that these misidentifications were best accommodated by a model in which facial expressions are recognised by registering their positions in a *continuous* two-dimensional space. Their theory has survived to the present day, its most recent variant being Russell's 'Circumplex model' (Russell, 1980); a two-dimensional system coding pleasure–displeasure and arousal–sleepiness.

A number of researchers have shown that the two-dimensional model is not only applicable to the perception of emotion from faces (Schlosberg, 1952; Abelson & Sermat, 1962; Russell & Bullock, 1985), but also from vocal signals (Green & Cliff, 1975), emotional words (Bush, 1973; Russell, 1980), and ones own emotional experience (Russell, 1980). This would indicate that the model is not tied to facial expression processing per se, but instead reflects a multi-modal level of processing that can be accessed by all of the above modalities. A clear implication of these findings is that the two-dimensional account does not relate to the *perceptual* representation of facial expression, but instead to a post-perceptual stage coding some property of the actual emotions expressed. Even so, a recent study by Yamada (1993) showed that a factor analysis of shape vectors describing schematic facial expressions generates a similar two-dimensional structure to Russell's Circumplex model. In addition, Yamada has also shown that each dimension of his framework is correlated with one of the dimensions of the Circumplex model of Russell (1980) (i.e. pleasure–displeasure and arousal–sleepiness) (Yamada & Shibui, 1998). Hence, contrary to earlier assumptions, the Circumplex model may constitute an important aspect of both the perceptual and post-perceptual (conceptual) analysis of facial expressions.

A problem with Yamada's aforementioned studies, however, is that he used *schematic* facial expressions. And although his additional study has shown that measurements of human facial expressions can produce a three-dimensional canonical discriminant model for facial expression categorisation (Yamada, Matsuda, Watari, & Suenaga, 1993), no attempt was made to correlate the dimensions of this 'human expression' model with Russell's Circumplex dimensions (see also Ueki, Morishima, Yamada, & Harashima, 1994). Hence, we were interested to determine whether an analysis of the visual information in *human* facial expressions would lend support to the idea that the perceptual coding of facial affect is represented in a two-dimensional system. For example, is it the case that just two components are crucial for categorising the seven expression categories used in this study?

1.3.3. Bruce and Young's (1986) functional model of face recognition

A number of studies have demonstrated a functional independence between the recognition of facial identity and facial expression. These include, cognitive studies of neurologically normal participants (Bruce, 1986; Young et al., 1986; Campbell, Brooks, de Haan, & Roberts, 1996), double dissociations in brain-injured participants (Parry, Young, Saul, & Moss, 1991; Young et al., 1993), single cell recording in non-human primates (Hasselmo et al., 1989), and functional imaging studies of brain activation (George et al., 1993; Sergent et al., 1994). Similarly, studies have shown that the identity and sex of faces are also processed independently; although the evidence for this is less extensive and is confined mostly to cognitive studies of neurologically normal participants (Bruce, 1986; Bruce, Ellis, Gibling, & Young, 1987).

These findings lend strong support to Bruce and Young's (1986) proposal that facial cues to identity, expression, and sex are processed by separate parallel routes; particularly because of the wide varieties of methodologies used in these studies. However, with one notable exception, we are not aware of any studies that have investigated whether the *visual cues* to these different facial characteristics are conveyed by different components of the face. The exception is a PCA study by O'Toole et al. (1993) which showed evidence for the partially separate coding of identity and sex: sex cues were shown to be coded by components with large eigenvalues, whereas identity cues were coded by some components with small eigenvalues, and some components with large eigenvalues (Deffenbacher, Hendrickson, O'Toole, Huff, & Abdi, 1998). In this present study we aimed to replicate O'Toole et al.'s finding, and to determine whether facial expressions are also coded by a largely unique set of components.

1.3.4. From PCA to mental function

Before describing the research, it is important to clarify our view on how PCA of facial images relates to human face recognition. First and foremost, the purpose of this research is not to argue that the brain recognises a face's identity, expression or sex, by performing a PCA on the pixel intensities of a facial image. To echo the recent remarks of Burton et al. (1999), our aim is not to demonstrate that the *details* of our PCA procedure are implemented in the human brain. Instead our research addresses the hypothesis that a form of linearised compact coding of human faces (analogous to PCA) can provide a plausible psychological mechanism for not only the *representation* of different facial characteristics (identity, expression, sex, and race), but also the *functional dissociations* that occur between them. In other words, confirmation of this hypothesis would demonstrate that the PCA we have used is a plausible statistical *analogue* of the front-end coding of faces, and not a literal account.

2. Computer analysis

2.1. Stimulus preparation

2.1.1. The Ekman and Friesen (1976) faces

The stimuli consisted of greyscale pictures of facial expressions from the Ekman and Friesen (1976) pictures of facial affect series. This set contains multiple examples of seven facial expressions (happiness, sadness, anger, fear, disgust, surprise, and neutral) posed by 14 different models (six males, eight females); the majority of which are shown posing at least one example of each of the seven expressions. The full set of images was used in each of the principal component analyses reported.

There are at least two advantages to using the Ekman and Friesen (1976) faces. First, Ekman and his colleagues have shown that each of the above emotions is associated with distinct facial musculatures that are recognised by a number of cultures throughout the world (Ekman, 1972, 1994). Second, these stimuli have been used in numerous psychological studies that have verified that the expressions are recognised as the intended emotions.

To avoid confusion, we will refer to the individual photographs of faces in the Ekman and Friesen series as 'faces', the individual people who acted as models as 'facial identities', and the different categories of emotional signals (e.g. anger, fear, sad, etc.) as 'facial expressions'.

2.1.2. Shape-free procedure

Two different methods of pre-processing the images were compared (Craw & Cameron, 1991). For the first (full-image) method, the images were standardised for their eye positions. For the second, each face was 'morphed' to an average face shape; in line with previous studies, we will refer to these average-morphed images as 'shape-free' faces. The average-morph procedure consisted of two stages. These are described below.

2.1.2.1. Stage 1: delineation. Photographs of faces from the Ekman and Friesen series were scanned from 35-mm slides to produce 256 greyscale (eight-bit) computer files with dimensions 190×285 pixels. Next, a standard grid containing 35 feature points was manually positioned onto each face. The locations of these points were specified with reference to anatomical landmarks (e.g. corners of the mouth, tip of the nose, etc.), with each facial feature represented by a set number of points; for example, the mouth was represented by four points, and the jaw line by five. This meant that across all faces in the Ekman and Friesen set, there was conformity with respect to the anatomical positioning of the 35 points, although their exact spatial position varied. The positions of the 35 feature points for each face were then stored as separate 'coordinate files' of x, y coordinates.

2.1.2.2. Stage 2: morphing to the average shape. An average face shape (or average coordinate file) was produced by calculating the mean x and y coordinate for each of the 35 feature points across the entire set of faces. The following 'average-morphing' process was then applied to each of the faces in the Ekman and Friesen set.

The standard grid on each face consisted of a mesh of triangular tessera produced by joining specified feature points on each face; for example, one triangulation comprised the right- and left-most corners of the mouth and the mid-point of the upper lip. The average face shape consisted of exactly the same grid, so there was correspondence between the relative locations of the triangles in each of the original faces and average face. To morph a facial expression, for example a happy face, to the average, the greyscale pixel values of each of the happy face's triangles were mapped onto the corresponding triangles in the average face. Where any of the average-face triangles was larger than in the happy face, 'stretching' of the spatial distribution occurred, similarly, 'shrinking' of the spatial distribution occurred when one of the average-face triangles was smaller. Fig. 3 shows examples of six facial expressions and their shape-free (average morphed) equivalents. For both the shape-free images and faces standardised for eye-position alone, the area outside the face region was set to a uniform black. This was done to exclude as much irrelevant background information as possible from the PCA.

2.2. The principal component analysis

2.2.1. PCA of pixel information

Previous research has shown that approximately 50 components are sufficient to reconstruct accurate representations of faces (Hancock et al., 1996; Hancock et al., 1998). We were guided by this finding, and 50 components were extracted for each of the full-image PCA and shape-free PCA. This generated 50 eigenfaces for each analysis, and a corresponding signature of 50 component values for each of the Ekman and Friesen faces. Note that a complete PCA would have computed 109 components (plus the mean pixel values) because there are 110 faces in the Ekman and Friesen set. Hence, we were extracting considerably fewer components than were actually available.

Fig. 4a shows the first eight eigenfaces extracted from the full-image PCA, and Fig. 4b, the first eight extracted from the shape-free PCA. Pre-analysis, the faces were pre-processed to have zero mean, thus, the resultant eigenfaces code deviations from the mean greyscale value of the images.

Two aspects of these images are worth noting. First, the better correspondence between facial features in the shape-free images has produced eigenfaces with better-defined edges and features. Second, some of the eigenfaces in both sets resemble facial expressions. For example, in Fig. 4a, faces 5 and 8 look surprised, face 7 looks sad, and 3 somewhat angry. Clearly, the appearance of the eigenfaces is not a measure of the ability of PCA to code facial expressions, but it is nonetheless encouraging that these images resemble the expressions in the Ekman and Friesen set. Note, expressions are less obvious for the shape-free eigenfaces (Fig. 4b) because these were abstracted from images that were pre-processed to have the same average face shape.

2.2.2. PCA of shape information

The 2D locations of the feature points on each face were also submitted to a separate PCA by treating each face (i.e. coordinate file) as a 62-dimensional vector (i.e. one x and one y coordinate for each of 31 of the feature points). Note that as a result of standardising the faces for their eye position, four of the feature points had the same positions in every face and hence were not included in this analysis. Note also that because there was significantly less shape information than pixel information, only 20 components were extracted for the shape analysis.

In summary, the Ekman and Friesen faces were submitted to three PCAs: (1) a PCA of the pixel values of the faces standardised for their eye positions (full-image PCA), (2) a PCA of the pixel values of the faces morphed to an average face shape (shape-free PCA), and (3) a PCA of the position of feature points in the faces (shape only PCA). All of the PCAs used an Euclidean distance model to extract the coefficients (eigenfaces).

3. Data analysis

3.1. Analysis of PCA data using Stepwise Linear Discriminant Analysis (LDA)

The first 50 components of the full-image PCA were submitted to three stepwise linear discriminant analyses (LDA), with each LDA examining a different dependent variable (facial identity, facial expression, and sex). Similar LDAs were also conducted for: (1) the first 50 components of the shape-free PCA; (2) the first 20 components of the shape information PCA, and (3) the first 30 components of the shape-free PCA and the first 20 components of the shape information PCA combined (i.e. a total of 50 components). To outline the processes involved in the LDA statistic, the following section contains a brief description of a stepwise linear discriminant analysis. The independent variables in this analysis are the component values and the dependent variable is facial expression.

