Spatial Frequency and Valence Interact in Complex Emotion Perception

Brittany S. Cassidy,[1] Robert W. Wiley,[1] Mattea Sim,[2] and Kurt Hugenberg[2]

[1]University of North Carolina at Greensboro

[2]Indiana University, Bloomington

Correspondence should be addressed to:

Brittany S. Cassidy

Department of Psychology

University of North Carolina at Greensboro

296 Eberhart, PO Box 26180

Greensboro, NC 27412, USA

Email: bscassid@uncg.edu

Author note:

The authors declare no conflicts of interest. This research was supported by NSF-1748461 awarded to KH.

Abstract

Research on spatial frequency contributions to facial emotion identification has largely focused on basic emotions. The present experiment characterized spatial frequency contributions to decoding complex emotions, which can be less visible and intense than basic emotions. We investigated the effects of spatial frequency, expression valence, and perceptually available features (full face vs. eyes only) on decoding accuracy. We observed main effects of all factors, with better performance for high (relative to low) spatial frequency, for positive (relative to negative) emotions, and for full face (relative to eyes only) conditions. We also observed an interaction of all these factors. The high spatial frequency advantage in decoding accuracy was eliminated for full faces expressing more positive complex emotions. These findings suggest advantages from high spatial frequency content in accurately decoding complex emotions may attenuate when positive complex emotions are decoded from the spatial frequency content of a broader constellation of features.

Keywords: Spatial frequency, complex emotions, emotion recognition, valence

Abstract word count: 149/200

Word count: 4000/4000 (Abstract: 149; Main text and footnotes: 3213; References: 638)

Citations: 25/25

Spatial Frequency and Valence Interact in Complex Emotion Perception

People convey their inner lives through facial emotions (Baron-Cohen et al., 2001) varying in complexity. Compared to basic emotions (e.g., sad), complex emotions are considered to be more uniquely human, cognitive, and internally caused (e.g., worried; Demoulin et al., 2004). Distinguishing amongst these complex emotions is critical to appropriately react to others (Baron-Cohen et al., 2001). Mistaking an irritated glance for a flirtatious one could be disastrous. Whereas past research has extensively investigated perceptual processes affecting basic emotion identification (e.g., Kumar & Srinivasan, 2011), little work has examined perceptual processes involved in complex emotion decoding. Identifying such processes is important because accurately decoding complex emotions is a highly functional ability. Indeed, identifying complex emotions allows people to better anticipate others' behaviors.

One body of work has shown that *spatial frequency content* affects identifying basic emotions (e.g., Kumar & Srinivasan, 2011). Whereas low spatial frequencies (LSFs) provide coarse information about faces, high spatial frequencies (HSFs) provide finer details (Goffaux & Rossion, 2006). One account of spatial frequency contributions to basic emotion identification comes from work (e.g., Vuilleumier et al., 2003) showing that threat-related signals are chiefly processed via a subcortical pathway especially responsive to LSFs and that enables quick responses to potential threats. By contrast, finer details are chiefly processed by a cortical pathway especially responsive to HSFs. Beyond differences in what they convey (Demoulin et al., 2004), complex (relative to basic) emotions are often less visible and intense (Shaver et al., 1992), suggesting that finer details may facilitate decoding. Complex emotion decoding also reliably elicits cortical activation implicated in mentalization (Adams et al., 2009). Identified spatial frequency contributions to basic emotion identification may thus apply less to complex emotions because decoding complex emotions is more important for nuanced social interactions than immediate responses to existential threats.

Despite extensive work on spatial frequency contributions to basic emotion perception, only one experiment (Jennings, Yu, & Kingdom, 2017) has investigated contributions to perceiving complex emotions. In that study, participants made valence and arousal estimates for complex emotions while viewed across spatial frequencies. Jennings and colleagues found that these estimates did not differ across spatial frequencies. Thus, whereas HSFs and LSFs may both contribute to classifying complex emotions across arousal and valence, it remains unclear how they affect *accuracy* for decoding complex emotions. For example, whereas worried and irritated are both negative and similarly arousing, they express subtly but importantly different inner states. Given our focus on accuracy, this distinction is important. There may be sufficient information from HSFs and LSFs to extract valence and arousal, but perhaps not to accurately decode the emotion. Instead, accuracy may rely on HSFs given the finer face details differentiating complex emotions. Such a finding would align with work suggesting LSFs facilitate facial cue integration into a global percept and HSFs facilitate analyzing finer face details (Goffaux & Rossion, 2006).

