Current Biology 19, 1543–1548, September 29, 2009 ©2009 Elsevier Ltd All rights reserved DOI 10.1016/j.cub.2009.07.051

Report

Cultural Confusions Show that Facial Expressions Are Not Universal

Rachael E. Jack,[1,2,*] Caroline Blais,[3] Christoph Scheepers,[1] Philippe G. Schyns,[1,2] and Roberto Caldara[1,2,*]
[1]Department of Psychology
[2]Centre for Cognitive Neuroimaging (CCNi)
University of Glasgow, Glasgow G12 8QB, Scotland, UK
[3]Départment de Psychologie, Université de Montréal, Montreal, PQ H3C 3J7, Canada

Summary

Central to all human interaction is the mutual understanding of emotions, achieved primarily by a set of biologically rooted social signals evolved for this purpose—facial expressions of emotion. Although facial expressions are widely considered to be the universal language of emotion [1–3], some negative facial expressions consistently elicit lower recognition levels among Eastern compared to Western groups (see [4] for a meta-analysis and [5, 6] for review). Here, focusing on the decoding of facial expression signals, we merge behavioral and computational analyses with novel spatiotemporal analyses of eye movements, showing that Eastern observers use a culture-specific decoding strategy that is inadequate to reliably distinguish universal facial expressions of "fear" and "disgust." Rather than distributing their fixations evenly across the face as Westerners do, Eastern observers persistently fixate the eye region. Using a model information sampler, we demonstrate that by persistently fixating the eyes, Eastern observers sample ambiguous information, thus causing significant confusion. Our results question the universality of human facial expressions of emotion, highlighting their true complexity, with critical consequences for cross-cultural communication and globalization.

Results

To examine the decoding of facial expressions across cultures, we recorded the eye movements of 13 Western Caucasian (WC) and 13 East Asian (EA) observers while they performed a seven-alternative forced-choice (7AFC) facial expression categorization task (i.e., "happy," "surprise," "fear," "disgust," "anger," and "sadness" plus "neutral") with same-race (SR) and other-race (OR) Facial Action Coding System (FACS)-coded faces [7, 8]. We chose FACS-coded faces both for the purpose of presenting well-controlled stimuli and for their assumed universality in transmitting facial expression signals, although we fully acknowledge their real-world limitations. We then related, for each expression, categorization performance with corresponding eye movement strategies (see Experimental Procedures).

Task Performance

A three-way (two cultures of observers, two races of face, seven facial expressions) mixed analysis of variance (ANOVA) on mean categorization accuracy (see Table S1 available online) showed a significant culture of observer × facial expression interaction [$F(6,144) = 5.608$, $p < 0.001$]. Post hoc Bonferroni comparisons showed that EA observers made significantly more errors when categorizing "disgust" ($p < 0.05$) and "fear" ($p < 0.001$) than WC observers did. In contrast, WC observers categorized all facial expressions with comparably high accuracy. Within-group homogeneity was confirmed for both groups: A one-way repeated-measures ANOVA across individual observers revealed no significant differences within the WC group. Only two significant differences were found within the EA group [$F(12,156) = 7.33$, $p < 0.001$)], with post hoc Bonferroni comparisons showing both to be related to one unusually accurate observer ($p < 0.001$).

Although consistent with previous observations [5, 9, 10, 11], a critical question remains: Why do EA observers systematically miscategorize certain facial expressions (i.e., "fear" and "disgust")? Further inspection of EA categorization errors revealed that "fear" and "disgust" were consistently confused with "surprise" and "anger," respectively (see Figure S1 for categorization confusions).

Eye Movements

Eye movements provide an index of overt attention and can therefore reveal the information strategically selected to categorize expressions. Thus, we examined the location, frequency, and temporal order of fixations in both observer groups.

To the ANOVA design of task performance, we added the fourth factor of fixations to face regions (i.e., "left eye," "right eye," "bridge of nose," "center of face," and "mouth"; see Experimental Procedures). We revealed a significant culture of observer × face region interaction [$F(4,96) = 3.65$, $p < 0.01$)]. Post hoc comparisons showed that EA observers made significantly more "left eye" ($p < 0.01$) and "right eye" ($p < 0.001$) fixations compared to "mouth." Figure 1A summarizes this interaction, with the corresponding fixation maps collapsed across all seven expressions (see Figure S2 for the complete analysis, showing EA bias fixations toward the eyes across all seven expressions). In contrast, WC observers fixated all face regions equally. Figure 1B presents the fixation maps for the expressions eliciting significant errors (i.e., "fear" and "disgust") and the expressions with which they were systematically confused (i.e., "surprise" and "anger," respectively).