3.1.1. A description of a LDA for facial expression

Prior to the analysis, the 'signature' (component values for the 50 eigenfaces) of each facial image (photograph) is identified as one of the seven categories of the dependent variable (i.e. a happy, sad, angry, afraid, disgust, surprise or neutral facial expression). For ex-

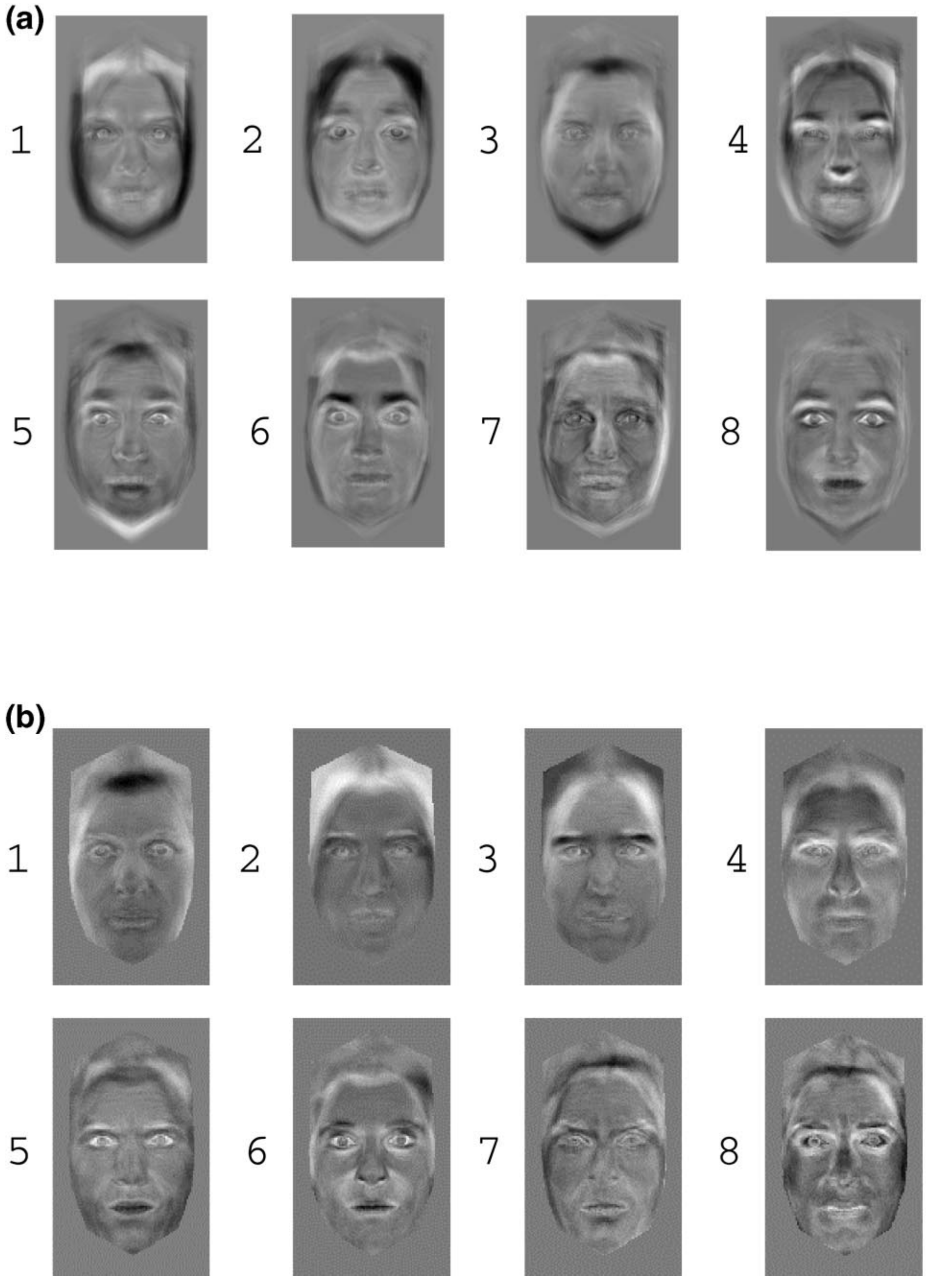


Fig. 4. (a) The first eight eigenfaces abstracted from a PCA of the Ekman and Friesen (1976) faces in full-image format. (b) The first eight eigenfaces abstracted from a PCA of the Ekman and Friesen (1976) faces in shape-free format (i.e. morphed to average-face shape).

ample, the signature for facial image 1 is labelled ‘happy’, the signature for facial image 2, as ‘fear’, and so on. The analysis then operates by selecting the components that show small within-category variability relative to total variability; Wilk’s lamba is used as the criterion measure. This selection process works in a similar manner to a stepwise multiple regression. At step one, the variable (component) with the smallest Wilk’s lamba, is entered into the analysis. The criterion for entry is then recalculated for all variables not in the model, and at step two the component with the next smallest lamba value is entered next. At step three the status of the first variable is reassessed, and if it falls below a specified criterion for removal, it is rejected. This process continues until no further variables meet the criterion for entry or removal. Note that if at the first step none of the variables satisfy the criterion for entry, then the analysis terminates, indicating that the components abstracted by the PCA do not reliably differentiate among the different emotion categories. For all of the discriminant analyses reported, the criteria for entry and removal were based on an F-statistic. This is a measure of change in Wilk’s lamba for each independent variable when a variable is entered or removed from the model. F-to-enter was set at $F > 3.84$, and F-to-remove at $F < 2.71$. An additional statistic used to determine whether a variable is entered into a model is *tolerance* — the degree of linear association between the independent variables. However, given the components are by definition uncorrelated, we have not discussed this statistic.

Following the selection of components, the next stage of the LDA generates functions that compute linear combinations of the values associated with these components. These are known as canonical discriminant functions. The maximum number of canonical functions in any one analysis corresponds to the number of categories in the dependent variable minus one (i.e. six if the dependent variable is facial expressions). Each facial image is assigned a value on each discriminant function, and these values are used to predict the category membership of each. Thus, the role of the canonical discriminant functions is to recode the variables (component values) in a form that maximises the between-group variance (the differences between the various expression categories), while at the same time minimising within group variance (the differences between exemplars of the same expression). In the simplest situation where the dependent variable contains just two categories (e.g. happy and sad), the optimal type of discriminant function would generate a bimodal distribution with happy faces clustered in one peak, sad faces in the other, and a large void separating the two. Similarly, for a dependent variable with seven categories, then a good discriminant model would produce a dimensional space (of up to six dimensions) consisting of high-density clusters of within-category cases (e.g. happy, sad, anger, etc.) separated by large areas of low density. A measure of the canonical functions' ability to discriminate between the dependent variable categories (e.g. happy, sad, anger, etc.) is derived by comparing the predicted to the actual category membership of each facial image.

A point worth noting about the 'standard' method of discriminant analysis described above is that it tends to overestimate the predictive power of the model; this is because the category membership of every facial image is provided at the start of the analysis. A more conservative measure of a discriminant model's power can be achieved using the 'Jackknife' method. For this variation, it is necessary to conduct as many analyses as there are facial images. For each analysis, the category membership of all but one facial image is provided, with a different facial image being left uncategorised in each analysis. The model then predicts the category membership of each *uncategorised* facial image using the canonical discriminant functions derived from the *categorised* facial images. A measure of the Jackknife model's performance is derived by calculating the number of uncategorised facial images that are correctly identified across the entire set of analyses. In the following section, the results of both forms of linear discriminant analysis (standard and Jackknife) are reported for each of the four types of LDA.

Table 1
The results of the stepwise linear discriminant analyses for expression, identity and sex, applied to the four sets of PCA data (full-image, shape-free, shape only, and shape-free + shape)[a]

	PCA			
	Full image	Shape-free	Shape only	Shape-free + Shape
Standard method				
Emotion	67 (%)	95 (%)	88 (%)	98 (%)
Identity	100 (%)	100 (%)	97 (%)	100 (%)
Sex	100 (%)	100 (%)	94 (%)	100 (%)
Jackknife method				
Emotion	53 (%)	69 (%)	77 (%)	83 (%)
Identity	99 (%)	99 (%)	89 (%)	99 (%)
Sex	99 (%)	100 (%)	94 (%)	100 (%)

[a] The results of the Standard (top) and Jackknife (bottom) methods of analyses are shown separately.

3.2. Question 1: can PCA support facial expression recognition?

Table 1 shows the results of the stepwise linear discriminant analyses for expression, identity and sex, applied to the four sets of PCA data (full-image, shape-free, shape information, and shape-free + shape). The results of the standard (Table 1, top) and Jackknife (Table 1, bottom) methods of analyses are shown separately. It is clear that emotion, identity and sex were all categorised with well above chance accuracy in all of the analyses (maximum permitted chance values calculated from binomial probability: emotion, 20%; identity, 12%, and sex, 58%).

We were interested to determine the extent to which the four types of PCA outputs (full-image, shape-free, shape only and shape-free + shape) could support facial expression recognition. To do this we used a probabilistic measure produced by each LDA: the probability of membership of the intended category (i.e. the probability that each facial expression was categorised correctly). These probabilities were calculated for both standard and Jackknife LDAs, and each data set (standard and Jackknife) was submitted to pairwise Mann–Whitney tests (Bonferroni corrected) investigating PCA output (full-image, shape-free, shape only and shape-free + shape). Both sets of analyses showed effectively the same patterns of effects, full-image < [shape = shape-free] < shape-free + shape. All significant effects were statistically reliable at $P < 0.008$.

The results indicate that the standard and Jackknife LDAs produced statistically indistinguishable patterns. Both LDAs showed that the shape-free PCA produced better expression categorisation than the full-image PCA. This demonstrates that shape-free faces not only improve hit rates for PCA-based models of facial identity recognition, they also benefit facial expression categorisation. On reflection, this is a little surprising because the average-morphing process *distorts* the shape cues in the facial expressions (i.e. raised eyebrows, open/closed mouth, eye width, etc.), a component of facial expressions that is generally regarded as important for their recognition. Consequently, the improved categorisation rate for the shape-free faces implies that texture information may play a more important role in facial expression perception than has been previously assumed. That said, we should perhaps be cautious of reading too much into this finding because it is questionable to what extent the texture information in these faces can be regarded as separate from their shape information. For example, one would probably regard the presence/absence of white teeth, and wrinkles at the corners of the eyes, forehead, cheeks, and so on, as texture rather than shape information, yet all are correlated with particular facial shapes (i.e. open mouths, raised eyebrows, narrowed eyes, etc.). Nonetheless, our results indicate that the role of texture information in facial expression recognition is significant, and deserves further investigation.

Two further results of the above analyses are also worth noting. First, the LDAs investigating facial expression showed good identification rates for the shape PCA data (i.e. [shape = shape-free] > full-image). This result is in contrast to the LDAs investigating identity and sex which show the lowest identification rates for the shape only condition (Table 1), replicating previous PCA research for facial identity (Costen et al., 1995; Hancock et al., 1996; Hancock et al., 1998). The second point to note is that the combined analysis of the shape-free components and shape components (shape-free + shape) produced the best expression categorisation rates for both analyses. Similarly, previous studies investigating PCA of facial identity have shown that a combination of shape components and shape-free components generally produces the best results (Costen et al., 1995; Hancock et al., 1996; Hancock et al., 1998).

In summary, our results show that PCA can code facial expressions in a form that can support their recognition. Moreover, consistent with previous studies examining PCA of facial identity, pre-processing the faces to the same average face shape significantly improved the categorisation rates for facial affect. In contrast to the results for facial identity and sex, however, we found that PCA of a limited number of anatomical feature points (31) also provided an efficient means of coding facial expressions. Optimal categorisation rates were found for the combined analysis of the shape components and shape-free components.

3.3. Question 2: can PCA code facial expressions in a psychologically plausible form?

To assess the psychological plausibility of PCA for facial expressions we compared the results of the different LDAs to data from two groups of human participants. One group was asked to identify the expressions displayed by each of the Ekman and Friesen faces; the second group was asked to rate the same faces on the dimensions pleasure–displeasure and arousal–sleepiness (the psychological dimensions of the Circumplex model of Russell, 1980). Brief descriptions of the methods used to obtain these data are included in the following sections.

