Expression-dependent susceptibility to face distortions in processing of facial expressions of emotion

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Abstract

Our capability of recognizing facial expressions of emotion under different viewing conditions implies the existence of an invariant expression representation. As natural visual signals are often distorted and our perceptual strategy changes with external noise level, it is essential to understand how expression perception is susceptible to face distortion and whether the same facial cues are used to process high- and low-quality face images. We systematically manipulated face image resolution (experiment 1) and blur (experiment 2), and measured participants' expression categorization accuracy, perceived expression intensity and associated gaze patterns. Our analysis revealed a reasonable tolerance to face distortion in expression perception. Reducing image resolution up to 48×64 pixels or increasing image blur up to 15 cycles/image had little impact on expression assessment and associated gaze behaviour. Further distortion led to decreased expression categorization accuracy and intensity rating, increased reaction time and fixation duration, and stronger central fixation bias which was not driven by distortion-induced changes in local image saliency. Interestingly, the observed distortion effects were expression-dependent with less deterioration impact on happy and surprise expressions, suggesting this distortion-invariant facial expression perception might be achieved through the categorical model involving a non-linear configural combination of local facial features.

Keywords: Facial expression; image resolution; image blur; expression categorization; expression intensity; gaze behaviour

1. Introduction

The ability of perceiving and interpreting other people's facial expressions of emotion plays a crucial role in our social interactions, and we are reasonably good at recognizing common facial expressions that represent our typical emotional states and are associated with distinctive pattern of facial muscle movements, such as happy, sad, fear, anger, disgust and surprise (Ekman & Friesen, 1976; Ekman & Rosenberg, 2005), even when these expressive faces appear under very different viewing conditions. For instance, varying face image size to mimic viewing distance in typical social interactions (ranging from arm's length to 5 m; Guo, 2013) or changing face image viewpoint from full frontal view to mid-profile or profile view (Matsumoto & Hwang, 2011; Guo & Shaw, 2015) has little impact on our categorization accuracy of common facial expressions, suggesting the existence of an invariant facial expression representation in our visual system (within given limits) that would be useful for efficient face perception and advantageous to our social interactions.

In addition to view distance and viewpoint, the quality of face image is another common variable we often experience in face perception. Broadly, our visual inputs are not always clean and free of distortions. For instance, we often need to select, extract and process visual information from a noisy environment (e.g., due to rain, snow, fog). Ageing will also decrease optical quality and certain treatments such as refractive surgery will induce significant optical aberrations. Furthermore, the digitized images and videos we view daily (via TV, computer screen, mobile phone, etc.) are subject to a variety of distortions during acquisition, compression, storage, transmission and reproduction (Sheikh, Bovik, & de Veciana, 2005). Any of these causes can result in a degradation of visual quality, typically represented as blurred (e.g., out-of-focus, foggy or raining weather) and low-resolution visual inputs (e.g. images taken by CCTV and mobile phone, or due to compression, denoising and data transmission errors). This raises the question as whether and how we adjust our perceptual processing strategy to compensate degraded visual inputs and maintain a relatively invariant facial expression categorization.

Considering that human visual system has evolved and/or learned over time to process visual signals embedded in natural distortions, it is reasonable to assume that we should have developed certain tolerance to degradation in image quality (Röhrbein, Goddard, Schneider, James, & Guo, 2015). Indeed, psychophysical and computational studies have demonstrated that we could essentially classify natural scenes or understand scene gist in low-resolution (up to 16 × 16 pixels depending on image complexity) or blurred images (e.g., Castelhano & Henderson, 2008; Torralba, 2009; Watson & Ahumada, 2011). For expressive face images, recent behavioural studies have shown that our expression recognition accuracy remained quite consistent until the image resolution was reduced to around 15 × 10 pixels, in which almost no useful local facial information was left for visual analysis (Johnston, McCabe, & Schall, 2003; Du & Martinez, 2011). However, it is unclear to what extent this 'invariant' facial expression recognition is affected by different types of image distortions, such as image blur. As different facial expressions use different diagnostic spatial frequency bands to transmit expressive facial cues (Smith & Schyns, 2009), image blur may have different impact on expression recognition performance as image resolution. It is also unclear whether the perceived expression intensity, an integral part of expression perception which could lead to changes in behavioural emotional responses (e.g., we may respond differently to the perceived angry expression in low- vs high-intensity), is also invariant across the change of face image qualities (e.g., the visibility of facial musculature patterns and local facial features may vary according to image quality, and subsequently affect the perceived intensity for a given expression), and whether the same diagnostic visual cues in low- and high-quality face images are used for expression perception.

Previous eye-tracking research on the effect of image distortion on scene-viewing gaze allocation has generated inconsistent findings. While some studies have suggested that we might use the same diagnostic visual cues in low- and high-resolution scenes (e.g., the location of fixations on low-resolution images tended to be similar to and predictive of fixations on high-resolution images; Judd, Durand, & Torralba, 2011), other studies have observed that viewing of noisy images (e.g., applying masking, low- or high-pass spatial frequency filters to different image regions) was associated with shorter saccade distances, longer fixation durations and stronger central fixation bias (Loschky & McConkie, 2002; van Diepen & d'Ydewalle, 2003; Nuthmann, 2013; Röhrbein et al., 2015), indicating scene-viewing gaze allocation may change with image distortion.

When viewing expressive faces, we tend to scan all key internal facial features (i.e. eyes, nose, and mouth) to extract and then integrate emotional featural cues in order to reliably categorize facial expressions (Guo, 2012, 2013), but look more often at local facial regions that are most characteristic for each facial expression, such as mouth in happy faces and eyes in angry faces (Jack, Blais, Scheepers, Schyns, & Caldara, 2009; Eisenbarth & Alpers, 2011; Schurgin et al., 2014). If this pattern of gaze distribution is tightly coupled with expression categorization performance, then the image quality-invariant expression perception would suggest consistent gaze pattern across different face image distortions. If, on the other hand, this pattern of gaze distribution could be dissociated with expression categorization performance, then face distortion might significantly affect our face-viewing gaze allocation.

In separate eye-tracking experiments with a self-paced expression categorization task, we systematically investigated our perceptual sensitivity (categorization accuracy, perceived expression intensity, and reaction time) to face image resolution and blur. We aimed to examine the extent to which (1) expression perception is invariant across different degrees and types of face distortions, (2) there is a tight correspondence between specific gaze allocation and expression recognition performance.

2. Experiment 1: Effect of image resolution on facial expression categorization

2.1. *Methods*

Twenty-six undergraduate students (12 male, 14 female), age ranging from 18 to 23 years old with the mean of 19.85 ± 0.29 (Mean ± SEM), volunteered to participate in this study. This sample size is compatible with previous studies in this area (e.g., Jack et al., 2009; Guo, 2012, 2013). All participants had normal or corrected-to-normal visual acuity. The Ethical Committee in School of Psychology, University of Lincoln approved this study. Written informed consent was obtained from each participant, and all procedures complied with the British Psychological Society Code of Ethics and Conduct, and were in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki).

The general experimental setup and testing procedure has been described in our previous publications (e.g., Guo & Shaw, 2015; Green & Guo, 2017). Briefly, digitized grey-scale face images in full frontal view were presented through a ViSaGe graphics system (Cambridge Research Systems, UK) and displayed on a non-interlaced gamma-corrected colour monitor (30 cd/m^2 background luminance, 100 Hz frame rate, Mitsubishi Diamond Pro 2070SB) with the resolution of 1024 × 768 pixels. At a viewing distance of 57 cm, the monitor subtended a visual angle of 40 × 30°.