We tested whether HSFs facilitate complex emotion decoding accuracy. Insofar as complex emotions subtly differ, HSFs seemed well-suited for detecting details comprising those subtleties. Of additional interest was whether an HSF advantage in complex emotion decoding varied by emotional valence. Multiple possibilities seemed plausible. First, insofar as complex emotions are perceptually nuanced relative to basic emotions across emotion type, perhaps an HSF advantage would occur equivalently across valence. Second, it is possible that the HSF advantage we predict might be smaller or eliminated for positive expressions. Indeed, past work indicates that both LSFs and HSFs may be used to decode positive basic expressions (happiness; Becker et al., 2012; Kumar & Srinivasan, 2011). If similar effects occur with complex emotions, the hypothesized HSF advantage would be attenuated for complex emotions. Relatedly, people with processing advantages for positive information better decode more positive than negative complex emotions (Franklin Jr. & Zebrowitz, 2016).

A third possibility was also possible: insofar as LSFs facilitate the recognition of threatening stimuli via a subcortical pathway, perhaps the HSF advantage we predict would be smaller or even eliminated for negative expressions. However, this seemed unlikely based on past research. Although LSFs (Vuilleumier et al., 2003) and HSFs (Goren & Wilson, 2006) facilitate some negative emotion recognition (e.g., fear), studies showing LSF advantages often emphasize general threat interpretations versus accurate discrimination between similar-valence expressions. Because emphasizing accuracy may attenuate negative reactivity (e.g., Lockenhoff & Carstensen, 2007), we consistently expected an HSF advantage in decoding more negative complex emotions. The current experiment used an oft-studied range of complex emotions (Baron-Cohen et al., 2001) that perceivers decoded and evaluated on valence to investigate these possibilities.

Finally, complex emotion decoding research often focuses on reading minds “in the eyes” (Baron-Cohen et al., 2001). Neurotypical perceivers often decode complex emotions from eye regions alone. Thus, of additional interest in the current work was whether spatial frequency content from full faces and eye regions differentially affected complex emotion decoding. Eye regions specifically enable emotion recognition (Royer et al., 2018). If the content of eye regions drives HSF advantages, advantages should emerge irrespective of viewing full faces or eye regions. Alternatively, the content of a global constellation of meaningful features could drive relative advantages. Indeed, features beyond eye regions enable emotion decoding (Wegrzyn et al., 2017), with coarse signals from constellations of features proposed to explain happy face advantages (Becker & Srinivasan, 2014). If true, smaller HSF advantages (potentially among more positive complex emotions) may emerge toward full faces, but not eye regions, because faces contain broader constellations of signal that, together, may facilitate decoding.

Given the increasing interest understanding complex emotion decoding (Adams et al., 2009; Demoulin et al., 2004), herein we combine techniques from the complex emotion literature (e.g., "reading the mind in the eyes") and the basic emotion perception literature (e.g., spatial frequency) to better characterize complex emotion decoding. Here, people completed a four-alternative forced choice task where they decoded complex emotions from full faces or eye regions. Spatial frequency content was manipulated within participants. People evaluated each emotion's valence, allowing us to test how spatial frequency content and valence interact in complex emotion perception.

Method

Participants

Based on work testing perceptual contributions to decoding complex emotions (Cassidy et al., in press), we targeted 70 participants per between-participants condition, oversampling to ensure enough participants. One-hundred seventy people from MTurk participated. One was excluded for entering an incorrect survey code, yielding 169 analyzed participants (M_{age}=36.98 years, SD=11.10; $M_{years\ of\ education}$=16.07, SD=2.05; 66 female[1]). This experiment was IRB approved. Data and code available upon request.

Materials and Procedure

Stimuli

Thirty-six images (evenly split among one male and one female actor) from the McGill Face Database (Schmidtmann et al., 2020) were selected that depicted the 36 complex emotions used in the "Reading the Mind in the Eyes" task (RME; Baron-Cohen et al., 2001). Teeth were visible in two images ("friendly" and "uneasy"), meaning valence effects are not attributable to teeth. Accuracy norms indicated similar decoding accuracy for the male (M=0.61, SD=0.18) and female (M=0.59, SD=0.17) actor in 4AFC tasks, $t(34)$=0.34, p=.73. Critically, using the same actors holds faces constant while only varying their emotions.