3.3.1. A comparison with human recognition

3.3.1.1. Human participants' identification of facial expressions. Participants: Twenty subjects (12 male, eight female) from the MRC Cognition and Brain Sciences Unit participated in the experiment. Participants were between the ages 18 and 36 (mean = 26.60, S.D. = 6.33) and had normal or corrected vision.

Design and procedure: The 110 pictures from the Ekman and Friesen series were presented individually, in random order, on a computer monitor. Each trial consisted of a 500-ms presentation of a fixation cross, a blank interval of 500 ms, and then one of the Ekman and Friesen faces, which remained in view for a maximum of 5 s. Participants were asked to categorise each face's expression by pressing one of seven keys on a button-box marked with the labels *happy*, *sad*, *anger*, *fear*, *disgust*, *surprise*, and *neutral*. A response terminated the presentation of a picture and initiated the next after an interval of 2 s. Participants were told that their response times were not being measured, and that they should try to respond as accurately as possible. No feedback was given.

For each face we calculated the mean proportion of responses attributed to each of the seven response options by the human participants. A similar measure was also obtained from each LDA for facial expression — each face's probability of membership of each of the seven facial expression categories (i.e. the probability that each facial expression was an exemplar of each of happy, sad, anger, fear, disgust, surprise and neutral). Next, on a face-by-face basis, we estimated the degree of similarity between the probability distribution produced by the LDA, and the mean distribution of the human participants' responses. This was done by treating each distribution as a six-element vector, and taking the dot product (i.e. the sum of the elementwise products) between the two. The process was carried out

Table 2
The mean similarity values between human participants' categorisation of Ekman and Friesen (1976) facial expressions and each face's probability of membership of the seven emotion categories produced by the LDAs of the four PCA data sets (full-image, shape-free, shape only, and shape-free + shape)[a]

LDA	PCA			
	Full image	Shape-free	Shape only	Shape-free + Shape
Standard	0.50 (0.29)	0.75 (0.21)	0.70 (0.23)	0.80 (0.18)
Jackknife	0.41 (0.30)	0.56 (0.31)	0.63 (0.28)	0.72 (0.27)

[a] Mean similarity values are shown for both the standard, and Jackknife methods of LDA.

separately for the LDA probability measures from each of the four PCA outputs (full-image, shape-free, shape only, and shape-free + shape).

The mean similarity values for each of the four image types (full-image, shape-free, shape only, and shape-free + shape) are listed separately in Table 2; S.D. are shown in parentheses. Note that the values shown in Table 2 are not associated with any statistically significant cut-off point. They are simply estimates of the degree of similarity between the LDA data and the human data. A value of zero would indicate that the response distributions produced by the LDA do not in any way resemble the participants' responses, whereas a value of one would indicate that they are identical.

The mean similarity values shown in Table 2 are impressive, particularly for the shape-free plus shape procedure. These scores are all the more impressive, however, when we consider that human classification of facial expressions is not completely reliable; the mean estimated level of agreement among the human participants is not dissimilar to these scores (level of agreement for human participants = 0.74). Note that agreement among the participants was calculated by treating the overall distribution of participants' scores for each face as a separate six-element vector, and then dividing the sum of squares of the elements in each vector by the number of participants squared. Given that this measure is different from the estimate of similarity between the patterns of categorisations produced by the LDAs and the participants, it is difficult to make a quantitative comparison between the two. Nonetheless, it is clear from these results that PCA can code facial expressions in a form that may not only model human participants' *correct* categorisations, but also their *misidentifications*.

To illustrate this more clearly, the top half of Table 3 shows a confusion matrix derived from the probability of membership measures obtained from the stepwise LDA (Jackknife method) of the shape-free plus shape components — the data that produced the best overall match to the human participants. The bottom half of Table 3 shows the mean confusion matrix obtained from the 20 human participants. The two matrices have the same format. The vertical labels on the left indicate the intended facial expressions (as defined by Ekman and Friesen, 1976), and the labels across the top of the

Table 3
Confusion matrices for the Ekman and Friesen (1976) facial expressions corresponding to: (1) the probability of membership values produced by the LDA of the shape-free plus shape PCA data (top), and (2) the human participants categorisation of the facial expressions (bottom)[a]

Facial expressions		Anger	Disgust	Fear	Happy	Neutral	Sad	Surprise
Discriminant analysis (Shape-free + shape PCA)								
Anger		86	14	0	0	0	0	0
Disgust		17	72	0	11	0	0	0
Fear		0	0	97	3	0	0	0
Happy		0	0	0	98	2	0	0
Neutral		0	0	0	1	69	23	7
Sad		0	0	0	2	26	72	0
Surprise		0	0	6	0	2	0	92
Total correctly identified	84							
Human recognition								
Anger		73	10	2	0	6	4	5
Disgust		15	79	0	0	3	1	1
Fear		1	2	76	0	1	2	18
Happy		0	0	0	98	2	0	0
Neutral		4	1	0	3	88	3	1
Sad		1	8	5	0	9	74	3
Surprise		0	0	10	1	0	0	89
Total correctly identified	82							

[a] All values in percentages. The two matrices have the same format. The vertical labels on the left indicate the intended facial expressions (as defined by Ekman and Friesen, 1976), and the labels across the op of the table the degree of certainty with which each facial expression type was categorised as happy, sad, etc.

table the degree of certainty with which each facial expression type was categorised as happy, sad, etc.

There are a number of similarities between these two matrices that are worthy of comment. First, the overall probability with which the discriminant model assigned expressions to their correct categories was highly comparable to the total number of correct responses produced by the human participants. Second, for both matrices, the most frequently selected label for each facial expression category was the intended emotion (i.e. the diagonal). Furthermore, a χ^2-test comparing the diagonals of the two matrices indicates that the distributions of the responses do not significantly differ, $x^2(6) = 6.24$, $P > 0.3$. Third, the discriminant model showed a similar pattern of confusions to the human participants. For example, anger and disgust were confused with one another, as were sadness and neutral, and surprise was mistaken for fear. However, not all of the human confusions are captured by the LDA. For example, although the human participants mistook fear for surprise, the superior recognition of fear by the LDA meant that this confusion was not produced by the linear discriminant model. Overall, however, the similarity between the two data sets is impressive.

In considering these results, it is important to remember that the LDA matrix is obtained from an analysis of purely physical information (greyscale pixel values, and shape vectors), and that neither the PCA or LDA has any information relating to any other relationship between the different emotions (e.g. the fact that anger and disgust are more similar *emotions* than are anger and surprise). Consequently, these data demonstrate the somewhat remarkable finding that a model of facial affect recognition based on the linearised coding of the *visual information* in facial images, can provide a reasonable first approximation of human recognition. We felt that this observation was worthy of further investigation and in the following section we address this issue in more detail.

3.3.2. *A two-dimensional account of human facial expression recognition*

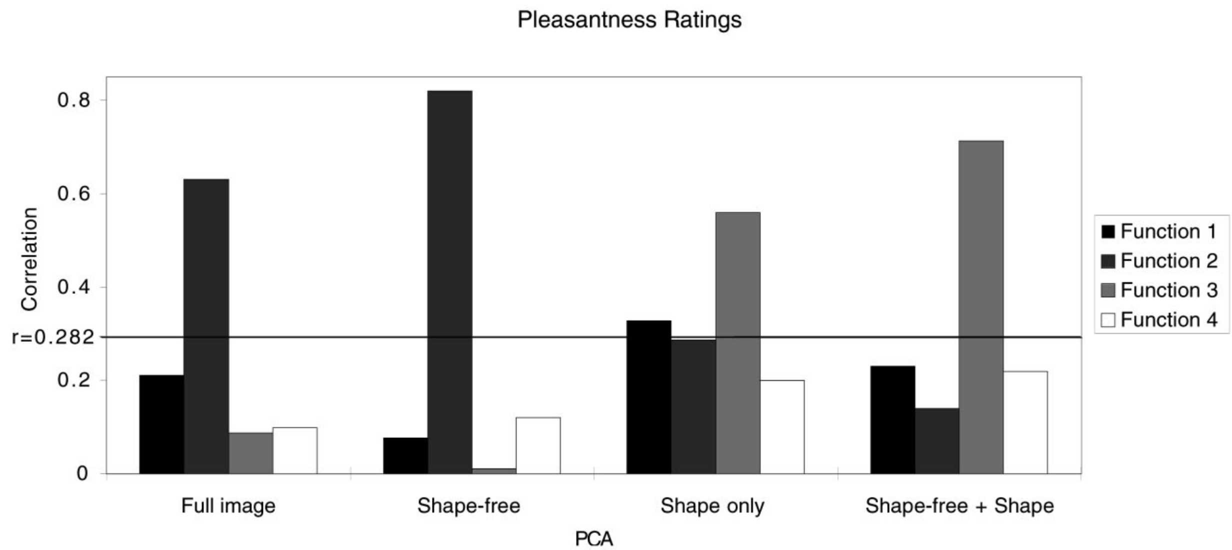
A number of authors have suggested that human misidentifications in facial affect recognition (discussed in the previous section) are best accounted for by a continuous two-dimensional model (Schlosberg, 1952; Russell & Bullock, 1985). Hence, in view of our results, we thought that it was important to investigate whether ratings of the Ekman and Friesen faces on Russell's pleasure–displeasure and arousal–sleepiness dimensions were correlated with the dimensions produced by the PCAs (the components) and LDAs (the canonical discriminant functions). To make this comparison we obtained ratings of pleasure–displeasure and arousal–sleepiness for each of the Ekman and Friesen faces using the 'Affect Grid' devised by Russell, Weiss and Mendelsohn (1989). The method used is described below.

3.3.2.1. Human participants' pleasure–displeasure and arousal–sleepiness ratings. Participants: Ten members of the MRC Cognition and Brain Sciences Unit subject panel (five male, five female) participated in the experiment for payment. The participants were between the ages 25 and 39 years (mean = 31.7, S.D. = 5.23) and had normal or corrected-to-normal vision. None had taken part in the earlier experiment examining the identification of the same facial expressions.

Design and procedure: Participants rated the facial expressions using the affect grid of Russell et al. (1989); a two dimensional matrix of 9×9 squares. One dimension of the grid corresponds to pleasure–displeasure, the other to arousal–sleepiness. The nature of the grid was explained to participants in detail using a procedure adapted from Russell et al. (1989). To ascertain that the participants understood how to use the grid, prior to the start of the experiment each was asked to indicate the areas of the grid corresponding to each of three emotions/moods. The moods selected were calm, excited and bored; these were chosen because they are not represented in the Ekman and Friesen set. All of the participants identified these areas correctly.

The Ekman and Friesen faces were presented as individual photographs in a pseudo-random order. The participant's task was to indicate the mood/emotion expressed by each face by marking a cross in a square of the affect grid; a different grid was used for each face. Participants were given as much time as they wanted to rate each face. At the start of the experiment, they rated seven practice faces depicting the emotions happiness, sadness, anger, fear, disgust, surprise, and neutral; these were taken from a separate set of facial expression stimuli (Matsumoto & Ekman, 1988). Participants' mean pleasure and arousal ratings for the individual faces are shown in Appendix A.

3.3.2.2. Correlations between the human ratings and the canonical discriminant functions. Earlier we discussed that the LDA statistic uses canonical discriminant functions to categorise faces in terms of the dependent variable (e.g. as different facial expressions). These functions are the summed linear product of coefficients applied to the values of selected components. Six functions are generated by each LDA for facial expressions, producing six separate discriminant values for each face. Thus, the LDA recodes the representations of facial expressions from a 50-dimensional space (50 components) to a six-dimensional space (six discriminant functions) by summing across expression-relevant components, and ignoring, or minimising, the influence of components associated primarily with 'non-expression-relevant' information (e.g. hair colour, head size, eyebrow thickness, etc.).