Western Caucasian face images, consisting of four female and four male models, were selected from the Karolinska Directed Emotional Faces CD ROM (Lundqvist, Flykt, & Öhman, 1998). Each of these young adult models posed six common facial expressions (happy, sad, fearful, angry, disgusted, and surprised). Although they may have real-world limitations, and categorization performance for some expressions could be subject to culture influence, these well-controlled face images were chosen for their comparability and universality in transmitting facial expression signals, at least for our age-matched observer group (Western Caucasian young adults). The faces were processed in Adobe Photoshop to remove external facial features (e.g., hair), to ensure a homogenous grey background, and then to downsize to 384 × 512 pixels (referred as resolution 1). For each of these ‘resolution 1’ face images, three subsequent faces were constructed by further downsizing to 48 × 64 pixels (resolution 1/8), 24 × 32 pixels (resolution 1/16), 12 × 16 pixels (resolution 1/32). To provide a constant presentation size for all face images, the three downsized faces were scaled back to 384 × 512 pixels (14 × 19°) using bilinear interpolation, which preserves most of the spatial frequency components. As a result, 192 expressive face images were generated for the testing session (4 face resolutions × 6 expressions × 8 models, see Figure 1 for examples). These images were gamma corrected and displayed once in a random order during the testing to minimise the potential practice or carryover effects (e.g. exposing to the same face identity displaying the same expression in consecutive trials).

Figure 1. Examples of six common facial expressions (from left to right: happiness, sadness, fear, anger, surprise, disgust) at varying image resolutions (from top to bottom: resolution 1, resolution 1/8, resolution 1/16, resolution 1/32).

All of our participants were aware of universal facial expressions. Before the testing, they were shown a PowerPoint presentation containing one male and one female model posing happiness, sadness, fear, anger, disgust, and surprise (sampled from Pictures of Facial Affect), and were asked to label each facial expression as carefully as possible without time constraint. All of them could recognize these facial expressions or agree with the classification proposed by Ekman and Friesen (1976).

A self-paced task was used to mimic natural viewing condition. During the experiments the participants sat in a chair with their head restrained by a chin-rest, and viewed the display binocularly. To calibrate eye movement signals, a small red fixation point (FP, 0.3° diameter, 15 cd/m^2 luminance) was displayed randomly at one of 9 positions (3 × 3 matrix) across the monitor. The distance between adjacent FP positions was 10°. The participant was instructed to follow the FP and maintain fixation for 1 s. After the calibration procedure, the participant pressed the response box to initiate a trial. The trial was started with an FP displayed 10° left or right to the screen centre to minimize central fixation bias (Tatler, 2007). If the participant maintained fixation for 1 s, the FP disappeared and a face image was presented at the centre of the monitor. During the self-paced, free-viewing presentation, the participant was instructed to "categorize this facial expression as accurately and as quickly as possible", and to respond by pressing a button on the response box (for collecting reaction time data) with the dominant hand followed by a verbal report of the perceived facial expression (6-alternative forced choice: happiness, sadness, fear, anger, disgust, and surprise) and its intensity on a 9-point scale, in which 1 represents 'not expressive at all' and 9 represents 'extremely expressive'. No reinforcement was given during this procedure.

Horizontal and vertical eye positions from the self-reported dominant eye (determined through the Hole-in-Card test or the Dolman method if necessary) were measured using a Video Eyetracker Toolbox with 250 Hz sampling frequency and up to 0.25° accuracy (Cambridge Research Systems). The software developed in Matlab computed horizontal and vertical eye displacement signals as a function of time to determine eye velocity and position.

Fixation locations were then extracted from the raw eye-tracking data using velocity (less than 0.2° eye displacement at a velocity of less than 20°/s) and duration (greater than 50 ms) criteria (Guo, Mahmoodi, Robertson, & Young, 2006).

While determining fixation allocation within key internal facial features (i.e. eyes, nose, and mouth), a consistent criterion was adopted to define boundaries between local facial features for different faces (for details see Guo, Tunnicliffe, & Roebuck, 2010) to ensure equal size of individual internal feature across faces of different expressions from the same model. Specifically, the 'eye' region included the eyes, eyelids, and eyebrows; the 'nose' or 'mouth' region consisted of the main body of the nose (glabella, nasion, tip-defining points, alar-sidewall, and supra-alar crease) or mouth and immediate surrounding area (up to 0.5°). The division line between the mouth and nose regions was the midline between the upper lip and the bottom of the nose. Each fixation was then characterized by its location among feature regions and its time of onset relative to the start of the trial, and the number of fixations directed at each feature was normalized to the total number of fixations sampled in that trial.

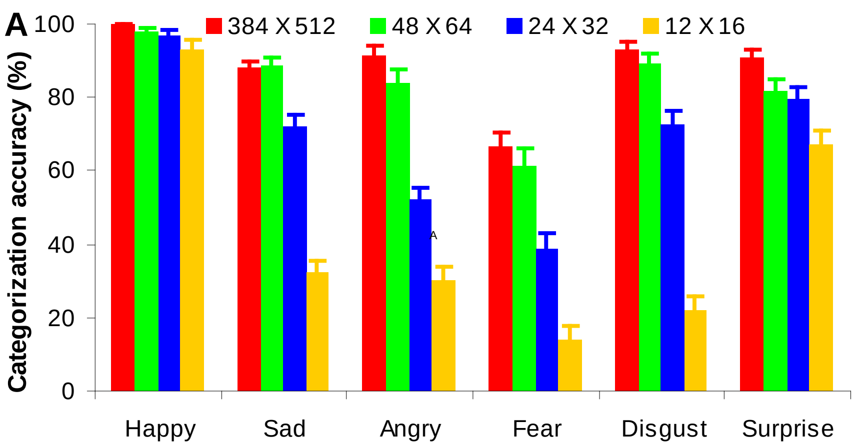
2.2. *Results and Discussion*

It is already well-established that humans show different perceptual sensitivities and gaze distributions in recognizing different categories of facial expressions (e.g., Palermo & Coltheart, 2004; Guo, 2012, 2013; Pollux, Hall, & Guo, 2014; Guo & Shaw, 2015). For instance, in comparison with other expressions, happy faces tend to be associated with higher categorization accuracy, shorter reaction time, and greater proportion of fixations directed at the mouth region. In this paper, we mainly report the effect of face image resolution on participants' behavioural performance and gaze patterns in expression categorization.

2.2.1. Analysis of behavioural responses in expression categorization

To examine the extent to which face image resolution affected our observers' ability of perceiving different facial expressions, we conducted 4 (face resolution) × 6 (expression type) repeated-measures analyses of variance (ANOVAs) with expression categorization accuracy, perceived expression intensity and reaction time as the dependent variables. For each ANOVA, Greenhouse–Geisser corrections were applied where sphericity was violated. Only significant main effect and interaction effect were reported.

For expression categorization accuracy (Fig. 2A), the analysis revealed significant main effect of face resolution (F(3,75) = 392.32, p < 0.001, η^2 = 15.69) and expression type (F(3.73,93.27) = 71.93, p < 0.001, η^2 = 2.88), and significant interaction between face resolution and expression type (F(8.32,207.93) = 21.18, p < 0.001, η^2 = 0.85). Although reducing face image resolution has decreased the averaged categorization accuracy across all facial expressions monotonically, it had different degrees of impact on different expression categories. Specifically, compared with categorization accuracy for expressions at the highest face resolution (resolution 1), our participants showed indistinguishable accuracy for happiness at other resolutions (Bonferroni correction for multiple comparisons, all *ps* > 0.05), reduced accuracy for surprise at the lowest resolution (resolution 1/32 *vs* resolution 1, p < 0.001; resolution 1/32 *vs* resolution 1/8 or 1/16, p > 0.05), and reduced accuracy for other expressions at resolution 1/16 and 1/32 (all *ps* < 0.01).