Grayscale images cropped and resized to 628×456 pixels were Gaussian filtered to obtain low-pass (<8 cycles per image) and high-pass (>32 cycles) filtered faces (see Devillez et al., 2019). These parameters complemented cut-offs in spatial frequency and emotion perception research (e.g., Kumar & Srinivasan, 2011), removing frequencies optimal for face recognition (Goffaux & Rossion, 2006). Eye regions (126×456 pixels) were cropped from filtered faces. All filtered images (Figure 1) were equated for luminance.

Task

Participants completed a self-paced task. Participants were randomly assigned to decode from full faces (N=92) or eye regions (N=77). On each trial, participants viewed a face [eye region] and four emotions (one target and three foils; see https://www.autismresearchcentre.com/tests/eyes-test-adult/) labels below it. The labels were unique to each trial and were normed to ensure comparable emotional qualities (e.g., valence and arousal; see Baron-Cohen et al., 2001 for details). Past work using these targets and foils found valence-based differences in decoding depending on perceiver motivations (Franklin Jr. & Zebrowitz, 2016), suggesting that any valence effects in decoding accuracy may not be solely attributable to target and foil selection. Participants selected the emotion best describing the expression. No participant saw the same image presented as LSF and HSF because spatial frequency-to-emotion mappings were counterbalanced within-participants.

After decoding, participants rated image valence ("How positive or negative is this image?" rated from 1 *[very negative]* to 7 *[very positive]*). Given our interest in valence effects, we ensured that images likely to be rated more positively or negatively were evenly represented across conditions. Using negative, neutral, and positive valence designations for the original RME images (see Harkness et al., 2005) we verified that items in these designations were evenly distributed among spatial frequency conditions, χ^2 (2, N=36) < 0.01, p > .99, and actors, χ^2 (2, N=36) = 0.58, p = 0.75. Because the images differed from the original RME images, we verified that valence ratings were consistent with prior designations by entering the mean valence rating per item into an ANOVA on these designations. Contrasts characterizing a Valence effect, F(2, 33) = 26.97, p<.001, showed negative items (M=3.45, SD=0.47) were more negatively rated than neutral (M=4.02, SD=0.47), t(33) = 3.24, p=.008, and neutral items were more negatively rated than positive, t(33) = 4.88, p<.001. Although these ratings mapped onto prior designations, we used participant evaluations in our analyses because they treated valence continuously and matched the task stimuli. Evaluations were highly consistent across participants (ICC = .98), reflecting consensual valence evaluations of faces (Oosterhof & Todorov, 2008).

Post-task ratings (1 *[not at all]* to 7 *[completely]*) suggested participants followed instructions ("Did you follow the instructions to the best of your ability?"; M=6.65, SD=0.70) and did not randomly respond ("Did you make evaluations at random?"; M=1.82, SD=1.61).

Analytic Strategy

We fitted a mixed-effects model using *lme4* (Bates et al., 2015) in R, estimating confidence intervals using the confint function. P-values were calculated using *lmerTest*

(Kuznetsova et al., 2017). Estimated marginal means were obtained using *emmeans* with the Tukey method to control for family-wise error rate (Lenth, 2018).

Results

Decoding accuracy (decoded = 1, not decoded = 0) was submitted to a model logistically regressing Decoding on Features (full face = -1, eyes = 1), Spatial Frequency (LSF = -1, HSF = 1), and Valence, and their interactions as fixed effects.[2] Valence evaluations were standardized around each participant's mean evaluation. The random effects structure included by-participant random intercepts and random slopes for Spatial Frequency and Valence, and by-item random intercepts and random slopes for Spatial Frequency. Accounting for variability from differences between actors, random effects by-items were nested within actor.

The random effects structure showed variability across intercepts for participants (SD = 0.72, 95% CI [0.60, 0.82]) and items (SD = 0.69, 95% CI [0.49, 0.85]). Valence effects varied across participants (SD = 0.02, 95% CI [0.0004, 0.17]). Spatial Frequency effects varied across participants (SD = 0.14, 95% CI [0.006, 0.24]) and items (SD = 0.18, 95% CI [0.007, 0.61]). There was no variability across intercepts for actor (SD < 0.001, 95% CI [0, 0.22]). Spatial frequency effects did not vary by actor (SD < 0.001, 95% CI [0, 0.08]).