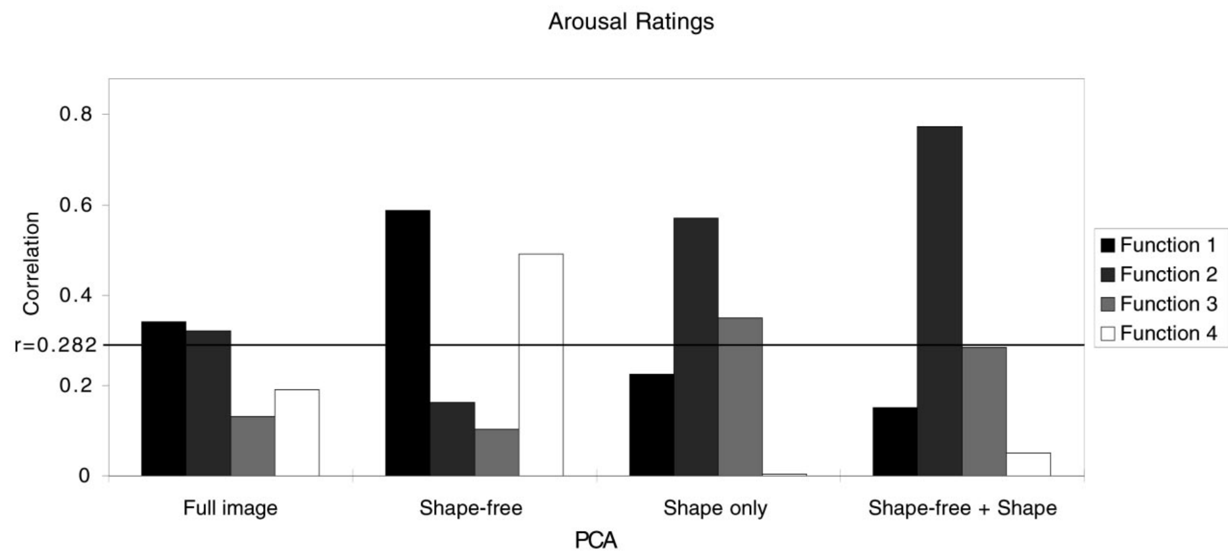


Fig. 5. Coefficients for the correlations between each of the first four discriminant functions of the LDA investigating facial expression and participants' ratings of the Ekman and Friesen (1976) faces for pleasure (top graph), and arousal (bottom graph).

There are clear similarities between this form of data compression and the idea that facial expressions are recognised by registering their positions on a limited number of continuous dimensions (Schlosberg, 1952; Frijda, 1969; Russell, 1980). Hence, we first investigated whether the dimensions of Russell's Circumplex model (pleasure–displeasure and arousal–sleepiness) were correlated with any of the canonical discriminant functions produced by the LDAs of facial expression.

For each image type (full-image, shape-free, shape only, and shape-free + shape), separate Pearson correlation coefficients were calculated between the faces' discriminant values for each of the first four discriminant functions and the participants' mean pleasure ratings and their mean arousal ratings. Note, only the *first four* discriminant functions from each analysis were used because each LDA indicated that the fifth and sixth functions did not reflect true population differences, only random variation. The absolute values of the coefficients are summarised in Fig. 5. The horizontal line indicates a statistical cut-off point of $r = 0.281$, which is significant at $P < 0.003$ (two-tailed); this low value was chosen to adjust for the total of 16 correlations computed for each of the pleasure and arousal ratings. Even at this conservative level, however, significant correlations were found between the discriminant functions and participants' pleasure and arousal ratings. It is also interesting that, for the main part, the pleasure and arousal ratings were correlated with different functions in each LDA.

The results indicate that the dimensions of Russell's Circumplex model are correlated with the dimensions used by each LDA to categorise the facial expressions. Hence, these results demonstrate that the PCA and LDA can together extract a model that is consistent with psychological models of facial expression. Next, we went on to investigate whether these correlations arose because each of the pleasure and arousal ratings showed marked correlations with a limited number of unique components, or whether the correlates of pleasure and arousal were distributed across a large number of components.

3.3.2.3. Correlations between the participants' ratings and the components. Each of the four PCA data sets (full-image, shape-free, shape only, and shape-free + shape) were submitted to two separate stepwise multiple linear regression analyses; in one multiple regression, the participants' mean pleasure ratings were the dependent variable, in the other, their mean arousal ratings were the dependent variable. The R^2-values from these analyses are summarised in Table 4. All were highly significant ($P < 0.0001$); indicating that the participants' ratings of pleasure and arousal were correlated with dimensions describing the physical structure of the emotional facial expressions. Note, however, that neither the pleasure nor arousal ratings showed strong correlations with just *one* or *two* components, instead they were relatively weakly correlated with a large number of components; the number of components in each model ranged from six (shape, arousal), to 25 (shape-free, pleasure). Collectively, however, these sets of components appear to have produced relatively powerful linear regression models.

The above results demonstrate that Russell's psychological model of facial affect is reflected in the components generated by the PCA and in the functions produced by the LDA of these components. This indicates that PCA can provide a psychologically plausible method of coding facial expressions. In considering this result, it is important to remember that Russell and others have shown that the Circumplex model is not only applicable to facial expressions, but also to emotional vocal expressions, emotional words, and emotional experience. This implies that the model constitutes a conceptual representation of emotion that can be accessed from any modality. Notwithstanding, our own study demonstrates that these two dimensions are also represented in the *visual structure* of Ekman and Friesen's facial expressions, and hence, may underlie the perceptual coding of facial expressions.

We should point out that some authors have suggested that the dimensions extracted from participants' ratings (or sorting) of emotional material are, to some extent, dependent on the emotion categories included (Gehm & Scherer, 1988). Hence, it would be interesting to determine whether a similar correspondence between the visual and emotional representations is found for a wider range of facial expressions. For the present, however, the interest of this result is that the dimensions extracted from a statistical analysis of 54 150 variables (pixels) coding the visual structure of facial expressions are consistent with the dimensions derived from behavioural data. Hence, for the Ekman and Friesen faces, there is a considerably good mapping between the visual composition of the facial expressions, and the representation of the emotions expressed. In Section 4, we consider the implications of this finding for models of the mental representation of facial expression processing.

3.4. Are the facial cues to identity, expression and sex coded by similar or different sets of components?

3.4.1. Identifying the components for different facial attributes

Earlier we discussed that each stepwise LDA operates by selecting the components that are important for

Table 4
The R^2-values for separate multiple linear regression analyses[a]

Rating scales	PCA			
	Full images	Shape-free	Shape only	Shape-free + shape
Pleasantness	0.82	0.83	0.65	0.80
No. of components in model	24	25	10	18
Arousal	0.75	0.74	0.54	0.73
No. of components in model	23	18	6	11
Total no. of components in analysis	50	50	20	50

[a] Each multiple regression included one of four sets of PCA data (full-image, shape-free, shape only, and shape-free + shape) as the independent variables, and one of two sets of the human participants' ratings as the dependent variable (i.e. pleasure ratings or arousal ratings). Also shown are the number of components included in each model and the total number of components submitted to each linear regression.

Table 5
The components selected by separate stepwise linear discriminant analyses when the maximum number of steps in the analyses was restricted to 10[a]

PCA	Facial attribute	Number of components selected	Components selected by '10-step' LDAs	Percent correct categorisations
Full image				
	Expression	8	8, 5, 19, 9, 24, 15, 6, 13	67
	Identity	10	1, 2, 4, 3, 7, 6, 10, 13, 11, 5	97
	Sex	10	2, 1, 3, 10, 7, 4, 16, 11, 6, 17	100
Shape-free				
	Expression	10	5, 6, 7, 16, 17, 11, 27, 15, 3, 29	73
	Identity	10	1, 2, 3, 4, 9, 8, 11, 10, 5, 6	100
	Sex	10	3, 4, 5, 1, 6, 11, 13, 21, 2, 8	100
Shape only				
	Expression	8	S1, S2, S4, S8, S3, S6, S5, S15	88
	Identity	10	S5, S3, S4, S7, S2, S6, S11, S8, S15, S9	92
	Sex	9	S4, S2, S11, S5, S6, S19, S17, S8, S3	95
Shape-free + Shape				
	Expression	10	S1, S4, S2, S8, S3, S6, 11, 27, 15, 7	95
	Identity	10	1, 2, 3, 4, 9, 8, 11,10, 5, 6	100
	Sex	10	3, 4, S5, S11, 6, 14, 21, 5, 1, 11	100

[a] The results of three '10-step' LDAs investigating the categorisation of facial expression, the categorisation of facial identity, or the categorisation of faces' sex, are shown for each of the four PCA data sets (full-image, shape-free, shape only, and shape-free + shape). Components prefixed by an 'S' were produced by the shape only PCA.

discriminating between the relevant dependent variable (i.e. expression, identity or sex). Therefore, it seems reasonable to infer that the components selected by an LDA investigating facial expression are important for coding expression-relevant information, whereas the components selected by an LDA investigating facial identity are important for coding identity information, and so on. One problem with this inference, however, is that the maximum number of components that any LDA can select corresponds to the maximum number of steps in the analysis, which is relatively high (default maximum number of steps is twice the number of independent variables (components)). Consequently, it is possible that some of the components selected by an LDA may play a relatively minor role in discriminating between the members of the dependent variable. In order to identify the *major contributors* to the categorisation of each of expression, identity, and sex (i.e. to seek a low dimensional solution to the categorisation of these facial characteristics) we ran a new set of LDAs (standard version) in which we restricted the number of steps in each analysis to a maximum of 10; this meant that the maximum number of components that could be selected by each LDA was 10. In what follows, we will refer to these components as the '*important components*' for each of identity, expression, and sex. Note that a cut-off point of 10 steps was selected because it produced similar numbers of correct categorisations to the original LDAs, supporting our suggestion that some of the components were contributing very little to the LDA model.

Table 5 summarises the components selected by the '10-step' LDAs (for expression, identity and sex) for each of the four image types (full-image, shape-free, shape only, and shape-free + shape). The percent correct categorisations produced by these analyses are also shown on the far right of Table 5. Comparing these correct categorisations rates to those observed in Table 1, we can see that reducing the maximum number of components in each LDA to 10 has little effect on the efficiency of the discriminant models.

Table 6
Calculated from Table 5. The overlap between the components included in the LDA models for the categorisation of each of facial expression, facial identity, and the faces' sex[a]

	PCA			
	Full images	Shape-free	Shape only	Shape-free + shape
Expression & identity	3	4	7	1
Expression & sex	1	4	6	1
Identity & sex	8	8	7	6

[a] 'Expression & identity' refers to the overlap between the components included in the LDA model for categorising facial expression and the LDA model for categorising facial identity, and so on. The overlaps are shown separately for each of the four PCA data sets (full-image, shape-free, shape only, and shape-free + shape).

Table 6 shows the degree of overlap between the first 10 expression components, first 10 identity components, and first 10 sex components for each of the four image types (full-image, shape-free, shape only, and shape-free + shape). Two important findings are illustrated by this table. First, for three of the image types (full-image, shape-free, and shape + shape-free), expression shares relatively few components with either identity or sex. This was most marked for the LDA of shape components plus shape-free components combined, which showed that expression shared only one component (component 11 from the shape-free PCA) with each of identity and sex. The second point to note is that identity and sex share a number of their first 10 components. Interestingly, this second observation does not concur with a study by O'Toole et al. (1993) which demonstrated that *partially separate sets* of components are optimal for coding a face's identity and sex. We think that our different findings may reflect the different methodologies used, and we return to this issue in Section 4.