To further characterize biases in information sampling strategies, we analyzed the order in which the face regions were visited by using minimum description length (MDL; see Experimental Procedures). MDL is a statistical method that extracts regular patterns from data set sequences [12, 13]. Here, a sequence consisted of the succession of fixations on face regions (e.g., "left eye" → "right eye" → "left eye"). To illustrate the MDL results, we focused on the same four facial expression categories as above (i.e., "surprise," "fear," "disgust," and "anger"; see Figure S3 for MDL applied to all conditions of the design). In Figure 2, color-coded circles corresponding to face regions represent the fixation sequences. For example, the fixation sequence "left eye" → "right eye" → "left eye" (indicated by the black arrow) is represented by a succession of circles colored blue, green, and blue.

*Correspondence: rachael@psy.gla.ac.uk (R.E.J.), roberto@psy.gla.ac.uk (R.C.)

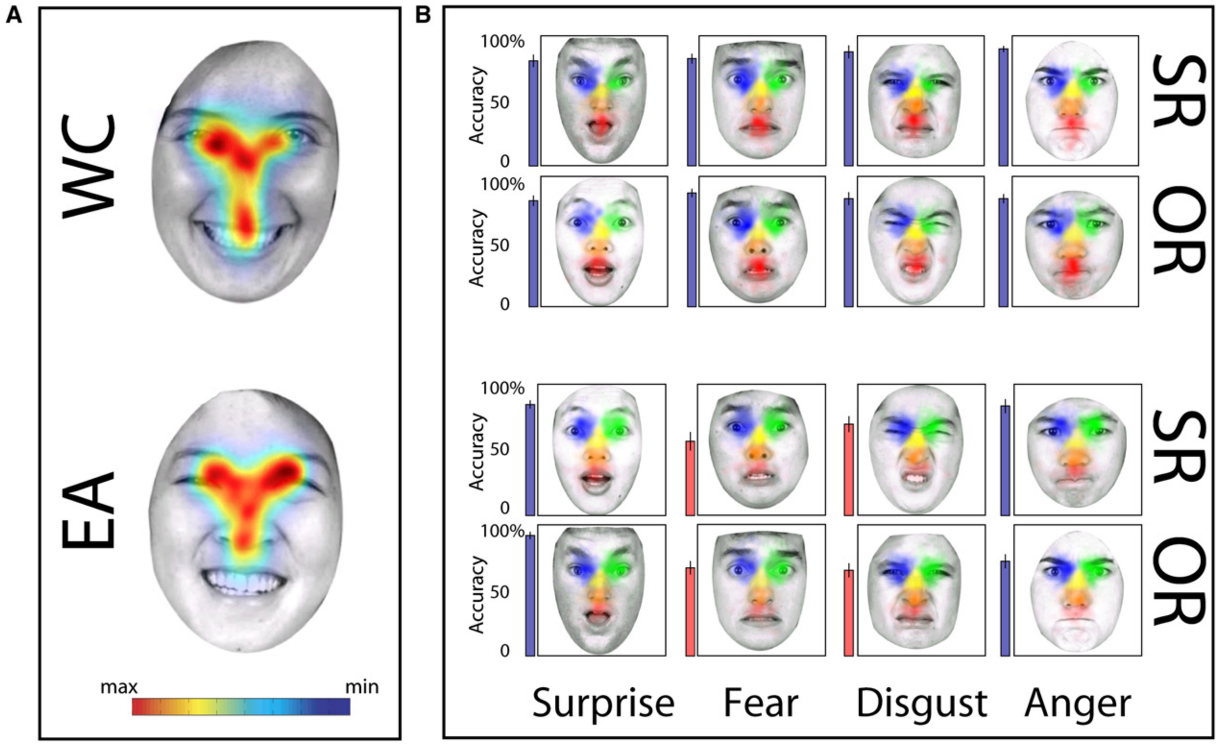

Figure 1. Fixation Distributions

(A) Fixation distributions for each observer group collapsed across race of face and seven expression categories (see Figure S2 for fixation distributions for each condition separately). Color-coded distributions represent the density of fixations across face regions, with red showing the most densely fixated regions. Note that for East Asian (EA) observers, fixations are biased toward the upper part of the face as compared to Western Caucasian (WC) observers, where fixations are more evenly distributed across the face, including the mouth.

