# Complementary methodologies to investigate spatial frequencies in facial expression recognition

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## Theoretical context

Most of the studies on facial expression recognition have used arbitrary cut-off to isolate the impact of different range of spatial frequencies (SFs; Fig. 1a). For example, two studies[1,2] revealed that low SFs play a central role in the recognition of pain. However, our own work using the Bubbles method[3] suggests that pain categorization relies on mid-to-high SFs[4], a SF range that has been disregarded in previous studies. Using a more ecological method that simulates the distance of stimuli presentation[5], we also revealed that pain recognition is optimal in a short to medium distance (1.2–4.8m)[4]. Here we were interested in the generalization of these results for other basic expressions using these two complementary methodologies.

## Method

40 participants took part in the experiments (18-35 years old; $M$ = 23, $SD$ = 3.46). Both tasks consisted of an 8-expression categorization task using the STOIC facial expression database (six basic expressions, neutral and pain; see ref. 4 for data on pain). Mean accuracy was maintained halfway between chance (i.e. 12.5% and 50% correct for each task, respectively) and perfect accuracy using QUEST[6].

### SF Bubble's method[3] (experiment 1)

- A data-driven method which randomly samples SFs on each trial to reveal the useful visual information for facial expression recognition (Fig. 1b).

a)

b)

*Figure 1.* **a)** Example of stimuli filtered with a second-order butterworth filter (from left to right : broadband, low-pass (< 8 cycle per face; cpf), band-pass (between 8 and 32 cpf) and high-pass (> 32 cpf)). Note that mid SFs (8-32 cpf) are usually not included in experiments on facial expression perception and spatial frequencies. **b)** Example of stimuli filtered with the Bubble's method. The main interest of the SF Bubble's method is that it allows the investigation of the whole spatial frequency spectrum, whithout the use of arbitrary cut-offs.

### Distance method (experiment 2)

- Presentation of reduced size images simulating increasing viewing distance using the Laplacian Pyramid toolbox[5] (Fig. 2).

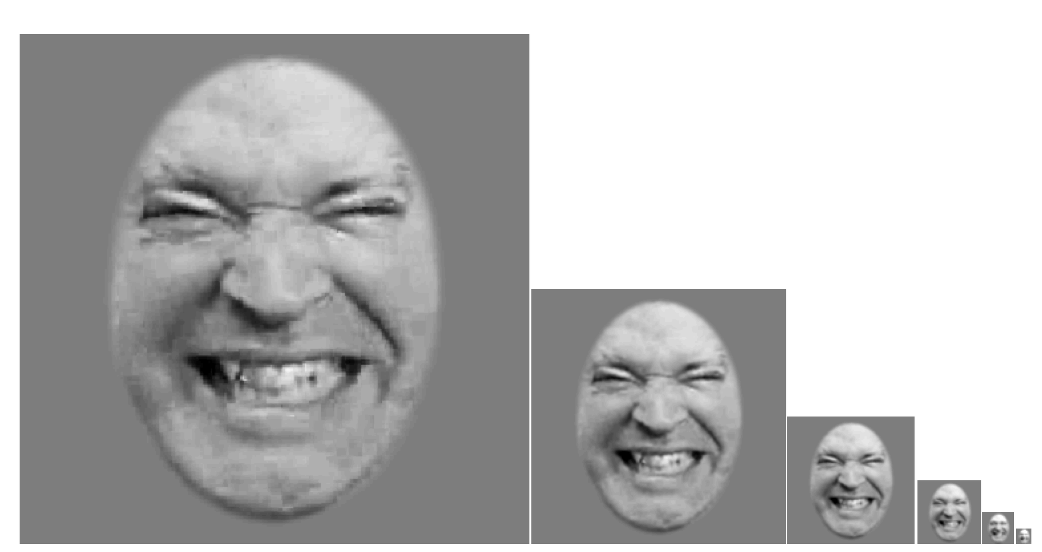

*Figure 2.* Example of stimuli created with the Laplacian Pyramid toolbox simulating increasing viewing distances (from left to right : 3.26, 1.63, .815, .41, .20, .10 degree of visual angle respectively equivalent to a perceived distance of 1.2, 2.4, 4.8, 9.6, 19.2, and 38.4 meters).

## Analyses and results

For experiment 1, multiple regression analysis on the SF filters and accuracies across trials were computed. SF peaks were measured by submitting the classification vector to a 50% area SF measure (ASFM; Fig 3a). For experiment 2, unbiased hit rates[7] were computed to quantify performance at each distance (Fig. 3b). The relationship between the two methodologies is linear. That is, SF tuning for all basic facial expressions, except for surprise, falls into the mid SF range and a drop in performance occurs when the simulated distance no longer reveals mid SFs. We used curve fitting analyses to verify the point of subjective equality (PSE) and the slope of each facial expression. Repeated measures ANOVAs on PSE and slope revealed a significant effect of facial expression (PSE = $F(6, 114)$ = 45.057, $p< .001$; slope = $F(6, 108)$ = 30.668, $p< .001$) and follow-up paired sample t-tests (corrected p = 0.05/21) revealed significant differences between expressions. For exemple, surprise is found to be the least sensitive expression to the effect of distance (M=0.69 ± 0.14) which is consistent with its lower SF peak.