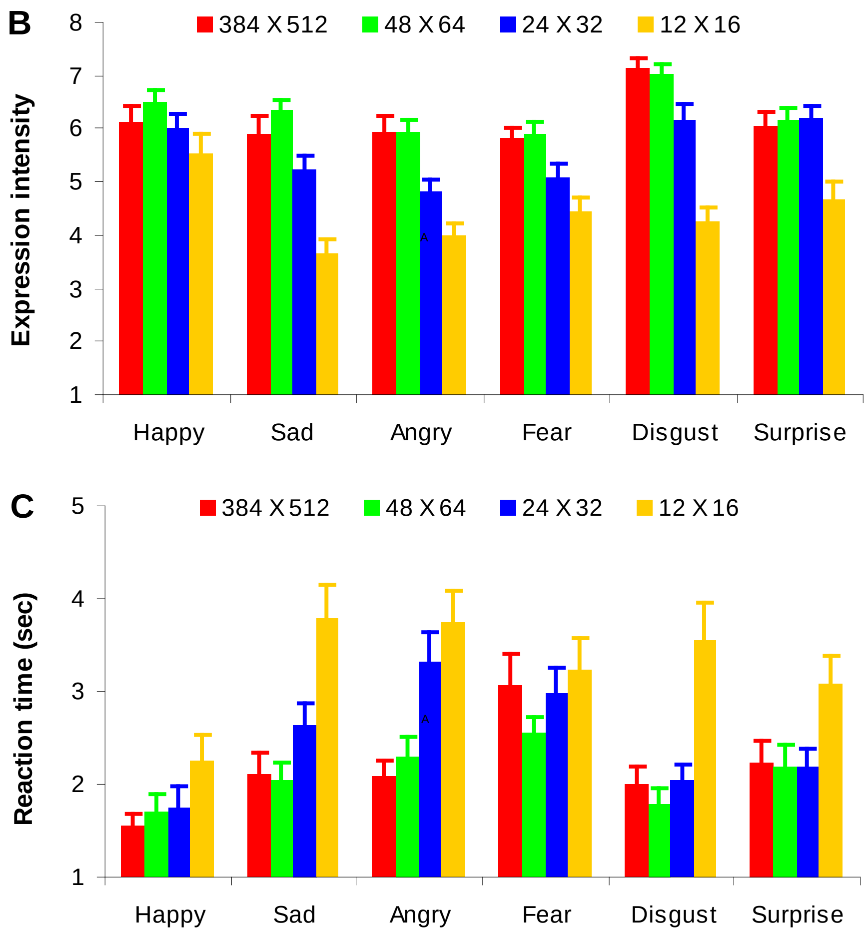


Figure 2. Mean expression categorization accuracy (A), perceived expression intensity (B) and reaction time (C) for expression judgement as a function of face image resolution. Error bars represent SEM. In general, reducing image resolution up to 48 × 64 pixels had little overall impact on expression judgement (categorization accuracy, intensity rating and reaction time), further resolution reduction led to decreased expression categorization accuracy and intensity rating, and increased reaction time.

The perceived expression intensity (Fig. 2B) was also significantly modulated by different face image manipulations (face resolution: $F(1.18,29.46) = 22.95$, $p < 0.001$, $\eta^2 = 0.92$; expression type: $F(3.18,79.58) = 31.67$, $p < 0.001$, $\eta^2 = 1.27$; face resolution × expression type: $F(8.09,202.21) = 13.05$, $p < 0.001$, $\eta^2 = 0.52$). Compared with faces at higher resolution (resolution 1 and 1/8), the perceived expression intensity across all facial expressions was significantly reduced for faces at lower resolution (resolution 1/16 and 1/32) (all *ps* < 0.01). Similar changes were also observed for individual expression category such as sad, anger, fear and disgust (all *ps* < 0.01). On the other hand, the perceived intensity was not affected by the tested face resolutions for happy expression (all *ps* > 0.05), and was only reduced for surprise expression at resolution 1/32.

The reaction time (Fig. 2C) was further significantly affected by face resolution ($F(1.74,43.58) = 34.17$, $p < 0.001$, $\eta^2 = 1.37$), expression type ($F(5,125) = 31.57$, $p < 0.001$, $\eta^2 = 1.26$), and their interactions ($F(4.89,122.2) = 5.51$, $p < 0.001$, $\eta^2 = 0.22$). Across all facial expressions, the reaction times were the fastest for faces at resolution 1 and 1/8 ($p = 1$), were slower for resolution 1/16 (all *ps* < 0.01), and were the slowest for resolution 1/32 (all *ps* < 0.01). For individual expressions, the reaction times were indistinguishable for fearful faces at different resolutions (all *ps* > 0.05), were slower for sad and angry faces at resolution 1/16 and 1/32 than resolution 1 and 1/8 (all *ps* < 0.01), and were only prolonged when detecting happy, disgust and surprise faces at resolution 1/32 (all *ps* < 0.01).

2.2.2. Analysis of gaze behaviour in expression categorization

We first examined to what extent face image resolution would affect the number of fixations participants needed to categorize different facial expressions, 4 (face resolution) × 6 (expression type) ANOVA with averaged number of fixations directed at each face as the dependent variables revealed significant main effect of face resolution ($F(1.9,47.54) = 6.34$, $p = 0.004$, $\eta^2 = 0.25$; Fig. 3A) and expression type ($F(5,125) = 41.46$, $p < 0.001$, $\eta^2 = 1.66$), and significant interaction effect ($F(8.22,205.53) = 3.98$, $p < 0.001$, $\eta^2 = 0.16$). Across all facial expressions, the faces at resolution 1/32 attracted slightly more number of fixations than those faces at resolution 1/8 and 1/16 (all *ps* < 0.01). For individual expression categories, happy, anger and disgust expressions attracted similar amount of fixations regardless of image resolutions (all *ps* > 0.05), whereas sad, fear and surprise expressions attracted more fixations when presented at resolution 1/32 than at other resolutions (all *ps* < 0.01).

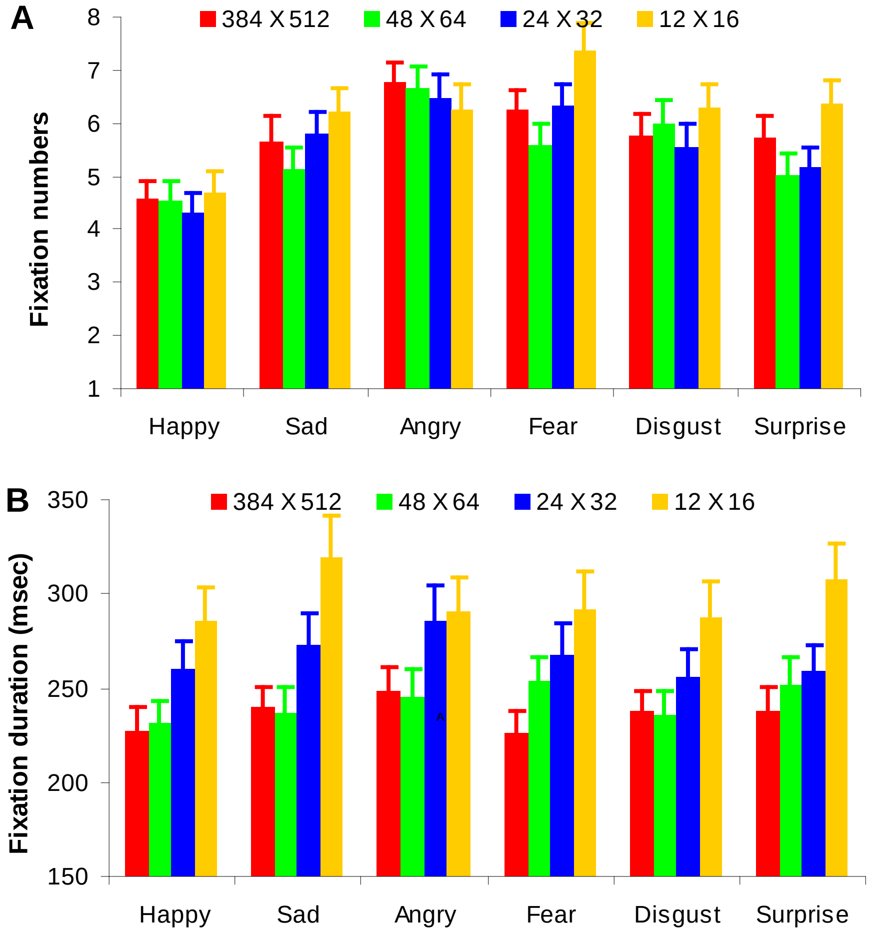


Figure 3. Average number of fixations (A) and average fixation duration across all fixations (B) directed at the expressive face as a function of face image resolution. Error bars represent SEM. Across all expressions, low-resolution images (24×32, 12×16 pixels) tended to attract more fixations with longer durations.