3.4.2. Shape cues for expressions, texture cues for identity and sex?

The data shown in Tables 5 and 6 suggest that shape cues (eye width, jaw drop, etc.) may be relatively more important than texture cues for facial *expression* categorisation, whereas the opposite may apply for categorising the identity or sex of a face. This was most evident for the shape plus shape-free condition, which selected six shape components for expression, two shape components for sex and none for identity. Four additional aspects of the data are also consistent with these posited differences in the roles of shape and texture. First, the analysis of the full-images (which contain both texture and shape information) also showed minimal overlap between the components selected by the expression analysis and those selected by the identity and sex analyses. Second, shape information alone produced less good categorisation of the faces' identities and sex than the full-images, however, the opposite pattern applied to facial expression categorisation. Third, there was minimal evidence of the separate coding of expression and identity from the shape information analyses, for which only shape information was available. Fourth, although the pattern observed for the shape-free images (for which the shape cues are largely degraded) is consistent with some degree of selective coding of expression from identity and sex, it is less marked than that observed for the full-image, and shape-free plus shape analyses: this fits with our earlier suggestion that following the average-morphing process, shape information remains evident, to some extent, in the texture cues such as wrinkles, shadows, and the presence/absence of teeth, etc.

3.4.3. Examples of eigenfaces coding each of expression, identity and sex

Given the manner in which expression, identity, and sex are coded by the components, it is interesting to take a look at some of the important eigenfaces (components) for these facial characteristics. To do this, we examined components abstracted from the full-images because the shape-free images produced a less obvious dissociation between the components for each of expression, identity, and sex.

It is difficult to determine what characteristics an eigenface is coding by simply inspecting the visual representation of its average weighting (i.e. the sorts of images shown in Fig. 4). So to aid their interpretation we have produced sequences containing reconstructions of a single person's face in which the weightings applied to the eigenface of interest have been varied to reflect the range of component values for this eigenface. More specifically, each sequence comprises a series of reconstructions of model PE posing a neutral expression. Each image has been produced by weighting all eigenfaces, except the eigenface of interest, with their appropriate component values for this face. For each sequence, the weighting applied to the eigenface of interest has been varied from −3 S.D. (far left image) to +3 S.D. (far right image) from the mean in 1 S.D. steps; producing a different facial image for each 1 S.D. step. Sequences of images are shown for two expression eigenfaces (Fig. 6a), two identity eigenfaces (Fig. 6b), and one sex eigenface (Fig. 6c). All sequences were generated using the eigenfaces produced by the PCA of the full-images.

Examining the expression eigenfaces (Fig. 6a) individually, we can see that component 5, appears to code eye width and open/closed mouth (jaw drop), whereas component 9, seems to resemble a smile that incorporates changes in the muscles around the mouth *and* eye regions; that is, a Duchenne smile (Ekman, Davidson, & Friesen, 1990). Note, however, that neither of these two expression eigenfaces show any obvious changes in the *identity* of the face. Fig. 6b shows two identity eigenfaces: component 1 codes principally face width and hair tone, while the principal feature coded by component 7 appears to be nose width. Neither of these identity components, however, produce marked changes in their faces' *expression*. Finally, Fig. 6c shows an eigenface that is particularly important for sex categorisation (component 2); this component alone can categorise approximately 83% of the faces' sex correctly. Interestingly, the expression of this sex component does not seem to alter across this sequence, although facial identity does; but then, it is difficult to imagine how a person's face could 'change sex' without it also having some effect on the person's perceived identity. This is consistent with our earlier observation that expression is coded by largely different sets of

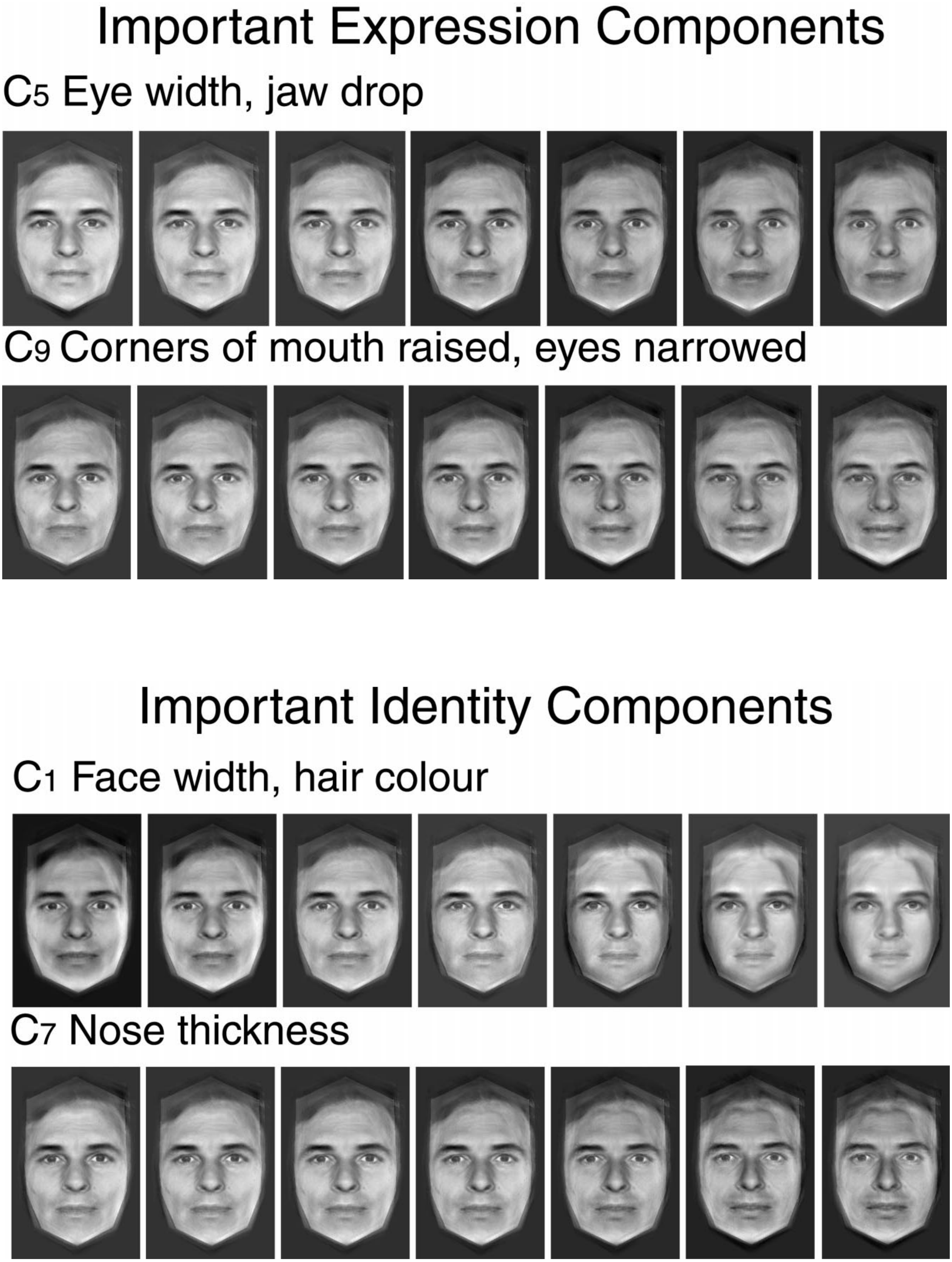

Important Expression Components
C5 Eye width, jaw drop
C9 Corners of mouth raised, eyes narrowed
Important Identity Components
C1 Face width, hair colour
C7 Nose thickness

Fig. 6.

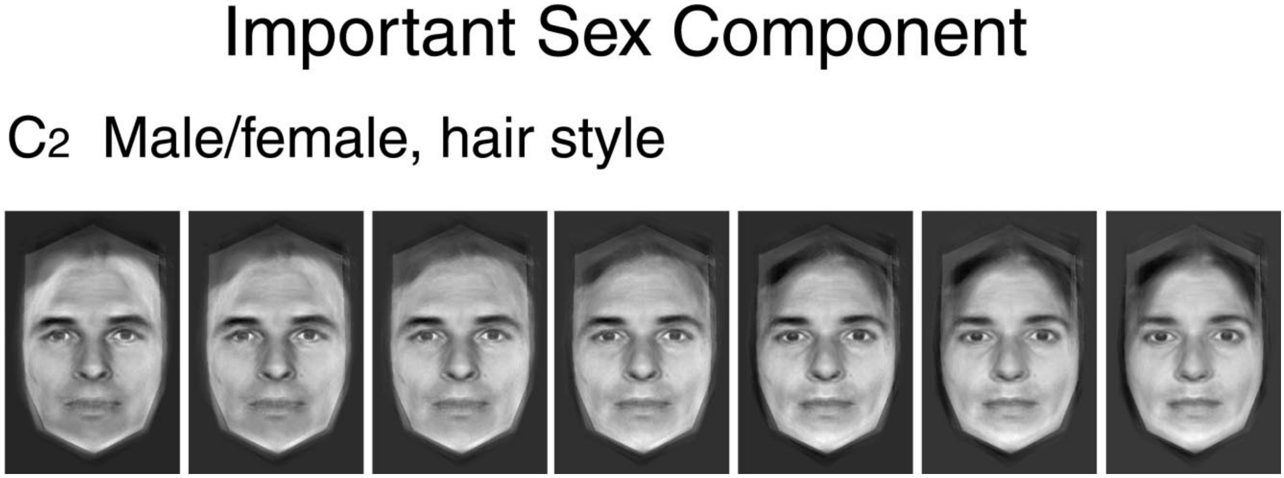


Fig. 6. Separate sequences of reconstructed images are shown for each of two eigenfaces that are important for categorising facial expression, component 5 (C_5) and component 9 (C_9), two eigenfaces that are important for categorising facial identity, component 1 (C_1) and component 7 (C_7), and for a single eigenface that is important for categorising the faces' sex, component 2 (C_2). For each sequence, all eigenfaces, except the eigenface of interest, have been weighted with the appropriate component values for model PE posing a neutral expression. The weights applied to the eigenface of interest have been varied from -3 S.D. (far left image) to $+3$ S.D. (far right image) from the overall mean component value.

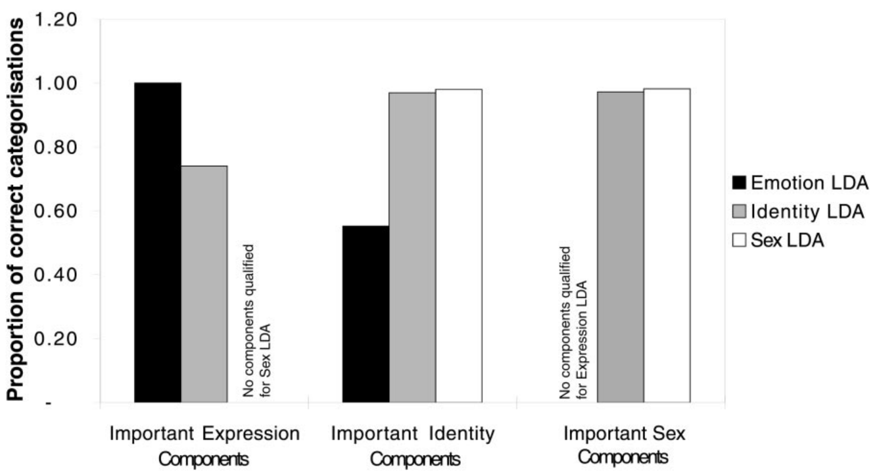


Fig. 7. Separate linear discriminant analyses investigating the categorisations of the faces' expression, identity, and sex, respectively (see legend) were conducted under each of three conditions (see x axis): (1) when only the important expression components were included in the LDAs; (2) when only the important identity components were included in the LDAs, and (3) when only the important sex components were included in the LDAs. The correct categorisations are presented as a proportion of the number of correct categorisations observed when all 50 components were included in the same LDAs.

components to identity and sex, while identity and sex are coded by more overlapping sets of components.