Supporting an HSF advantage, a Spatial Frequency effect showed better decoding from HSF (*Estimate*=0.54, 95% CI [0.48, 0.61]) than LSF (*Estimate*=0.46, 95% CI [0.39, 0.52]) content, b = 0.17, SE = 0.04, z = 4.06, p < .001, 95% CI [0.09, 0.26]. A Features effect showed better decoding from full faces (*Estimate*=0.57, 95% CI [0.50, 0.63]) than eyes (*Estimate*=0.44, 95% CI [0.37, 0.51]), b = -0.26, SE = 0.06, z = 4.18, p < .001, 95% CI [-0.39, -0.14]. There was a positive Valence effect, b = 0.19, SE = 0.03, z = 5.59, p < .001, 95% CI [0.12, 0.26].

These factors interacted to affect decoding complex emotions. Qualifying a Features × Spatial Frequency interaction, $b = 0.08$, $SE = 0.03$, $z = 2.53$, $p = .01$, 95% CI [0.02, 0.14], was the three-way interaction, $b = 0.07$, $SE = 0.03$, $z = 2.14$, $p = .03$, 95% CI [0.01, 0.14] (Figure 2). We characterized the three-way interaction by testing spatial frequency effects on decoding when viewing full faces or eyes one standard deviation below (more negative) and above (more positive) the mean valence evaluation.

For full faces expressing more positive complex emotions, people had similarly high decoding accuracy when viewing HSFs (*Estimate*=0.61, 95% CI [0.53, 0.68]) and LSFs (*Estimate*=0.61, 95% CI [0.54, 0.68]), $OR = 0.98$, $SE = 0.14$, $z = 0.15$, $p = .99$, 95% CI [0.69, 1.39]. For eyes expressing positive complex emotions, however, people better decoded from HSFs (*Estimate*=0.55, 95% CI [0.47, 0.63]) than LSFs (*Estimate*=0.41, 95% CI [0.34, 0.50]), $OR = 1.75$, $SE = 0.25$, $z = 3.97$, $p < .001$, 95% CI [1.22, 2.52]. For full faces and eyes expressing more negative complex emotions, people better decoded from HSFs (Full faces: *Estimate*=0.57, 95% CI [0.48, 0.65]; Eyes: *Estimate*=0.44, 95% CI [0.36, 0.53]) than LSFs (Full faces: *Estimate*=0.47, 95% CI [0.39, 0.55]; Eyes: *Estimate*=0.34, 95% CI [0.27, 0.41]), $OR_{full\ faces} = 1.49$, $SE = 0.20$, $z = 2.96$, $p = .02$, 95% CI [1.05, 2.11], $OR_{eyes} = 1.57$, $SE = 0.22$, $z = 3.16$, $p = .009$, 95% CI [1.09, 2.27].

We also explored features effects on decoding for valenced emotions viewed with HSFs or LSFs. When viewing LSFs, people better decoded positive complex emotions from full faces than eye regions, $OR = 2.25$, $SE = 0.35$, $z = 5.23$, $p < .001$, 95% CI [1.51, 3.35]. No difference emerged from HSF content, $OR = 1.26$, $SE = 0.22$, $z = 1.32$, $p = .55$, 95% CI [0.81, 1.96]. People better decoded negative complex emotions from full faces versus eye regions irrespective of spatial frequency content (LSF: *OR* = 1.74, *SE* = 0.26, *z* = 3.66, *p* = .001, 95% CI [1.18, 2.57]; HSF: *OR* = 1.65, *SE* = 0.30, *z* = 2.79, *p* = .03, 95% CI [1.04, 2.63]).

There was no Task × Valence interaction, *b* = 0.002, *SE* = 0.03, *z* = 0.07, *p* = .94, 95% CI [-0.05, 0.07], and no Spatial Frequency × Valence interaction, *b* = -0.03, *SE* = 0.03, *z* = 1.19, *p* = .23, 95% CI [-0.11, 0.02].

Comparison to Accuracy Norms

If HSFs facilitate complex emotion decoding over LSFs, comparing decoding accuracy to accuracy norms from unedited images should reflect this pattern. To this end, we calculated mean decoding accuracies when each item was seen as an LSF or HSF full face or eye region. Four paired t-tests compared decoding accuracy for task and unedited images.