Previous studies have indicated that the mean fixation duration of each single fixation is associated with the target discriminability or the amount of information needed to be processed from the fixated region (e.g., Guo et al., 2006; Röhrbein et al., 2015). The reduced visibility of facial features in the degraded faces may increase local facial information ambiguity and consequently lead to longer fixation duration. This possibility was examined by a 4 (face resolution) × 6 (expression type) ANOVA with the averaged fixation duration across all fixations directed at each face as the dependent variables. The analysis revealed significant main effect of face resolution ($F(1.53,38.21) = 26.48$, $p < 0.001$, $\eta^2 = 1.06$; Fig. 3B) and expression type ($F(3.48,86.88) = 3.59$, $p = 0.01$, $\eta^2 = 0.14$). Across all the expressions, faces at resolution 1/32 attracted the longest fixation duration, followed by faces at resolution 1/16, and then at resolution 1/8 and 1 (all *ps* < 0.01). To correct for the longer reaction time associated with categorizing expressions at lower image resolutions (Fig. 2C), fixation rate (number of fixations per second) was also compared across the face resolutions. In comparison with faces at resolution 1 (3.03 ± 0.12) and resolution 1/8 (2.96 ± 0.13), fixation rate was significantly decreased at resolution 1/16 (2.61 ± 0.13) and was the lowest at resolution 1/32 (2.19 ± 0.12) ($F(3,75) = 74.83$, $p < 0.001$, $\eta^2 = 2.99$).

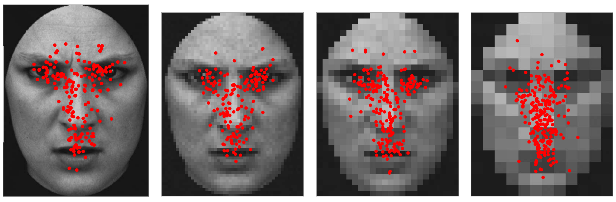


Figure 4. Example of overall face-viewing fixation distribution on an angry face in different image resolutions. The red dots within each face image indicate the position of each fixation sampled during this face-viewing trial across all human participants.

It seems that across all the expressions, reducing face image resolution significantly increased the number of fixations directed at the expressive faces (Fig. 3A) and individual fixation durations (Fig. 3B). We then examined detailed fixation distribution (see Fig. 4 for an example) to determine which facial features participants attended frequently when categorizing and rating expressions across different image resolutions. 3 (face region) × 4 (face resolution) × 6 (expression type) ANOVA with the proportion of fixations directed at each face region as the dependent variables revealed significant face region effect ($F(2,50) = 36.98$, $p < 0.001$, $\eta^2 = 1.48$) and interaction effects (face region × expression type: $F(6.12,152.94) = 17.5$, $p < 0.001$, $\eta^2 = 0.7$; face resolution × face region: $F(3.78,94.61) = 65$, $p < 0.001$, $\eta^2 = 2.6$; face resolution × face region × expression type: $F(30,750) = 2.04$, $p = 0.001$, $\eta^2 = 0.08$). No other significant main and interaction effects were found.

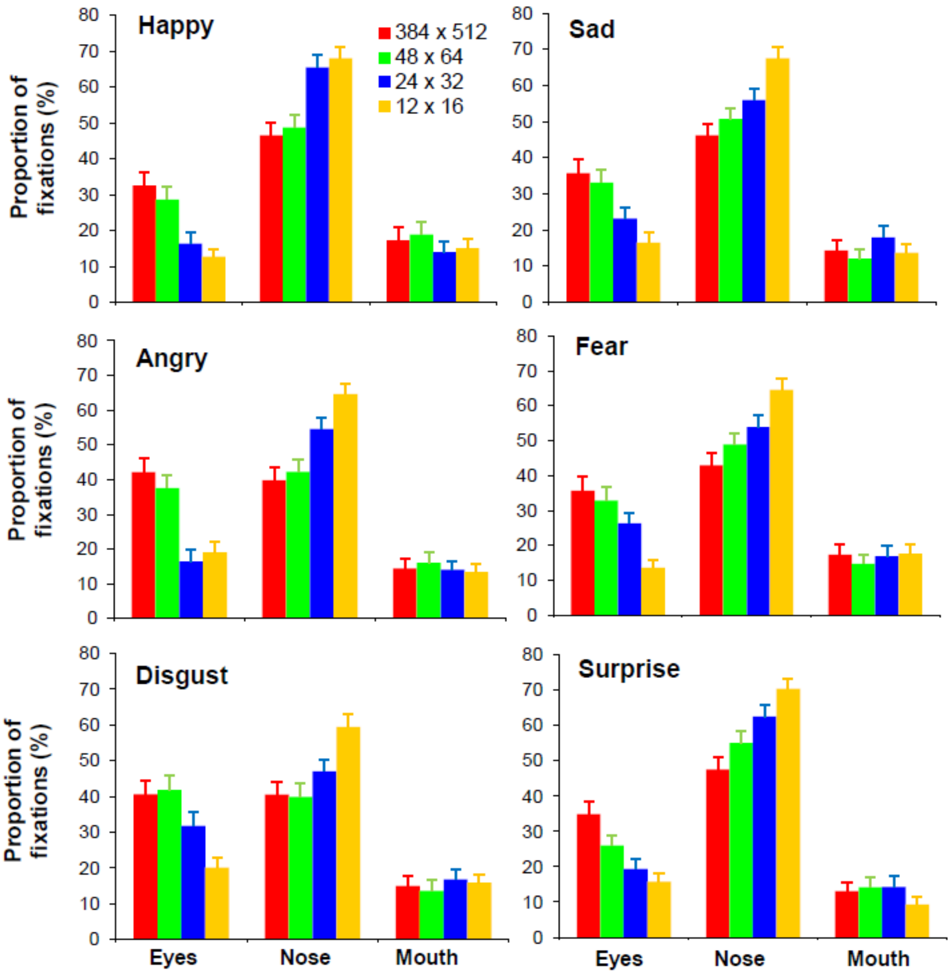


Figure 5. Proportion of fixations directed at the eyes, nose, and mouth regions when categorizing different facial expressions with varying face image resolutions. Error bars represent SEM. In general, reducing image resolution up to 48 × 64 pixels had little impact on face-viewing fixation distribution, further resolution reduction led to stronger central fixation bias at the nose region.

Regardless of facial expressions, in comparison with faces at resolution 1, faces at resolution 1/32 tended to attracted fewer fixations allocated at the eye region (all *ps* < 0.01; Fig. 5), more fixations at the nose region (all *ps* < 0.01), and similar amount of fixations at the mouth region (all *ps* > 0.05). The degree of such fixation allocation shift from the eyes to nose, however, was dependent upon expression type and face resolution. For surprise expression, reducing face image resolution from 1 to 1/32 led to a gradual decline of fixations at the eyes but a gradual increase of fixations at the nose (all *ps* < 0.01). For other expressions, image resolution 1 and 1/8 induced the same pattern of face-viewing gaze distribution (all *ps* > 0.05). However, for sad, fear and disgust expressions, reducing resolution from 1/8 to 1/32 led to a gradual decrease of fixations at the eyes but an increase at the nose (all *ps* < 0.01). For happy expression, although resolution 1/16 and 1/32 induced similar fixation allocation shift from the eyes to nose, there was no significant difference in gaze distribution between these two resolutions (all *ps* > 0.05). For angry expression, on the other hand, reducing resolution from 1/16 to 1/32 led to an increase of fixations at the nose ($p < 0.01$) but no change at the eyes ($p > 0.05$).