(B) Fixation distributions for "surprise," "fear," "disgust," and "anger." Color-coded distributions presented on grayscale sample stimuli show the relative distributions of fixations across face regions. Color coding is as follows: blue, "left eye"; green, "right eye"; yellow, "bridge of nose"; orange, "center of face"; red, "mouth." Higher color saturation indicates higher fixation density, shown relative to all conditions. Note that the red "mouth" fixations for EA observers are less intense as compared to WC observers across conditions. Color-coded bars to the left of each face represent the mean categorization accuracy for that condition, with red indicating a significant difference in categorization errors between groups ($p < 0.05$). Error bars indicate standard error of the mean.

MDL results revealed a clear contrast: EA observers made significantly more systematic fixation sequences than WC observers (as shown by a chi-square test of association [$\chi^2(1) = 366.79$, $p < 0.001$]). Note that the high number of color-coded successions of circles for EA observers in Figure 2 is valid across all experimental conditions (see Figure S3) and for a majority of individual observers (see Figure S4).

A significant majority of these fixation sequences involved exclusively "left eye" and "right eye" [$\chi^2(1) = 395.38$, $p < 0.001$], with significantly more use for negative expressions (i.e., "fear," "disgust," and "anger") compared to other expressions [$\chi^2(1) = 15.97$, $p < 0.001$]. Furthermore, EA observers used similar fixation sequences for the expressions that they consistently confused (i.e., "surprise" and "fear"; "disgust" and "anger"). Therefore, by persistently biasing fixations toward the eyes, EA observers could have extracted eye information that was too similar to discriminate certain expressions.

Model Observer

To objectively determine whether sampling the eyes while neglecting more diagnostic face regions (e.g., the mouth region for "fear" and "disgust" [e.g., 14]) could elicit behavioral confusions, we built a model observer that sampled information to categorize expressions (see Experimental Procedures). Figure 3 illustrates the model observer with "fear" and "surprise," "anger," and "disgust" as above (see Figure S5 for a complete illustration of the computations).

Consider the facial information sampled by the model observer in Figure 3A. When sampling the eye region of "fear," the information is most similar to (i.e., confusable with) that of "surprise" and less so for other expressions (see red box). Thus, sampling from the eye region produces a pattern of confusions (i.e., Pearson correlation values), represented by the dashed red line in Figure 3B. In contrast, sampling from the mouth (see green box) produces a different pattern of confusions (dashed green line in Figure 3B), whereby "fear" and "surprise" are distinguishable. Our model randomly sampled information from the face, compared (i.e., fitted) each confusion pattern to the behavioral confusion pattern of EA observers (solid black line in Figure 3B), and rank ordered each sample according to its fit to EA observers' behavioral confusions.

Figure 4 illustrates the results with "surprise," "fear," "anger," and "disgust." Color-coded contour plots represent the rank order of all samples from "best" (red) to "worst" (blue) R^2 values. The model observer most closely replicated EA observers' confusions when sampling the eye (delimited with orange contours) and eyebrow (delimited with red contours) regions. Note the higher density of EA observer fixations (based on error trials, shown by the relative distributions in

