Face Recognition in the Machine Reveals Properties of Human Face Recognition

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\begin{abstract}
Psychophysical studies suggest that face recognition takes place in a narrow band of low spatial frequencies (“critical band”). Here, we examined the recognition performance of an artificial face recognition system as a function of the size of the input images. Recognition performance was quantified with three discriminability measures: Fisher Linear Discriminant Analysis, non Parametric Discriminant Analysis, and mutual information. All of the three measures revealed a maximum at the same image sizes. Since spatial frequency content is a function of image size, our data consistently predict the range of psychophysical found frequencies. Our results therefore support the notion that the critical band of spatial frequencies for face recognition in humans and machines follows from inherent properties of face images.

\textit{Key words:} Face recognition, psychophysics, discriminability measures, spatial frequencies

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\end{abstract}

\section{Introduction}

A considerable number of psychophysical studies coincide in that mechanisms for face recognition in humans do not use all available visual information about faces equally. The visual information we refer to concerns the spatial frequency composition of face images. Specifically, a narrow band settled at the lower end of the frequency spectrum seems to be optimally suited for the recognition
of previously learnt faces. The frequency band is centered at about 10 to 15 cycles per face, and its bandwidth is about 2 octave \[1,2,3,4,5,6,7,8\]. Thus, face recognition (and also object recognition in general) follows a bandpass characteristics in humans. Furthermore, this result does not depend, to a first approximation, on viewing instance \[4,8\]. The unit for spatial frequencies “cycles per face” (or “cycles per object”) expresses this scale invariance. Nonetheless, to the best of our knowledge, no conclusive explanation for the bandpass characteristic of face recognition has emerged so far. A recent study conducted by one of the authors linked this characteristic to inherent properties of face images. By examination of the responses of a model of simple and complex cells to face images, Keil could show that higher response amplitudes are obtained at spatial frequencies consistent with the corresponding psychophysical data \[9\]. Therefore, the visual system should encode visual information for processing faces preferably at those spatial frequencies, where the highest signal-to-noise ratio is obtained. Only then a fine discrimination between signals will be possible. Or, otherwise expressed, only then we will be able to learn and perceive fine differences between otherwise similar faces. Given this link between the statistics of facial images and psychophysical data, we reasoned that an artificial face recognition system should reveal similar properties as the human visual system does: we expected to see an optimal recognition performance of the artificial system at the same spatial frequencies as observed with humans. To this end, we explored several measures of recognition performance. Furthermore, as suggested by the results from ref. \[9\], internal face features are the principal cause for the bandpass characteristic of face recognition. This holds especially true for the eyes, but also for mouth and nose, albeit to a less extent. Consequently, we suppressed external features (hairline, shoulder regions) in the present study. The results of the present study suggest that the machine indeed does it like humans – recognition performance peaks within a narrow band of low spatial frequencies.

This paper is organized as follows: the next section describes the image processing and the separability criteria that have been considered in the experiments, section 3 shows the obtained results, and section 4 summarizes and concludes this work.

2 Methods

2.1 Processing of face images

For our experiments, we used images from the FRGC Database (http://www.bee-biometrics.org/). In these images, faces appear against uniform, grey back-
ground, and with homogeneous illumination conditions for all subjects. The database consisted of 3772 high quality images from 275 different persons, where four to 32 images exist for each subject. To perform the experiments we first aligned and then resized the images such that each resulting image had an eye-to-eye distance of 50 pixels. Figure 1 shows some examples of the such normalized images.

Due to their relatively high variability, we decided to suppress external face features by windowing each face image with a 4-term Blackman-Harris window (“B.H.-window”). This window was compared to 15 alternative windows, and scored the highest similarity with corresponding images whose external features were removed manually [9]. For each image, the window was centered at the position of the nose \((x_{\text{nose}}, y_{\text{nose}})\). The nose position was estimated from the coordinates of the left and the right eye \((x_{\text{le}}, y_{\text{le}}), (x_{\text{re}}, y_{\text{re}})\), respectively, and the mouth \((x_{\text{mouth}}, y_{\text{mouth}})\):

\[
\begin{align*}
x_{\text{nose}} &= \text{rnd} \left( \frac{x_{\text{le}} + x_{\text{re}}}{4} + \frac{x_{\text{mouth}}}{2} \right) \\
y_{\text{nose}} &= \text{rnd}[0.95 \times \text{rnd}(y_{\text{le}} + (y_{\text{mouth}} - (y_{\text{le}} + y_{\text{re}})/2)/2)]
\end{align*}
\]

The operator \(\text{rnd}(\cdot)\) denotes rounding of its argument to the nearest integer value. Figure 2 illustrates result of applying the B.H.-window to the images of Figure 1.