Decoding accuracy for HSF (*M* = 0.59, *SD* = 0.20) and unedited (*M* = 0.60, *SD* = 0.18) full faces was similar, *t*(35) = 0.27, *p* = .79, *d* = 0.05. It was better for unedited than LSF full faces (*M* = 0.54, *SD* = 0.20), *t*(35) = 2.03, *p* = .05, *d* = 0.34, HSF eye regions (*M* = 0.50, *SD* = 0.17), *t*(35) = 2.86, *p* = .001, *d* = 0.48, and LSF eye regions (*M* = 0.39, *SD* = 0.15), *t*(35) = 6.13, *p* < .001, *d* = 1.02. These patterns support HSFs facilitating complex emotion decoding when signal comes from full faces relative to eye regions.

Discussion

Although LSFs and HSFs both affect classifying complex emotion valence (Jennings et al., 2017), HSFs elicited better complex emotion decoding than LSFs overall. This finding suggests that fine details conveyed by HSFs facilitate distinguishing among complex emotions and has theoretical implications. Whereas prior work suggests dual routes by which LSFs and HSFs affect basic emotion detection, the current findings suggest greater reliance on a cortical route well-suited for analyzing finer details conveyed by HSFs when decoding complex emotions. Indeed, processing complex emotions elicits cortical activity implicated in mentalization (Adams et al., 2009).

Full faces were also more accurately decoded than eyes-only faces. This too is consistent with the fact that facial expressions of complex emotions are subtler than their basic emotion counterparts, suggesting that more expression signal available in the full-face stimuli facilitate accurate decoding. Better decoding from full faces also suggests that signal beyond eye regions facilitates decoding complex emotions (similar to Wegrzyn et al., 2017). Further, positive complex emotions were more accurately decoded than were negative complex emotions, an effect that is broadly consistent with other positive valence expression advantages observed in the literature (CITES).

Importantly, we also observed a higher-order interaction of all three of these variables, indicating that the HSF advantage which was observed consistently across conditions, was eliminated for positive, full face stimuli. This finding in full faces suggests that happy face processing advantages irrespective of spatial frequency content (Becker et al., 2012) extend to decoding complex positive emotions. It also complements work suggesting that positive emotions are distinguishable from one another (e.g., pride; Tracy & Robins, 2004). That LSFs and HSFs elicited similar decoding of positive complex emotions in full faces suggests that these emotions contain broader constellations of meaningful content (e.g., from mouths) that, when perceived together, facilitate decoding. Notably, better decoding of positive complex emotions also emerged from LSFs in full faces than eye regions, supporting that LSFs from faces versus eye regions convey more meaningful signal. These differences suggest multiple routes by which positive complex emotions may be advantaged in processing and recognition, a theoretical position suggested by past work (Becker & Srinivasan, 2014).

Gross movements detectable across spatial frequencies might have also facilitated decoding positive complex emotions from full faces if these movements vary more among positive than negative emotions. Future work may examine this possibility. Similar decoding of positive complex emotions, however, emerged from the content of faces and HSF eye regions.[3] Unlike negative complex emotions, the fine details conveyed by HSFs in eye regions may convey enough signal to decode positive complex emotions.

A limitation of this work is that it was conducted online. In-lab experiments may control for important factors affecting stimulus perception. Treating participants and items as random factors, in part, mitigates our findings being explained by such differences. However, future experiments could expand on the nature of the current findings. A second limitation is that we used static stimuli. Because inferences about static and dynamic faces can differ (Krumhuber et al., 2019), future work would benefit from using dynamic faces.

Together, this experiment provides novel evidence characterizing how perceptual processes facilitate social understanding. HSFs may enable distinguishing between fine face details separating complex emotions. The extent of HSF advantages, however, may depend on emotional valence and by what facial features are visible when decoding.

Footnotes

[1]Of 169 participants, 138 identified as White. Because targets were White, we verified the effects of interest were significant when including race (non-White = -1, White = 1) in the model and that race did not explain additional variance, χ^2 (8) = 2.99, *p* = .93.

[2]Unlike basic emotion research (e.g., Kumar & Srinivasan, 2011), the current work had unlimited dwell times. To mitigate concerns that dwell times affected our effects, we removed 159 trials where reaction times were over 3SDs from individual means and re-ran the model controlling for standardized reaction time. All effects maintained direction and significance.