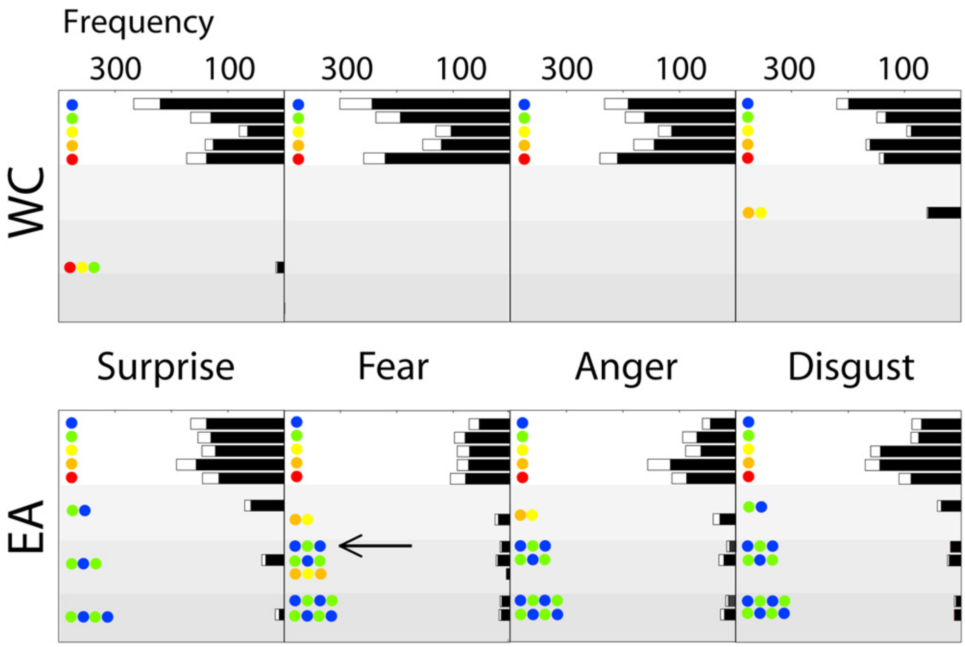

Figure 2. Fixation Sequences for "Surprise," "Fear," "Anger," and "Disgust"

Successions of color-coded circles represent the fixation sequences extracted via minimum description length analysis, with each circle representing a face region. Face regions are color-coded as in Figure 1B. For example, the succession of blue → green → blue circles (indicated by the black arrow) corresponds to the fixation sequence "left eye" → "right eye" → "left eye." Single color-coded circles correspond to fixations that do not appear as part of a sequence. Black and white bars to the right of the fixation sequences represent how frequently the fixation sequence appeared in the data set, with black indicating correct trials and white indicating incorrect trials. Different levels of gray in each condition represent the order of the fixation sequences (see Experimental Procedures). Note the higher number of fixations sequences for EA observers compared to WC observers across expressions (see also Figure S3).

Figure 4, scale on right) within face regions ranked as "best fit" (see Figure S6 for analysis conducted across all expressions). This demonstrates that EA behavioral confusions are symptomatic of a strategy that samples ambiguous information (i.e., the eyes and eyebrows) and neglects diagnostic features (i.e., the mouth).

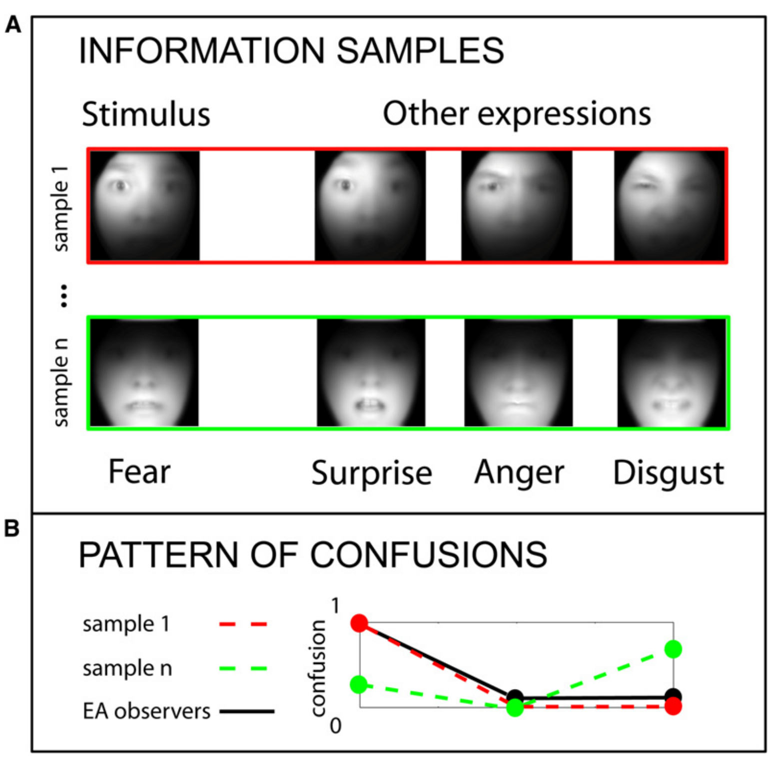

Figure 3. The Model Observer: Illustration of the Procedure to Compute Estimated Patterns of Confusion

(A) Information samples. To compute estimated patterns of confusion, we used the model to sample face information from the stimulus expression (e.g., "fear") and from the same location on the other expressions (e.g., "surprise," "anger," and "disgust"). The face images illustrate an example of the information sampled.