3.4.4. LDAs of the first 10 components

As an additional method of investigating the degree of overlap among the *important* (full-image) components for each of expression, identity, and sex, we conducted three types of linear discriminant analyses investigating the categorisation of facial expression, facial identity, and sex, respectively. Each of these three LDAs was conducted under each of three conditions: (1) when only the important expression components were included, (2) when only the important identity components were included, and (3) when only the important sex components were included (Table 5). Fig. 7 summarises the number of correct categorisations as a proportion of the scores obtained when all 50 components were included.

Fig. 7 illustrates that when *only* the important expression components were included in the LDAs for each of expression, identity and sex (left three bars), then the correct categorisations for identity and sex suffered; in fact, the LDA model investigating sex categorisation in this condition indicated that none of the important expression components qualified for inclusion in the model. Similarly, correct categorisations for expression suffered when only the important identity components were included (middle three bars), or when only the important sex components were included (right three bars); this pattern is more marked for the important sex components condition because none of the sex components qualified for inclusion in a LDA model for categorising the faces' expressions.

Two further points are worth noting from these data. First, the observed decrement in performance for identity in the important expression components condition, and for expression in the important identity components condition was *not* equivalent to chance. This reflects the fact that although some components code primarily facial expression information, while other components code primarily facial identity information, there are also components that code *both* facial characteristics (Tables 5 and 6). This overlap may be important, and we return to this issue in Section 4. The second point to note is that the identity and sex categorisations were virtually identical for the important identity components condition and for the important sex components condition. Again, this supports our earlier observation that the components for these two facial characteristics show a large degree of overlap.

The finding that some components code primarily expression information while others code primarily identity information is entirely consistent with the large number of studies demonstrating these two facial characteristics are processed largely independently of one another. However, our observation that identity and sex are coded by *similar* sets of components is rather more difficult to square with the observation of Bruce et al. (1987) that a face's sex is processed independently of its identity (see also Bruce, 1986). For the present, we simply note this inconsistency, and in Section 4 we consider this issue in more detail.

3.4.5. Constructing facial images from canonical function coefficients

As we discussed earlier, each canonical discriminant function is the summed linear product of coefficients applied to selected components. For example, the LDA for expression (full-image PCA) identified eight components as important for expression categorisation. The first and second canonical discriminant functions from this analysis are shown below.

$$D_1 = 0.84C_5 + 0.50C_6 + 1.0C_8 + -0.42C_9 + -0.40C_{13} + -0.09C_{15} + 0.14C_{19} + -0.06C_{24}$$

$$D_2 = 0.27C_5 + 0.26C_6 + -0.25C_8 + 0.58C_9 + -0.37C_{13} + 0.72C_{15} + 0.55C_{19} + -0.21C_{24}$$

From these functions we constructed *visual representations* of each canonical discriminant function. This was done by weighting each of the eight components (in this case C_5, C_6, C_8, C_9, C_{13}, C_{15}, C_{19}, and C_{24}) with their corresponding discriminant function coefficient, and all other eigenfaces with the average component value for the eigenvector. The top row (+ve) of Fig. 8a shows images that were constructed from the first five discriminant functions from the LDA model for facial expression categorisation (full-image PCA). The first face in the top row corresponds to canonical discriminant function 1, the second face to canonical discriminant function 2, and so on. The bottom row (−ve) of Fig. 8a shows the images that were produced when the same process was repeated, but with the sign of each of the eight coefficients reversed; again, all remaining components were weighted with the average component value for the eigenvector. This gave two facial images (+ve and −ve) for each discriminant function, with each pair of images corresponding to visual representations of the different ends of a dimension constructed to categorise facial expressions. The same sorts of images were also produced from the coefficients corresponding to the first five discriminant functions from the identity analyses (Fig. 8b), and the single discriminant function obtained from the sex analysis (Fig. 8c).

We reasoned that if the components for expression are primarily involved in coding facial expressions, then we would expect to find more marked differences in expression relative to identity, for the faces generated from the discriminant functions produced by the facial expression LDA. Similarly, the opposite pattern should be found for the faces generated from the identity discriminant function coefficients (i.e. large differences in identity and minimal differences in expression). As shown in Fig. 8, this is exactly the result that we observed. Similarly, Fig. 8c also illustrates that two images constructed from the +ve/−ve coefficients of the single canonical discriminant function for sex, resemble male and female faces with a similar expression.

The images shown in Fig. 8 give us some impression of the structure of the LDA 'classification spaces' used to categorise the faces' expression, identity and sex. For example, the first discriminant function for expression would seem to code surprise expressions at one end and closed mouth happy expressions at the other. Function 2, ranges between open mouth happy and anger/disgust, function 3 from fear to sadness, and so on. It is remarkable how well the different facial expressions are characterised by these functions, but at the same time it is immediately apparent that the identity and sex of the Ekman and Friesen faces are not at all readily discernible from these images. The very opposite, however, is true for the images generated from the identity discriminant coefficients. Similarly, changes in facial affect are not discernible from the sex function images, although, as we found with the sequence of images constructed from the sex component shown in Fig. 6 (component 2), the identity of the face does appear to change along with its sex. Again, this is consistent with our earlier observation that the faces' expressions are coded by largely different components to their identity and sex, which, in turn, are coded by overlapping sets of components.

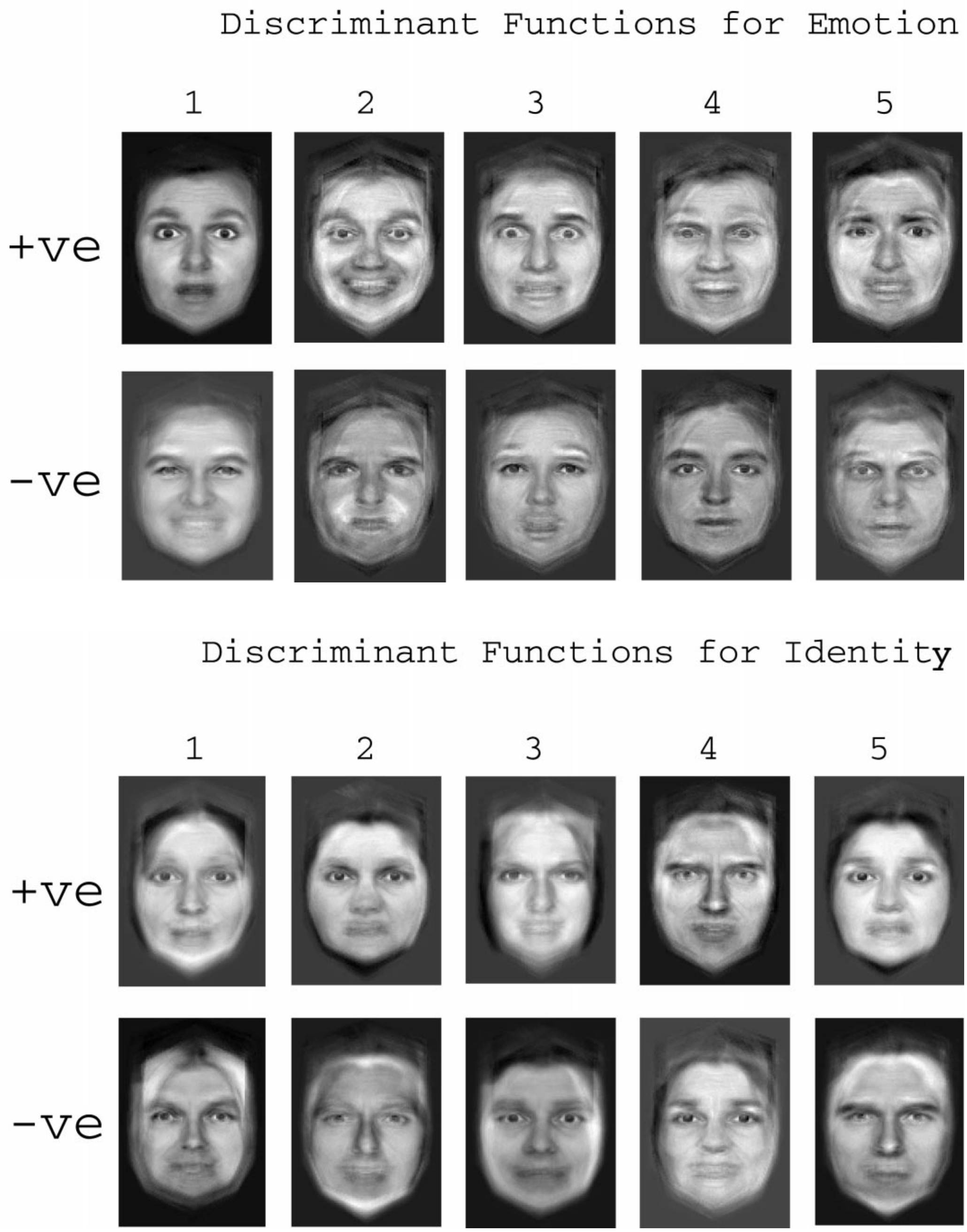


Fig. 8. (a) Visual representations of the first five canonical discriminant functions from the LDA investigating facial expression categorisation of the full-image PCA data. (b) Visual representations of the first five canonical discriminant functions from the LDA investigating facial identity categorisation of the full-image PCA data, and (c) a visual representation of the single canonical discriminant functions from the LDA investigating sex categorisation of the full-image PCA data. In each case, the top image (+ ve) for each function was produced by weighting each of the eigenfaces included in the LDA model with their corresponding coefficient values for the function; all other eigenfaces were weighted with their corresponding average component value. The bottom image (− ve) was produced using exactly the same procedure, but with the sign (+ ve/ − ve) of the coefficient value reversed.

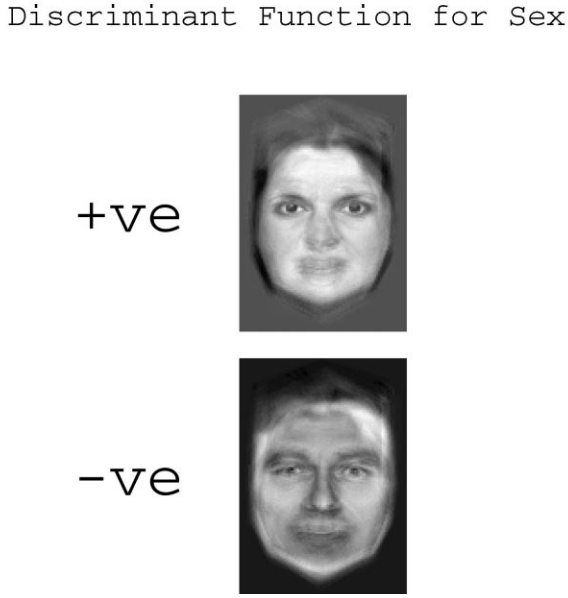


Fig. 8. (*Continued*)

4. General discussion

4.1. Question 1: can PCA support facial expression recognition?

Our study addressed two main questions. The first was whether PCA can code the visual information needed to distinguish between different facial expression categories. To investigate this, three different sets of 'facial information' were submitted to separate PCAs: (1) the pixel values of the full-images, (2) the pixel values of the shape free (average-morphed) faces, and (3) shape information from the full-images. The results of a series of LDAs showed that although the full-image PCA could support the categorisation of facial expressions, pre-processing the faces to the same average-face shape significantly improved the number of correct categorisations. In addition, the PCA of shape information alone demonstrated that a limited number of feature positions can also support good categorisation of facial expressions; this is in contrast to the findings for facial identity and sex, which showed less good identification rates from the shape PCA (see also Hancock et al., 1996). Consistent with previous results for facial identity (Costen et al., 1995; Hancock et al., 1996), however, optimal categorisation rates for facial expressions were obtained by combining the outputs of the shape vector PCA and shape-free PCA.