3. Experiment 2: Effect of image blur on facial expression categorization

The study in Experiment 1 has indicated that our visual system seems to have a reasonable tolerance to the change of face image resolutions. In general, reducing image resolution up to 48 × 64 pixels had little impact on the expression categorization accuracy and perceived expression intensity. Although face images with the lowest resolution (12 × 16 pixels) had induced an increased reaction time and decreased expression intensity rating, our participants still demonstrated well-above chance categorization accuracy for happy and surprise expressions. For the associated face-viewing gaze behaviour, reducing image resolution led to longer fixation duration and stronger central fixation bias (i.e. more fixations were diverted from the eye region and were allocated at the nose region). Furthermore, this image resolution-induced change in gaze allocation seemed to be coincided with the change in expression categorization performance (expression accuracy and intensity judgements), suggesting a potential link between expression perception and face-viewing gaze behaviour.

In addition to image resolution (e.g., viewing face pictures on low-quality CCTV or mobile device), image blur is another common variant in natural distortion (e.g., viewing faces in the distance or in the visual periphery). As different distortion processes may disturb natural image statistics to different degrees (Sheikh et al., 2005) and hence attract attention away from local regions that are salient in undistorted images, it is plausible that in comparison with image resolution, image blur might demonstrate different impact on facial expression perception and associated gaze allocation. Furthermore, it has been argued that proximal (e.g., fear, sadness) and distal expressions (e.g., happiness, surprise) may use different diagnostic spatial frequency bands to transmit expressive facial cues (Smith & Schyns, 2009), and consequently might show different susceptibilities to image blur. These possibilities were systematically examined in Experiment 2.

3.1. *Methods*

Nineteen undergraduate students (9 male, 10 female), age ranging from 20 to 25 years old with the mean of 20.63 ± 0.3, volunteered to participate in this study. All participants had normal or corrected-to-normal visual acuity. The Ethical Committee in School of Psychology, University of Lincoln approved this study. Written informed consent was obtained from each participant, and all procedures complied with the British Psychological Society Code of Ethics and Conduct.

Expressive face images were selected from the same eight models used in Experiment 1 (six common facial expressions per model). The faces were processed in Adobe Photoshop to remove external facial features (e.g., hair), to ensure a homogenous grey background, and then to downsize to 384 × 512 pixels (14.76 × 19.69°). For each of these processed face images, three subsequently blurred faces were constructed by decomposing the 'original' face into three nonoverlapping spatial frequency bandwidths of one octave each (30–15, 15–7.5, and 7.5–3.8 cycles/image; Smith, Cottrell, Gosselin, & Schyns, 2005). As a result, 192 expressive face images were generated for the testing session (4 face blurs × 6 expressions × 8 models, see Figure 6 for examples). The experimental setup, testing procedure, participant task instruction, data acquisition and analysis protocol were the same as those used in Experiment 1.

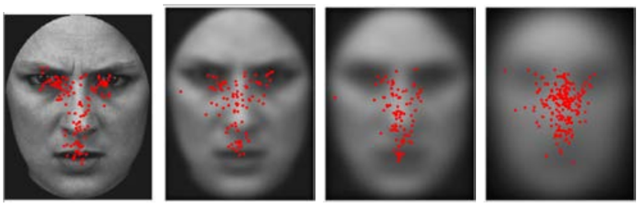


Figure 6. Examples of an angry expression at varying image blurs (from left to right: original face, three blurred faces with spatial frequency bandwidths of 30–15, 15–7.5 and 7.5–3.8 cycles/image) and overall face-viewing fixation distribution on these faces. The red dots within each face indicate the position of each fixation sampled during this face-viewing trial across all human participants.

3.2. *Results and Discussion*

3.2.1. Analysis of behavioural responses in expression categorization

To examine the extent to which the face image blur affected our expression categorization performance, we conducted 4 (face blur) × 6 (expression type) ANOVAs with expression categorization accuracy, perceived expression intensity and reaction time as the dependent variables. For expression categorization accuracy (Fig. 7A), the analysis revealed significant main effects of face blur ($F(3,54) = 271.43$, $p < 0.001$, $\eta^2 = 15.08$) and expression type ($F(5,90) = 94.69$, $p < 0.001$, $\eta^2 = 5.26$), and significant interaction effect ($F(5.99,107.77) = 10.71$, $p < 0.001$, $\eta^2 = 0.60$). Across all expressions, participants showed indistinguishable categorization accuracy between original faces and faces with 30–15 cycles/image bandwidth ($p = 0.07$), but decreased accuracy for faces with 15–7.5 cycles/image bandwidth and the lowest accuracy for faces with 7.5–3.8 cycles/image bandwidth (all *ps* < 0.01). The same trend for the change of categorization accuracy was also observed for individual expression categories except for happy expression, in which only faces with 7.5–3.8 cycles/image bandwidth had a reduced categorization accuracy (all *ps* < 0.01).

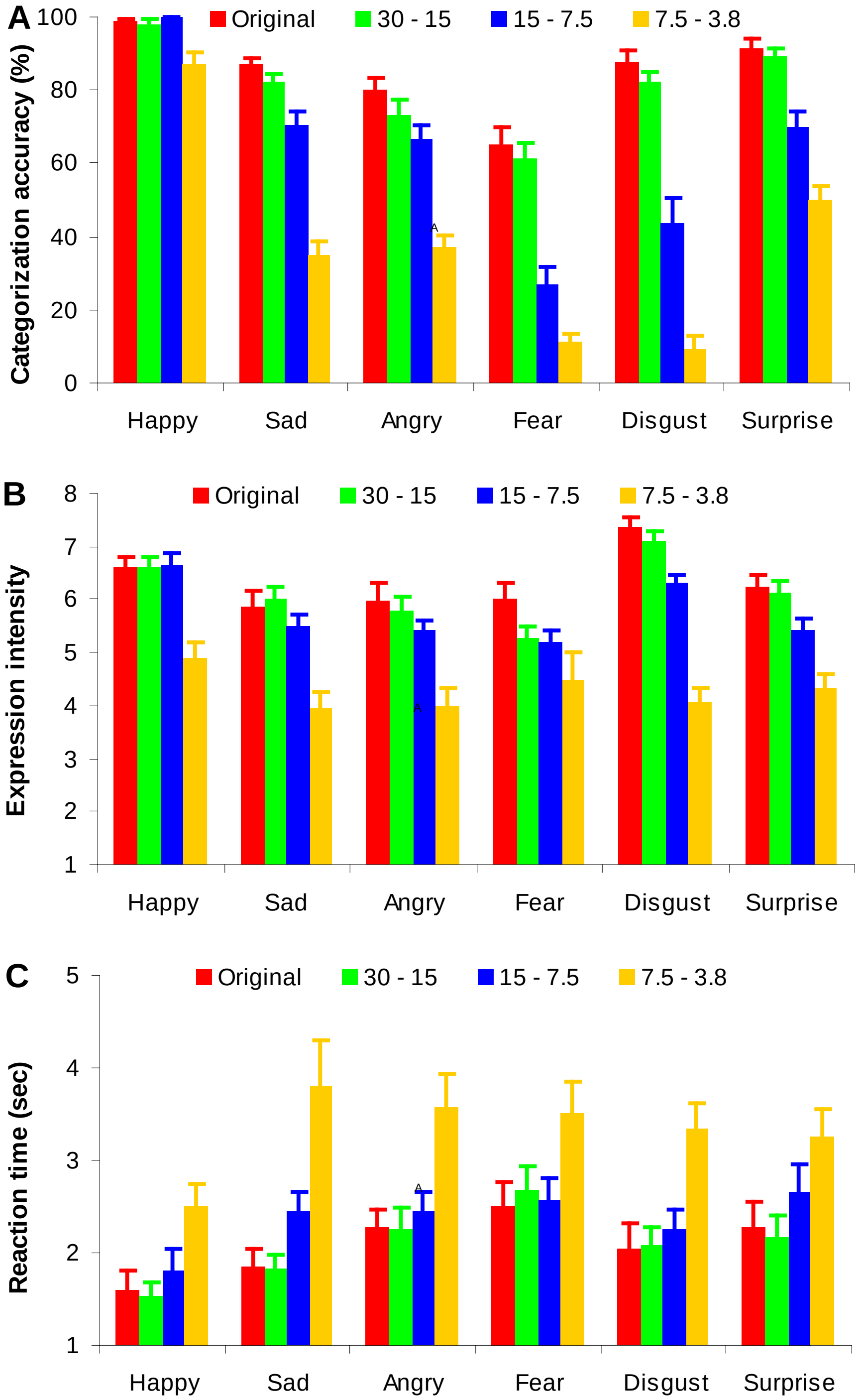


Figure 7. Mean expression categorization accuracy (A), perceived expression intensity (B) and reaction time (C) for expression judgement as a function of face blur. Error bars represent SEM. In general, increasing image blur up to 15 cycles/image had little overall impact on expression judgement (categorization accuracy, intensity rating and reaction time), further face distortion led to decreased expression categorization accuracy and intensity rating, and increased reaction time.