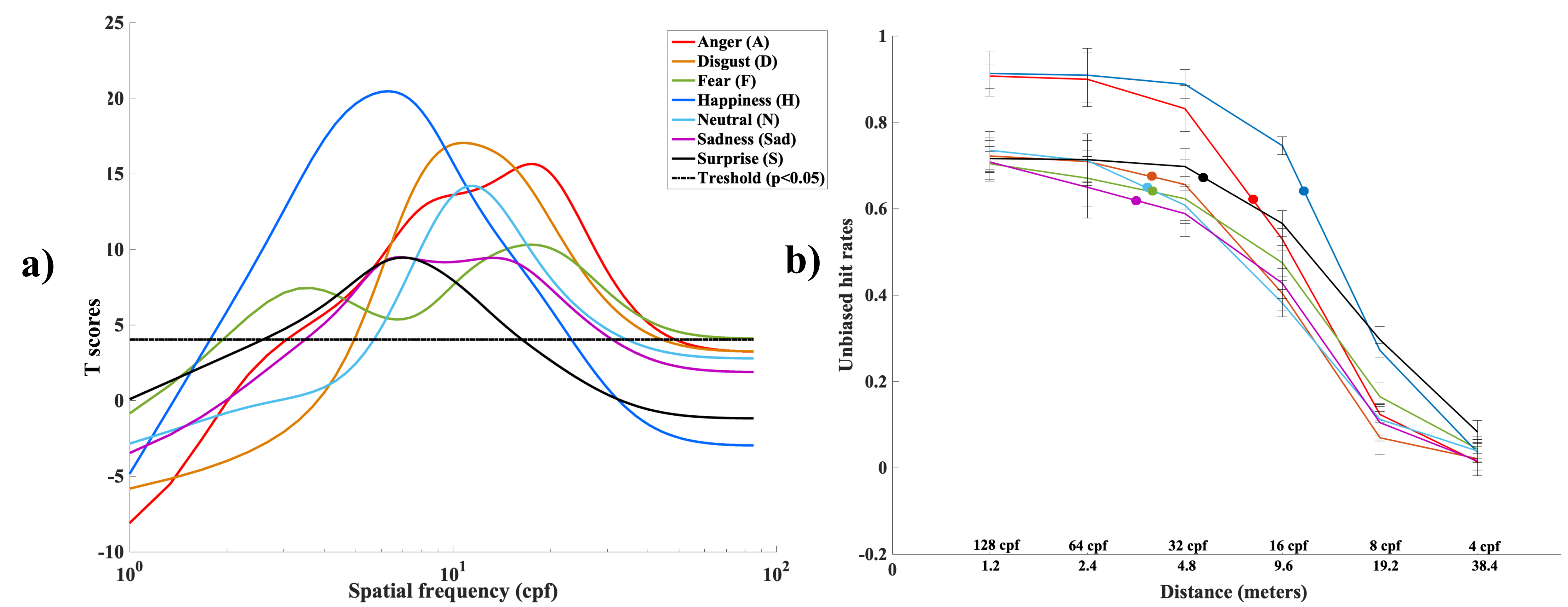


*Figure 3.* **a)** SF tuning for basic facial expression categorization as revealed by SF Bubble's method (experiment 1). ASFM peaks for each emotion are as follows: A (21.33cpf), D (18.67cpf), F (20.67cpf), H (10.33cpf), N (15.67cpf), Sad (18.33cpf) and S (7.67cpf). The black dotted line represents the statistical threshold for significance (p<0.05). **b)** Unbiased hit rates for emotion categorization as a function of viewing distance. Error bars represent the standard error. PSE for each facial expression are represented by a filled dot. Significant differences in PSE across expressions are as follows: H > A = S > D = N = F = Sad.

## Conclusion

Similarly for pain, results suggest that recognition of basic facial expressions relies on mid SFs with the exception of surprise. These results are consistent with surprise being characterized as having a rich low SF signal and considered as a distal facial expression[8]. Finally, this study highlights the relevance of using complementary methodologies to investigate SFs in facial expression recognition, but foremost, that any study that excludes mid SFs can not capture an accurate profile of the role of SFs in these tasks.

**References 1)** Wang, Eccleston & Keogh (2015). *Pain*, 156(9), 1670-1682. **2)** Wang, Eccleston & Keogh (2017). *Pain*, 158(11), 2233-2242. **3)**Willenbockel et al., (2010). *J. of Exp. Psychology*. 36(1), 122. **4)** Charbonneau et al., (2021). *Sci Rep* 11(14357). **5)** Burt & Aldeson, (1983) *IEEE Transactions on communications*, 31(4), 532-540. **6)** Watson & Pelli (1983). *Perception & Psychophysics*, 33, 113-120. **7)** Armistead (2013). *Weather forecasting*, 28(3), 802-814. **8)** Smith & Schyns (2009). *Psychol. Sci.* 20(10), 1202-1208.

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