In response to question 1, then, our results show that PCA can code facial expressions in a form that can support facial expression identification.

As we discussed in the introduction, Padgett and Cottrell (1995) and Padgett et al. (1996) have also investigated the application of PCA to models of facial expression recognition. These authors have adopted a 'part-based' approach to the PCA of facial expressions whereby the eye and mouth regions of the face are each submitted to separate analyses. However, in the light of recent studies showing that humans process configural cues in facial expressions (Calder et al., 2000; White, 2000) we feel that Padgett and Cottrell's approach is less psychologically plausible than the whole-face approach we have used here. To be fair, one of the reasons why Padgett and Cottrell adopted a part-based method was that a whole face analysis they reported produced less good results. In view of this observation, it is worth emphasising again that a whole-face approach to PCA can produce good hit rates *if* the faces are pre-processed to have the same average-face shape (i.e. shape-free images).

It is worth emphasising that we do not want to suggest that the human face recognition system uses an average-morphing algorithm comparable to the one used in this study. There are obvious reasons why some form of standardisation procedure might be used (e.g. image size on the retina when faces are viewed at different distances, etc.).

4.2. Question 2: can PCA code facial expressions in a psychologically plausible form?

4.2.1. Psychological models of facial expression recognition

Perhaps the most striking aspect of our PCAs is that they not only capture the human participants' correct identification rates for facial expressions, they also capture a number of their frequent misidentifications. Schlosberg (1941, 1952) and Woodworth and Schlosberg (1954) were the first to recognise that human misidentifications of facial affects are not random but instead form regular patterns. This led them to propose that facial expressions are recognised by locating their positions in a two-dimensional space. In more recent years, Russell and others have shown that the two-dimensional model is also applicable to the recognition of emotional signals from other domains (i.e. vocal, verbal, conscience experience). Consequently, it is of significant theoretical interest that participants' ratings on the two dimensions of Russell's Circumplex model are correlated with dimensions (i.e. components and canonical discriminant functions) extracted from an image-based analysis of 54 150 variables (pixels) coding the *visual information* in facial expressions. In other words, this suggests that the perceptual representation of facial expressions may mirror the psychological representation of the emotions expressed. As such, these findings provide further evidence that the perceptual encoding of facial expressions may rely on a form of linearised compact coding analogous to PCA.

These results would seem to lend strong support to the psychological validity of the perceptual space generated by our principal component analyses. Whether they lend strong support to a two-dimensional model of facial expression perception is less clear, however, because a number of other aspects of our results were not consistent with this theoretical viewpoint. For example, for each of the four PCA data sets (full-images, shape-free, shape only, and shape-free + shape), the linear discriminant analyses investigating facial expression showed that the first *four* canonical discriminant functions accounted for significant levels of variation between the expressions. Hence, although our data concur with a dimensional representation of facial expressions they do not concur with a system based on just *two* dimensions. More damaging for the two-dimensional account, however, is that other aspects of our current results, and Cottrell and colleague's results, are more consistent with a category-based account.

One result that is cited frequently in support of the category-based theory is Ekman and colleagues' observation that facial expressions corresponding to six basic emotions (happiness, sadness, anger, fear, disgust and surprise) are categorised readily by different cultures throughout the world (Ekman, 1982, 1992b; Ekman et al., 1987). Consequently, our results provide support for this category-based model by showing that the LDAs of the PCA data produce comparable categorisations to the human participants in Ekman's studies and our own. Further evidence of category-based effects from PCA comes from work by Padgett et al. (1996). These authors showed that their PCA-based model of facial expression recognition could produce a good approximation of human data showing categorical perception of morphed facial expression continua (Etcoff & Magee, 1992; Calder et al., 1996a; Young et al., 1997). These categorical perception studies have shown that computer-generated continua, composed of a series of equidistant morphs (blends) of two facial expressions (e.g. anger and fear), are categorised by human subjects in a 'step-like' (categorical) fashion. Hence, for the above example, the images at one end of the continuum would be categorised as *anger*, and those at the other end as *fear*, with an abrupt category boundary separating the two. Similarly, Padgett et al. (1996) have shown that their PCA-based model produces comparable categorisation of morphed facial expression continua to that of human subjects.

Overall, then, PCA does not seem to provide direct support for a purely categorical or a purely two-dimensional model of facial expression encoding. What it does provide, however, is a means of bridging the gap between the category-based and two-dimensional accounts by showing that empirical phenomena that have been attributed to one or other of these two models can be properties of a *single* dimensional system, such as PCA.

4.2.2. Are the facial cues to expression, identity, and sex coded by similar or different sets of components?

As we discussed in the introduction, a number of studies have demonstrated a functional independence between the recognition of facial expression and facial identity (Bruce, 1986; Hasselmo et al., 1989; Young et al., 1993). Encouragingly, our results were very much consistent with these findings in that expression and identity were coded by largely different sets of components for the full-image PCA and the combined outputs of the shape-free PCA plus shape PCA. In addition, these same analyses showed an even stronger dissociation between the components coding the faces' expressions and the faces' sex.

In considering the implications of this result, it is important to recognise that the process of generating components does not require the faces to be labelled with their expression, identity or sex. Hence, the fact that the components that are important for categorising expression are largely different to those that are important for categorising identity or sex, is simply a property of the statistical structure of the facial images. Moreover, it is worth emphasising that the components coding these facial characteristics are not only different, they are, by definition, uncorrelated. Hence, the functional independence between expression and identity reported in previous studies is clearly evident in a PCA-based system of face processing. This suggests that at least some of the functional dissociations reported between facial expression and facial identity processing might be driven by 'front-end' perceptual effects; that is, effects that relate directly to the fact that these two facial characteristics load on different dimensions of the visual stimulus.

As noted earlier, studies have also shown that a face's sex may be processed independently from its identity (Bruce, 1986; Bruce et al., 1987), however, we found little evidence of this dissociation at the level of the components. On reflection, the observation that identity and sex are coded by similar components to one another, but by different components to expression, is not at all inconsistent with the anatomical features associated with these three facial characteristics. Identity and sex are contained within largely rigid elements of the face that change slowly across a number of years, while facial expressions are conveyed by transient non-rigid facial muscle movements. Interestingly, this rigid/non-rigid dissociation is evident in the sequences of expression components, identity components, and the sex component shown in Fig. 6. These sequences illustrate that the identity components (Fig. 6b) and sex component (Fig. 6c) show structural changes in head size and nose shape. In contrast, the expression component sequences (Fig. 6a) show changes resembling movements of the facial muscles (e.g. eye widening, opening and closing the mouth, turning up the corners of the mouth).

These observations are consistent with a recent neuropsychological model of face processing proposed by Haxby, Hoffman and Gobbini (2000) (p. 1289). These authors suggest that the dissociation between facial identity and facial expression can be explained in terms of the hypothesis that different brain structures are used to process the visuo-structural properties of these two facial characteristics. They propose that the invariant (non-changeable) properties of a face needed to code facial identity are processed by the fusiform gyrus, whereas changeable aspects of the face, such as facial expressions, are processed by the superior temporal sulcus (STS). Our results concur with the model of Haxby et al. (2000) by showing that an image-based analysis of faces produces a dissociation between the components for facial identity (coding rigid/invariant facial features) and components for facial expression (coding non-rigid/changeable facial features). Furthermore, although Haxby et al. (2000) do not address where in the brain a face's sex is coded, the invariant property of this facial characteristic would infer that sex should also be processed by the same brain area as facial identity. Again, this is consistent with the fact that a face's identity and sex are coded by overlapping sets of components.

Yet in spite of the plausible anatomical, and neuropsychological reasons why identity and sex should share more components with one another than with expression, a previous PCA study by O'Toole et al. (1993) has found evidence for at least partially *separate coding* of identity and sex.

O'Toole et al. (1993) found that components with low eigenvalues (the early components extracted by the PCA) were optimal for coding the faces' sex, while components with high eigenvalues (the later components extracted by the PCA) were optimal for coding facial identity. One explanation for our different results may relate to the *numbers* of different pictures of each person's face used in O'Toole et al.'s study and our own. O'Toole et al. used *single* pictures of each of a large number of identities (100), whereas our own study used *multiple* pictures (5–11) of each of a relatively small number of identities (14). This may explain our different findings because the components with high eigenvalues code information relating to a large number of faces in the stimulus set, whereas components with low eigenvalues code information that may be associated with as few as *one* or *two* faces. Thus, given that our own study used multiple pictures of male and female faces *and* multiple pictures of each model, it is not terribly surprising that both sex and identity should be coded by overlapping sets of components with high eigenvalues (i.e. early components).

The different methods used to tap facial identity processing in these two studies may also be relevant. O'Toole et al. noted that their facial identity task was qualitatively different to their sex decision task. For the identity task the model computed whether a face was coded in memory (i.e. present/absent decision), whereas for the sex decision task, the model calculated which of two *sets of faces* (male and female) the face resembled most (i.e. a category-based decision). In our own study, all three decisions (expression, identity, sex) were essentially category-based decisions, because there were multiple examples of each of the category members (i.e. multiple pictures of each expression, multiple pictures of each model, and multiple pictures of male and female faces). Hence, it is plausible that the different facial identity tasks used by O'Toole et al. and ourselves were tapping different components of face recognition. One possibility is that O'Toole et al.'s method simulates human recognition memory for single pictures of previously unfamiliar faces (e.g. a format similar to the Recognition Memory Test of Warrington, 1984), whereas our own approach simulates the *identification* of well-learned familiar faces.

In relation to this discussion, we suggest that using multiple pictures of each face in PCA is a better analogue of human face recognition than using one picture of each face. After all, most of the faces that we are able to recognise have been encountered with different poses and expressions on a number of occasions. Hence, we suggest that the best 'PCA analogue' of the Bruce and Young (1986) face recognition units (FRUs) is not a single PCA signature for each familiar face, but rather individual clusters of PCA signatures — with each cluster representing one person's face.

4.3. Implications for models of face processing

4.3.1. The IAC/PCA model of face recognition

Our results have clear implications for the implementation of Bruce & Young's (1986) functional model of face recognition (Fig. 1). As we outlined in the introduction, Burton et al. (1999) have presented an implemented account of the facial identity route of the Bruce and Young architecture that incorporates both the perceptual analysis (via PCA), and higher cognitive processes (with an IAC architecture) involved in recognising faces. A long-term goal of this research is to produce an implemented account of all of the routes in the Bruce and Young architecture. However, as we outlined in the introduction, this is only possible if the input vector used in the current Burton et al. architecture (the output of a PCA) can code other facial characteristics. Our study shows that this is a plausible objective by demonstrating that the identity, sex, and expression of the same people's faces can be coded by a single PCA.