For perceived expression intensity (Fig. 7B), the analysis also revealed significant main effects of face blur ($F(1.26,22.63) = 41.61$, $p < 0.001$, $\eta^2 = 2.31$) and expression type ($F(2.54,45.67) = 22.67$, $p < 0.001$, $\eta^2 = 1.26$), and significant interaction effect ($F(4.79,86.23) = 5.49$, $p < 0.001$, $\eta^2 = 0.31$). Across all expressions, participants had indistinguishable expression intensity ratings between original faces and faces with 30–15 cycles/image bandwidth ($p = 0.08$), but reduced rating for faces with 15–7.5 cycles/image bandwidth and the lowest rating for faces with 7.5–3.8 cycles/image bandwidth (all *ps* < 0.01). The same trend for the change of expression intensity rating was also observed for individual expressions such as disgust and surprise. For happy, sad and angry expressions, the intensity rating was only reduced for faces with 7.5–3.8 cycles/image bandwidth (all *ps* < 0.01). The expression intensity of the blurred fearful faces had the same ratings regardless of spatial frequency bandwidths (all *ps* > 0.05), but was lower than that from the original fearful faces (all *ps* < 0.01).

For reaction time (Fig. 7C), the analysis revealed significant main effects of face blur ($F(1.23,22.2) = 24.81$, $p < 0.001$, $\eta^2 = 1.38$) and expression type ($F(5,90) = 12.67$, $p < 0.001$, $\eta^2 = 0.70$). Across all expressions, the reaction times were the fastest for the original faces and faces with 30–15 cycles/image bandwidth ($p = 1$), were slower for faces with 15–7.5 cycles/image bandwidth (all *ps* < 0.01), and were the slowest for faces with 7.5–3.8 cycles/image bandwidth (all *ps* < 0.01).

3.2.2. Analysis of gaze behaviour in expression categorization

4 (face blur) × 6 (expression type) ANOVA was conducted to examine to what extent face image blur would affect the number of fixations participants needed to categorize different facial expressions (Fig. 8A). The analysis revealed significant main effects of face blur ($F(1.4,25.26) = 4.29$, $p = 0.04$, $\eta^2 = 0.24$) and expression type ($F(5,90) = 16.31$, $p < 0.001$, $\eta^2 = 0.91$), and significant interaction effect ($F(7.07,127.23) = 2.41$, $p = 0.02$, $\eta^2 = 0.13$). Across all expressions, the faces with 15-7.5 and 7.5-3.8 cycles/image bandwidths attracted slightly

fewer fixations than the original faces and faces with 30-15 cycles/image bandwidths (all *ps* < 0.01). The same trend was observed for individual expressions such as happy and surprise. On the other hand, sad, anger, fear, and disgust expressions attracted similar amount of fixations regardless of image blur (all *ps* > 0.05).

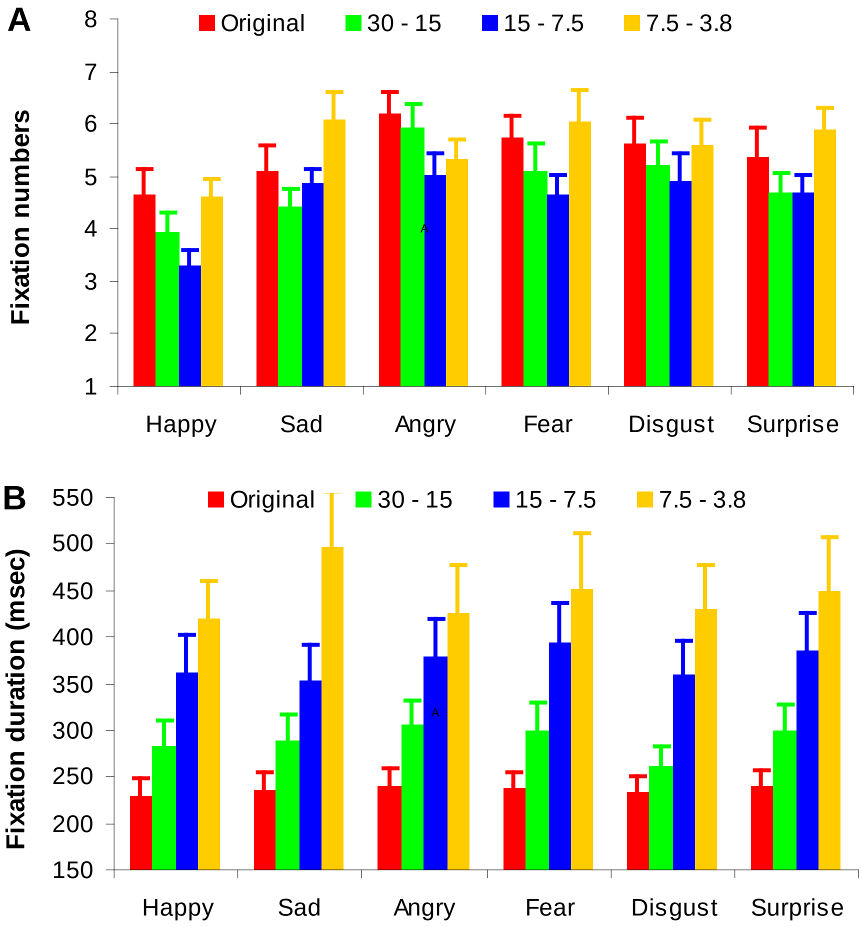


Figure 8. Average number of fixations (A) and average fixation duration across all fixations (B) directed at the expressive face as a function of face blur. Error bars represent SEM. In general, face blur led to increased individual fixation duration.

For individual fixation duration (Fig. 8B), the analysis of 4 (face blur) × 6 (expression type) ANOVA revealed significant main effects of face blur ($F(1.12,20.08) = 29.18$, $p < 0.001$, $\eta^2 = 1.62$) and expression type ($F(3.19,57.36) = 3.52$, $p = 0.02$, $\eta^2 = 0.2$). Across all expressions, the average fixation duration was increased monotonically with the increasing degree of face blur (all *ps* < 0.01). In other words, the fixation rate (number of fixations per second) was decreased monotonically with the increasing degree of face blur ($F(2.01,36.13) = 31.61$, p <

0.001, $\eta^2 = 1.56$), from 2.87 ± 0.15 for the original faces to 1.9 ± 0.13 for the faces with 7.5-3.8 cycles/image bandwidths (all *ps* < 0.01).

For detailed fixation distribution associated with expression categorization (Fig. 9), the analysis of 3 (face region) × 4 (face blur) × 6 (expression type) ANOVA with the proportion of fixations directed at each face region as the dependent variables revealed significant face region effect ($F(2,36) = 87.98$, $p < 0.001$, $\eta^2 = 4.89$) and some interaction effects (face region × expression type: $F(10,180) = 6.25$, $p < 0.001$, $\eta^2 = 0.35$; face blur × face region: $F(2.2,39.54) = 31.71$, $p < 0.001$, $\eta^2 = 1.76$). It seems that across different expression categories, face blur had similar impact on the change of fixation allocation at individual facial regions. Specifically, regardless of facial expressions increasing face blur towards 15-7.5 cycles/image bandwidth monotonically reduced the proportion of fixations directed at the eyes from 31% ± 5 to 10% ± 2, increased the proportion of fixations directed at the nose from 51% ± 4 to 77% ± 2 (all *ps* < 0.01), but did not affect the proportion of fixations directed at the mouth (all *ps* > 0.05). Further reduction in spatial frequency bandwidth had little further impact on gaze allocation at the eyes or nose regions (all *ps* > 0.05), but slightly reduced the proportion of fixations at the mouth to 5% ± 1 (all *ps* < 0.01).