(B) Pattern of confusions. The model then Pearson correlated the stimulus expression sample with each of the other expression samples. These correlations (plotted in dashed color-coded lines beneath each corresponding face) represented the confusions of the model and were fitted (using ordinary least squares) against the behavioral confusions of the EA observers (plotted in black). The behavioral confusions of the EA observers were calculated by categorizing each incorrect trial by response for each expression (e.g., for "fear" trials, the numbers of incorrect responses were computed for "surprise," "anger," and "disgust"). We repeated the sampling and correlation process for 10,000 individual samples selected randomly across the face and finally sorted each information sample according to its fit to the behavioral confusions of the EA observers ("best" to "worst" fits are shown in Figure 4). We followed the same procedure for each expression (see Figure S5 for a full illustration).

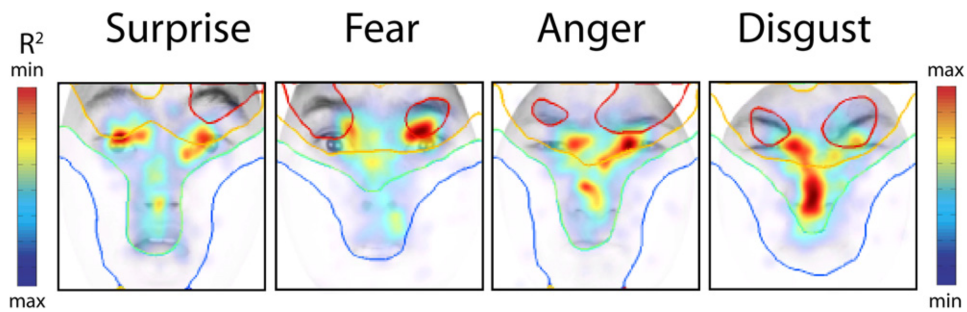

Figure 4. Model Observer and EA Observer Fixation Maps

Contour plots: color-coded lines represent the rank order of information samples according to fit, with red showing the "best" fit (scale on left). For example, by sampling the eyebrow (delimited in red) and eye region (delimited in orange) in "fear," the model produced a pattern of confusions most similar to that of the EA observers. In contrast, the lower part of the face (delimited in blue and green) produced a pattern of confusions most dissimilar to that of the EA observers.
Fixation patterns: for each expression, fixations leading to behavioral confusions are shown by relative distributions presented on grayscale sample stimuli. Red areas indicate higher fixation density for each expression (scale on right). Note the higher density of EA observer fixations within face regions ranked as "best fit." This demonstrates that the behavioral confusions of the EA observers are symptomatic of an information sampling strategy that selects ambiguous information (i.e., the eyes and eyebrows) while neglecting more diagnostic features (i.e., the mouth).

Discussion

Here, we report marked differences between EA and WC observers in the decoding of universal facial expressions. EA observers exhibited a significant deficit in categorizing "fear" and "disgust" compared to WC observers. Also, WC observers distributed their fixations evenly across the face, whereas EA observers systematically biased theirs toward the eye region. A model observer revealed that EA observers sample information that is highly similar between certain expressions (i.e., "fear" and "surprise"; "disgust" and "anger"). Despite the apparent lack of diagnostic information (see [14]), EA observers persisted in repetitively sampling the eye regions of "fear," "disgust," and "anger."

Do EA observers make categorization errors simply because they select ambiguous information? Behavioral results showed that in response to ambiguity, EA observers tended to bias their categorization responses toward less socially threatening emotions (e.g., "surprise"). Instead, facial expression categorization is likely to be conjunctively influenced by predetermined social motivations and cultural concepts (see [15–17]) as well as information sampling biases. However, our eye movement data refute "decoding rules" hypotheses of substituting an initial correct categorization with a more socially acceptable emotion [10, 11, 18] or attenuated intensity [9, 11].

Cultural differences in fixation patterns may reflect cultural specificity in the transmission of facial expression signals. EA observers systematically neglect critical aspects of FACS-codes faces (e.g., action units 20, 26, and 27 [14]), demonstrating that FACS-coded facial expression signals do not accurately represent the diagnostic features of EA facial expressions. Rather, EA fixation patterns predict the eye region as primarily diagnostic for facial expression categorization with minimal involvement of the mouth (see also [19]), as reflected by the EA emoticons (O.O) for surprise and (^.^) for happy [20].

Finally, our data question gaze avoidance in face processing for EA observers (see [21]). Instead, their fixation patterns probably reflect strategies developed to achieve diagnostic recognition [15], with modulations in fixation patterns across categorization tasks indicative of specific information selection (e.g., for identification [21]; see also [22–27]).