Our results have also demonstrated that different facial characteristics (expression, identity, and sex) are associated with particular sets of components. This suggests that the performance of a fully implemented version of the Bruce and Young model could be optimised if each route incorporated a mechanism for attending to its relevant components. For example, the facial identity route would emphasise the important components for facial identity, while the facial expression route would emphasise important components for facial expression, and so on. A plausible location for this mechanism in Burton et al.'s (1999) model of facial identity recognition would be the connections between the PCA input nodes (structural encoding) and the FRUs. Similarly, comparable systems could exist for the expression, lipspeech and directed visual processing routes.

The model we have outlined above is very much consistent with Bruce and Young's original conception, in that it emphasises the independent coding of different facial characteristics. However, it is important to remember that although we have found evidence for some degree of selective coding of expression and identity, and the selective coding of expression and sex, these dissociations are not complete. For example, for the full-image components, expression and identity shared three of their 'important components', expression and sex shared one, while identity and sex shared eight. Hence, for identity and expression, in particular, this pattern seems consistent with the idea that a dissociation between these two facial characteristics should be observable under most testing conditions, but not all. Interestingly, some recent evidence from Schweinberger and his colleagues (Schweinberger & Soukup, 1998; Schweinberger, Burton, & Kelly, 1999) suggests that this is in fact the case.

In a series of experiments Schweinberger and Soukup (1998) showed that 'to-be-ignored' changes in facial identity can significantly increase participants' RTs to categorise facial expressions. Intriguingly, the opposite is not true, and identity decisions are not significantly affected by to-be-ignored changes in expression. Schweinberger and Soukup (1998) argue that the Bruce and Young (1986) model is unable to accommodate their results because there is no obvious communication between the expression and identity routes. Thus, our observation that identity and expression are coded by both unique *and common* sets of components suggests that PCA could hold the key to modelling this effect.

4.3.2. Face space Valentine's (1991) model

Finally, it is also worth considering how our results relate to an influential model of the perceptual representation of facial identity devised by Valentine (1991). Valentine proposed that faces are represented in a multidimensional 'face space' in which the dimensions correspond to visual features that are used to encode faces. Two versions of the model were proposed: (1) a norm-based system in which faces are coded relative to a prototype or average face representation, and (2) an exemplar-based system in which there is no norm, and the faces are coded as points in multidimensional space. A number of authors have commented that PCA of faces is a good metaphor of Valentine's model (O'Toole et al., 1994; Bruce, Burton, & Hancock, 1995; Hancock et al., 1996), because principal components provide a functional analogue of the otherwise abstract dimensions of face space. In particular, Hancock et al. (1996) have shown that PCA provides a good account of distinctiveness effects with faces; the phenomenon that the face space model was originally devised to account for (see also Deffenbacher et al., 1998).

Note, however, that face space was developed principally as an account of *facial identity coding*. Consequently, with the exception of studies investigating how a face's race and sex might be coded in this model (O'Toole et al., 1995; Valentine, 1995), researchers have not considered how other facial characteristics, such as expression, might relate to his account. Hence, it is interesting that our own results demonstrate that PCA can generate a *single* multidimensional face space that can code a face's identity, sex, *and* expression. In other words, the face space metaphor may be a suitable system for coding all types of facial information, not just facial identity.

It is important to emphasise that the concept of a face space for all facial characteristics does not conflict with the idea that some of these characteristics may be coded independently of others (e.g. facial identity is coded largely independently of facial expression). As we have already discussed, the dimensions of a PCA space are, by definition, uncorrelated; making it possible for the independent processing of identity and expression to occur within this single MDS system. Similarly, it is also worth considering that the uncorrelated nature of a PCA-based model means that expression-relevant components are no more related to one another than they are to the identity-relevant or sex-relevant components, etc.; the same applies to the identity- and sex-relevant components themselves. Consequently, it is plausible that these individual components may constitute a more fine-grain form of independent coding occurring at a basic visuo-perceptual level. Furthermore, a detailed investigation of these individual components and their contribution to different facial characteristics (i.e. identity, expression, lipspeech, sex, etc.) could give us important insights into the perceptual representation of facial information. For example, an investigation of this sort could assess whether facial expressions are coded in terms of components corresponding to Ekman and Friesen's action units (muscle positions that can be combined to generate different facial expressions). In addition, this approach could provide interesting insights into why some rare cases of prosopagnosia are restricted to poor facial identity recognition per se (Bruyer et al., 1983; Tranel, Damasio, & Damasio, 1988), whereas the majority of cases show other face processing impairments (e.g. facial expression identification, the perception of a face's sex and age, etc.).

4.4. Summary and conclusions

Our study addressed two basic questions: (1) Can PCA code facial expressions in a form that can support their recognition, and (2) can PCA code facial expressions in a psychologically plausible form? The answer to question (1) is clearly yes, in that all four sets of PCA data (full-image, shape-free, shape only, and shape-free + shape) showed good categorisation rates for facial expression; with the shape-free + shape analysis producing an optimal performance with an overall recognition rate comparable to human observers. It is also relevant that morphing the faces to the same average face shape improved the categorisation rates for facial expression; this concurs with previous studies which have shown that shape-free faces produce similar improvements for PCA-based models of facial identity recognition.

In response to question (2), we have shown that PCA codes facial expressions in a form that is consistent with psychological accounts of facial expression recognition developed by social psychologists. These accounts fall into two camps, category-based systems and dimensional accounts, and empirical studies have shown that each model captures different aspects of facial expression processing. Consequently, it is of significant theoretical interest, that properties of both of these models can be accommodated in a single PCA-based system. In other words, PCA offers a means of bridging the gap between the category-based and dimensional accounts of facial expression recognition. As we have discussed, the PCA/LDA approach we have used is itself a dimensional solution. Nonetheless, all aspects of our results support a dimensional system comprising *more than* two dimensions. In this sense our PCA account differs from the type of two- or three-dimensional systems introduced by social psychologists.

Finally, our results also have implications for models of face processing. First, they give grounds for optimism that the development of the PCA/IAC model of Burton et al. (1999) into a fully implemented version of the Bruce and Young model is an attainable objective. Second, they demonstrate that Valentine's multidimensional face space model could be extended into a valuable metaphor for the encoding of all types of facial characteristics, and not just facial identity processing alone.

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Appendix A

Human participant's mean pleasure and arousal ratings for each of the Ekman and Friesen (1976) faces

Face identifier	Emotion	Mean pleasure ratings	Mean arousal ratings	Face identifier	Emotion	Mean pleasure ratings	Mean arousal ratings
A1–14	Ang	1.6	6.2	MF1–6	Hap	7.1	5.2
C2–12	Ang	1.8	4.4	MO1–4	Hap	6.5	5.2

Appendix A (*Continued*)

Face identifier	Emotion	Mean pleasure ratings	Mean arousal ratings	Face identifier	Emotion	Mean pleasure ratings	Mean arousal ratings
EM5–14	Ang	1.2	6.0	NR1–6	Hap	7.2	6.8
GS2–8	Ang	2.0	5.2	PE2–12	Hap	7.4	5.8
JB1–23	Ang	1.3	4.8	PE2–6	Hap	6.4	4.0
JJ3–12	Ang	1.6	6.7	PF1–5	Hap	6.8	5.8
JM5–3	Ang	1.6	4.0	PF1–6	Hap	6.0	4.3
MF2–5	Ang	1.5	4.3	SW3–9	Hap	7.0	4.7
MF2–7	Ang	1.0	6.3	WF2–11	Hap	6.2	5.7
MO2–11	Ang	1.7	6.1	WF2–12	Hap	6.3	4.8
MO2–13	Ang	1.6	6.5	A1–2	Neu	4.1	3.6
NR2–7	Ang	1.1	6.7	C2–23	Neu	3.3	2.3
PE2–21	Ang	1.3	5.8	EM2–4	Neu	3.5	3.8
PF2–4	Ang	1.7	5.4	GS1–4	Neu	3.1	2.9
SW4–9	Ang	1.4	5.8	JB1–3	Neu	2.9	2.7
WF3–1	Ang	1.3	5.7	JJ3–4	Neu	4.5	3.4
WF3–4	Ang	1.1	5.5	JM1–9	Neu	4.0	3.5
A1–25	Dis	2.6	4.8	MF1–2	Neu	3.3	2.5
C1–4	Dis	1.8	4.1	MO1–5	Neu	4.2	3.5
EM4–17	Dis	1.8	3.4	NR1–3	Neu	3.2	3.8
GS2–25	Dis	1.8	4.2	PE2–4	Neu	4.2	3.9
JB1–16	Dis	1.5	4.9	PF1–2	Neu	4.3	5.0
JJ3–20	Dis	1.9	4.6	SW3–3	Neu	4.0	4.0
JM2–8	Dis	1.8	5.0	WF2–5	Neu	2.1	3.5
MF2–13	Dis	1.3	6.2	A2–6	Sad	1.6	1.7
MO2–18	Dis	2.2	4.0	C1–18	Sad	0.4	3.1
NR3–29	Dis	1.0	4.7	EM4–24	Sad	1.5	2.4
PE4–5	Dis	2.1	4.3	GS2–1	Sad	1.5	2.0
PF1–24	Dis	1.7	4.6	JJ5–5	Sad	1.5	1.7
SW1–30	Dis	1.7	3.6	JM3–11	Sad	1.0	1.7
WF3–11	Dis	0.8	5.6	MF1–30	Sad	1.4	2.1
WF4–22	Dis	1.4	4.5	MO1–30	Sad	2.1	2.0
C1–23	Fea	0.9	7.6	NR2–15	Sad	1.8	2.4
EM5–21	Fea	1.6	5.4	PE2–31	Sad	1.0	3.6
EM5–24	Fea	1.6	5.8	PE5–10	Sad	1.2	1.6
GS1–25	Fea	1.4	6.4	PE5–7	Sad	1.0	2.0
JJ5–13	Fea	1.8	7.1	PF2–12	Sad	1.3	2.1
MF1–26	Fea	1.7	6.8	PF2–16	Sad	1.5	1.8
MF1–27	Fea	2.0	6.5	SW2–16	Sad	1.2	2.6
MO1–23	Fea	1.8	7.4	WF3–28	Sad	1.3	2.7
MO1–26	Fea	1.1	7.2	WF5–6	Sad	1.3	1.9
NR1–19	Fea	1.7	5.8	A1–24	Sur	4.1	6.9
PE3–16	Fea	1.1	6.7	C1–10	Sur	4.5	6.7
PE3–21	Fea	0.6	7.4	EM2–11	Sur	4.3	5.9
PF2–30	Fea	1.5	7.2	GS1–16	Sur	4.9	7.1
SW2–30	Fea	2.8	6.9	JB1–12	Sur	3.0	6.2
WF3–16	Fea	1.3	7.3	JJ4–13	Sur	3.5	7.2
A1–6	Hap	7.1	5.1	JM1–16	Sur	4.5	6.4
C2–18	Hap	7.1	6.2	MF1–9	Sur	4.9	5.8
EM4–7	Hap	7.2	3.7	MO1–14	Sur	3.6	7.0
GS1–8	Hap	6.9	5.4	NR1–14	Sur	2.7	7.3
JB1–9	Hap	6.9	6.2	PE6–2	Sur	3.5	5.8

Appendix A (*Continued*)

Human participant's mean pleasure and arousal ratings for each of the Ekman and Friesen (1976) faces

Face identifier	Emotion	Mean pleasure ratings	Mean arousal ratings	Face identifier	Emotion	Mean pleasure ratings	Mean arousal ratings
JJ4–7	Hap	6.9	4.8	PFI–16	Sur	6.1	6.9
JJ4–8	Hap	5.7	3.6	SW1–16	Sur	3.9	6.6
JM1–4	Hap	7.3	6.4	WF2–16	Sur	3.2	7.4

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