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Low-level image properties in facial expressions

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ABSTRACT

We studied low-level image properties of face photographs and analyzed whether they change with different emotional expressions displayed by an individual. Differences in image properties were measured in three databases that depicted a total of 167 individuals. Face images were used either in their original form, cut to a standard format or superimposed with a mask. Image properties analyzed were: brightness, redness, yellowness, contrast, spectral slope, overall power and relative power in low, medium and high spatial frequencies. Results showed that image properties differed significantly between expressions within each individual image set. Further, specific facial expressions corresponded to patterns of image properties that were consistent across all three databases. In order to experimentally validate our findings, we equalized the luminance histograms and spectral slopes of three images from a given individual who showed two expressions. Participants were significantly slower in matching the expression in an equalized compared to an original image triad. Thus, existing differences in these image properties (i.e., spectral slope, brightness or contrast) facilitate emotion detection in particular sets of face images.

1. Introduction

In psychological experiments, emotional face images are frequently used to investigate emotion processing. Neurophysiological studies showed first ERP modulations in visual areas for different emotional expressions around 100 ms after stimulus onset in some cases (e.g., Batty & Taylor, 2003; Hinojosa, Mercado, & Carretié, 2015; Holmes, Nielsen, & Green, 2008). Short reaction times in the detection of facial expressions (e.g., Bannerman, Milders, de Gelder, & Sahraie, 2009; Bayle, Schoendorff, Hénaff, & Krolak-Salmon, 2011; Calvo & Esteves, 2005) further corroborate the conclusion of fast processing of emotional faces. These early effects might not only be triggered by configural characteristics or semantic content but also by low-level image properties. In some cases (e.g., visual search with short exposure times), observers might use these low-level cues for detecting a particular expression (cf., Purcell & Stewart, 2006; Purcell, Stewart, & Skov, 1996). For example, in continuous flash-suppression experiments, faces with a fearful expression were detected faster than those with other expressions, and this effect was solely driven by low-level image properties (Gray, Adams, Hedger, Newton, & Garner, 2013; Hedger, Adams, & Garner, 2015). Additionally, an ERP study showed that besides veridical faces also so-called hybrid faces (low spatial frequency image of an emotionally expressive face superimposed on a high spatial frequency image of a neutral face) affect emotion-related as well as face-related early components (Prete, Capotosto, Zappasodi, Laeng, & Tommasi, 2015). Thus, the knowledge of low-level image properties of emotional faces and their relevance for the perception of facial expressions is of interest.

Processing in the human visual system involves spatial frequency (SF) filtering (De Valois & De Valois, 1980; Westheimer, 2001). Consequently, effects of SF content on face perception were reported (e.g., Blickhan, Kaufmann, Denzler, Schweinberger, & Redies, 2011; Goffaux, Hault, Michel, Vuong, & Rossion, 2005; Menzel, Hayn-Leichsenring, Langner, Wiese, & Redies, 2015). It has been shown that humans preferentially rely on different SF bands for the recognition of distinct facial expressions (e.g., Comfort, Wang, Benton, & Zana, 2013; Smith & Schyns, 2009). In fact, a large number of studies investigated the (order of) SF information used in facial expression processing (e.g., De Cesarei & Codispoti, 2013; Smith, Cottrell, Gosselin, & Schyns, 2005; Vuilleumier, Armony, Driver, & Dolan, 2003; Willenbockel et al., 2010). However, little is known about how photographs of facial expressions differ in their SF content. A study by Hedger et al. (2015) underlines the importance of stimulus properties in the interpretation of experimental findings. They compared the effective contrast of both

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fearful and neutral faces and found that the two types of emotions differed in most databases investigated. Moreover, this difference explains the advantage of fearful faces.

Besides the SF content of the images, other properties are assumed to influence expression recognition because they are encoded early in the visual system and are already known to affect the evaluation of faces. These properties include contrast (Russell, 2003, 2009), color (Stephen, Oldham, Perrett, & Barton, 2012; Young, Elliot, Feltman, & Ambady, 2013) and spectral slope (Blickhan et al., 2011; Menzel et al., 2015).

Although the existence of differences in low-level image properties between photographs of distinct facial expressions might seem trivial to the reader, the field lacks a systematic investigation of such differences. For non-face image databases that are frequently used in studies on emotion, it has been shown that differences in image properties exist and that they might affect affective responses (Juricevic, Land, Wilkins, & Webster, 2010; Lakens, Fockenberg, Lemmens, Ham, & Midden, 2013; Spehar et al., 2015). However, for face databases, there has been no comprehensive investigation on how image properties differ between depicted facial expressions and whether these differences affect perception. Therefore, we investigated low-level image properties of standardized high-quality photographs from three databases depicting emotional faces.

As a first step, we investigated effects of expression on image properties within a given dataset. Second, we studied the overall effects of expression across databases. Third, we investigated experimentally whether the naturally occurring differences in image properties facilitate the processing of emotional expressions in a matching paradigm.