In sum, our data demonstrate genuine perceptual differences between WC and EA observers and show that FACS-coded facial expressions are not universal signals of human emotion. From here on, examining how the different facets of cultural ideologies and concepts (see [28] for an overview and also [16, 17]) have diversified these basic social skills will elevate knowledge of human emotion processing from a reductionist to a more authentic representation. Otherwise, when it comes to communicating emotions across cultures, Easterners and Westerners will continue to find themselves lost in translation.

Experimental Procedures

Observers

Thirteen Western Caucasian (13 European, 7 female and 6 male, mean age 24 years 5 months) and 13 East Asian (12 Chinese and 1 Japanese, 8 female and 5 male, mean age 23 years 2 months) observers participated. All EA observers were East Asia nationals, with an average UK residence of one week and a minimum International English Language Testing System score of 6.0 at the time of testing. All participants had minimal prior experience of other-race (OR) faces (assessed by questionnaire; see Supplemental Experimental Procedures), had normal or corrected vision, gave written informed consent, and were paid £6 per hour for participating. The University of Glasgow Department of Psychology ethical committee approved the experimental protocol.

Materials

Stimuli [7] consisted of 56 images displaying six FACS-coded facial expressions ("happy," "surprise," "fear," "disgust," "anger," and "sadness") plus "neutral." Gender and race of face were equally distributed for each expression. Same-race (SR) faces for Chinese observers were Japanese faces [29, 30]. We cropped the images with Adobe Photoshop CS and aligned the eye and mouth positions with Psychomorph software [31]. Images (280 × 380 pixels) were viewed on a 1024 × 768 pixel white background on a 21-inch Iiyama HM204DTA monitor (120 Hz refresh rate) at a distance of 60 cm (a natural distance for social interaction [32], representing faces as the average size of a real face [33]) and subtended 10° × 14° of visual angle. Stimulus presentation was controlled by SR Research Experiment Builder software, version 1.4202. Eye movements were recorded at a sampling rate of 500 Hz (pupil-only mode) with an EyeLink II head-mounted eye tracker (SR Research), which has an average gaze position error of <0.5°, a resolution of 1 arc minute, and a linear output over the monitor's range.

Procedure

Participants performed a 7AFC facial expression categorization task with SR and OR faces. Prior to testing, we established participants' familiarity with the categorical labels, determined ocular dominance via the Miles test [34], and performed a nine-point fixation procedure (implemented in the EyeLink application programming interface) to establish optimal calibration (drift correction < 1° of visual angle).We tracked only the dominant eye, although viewing was binocular. A chin rest minimized head movements and maintained viewing distance. Images were presented pseudorandomly in one of four quadrants of the screen and remained until the participant responded. Manual responses were accompanied by a verbal response (to eliminate eye movements toward response keys), recorded by the experimenter.

Fixation Maps

In Figure 1, Figure 4, Figure S2, and Figure S6, fixation maps were computed for each condition by plotting all fixation (x, y) coordinates across time into a 380×280 matrix. To represent the foveated region (2° visual angle), we smoothed each fixation with a Gaussian kernel ($\alpha = 10$ pixels). Fixation maps in Figure 1 and Figure S2 are based on correct trials, whereas those in Figure 4 and Figure S6 are based on error trials.

Face Regions

We established face regions to provide a common frame of reference to describe the location of fixations and conduct MDL analysis. First, we applied the pixel test ($p < 0.05$; [35]) to fixation maps in each condition to reveal the significantly fixated regions, calculating a centroid for each significant region. We pooled all centroids across conditions and performed a k-means clustering [36] to calculate a single centroid for each nonoverlapping significantly fixated region. Five centroids corresponded to "left eye," "right eye," "bridge of nose," "center of face," and "mouth."

Minimum Description Length

MDL is a statistical method that extracts regular patterns from data set sequences [12, 13]. Here, a pattern consisted of the succession of fixations on face regions (e.g., "left eye" → "right eye" → "left eye"). We calculated fixation patterns by categorizing fixations by face region based on their minimum distance to a face region centroid. We collapsed fixations occurring consecutively within the same face region into a single fixation. We conducted MDL on each condition separately (correct and incorrect trials included) from zero (single fixation sequences) to third order (four fixation sequences) inclusive. To eliminate fixation sequences occurring by chance, we used the Monte Carlo simulation method to pseudorandomly sample the face regions (biased to replicate the distribution of observer fixations across face regions). We conducted 10,000 simulations per condition, computing a frequency distribution for each fixation pattern. We then calculated the probability of each fixation pattern appearing in the observer data set, including those occurring significantly frequently ($\alpha = 0.05$) in the results.