[3]No difference in decoding more positive complex emotions from LSF full faces versus HSF eye regions emerged, *OR* = 0.78, *SE* = 0.14, *z* = 1.43, *p* = .48, 95% CI [0.50, 1.22].

References

Adams, R., Rule, N., Franklin Jr., R., Wang, E., Stevenson, M., Yoshikawa, S., Nomura, M., Sato, W., Kestutis, K., & Ambady, N. (2009). Cross-cultural reading the mind in the eyes: an fMRI investigation. *Journal of Cognitive Neuroscience, 22*(1), 97-108.

Baron-Cohen, S., Wheelwright, S., Hill, J., Raste, Y., & Plumb, I. (2001). The "reading the mind in the eyes" test revised version: A study with normal adults, and adults with asperger syndrome or high-functioning autism. *Journal of Psychology and Psychiatry, 42*(241-251).

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1-48.

Becker, D., Neel, R., Srinivasan, N., Neufeld, S., & Kumar, D. (2012). The vividness of happiness in dynamic facial displays of emotion. *PLOS one, 7*(1), e26551.

Becker, D., & Srinivasan, N. (2014). The vividness of the happy face. *Current Directions in Psychological Science, 23*(3), 189-194.

Cassidy, B., Wiley, R., Sim, M., & Hugenberg, K. (in press). Decoding complex emotions and humanizationi show related face processing effects. *Emotion*.

Demoulin, S., Leyens, J., Paladino, M., Rodriguez-Torres, R., Rodriguez-Perez, A., & Dovidio, J. (2004). Dimensions of “uniquely” and “non-uniquely” human emotions. *Cognition and Emotion, 18*(1), 71-96.

Devillez, H., Mollison, M., Hagen, S., Tanaka, J., Scott, L., & Curran, T. (2019). Color and spatial frequency differentially impact early stages of perceptual expertise training. *Neuropsychologia, 122*, 62-75.

Franklin Jr., R., & Zebrowitz, L. (2016). Aging-related changes in decoding negative complex mental states from faces. *Experimental Aging Research, 42*(5), 471-478.

Goffaux, V., & Rossion, B. (2006). Faces are "spatial"—holistic face perception is supported by low spatial frequencies. *Journal of Experimental Psychology: Human Perception & Performance, 32*(4), 1023-1039.

Goren, D., & Wilson, H. (2006). Quantifying facial expression recognition across viewing conditions. *Vision Research, 46*(8-9), 1253-1262.

Harkness, K., Sabbagh, M., Jacobson, J., Chowdrey, N., & Chen, T. (2005). Enhanced accuracy of mental state decoding in dysphoric college students. *Cognition & Emotion, 19*(7), 999-1025.

Jennings, B., Yu, Y., & Kingdom, F. (2017). The role of spatial frequency in emotional face classification. *Attention, Perception, and Psychophysics, 79*, 1573-1577.

Krumhuber, E., Lai, Y., Rosin, P., & Hugenberg, K. (2019). When facial emotions do and do not signal minds: The role of face inversion, expression dynamism, and emotion type. *Emotion, 19*(4), 746-750.

Kumar, D., & Srinivasan, N. (2011). Emotion perception is mediated by spatial frequency content. *Emotion, 11*(5), 1144-1151.

Kuznetsova, A., Brockhoff, P., & Christensen, R. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software, 82*(13), 1-26.

Lenth, R. (2018). emmeans: Estimated marginal means, aka least-squares means. *R package version 1.4.7.*

Lockenhoff, C., & Carstensen, L. (2007). Aging, emotion, and health-related decision strategies: Motivational manipulations can reduce age differences. *Psychology and Aging, 22*(1), 134-146.

Oosterhof, N., & Todorov, A. (2008). The functional basis of face evaluation. *Proceedings of the National Academy of Sciences, 105*(32), 11087-11092.

Royer, J., Blais, C., Charbonneau, I., Dery, K., Tardif, J., Duchaine, B., Gosselin, F., & Fiset, D. (2018). Greater reliance on the eye region predicts better face recognition ability. *Cognition, 181*, 12-20.

Schmidtmann, G., Jennings, B., Sandra, D., Pollock, J., & Gold, I. (2020). The McGill Face Database: Validation and insights into the recognition of facial expressions of complex mental states. *Perception, 49*(3), 310-329.