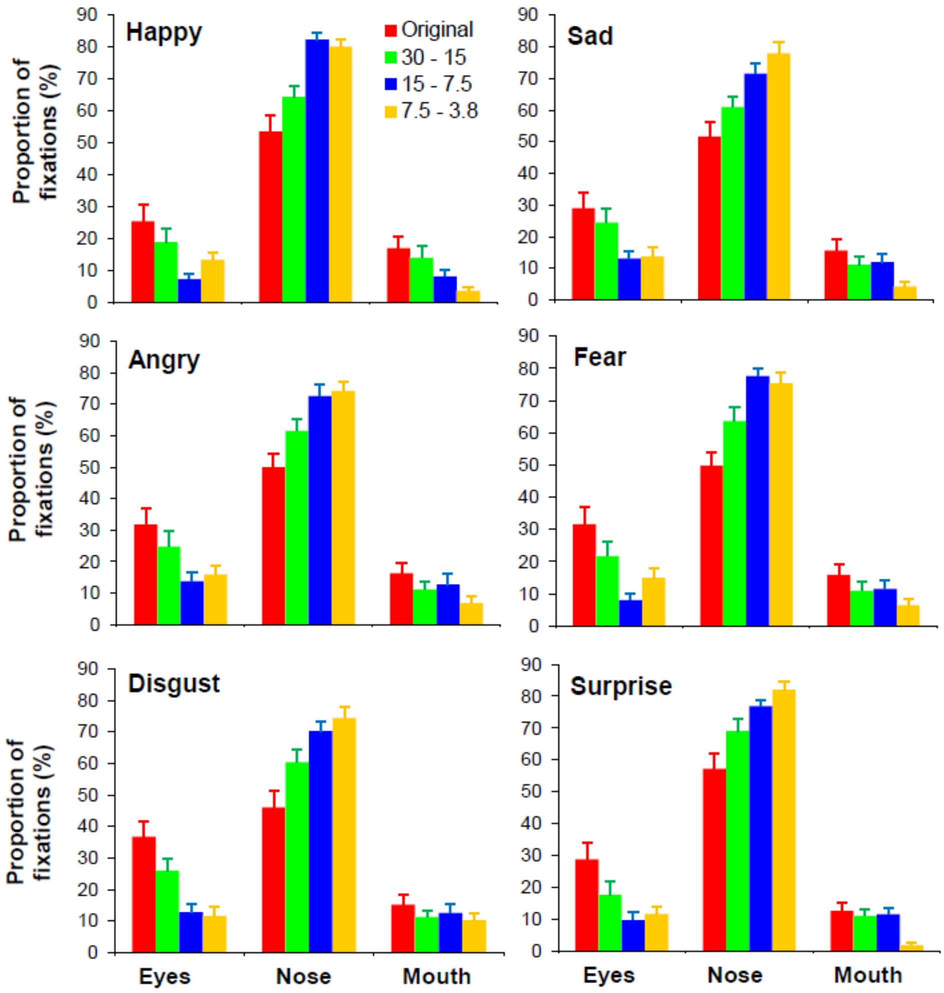


Figure 9. Proportion of fixations directed at the eyes, nose, and mouth regions when categorizing different facial expressions with varying face blur. Error bars represent SEM. In general, face blur led to stronger central fixation bias at the nose region.

4. Model comparison of image resolution and blur on local image saliency

Clearly manipulating face image resolution and blur could significantly modulate face-viewing gaze allocation at local facial features. In general lower quality faces tended to attract fewer fixations at the eyes but more fixations at the nose. As the same facial feature in faces of different image qualities may vary in low-level image salience (e.g., local structure, spatial frequency and contrast), it could be argued these changes of local image properties could (at least partly) account for the observed differences in gaze allocation at a given facial feature. For instance, in comparison with high quality face images, the low-level image salience at the nose region in the distorted faces might be increased, consequently the nose attracted more fixations. We examined this possibility by computing and comparing local image saliency in eyes, nose and mouth regions across face image manipulations.

For each of the face images used in this project, local image saliency was computed in Matlab using the most widely used computational salience model of Itti and Koch (2000), with the authors' original parameters and implementation (obtained from http://ilab.usc.edu). The model compares local image intensity, colour, and orientation, combines them into a single salience map with a winner-take-all network and inhibition-of-return, and then produces a sequence of predicted fixations that scan the whole face in order of decreasing salience.

We calculated the top six salient regions within each face image because our human participants on average made 5.8 fixations per images in face viewing. The number of predicted fixations at eyes, nose and mouth were then normalized to the total number of predicted fixations in that face.

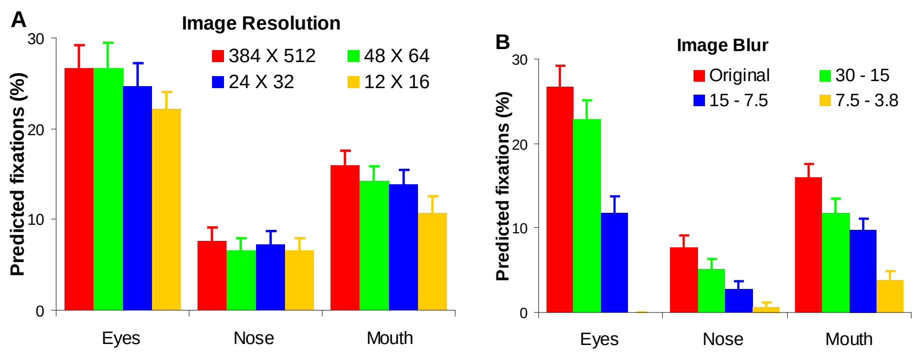


Figure 10. The proportion of predicted fixations at the eyes, nose, and month region within faces with varying image resolution (A) and image blur (B). Error bars represent SEM. In general, face distortion tended to decrease local image saliency across all the facial regions.

As shown in Figure 10, both reducing face resolution ($F(2.49,117.13) = 6.61$, $p = 0.001$, $\eta^2 = 0.14$) and increasing face blur ($F(3,141) = 99.13$, $p < 0.001$, $\eta^2 = 2.11$) would decrease the computed local image saliency across all the facial regions, but the degree of their impact was slightly different. When decreasing face image resolution, the reduction in local image saliency was only evident for the lowest resolution (resolution 1 *vs* resolution 1/32, $p = 0.001$; resolution 1 *vs* resolution 1/8 or 1/16, $p > 0.05$). Increasing face image blur, on the other hand, could monotonically decrease local image saliency across all the facial regions at each level of face blur (all *ps* < 0.01). Further comparison between actual (Fig. 5 and 9) and predicted fixation distribution (Fig. 10) clearly indicated that the increased fixations at the nose region in viewing of degraded face images was not driven by the reduced low-level local image saliency around the nose area.

5. General Discussion

In this study we have demonstrated that our capability of perceiving facial expressions of emotion has a reasonable tolerance to face distortion. Reducing image resolution up to 48 × 64 pixels or increasing image blur up to 15 cycles/image had little impact on our expression judgement (expression categorization and intensity rating) and associated gaze behaviour. Further face distortion led to decreased expression categorization accuracy and intensity rating, increased reaction time and individual fixation duration, and stronger central fixation bias (i.e. more fixations were allocated at the central part of face, nose region). Interestingly, our observers still demonstrated above-chance expression categorization accuracy (especially for happy and surprise expressions) for face images with resolution as low as 12 × 16 pixels or with spatial frequency bandwidth as low as 7.5 – 3.8 cycles/image. It seems that human facial expression perception is largely invariant across face distortions.