Model Observer

We used a model observer to build estimated patterns of confusions based on samples of face information. Each sample of information was obtained via a method that approximates the information extracted by the visual system during a fixation. First, we decomposed each image (averaged across all identities) into a four-level Laplacian pyramid [37]. We then filtered each level by applying a Gaussian window ($\alpha = 10$ pixels) to the same relative image location before recombining the levels to produce the desired image (see Figure S5A). To estimate patterns of confusions (i.e., similarity) based on the sampled information, the model observer Pearson correlated the stimulus expression (e.g., "fear" in Figure S5A) with each of the other expressive faces (e.g., "surprise," "anger," "disgust," "sadness," and "neutral" in Figure S5A). The correlation values (plotted in dashed color-coded lines in Figure S5B) representing the model observer confusions were fitted (using ordinary least squares) against the behavioral confusions of the EA observers (plotted in black in Figure S5B; see Figure S1 for confusion matrices). We repeated the sampling process for 10,000 individual samples randomly located across the face. Finally, we sorted each information sample according to its fit to the behavioral confusions of the EA observers (see contour plots of Figure S6 for rank order of "best" to "worst" fits). We followed the same procedure for each expression (except "happy," as it was seldom confused with any other expression).

Supplemental Data

Supplemental Data include Supplemental Experimental Procedures, one table, and six figures and can be found with this article online at http://www.cell.com/current-biology/supplemental/S0960-9822(09)01477-8.

Acknowledgments

P.G.S. and R.C. were supported by the Economic and Social Research Council and Medical Research Council (ESRC/MRC-060-25-0010). R.E.J. was supported by ESRC PhD studentship PTA-031-2006-00192, and C.B. was supported by a PhD studentship provided by Fonds Québécois de la Recherche sur la Nature et les Technologies.

Received: May 12, 2009
Revised: July 12, 2009
Accepted: July 13, 2009
Published online: August 13, 2009

References

1. Darwin, C. (1872). The Expression of the Emotions in Man and Animals (London: John Murray).
2. Ekman, P. (1994). Strong evidence for universals in facial expressions: A reply to Russell's mistaken critique. Psychol. Bull. *115*, 268–287.
3. Izard, C.E. (1994). Innate and universal facial expressions: Evidence from developmental and cross-cultural research. Psychol. Bull. *115*, 288–299.
4. Elfenbein, H.A., and Ambady, N. (2002). On the universality and cultural specificity of emotion recognition: A meta-analysis. Psychol. Bull. *128*, 203–235.
5. Russell, J.A. (1994). Is there universal recognition of emotion from facial expression? A review of cross-cultural studies. Psychol. Bull. *115*, 102–141.
6. Mesquita, B., and Frijda, N.H. (1992). Cultural variations in emotions: A review. Psychol. Bull. *112*, 179–204.
7. Matsumoto, D., and Ekman, P. (1988). Japanese and Caucasian Facial Expressions of Emotion (JACFEE) [slides] (San Francisco: Intercultural and Emotion Research Laboratory, Department of Psychology, San Francisco State University).
8. Ekman, P., and Friesen, W.V. (1978). Facial Action Coding System: A Technique for the Measurement of Facial Movement (Palo Alto, CA: Consulting Psychologists Press).
9. Ekman, P., Friesen, W.V., O'Sullivan, M., Chan, A., Diacoyanni-Tarlatzis, I., Heider, K., Krause, R., LeCompte, W.A., Pitcairn, T., Ricci-Bitti, P.E., et al. (1987). Universals and cultural differences in the judgments of facial expressions of emotion. J. Pers. Soc. Psychol. *53*, 712–717.
10. Matsumoto, D. (1992). American-Japanese cultural differences in the recognition of universal facial expressions. J. Cross Cult. Psychol. *23*, 72–84.
11. Matsumoto, D., and Ekman, P. (1989). American-Japanese cultural differences in intensity ratings of facial expressions of emotion. Motiv. Emot. *13*, 143–157.
12. Jorma, R. (1989). Stochastic Complexity in Statistical Inquiry Theory (River Edge, NJ: World Scientific Publishing Co.).
13. Zhao, W., Serpedin, E., and Dougherty, E.R. (2006). Inferring gene regulatory networks from time series data using the minimum description length principle. Bioinformatics *22*, 2129–2135.
14. Smith, M.L., Cottrell, G.W., Gosselin, F., and Schyns, P.G. (2005). Transmitting and decoding facial expressions. Psychol. Sci. *16*, 184–189.
15. Schyns, P.G. (1998). Diagnostic recognition: Task constraints, object information, and their interactions. Cognition *67*, 147–179.
16. Russell, J.A. (1991). Culture and the categorization of emotions. Psychol. Bull. *110*, 426–450.
17. Wierzbicka, A. (1992). Defining emotion concepts. Cogn. Sci. *16*, 539–581.
18. Buck, R. (1984). The Communication of Emotion (New York: Guildford Press).
19. Yuki, M., Maddux, W.W., and Masuda, T. (2007). Are the windows to the soul the same in the East and West? Cultural differences in using the eyes and mouth as cues to recognize emotions in Japan and the United States. J. Exp. Soc. Psychol. *43*, 303–311.
20. Pollack, A. (1996). Happy in the East (–) or smiling :-) in the West. New York Times, August 12, 1996. http://www.nytimes.com/1996/08/12/business/happy-in-the-east-or-smiling-in-the-west.html.
21. Blais, C., Jack, R.E., Scheepers, C., Fiset, D., and Caldara, R. (2008). Culture shapes how we look at faces. PLoS ONE *3*, e3022.
22. Gosselin, F., and Schyns, P.G. (2001). Bubbles: A technique to reveal the use of information in recognition tasks. Vision Res. *41*, 2261–2271.