We adopted the following procedure to assess the frequency-dependence of face recognition with our artificial system. Each image was down-sized to continuously smaller sizes. After down-sizing, we enhanced the highest spatial frequencies with a modified algorithm for suppressing illumination effects [10]. Specifically, we modified the algorithm such that its output mimicked the responses of retinal ganglion cells [11] in a way that contour enhancement at high spatial frequencies occurred (Figure 3). Consequently, our “Weber-filtered” images are dominated by the Nyquist frequencies associated with each image size. In this way, computational time could be saved over naive bandpass filtering.
Fig. 2. The images shown here are the result of applying a Blackman-Harris window to the images of Figure 1. The application of the Blackman-Harris window leads to a good suppression of external face features (e.g. hair and shoulders).

Fig. 3. Examples of images after applying the “Weber-filtering”. Compared to the original images (top row), Weber-filtering leads to enhancement of high spatial frequencies, and discounts illumination effects at the same time (bottom row).

2.2 Separability Measures

In order to measure the optimal dimensionality we need to define a formal class separability criterion. Class separability can be measured in terms of classification accuracy or class distribution. In the first case, the measure is highly dependent on the classifier used. In this paper we propose the use of a classifier-independent set of statistical measures to validate the psychophysical results for human face recognition.

Two types of class separability measures are described in the literature [12], where one is based on scatter matrices, and the other one is based on imposing an upper limit on the Bayes error (Bhattacharyya distance). In this paper we will focus on the former measure (scatter matrices), because the latter approach necessitates the estimation of probability distributions, which is a notoriously difficult endeavor.

A further statistical criterion to measure the separability between classes is
based on mutual information, which is defined as:

\[ I(X,Y) = \int \int p(X,Y) \log \left( \frac{p(X,Y)}{p(X)p(Y)} \right) dX dY \]  

(2)

where \( X \) and \( Y \) are two random variables, and \( p(X) \) and \( p(Y) \) their respective probability density functions. In this paper we compute mutual information between data points \( X \) and classes \( C \). A large value of mutual information in this case means that we have much information about the class \( C \) given the observation \( X \). On the other hand, if the mutual information is zero, then both variables are independent. Notice that the computation of mutual information also necessitates the estimation of corresponding probability distributions. However, Torkkola [13] recently proposed a method which makes the computation of mutual information feasible by using a quadratic divergence measure that allows an efficient non-parametric implementation, without prior assumptions about class densities. More concretely, his approximation is inspired by the quadratic Renyi entropy, and the method can be used with training data sets of the order of tens of thousands of samples.

### 2.3 Discriminant Analysis

Classic discriminant analysis techniques have often been applied to linear feature extraction in order to find the projection matrix that preserves the class separability of data points. Typically, two kind of statistics have been used for this purpose: (i) the within class scatter matrix that shows the scatter of samples around the same class, and (ii) the between class scatter matrix.

In order to formulate a criterion for class separability, each matrix has to be reduced to a single and unique number. This number should be large when the between class scatter is large – or when the within class variation is small. Several ways for computing the number have been defined in the literature:

\[ J_1 = \text{trace}(S_2^{-1}S_1) \]  

(3)

\[ J_2 = \ln |S_2^{-1}S_1| \]  

(4)

\[ J_3 = \frac{\text{trace}(S_1)}{\text{trace}(S_2)} \]  

(5)

In the classic feature extraction literature the \( J_1 \) criterium is used, given that it can be maximized using a closed formulation. The general technique to get the job done is known as Fisher Linear Discriminant Analysis (FLD) [14], and
uses as \( S_1 \):

\[
S_B = \frac{1}{K} \sum_{k=1}^{K} (m_k - m_0)(m_k - m_0)^T
\]

(6)

where \( m_k \) is the class-conditional sample mean and \( m_0 \) is the unconditional (global) sample mean. Furthermore, for \( S_2 \):

\[
S_W = \frac{1}{K} \sum_{k=1}^{K} S_k
\]

(7)

where \( S_k \) is the class-conditional covariance matrix for \( C_k \) estimated from the data.