Shaver, P., Wu, S., & Schwartz, J. (1992). Cross-cultural similarities and differences in emotion and its representation. In M. Clark (Ed.), *Review of Personality and Social Psychology* (Vol. 13, pp. 175-212).

Tracy, J., & Robins, R. (2004). Show your pride: Evidence for a discrete emotion expression. *Psychological Science, 15*(3), 194-197.

Vuilleumier, P., Armony, J., Driver, J., & Dolan, R. (2003). Distinct spatial frequency sensitivities for processing faces and emotional expressions. *Nature Neuroscience, 6*(6), 624-631.

Wegrzyn, M., Vogt, M., Kireclioglu, B., Schneider, J., & Kissler, J. (2017). Mapping the emotional face: How individual face parts contribute to successful emotion recognition. *PLOS one, 12*(5), e0177239.

Figure 1. Example images low-pass (LSF) and high-pass (HSF) filtered faces and eye regions from each actor. Each actor expressed 18 different complex emotions during the task.

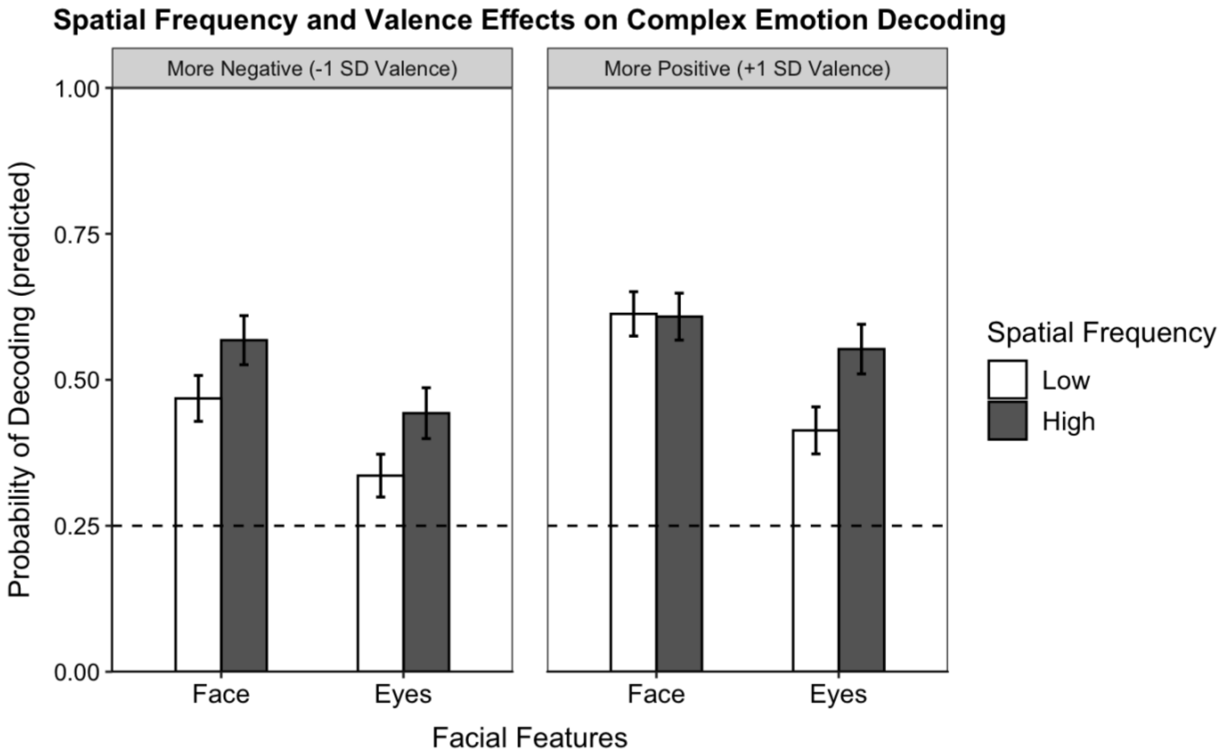

Figure 2. An interaction between Features, Spatial Frequency, and Valence on Complex Emotion Decoding emerged. HSF advantages emerged when decoding more negative complex emotions from both full faces and eye regions. An HSF advantage emerged when decoding more positive complex emotions from eye regions, but not from full faces. Error bars denote standard errors of the mean. Dashed line denotes chance level performance.