2. Study 1

2.1. Materials and methods

2.1.1. Stimuli

We used photographs from three different databases that depict Caucasian faces with different expressions (Fig. 1): FACES (Ebner et al., 2010), KDEF (Lundqvist, Flykt, & Öhman, 1998) and Radboud Faces database (Langner et al., 2010). From FACES, we used images of one specific set (Set a; Ebner et al., 2010) depicting young individuals (19–31 years old). Moreover, we discarded obviously overexposed and blurred images from the KDEF database. In total, we used 1141 images from 167 individuals. Table 1 shows the number of images and individuals, and lists the expressions displayed in the images. Three different versions of each image were used (Fig. 1): original (ORI), square cut from hair line to chin (CUT) and CUT images covered behind an oval mask to hide external features (MCUT; identical mask for all images). ORI images were resized by bicubic interpolation to 512 pixels height and a width of 410, 378 or 341 pixels, for FACES, KDEF or Radboud, respectively; and CUT as well as MCUT images were resized to 256 × 256 pixels, respectively. For Fourier transformation (see below), ORI images were extended to a square by padding with black bars (Fig. 1I). In total, we analyzed 3423 images.

2.1.2. Measurement of image properties

For luminance, redness and yellowness, we calculated mean pixel values for the L, a and b channel, respectively, of the Lab color space using Matlab®. We determined the image contrast as the standard deviation of the mean pixel values from greyscale images using ImageJ (note that for MCUT images only the oval cut-out was considered).

Images were converted to grey-scale using the Adobe Photoshop® CS5 program, followed by measuring the SF content of the images. Fourier slope, overall power and relative power in the low SF range (LSF; < 8 cycles/image), medium SF range (MSF; 8–24 cycles/image) and high SF range (HSF; > 24 cycles/image) were calculated using a script custom-written in Python®. For a detailed description of the Fourier transformation and slope determination, see Redies, Hänisch, Blickhan, and Denzler (2007). In brief, overall power was measured over the entire frequency range. Spectral slope was calculated between 10 and 127/255 cycles/image for the two image sizes, respectively, similarly to previous studies (Menzel et al., 2015; Redies et al., 2007). Because we excluded the low-frequency range (< 10 cycles/image), the changes in spectral slope do not represent modulations of relative power between the LSF, MSF and HSF ranges, but represents relative signal power within the MSF and HSF ranges. Relative power was determined by dividing the power of each frequency range (LSF, MSF and HSF, respectively) by the overall power of the image. Thresholds for the spatial frequency ranges in the present study were similar to those used in previous studies (e.g., Delplanque, N'Diaye, Scherer, & Grandjean, 2007; Kumar & Srinivasan, 2011; Schyns & Oliva, 1999; Vuilleumier et al., 2003).

2.1.3. Statistical analysis

First, to reveal differences within a given image set, we ran repeated-measures ANOVAs with expression as a within-subjects factor and gender as a between-subjects factor for each database and image manipulation separately. Data for each image set were centered. In case of a violation of the sphericity assumption, Greenhouse-Geisser-corrected *p*-values were considered.

Second, to investigate overall effects of expression on image properties across the three databases, we calculated mixed-effects models in R using the lme function from the nlme package (Pinheiro, Bates, Debroy, Sarkar, and R Core Team, 2015; R Core Team, 2015). Since we were interested in changes of the face and not the surroundings (e.g., amount of visible hair), we used only the image version MCUT for these analyses. We considered only the six expressions common to all three databases (angry, disgusted, fearful, happy, neutral and sad). Thus, 994 images from 167 individuals (84 male) entered the analyses. Extreme values for each measure within a database were removed using the Tukey criterion (Tukey, 1977; this procedure resulted in six data points excluded for contrast and two for overall power). Data for each database were then standardized with a mean of zero and standard deviation of one. We ran mixed-effects models for each image property separately. For each run, we included a nested database-individual random effect to account for different variation between databases and to account for correlation within database concerning the expression. Expression and gender as well as the interaction between the two, and two-way- and three-way interactions with database were included as fixed factors. We applied the method of maximum log-likelihood. Each final model was determined by stepwise backward selection based on the Akaike information criterion (AIC). We report *F*-test statistics for the fixed factors in the final model. Post-hoc *p*-values were adjusted by the Tukey method. For all analyses reported here, *p*-values smaller than 0.05 were considered significant.

2.2. Results

The repeated-measures ANOVAs revealed significant effects for image properties in each of the image subsets (Table 2). Thus, facial expression affected image properties in a given image set.

To investigate whether the differences of image properties between the expressions were similar across databases, we calculated mixed-effects models for each image property for the MCUT version of the images. For all investigated measures, we found a significant main effect of expression and interaction of expression and database (Table 3, Fig. 2). Moreover, we found a main effect of gender for the following measures: the a-channel, indicating that male faces led to more reddish images ($F(1, 165) = 7.16$, $MSE = 0.13$, $p = .0082$) and the spectral slope, indicating that images of female faces possessed a steeper slope ($F(1, 163) = 25.05$, $MSE = 0.37$, $p < .0001$). Within the databases, gender affected the spectral slope ($F(2, 163) = 4.00$, $MSE = 0.37$, $p = .0201$) differentially. Additionally, the interaction of expression and gender was significant for contrast ($F(5, 799) = 4.08$, $MSE = 0.15$,