23. Schyns, P.G., and Oliva, A. (1999). Dr. Angry and Mr. Smile: When categorization flexibly modifies the perception of faces in rapid visual presentations. Cognition *69*, 243–265.
24. Smith, F., and Schyns, P. Smile through your fear and sadness: Transmitting and identifying facial expression signals over a range of viewing distances. Psychol. Sci., in press.
25. Schyns, P.G., Petro, L.S., and Smith, M.L. (2007). Dynamics of visual information integration in the brain for categorizing facial expressions. Curr. Biol. *17*, 1580–1585.
26. Malcolm, G.L., Lanyon, L.J., Fugard, A.J.B., and Barton, J.J.S. (2008). Scan patterns during the processing of facial expression versus identity: An exploration of task-driven and stimulus-driven effects. J. Vis. *8*, 1–9.
27. Caldara, R., Schyns, P., Mayer, E., Smith, M.L., Gosselin, F., and Rossion, B. (2005). Does prosopagnosia take the eyes out of face representations? Evidence for a defect in representing diagnostic facial information following brain damage. J. Cogn. Neurosci. *17*, 1652–1666.
28. Han, S., and Northoff, G. (2008). Culture-sensitive neural substrates of human cognition: A transcultural neuroimaging approach. Nat. Rev. Neurosci. *9*, 646–654.
29. O'Toole, A.J., Deffenbacher, K.A., Valentin, D., and Abdi, H. (1994). Structural aspects of face recognition and the other-race effect. Mem. Cognit. *22*, 208–224.
30. O'Toole, A.J., Peterson, J., and Deffenbacher, K.A. (1996). An 'other-race effect' for categorizing faces by sex. Perception *25*, 669–676.
31. Tiddeman, B., Burt, M., and Perrett, D. (2001). Prototyping and transforming facial textures for perception research. IEEE Comput. Graph. Appl. *21*, 42–50.
32. Hall, E. (1966). The Hidden Dimension (Garden City, NY: Doubleday).
33. Ibrahimagić-Šeper, L., Čelebić, A., Petričević, N., and Selimović, E. (2006). Anthropometric differences between males and females in face dimensions and dimensions of central maxillary incisors. Med. Glas. *3*, 58–62.
34. Miles, W.R. (1930). Ocular dominance in human adults. J. Gen. Psychol. *3*, 412–430.
35. Chauvin, A., Worsley, K.J., Schyns, P.G., Arguin, M., and Gosselin, F. (2005). Accurate statistical tests for smooth classification images. J. Vis. *5*, 659–667.
36. MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1 (Berkeley, CA: University of California Press), pp. 281–297.
37. Simoncelli, E.P., and Freeman, W.T. (1995). The steerable pyramid: A flexible architecture for multi-scale derivative computation. In Proceedings of the 1995 International Conference on Image Processing, Volume 3 (Washington, DC: IEEE Computer Society), pp. 444–447.