The main problem with the classical FLD approach is that the optimization of the criterion (3) using \( S_B \) and \( S_W \) is blind for anything beyond second order statistics. As a consequence, it may be inaccurate for measuring separability of more complex structures. To remedy, Fukunaga and Mantock [15] propose to use a non-parametric estimated between-class scatter matrix \( S_B \), which has generally a full rank. This estimation was used in the non Parametric Discriminant Analysis algorithm (NDA), which has been shown to considerable improve the accuracy of the classic FLD. In a nutshell, the non parametric between class scatter matrix is estimated as follows.

Let \( x \) be a data point in \( X \) with class label \( C_j \), and by \( x_{\text{class}} \) the subset of the \( k \) nearest neighbors of \( x \) among the data points in \( X \) with class labels different from \( C_j \). We calculate a local between-class matrix for \( x \) as:

\[
\Delta^x_B = \frac{1}{k-1} \sum_{z \in x_{\text{class}}} (z - x)(z - x)^T
\]

(8)

The estimate of the between-class scatter matrix \( S_B \) is found as the average of the local matrices

\[
S_B = \frac{1}{N} \sum_{x \in X} \Delta^x_B
\]

(9)

The resulting \( S_B \) is used in the criterion (3) as the new \( S_1 \).

3 Results

We used the three separability measures described in the previous section (FLD, NDA and MI) for evaluating the recognition performance as a function
of image size. To this end, 20 subjects were randomly selected, with each of the subjects having more than 25 images to compute the different geometrical and statistical measures described above. All numerical experiments were carried out with the original image set, and a second image set obtained by applying Weber-filtering [10]. In this way we were able to address how our results depend on the presence of low spatial frequencies in the down-sized images.

Figures 5, 6, and 7 show the dependence of the FLD (Fisher Linear Discriminant Analysis), NDA (non Parametric Discriminant Analysis), and MI (mutual information) measures, respectively, on image size. Each of the three measures reveals a distinct maximum at approximately the same image size (around 22 × 22 pixels). As one can appreciate from the sample images shown in Figure 4, this image size translates to roughly 8 to 10 cycles per face, what compares favorably to the psychophysical results as described in the introduction. The recognition performance (in terms of discriminability) also reveals some dependency on whether the original images are used, or whether the face images were Weber-filtered. Specifically, the maxima show a trend to get more pronounced with Weber-filtering. At the same time, the amplitudes of NDA and MI (but not FLD) grow, indicating an increased recognition performance when only a small band of spatial frequencies is used. This behavior of our artificial face recognition system is also consistent with corresponding psychophysical observations with humans – the bandwidth for face recognition was estimated to be around two octaves (e.g., [7]).

Fig. 4. Examples at image sizes which are associated with maximum discrimination. (22 × 22). The image sizes translate to approximately 5−8 cycles per face width, and 6−12 cycles per face height, and are thus within the ballpark of the corresponding psychophysical data. Notice that here the re-sized original images are shown (i.e., without application of the Blackman-Harris window) to achieve a better visibility.

4 Summary and Conclusions

Psychophysical studies suggest that for face recognition, human observers make use of a narrow band at low spatial frequencies (10 to 15 cycles per face, bandwidth two octaves). Here, we evaluated the recognition performance of an artificial face recognition system as a function of image size. Recognition performance was measured by three different measures (Fisher Linear Discriminant Analysis, non Parametric Discriminant Analysis, and mutual informa-
Fig. 5. FLD (Fisher Linear Discriminant Analysis) Measure. Left plot shows results with the original images, right plot with Weber-filtered images.

Fig. 6. NDA (non Parametric Discriminant Analysis) Measure. Left plot shows results with the original images, right plot with Weber-filtered images.

which all indicated a performance maximum of the artificial system at an image size of about $22 \times 22$ pixels. This corresponds to spatial frequencies at around $8 - 10$ cycles per face, thus comparing well to the range of measured psychophysical data (although the psychophysical data are somewhat underestimated). We also found an effect of the presence of low spatial frequencies in the image. Recognition performance seems to even increase when low spatial frequencies are suppressed by Weber-filtering. In other words, decreasing the bandwidth of the spectrum of spatial frequencies in the face images increases the recognition performance, at least when measured by non Parametric Discriminant Analysis and mutual information. Such behavior is again in line with the narrow band of critical spatial frequencies found psychophysically.

The present study furthermore lends further support to the findings of Keil [9] in that the stimuli (i.e., face images) provide the explanation of the pref-
ference of a narrow spatial frequency band for both human and artificial face recognition. As a consequence, artificial face recognition systems should focus on these frequencies to achieve an optimal recognition performance (in terms of class separability). Because this critical spatial frequencies correspond to small image patches, a further advantage is an economic use of resources for both processing and storing faces.

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