However, different facial expressions tended to show different degree of tolerance to face distortions. Across all the distortion levels, face resolution and face blur had little or less impact on the recognition accuracy of happy and surprise expressions, but the strongest impact on fear and disgust expressions in which chance-level categorization accuracy was observed at the highest level of distortions (Fig. 2 and 7). These distortion-induced expression-dependent changes in behavioural performance were broadly consistent with previous studies (Johnston et al., 2003; Du & Martinez, 2011). For instance, when manipulating face image resolutions, Du and Martinez (2011) have also observed that although overall expression recognition accuracy remained quite consistent until the image was reduced to 10 × 15 pixels, fear and disgust were poorly recognized at every resolution and more susceptible to image degradation, while happiness and surprise were readily identified in that same resolution range. Such expression-sensitive susceptibility to image degradation might be due to possible adaptive advantage of different expressions. It has been proposed that production and perception of happy and surprise expressions might be coevolved to maximize information transmission (Fridlund, 1991), and are more suitable for long-distance communication and hence less prone to image distortion. Fear and disgust expressions, on the other hand, might be evolved to enhance or block sensory acquisition (e.g., increasing air intake in fear expression and constricting air intake in disgust expression; Susskind et al., 2008), and are more suitable for close-range communication and more prone to image distortion. It is also plausible that in comparison with happiness or surprise, fear and disgust share a greater overlap in facial structural configuration with other expressions (Johnston et al., 2003; Du & Martinez, 2011), and hence are less perceptually distinctive for categorization and more vulnerable to noisy visual signals.

Unlike previous studies, in this project we have collected expression categorization accuracy data along with the perceived expression intensity. Our analysis revealed that image distortion-induced reduction in intensity rating had a similar change in direction and speed as reduction in recognition accuracy (Fig. 2 and 7). Considering that judging expression category and intensity would need qualitative and quantitative analysis of expressive facial cues from key internal facial features (e.g., shapes of eyes, nose and mouth) respectively (Calvo & Nummenmaa, 2008), image resolution and image blur seems to have the same impact on qualitative and quantitative assessment of local facial regions. Interestingly, change of face viewing perspective from frontal to profile view had little overall impact on expression identification rates but significantly reduced intensity ratings (Guo & Shaw, 2015). It seems that the judgement of expression category and its intensity could be dissociated based on different viewing conditions, and our invariant facial expression perception is likely to be a categorical perception, similar as invariant face identity, race and gender judgement (Hancock, Bruce, & Burton, 2000; Liu & Chaudhuri, 2002; Bindemann, Scheepers, & Burton, 2009; Sæther, Van Belle, Laeng, Brennen, & Øvervoll, 2009; Brielmann, Bülthof, & Armann, 2014).

Another novelty in this project is that we have recorded and compared participants' face-viewing gaze behaviour across different image degradation levels. In agreement with previously reported 'holistic' gaze behaviour in face exploration (Guo, 2012; Gavin, Houghton, & Guo, 2017), regardless of facial expression categories our participants tended to scan all key internal facial features (i.e. eyes, nose, and mouth) to extract and then integrate expressive featural information in order to reliably decode facial expressions (Fig. 5 and 9). Similar as categorization accuracy, this gaze pattern also showed a tolerance to image distortions, implying a close correspondence between face-viewing gaze behaviour and expression perception. There was no qualitative difference in gaze distribution pattern among internal facial features across image distortion types and levels (e.g., the nose has always attracted the highest proportion of fixations, followed by the eyes and then the mouth region). Quantitatively, however, image degradation has led to the development of prolonged individual fixation duration and stronger central fixation bias towards the nose region, which could not be accounted for by degradation-induced changes in low-level local image saliency. It is likely that the overall facial configuration leads to qualitative similarity in face-viewing gaze distribution pattern, whereas face image quality leads to quantitative differences in gaze allocation at specific local face regions.

The observed image distortion-induced changes in face-viewing gaze behaviour were consistent with early research on scene perception. In comparison with high quality man-made and natural landscape scene images, noisy images (e.g., distorted with low image resolution, Gaussian low-pass filter, circular averaging filter or Additive Gaussian white noise) attracted longer individual fixation durations, shorter saccades and stronger central fixation bias (Judd et al., 2011; Röhrbein et al., 2015). This impact of image distortion on gaze behaviour was mainly determined by image noise intensity rather than noise type or image/scene category, indicating a generic oculomotor strategy adapted to process noisy visual inputs. It is possible that ambiguous visual information in noisy images would increase task difficulty in visual and cognitive processing, reduce the saliency of peripheral visual features and increase the difficulty of saccade target selection (Reingold & Loschky, 2002; Nuthmann, Smith, Engbert, & Henderson, 2010), that subsequently lead to longer fixation durations and shorter saccadic distance. Furthermore, the reduction in the overall saliency from out-of-focus regions would make saccade initiation to peripheral regions more difficult, resulting in fewer fixations to non-centre areas and stronger central fixation bias (Röhrbein et al., 2015).

Interestingly, these image noise-induced changes in face-viewing gaze behaviour did not always match with the changes in expression categorization performance. For instance, our participants' categorization accuracy for happiness was not affected by the reduced image resolution (Fig. 2A) and was slightly decreased only for face blur with 7.5–3.8 cycles/image bandwidth (Fig. 7A), but their gaze allocation started to show stronger central fixation bias for faces with resolution of 24 × 32 pixels (Fig. 5) or blur of 15–7.5 cycles/image bandwidth (Fig. 9). Currently it is unclear how common this dissociation between face-viewing gaze behaviour and the related perceptual performance exists in face perception, and to what extent it could modulate our face processing. This could be an interesting open question for future research.

It should also be noted that in order to enhance data comparability between testing conditions, this study has used a within-subject design and a relatively small set of stimuli with four image quality manipulations for each of six basic facial expressions from eight models, which inevitably had limited variability within each expression category and might induce practice effects (e.g., by seeing the same face identity displaying the same expression more than once). Although categorization of these ‘universal’ expressions is not heavily influenced by culture, race, gender and age bias (Bruce & Young, 2012), it remains to be seen to what extent the current findings can be generalized to less universal expressions (e.g., confusion, shame) expressions which could transmit more ambiguous facial signals and may be susceptible to individual differences from both expresser and perceiver.

Nevertheless, the current study represents an important step forward in our understanding of how ‘invariant’ facial expression representation could be achieved. Between two leading competing models of facial expression perception, the categorical model (Ekman & Rosenberg, 2005) argues that we have a finite set of predefined expression classifiers, each tuned to a specific emotion category; whereas the continuous or dimensional model (Russell, 2003) suggests that each emotion is represented as a feature vector (e.g., pleasure–displeasure) in a multidimensional space given by some characteristics common to all emotions (e.g., arousal and valence). Combined with our previous research, we have demonstrated that human capability of perceiving facial expressions of emotion has a good tolerance to face distortion, viewing distance (Guo, 2013), viewpoint (Guo & Shaw, 2015), and expression intensity (Guo, 2012). Such invariant expression perception is likely to be achieved through a configural computation of local facial features or face spaces proposed by the categorical model (Ekman & Rosenberg, 2005). As in this study we noticed that the combination of the same group of facial features (e.g., eyes, nose, and mouth) can transmit different diagnostic information representing different expressions which subsequently show different susceptibility to face distortions (e.g., happy and surprise expressions are the least affected by face distortions), it is plausible that the configural process in categorical expression perception is a non-linear integration of facial features. This nonlinear computation could be incorporated in future development of a refined computational model of categorical facial expression perception. Furthermore, it is worth mentioning that our past experience or 'social learning' process (Barrett, 2011) may play an important prole in the formation of 'invariant' facial expression representation. Indeed, recent training or perceptual learning studies have highlighted the learning mechanism for constructing invariant face or object representations, such as recognizing the same face or object identity through dynamically changing viewing perspectives (transform-invariant recognition or spatiotemporal persistence) (e.g., Wallis & Bülthoff, 2001; Cox, Meier, Oertelt, & DiCarlo, 2005; Schurgin & Flombaum, 2017).

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