The Role of Spatial Frequencies for Facial Pain Categorization

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Research Article

Keywords: spatial frequencies, facial, pain

Posted Date: February 17th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-198688/v1

Version of Record: A version of this preprint was published at Scientific Reports on July 13th, 2021. See the published version at https://doi.org/10.1038/s41598-021-93776-7.

Abstract

Studies on low-level visual information underlying pain categorization have led to inconsistent findings. Some are showing an advantage for low spatial frequency information (SFs) and others a preponderance of mid SFs. This study aims to clarify this gap in knowledge since these results have different theoretical and practical implications, such as how far away an observer can be in order to categorize pain. This study addresses this question by using two complementary methods: a data-driven method without a priori about the most useful SFs for pain recognition and a more ecological method that simulates the distance of stimuli presentation. We reveal a broad range of important SF for pain recognition starting from low to relatively high SFs and showed that performance is optimal in a short to medium distance (1.2 to 4.8 meters) but declines significantly when mid SFs are no longer available. This study reconciles previous results that show an advantage of LSFs over HSFs when using arbitrary cutoffs, but above all reveal the prominent role of mid-SFs for pain recognition across two experimental tasks.

Introduction

Pain is a subjective experience communicated to others to alert them of potential threats or to seek assistance [1, 2]. Effective communication of pain can operate through verbal and non-verbal cues. Among the non-verbal cues, facial expression is considered one of the most reliable indicators of pain [3, 4, 5]. The effective recognition of facial expressions of pain is of utmost importance, particularly in nonverbal populations such as infants [6, 7] and adults with dementia [8, 9]. However, for its communicative function to be fulfilled, the observer must accurately decode the facial expressions.

Studies investigating how pain is encoded through facial expressions have highlighted the occurrence of three features: the contraction of the eyebrows, the wrinkling of the nose with the raising of the upper lip, and the narrowing of the eyes [10, 11, 12]. The decoding of pain facial expressions relies on the processing of these features [13, 14]. Thus far, the study of low-level visual information underlying this processing has led to inconsistent findings. One of the first steps in vision concerns the decomposition of the visual signal in different spatial frequency (SF) bands [15]. Low SFs (LSFs; see Fig. 1) convey the coarse structures used when viewing faces from a distance [16] or in periphery [17] whereas high SFs (HSFs) convey edges and fine details available when faces are viewed from closer and at the fovea [18]. Two recent articles suggest that LSFs play a central role in the recognition of facial expressions of pain [19, 20]. However, as a communication signal, one would expect that pain signal would be best suited to a short-to-medium distance where one can benefit from immediate assistance. Furthermore, our previous work suggests that SFs between 11 and 21 cycles per face (cpf) are the most useful [14, 21]. According to the terminology used in previous research [19] and explained in more detail below, these SFs would correspond to mid SFs (MSFs).

One potential explanation for this discrepancy could lie with Wang and collaborators' [19] use of cutoffs to isolate the impact of LSF and HSF. In the literature, the cutoffs used to define LSF and HSF vary arbitrarily (e.g. LSF defined below 8 cpf in [19]; between 2 and 8 cpf in [22]; below 6 cycles per image in

[23]; and HSF defined above 32 cpf in [19, 24] or above 24 cycles per image [23]). To the best of our knowledge, such variation is not theoretically driven and is often informed by methodological issues (e.g. [25, 26]) or for replication purposes [27]. Furthermore, the use of such cutoffs hinders the potential contribution of MSFs, leading to an incomplete or incorrect account of the role of SF in pain perception.

The objective of this study is to offer a more complete account of the role of SF in pain perception by incorporating findings from two different methods. Therefore, experiment 1 aimed to reveal which SFs are the most useful for pain categorization among other emotional expressions (i.e. anger, disgust, fear, joy, sadness, surprise, neutral or pain). This kind of experiment is standard in the facial expression literature (e.g. [14, 19]) but instead of using cutoffs to create low-pass and high-pass filters [19], we used SF Bubbles. The fundamental basis of the Bubbles method and its variants (e.g. SF Bubbles, orientation Bubbles), is that it allows the random sampling of information (e.g. local image features, SFs, or orientations, see refs [28–38]) contained in a visual stimulus in order to reveal the relative importance of this information for efficient visual processing. Here in the SF Bubbles method, SFs contained in facial expression images were randomly sampled on each trial (see the *Methods* section for more details on the stimuli creation procedure), allowing to calculate the probability that participants will accurately identify the facial expression presented based on the presence or absence of certain SFs. Therefore, if the sampled SFs are useful for processing a particular facial expression, it will increase the likelihood that participants will respond accurately, and conversely, if they are not useful, it decreases the likelihood that participants will respond accurately.

Experiment 2 aimed to reveal the optimal SFs for pain recognition through the manipulation of the face retinal size (equivalent to the distance between the stimulus and the observer). As in experiment 1, participants were asked to categorize the perceived facial expressions as corresponding to anger, disgust, fear, joy, sadness, surprise, neutral or pain although face images were presented in different sizes. The objective of this experiment was to verify the impact of distance on the ability to categorize the facial expression of pain. Since layers of HSFs are progressively peeled off by increasing distance between the observer and the distal stimulus, this experimental manipulation also allows to investigate the role of relatively high SFs in the presence of lower SFs. This method is also considered more ecological since in everyday life, the distance at which one sees people's facial expressions can vary considerably.

Results

Although several of the following experiments included all of the six basic emotions and neutral, only data related to pain will be presented since this article focuses on the mechanisms of pain perception in faces (see *data availability* section for the link).

Experiment 1 - SFs for pain categorization

First, SF tunings were calculated by conducting what amount to a multiple regression analysis on the SF filters and accuracies across trials. A weighted sum of SF filters was calculated by allocating positive

weights (z-scored accuracies) to filters that led to correct responses and negative weights (z-scored accuracies) that led to incorrect responses. Using the expected mean and standard deviation of the null hypothesis given by the Stat4Ci toolbox [39], the SF filters were then transformed into z scores. One-sample t-tests were then conducted on each SF. The statistical threshold ($p < .05$; $t_{crit} = 4.04$; dashed line in Fig. 2) was obtained by the pixel test from the Stat4Ci. It compensates for the multiple comparisons across SF, while taking into account the fact that adjacent SF are not totally independent from one another. We also measured the SF peaks by submitting the classification vector to a 50 % area SF measure (ASFM; analogous to a 50 % area latency measure commonly used in electroencephalography analysis; see [40]). The ASFM corresponds to the SF point that splits the area under the curve and above the significance threshold in two equal parts. Moreover, to verify whether we replicate past observation of an advantage of LSF over HSF, we compared the usefulness of LSF and HSF in our data. For this, we used a bootstrap procedure in which 10,000 resampled classification vectors (in *t* scores) were first produced. Then, in each of these classification vectors, we selected the highest t-score value reached among the SFs below 8 cpf, and the highest t-score value among the SF over or equal to 32 cpf. These values were then compared to one another.

Figure 2 shows the SF tuning for categorizing pain. More precisely, information between 4.5 and 48.4 cpf was significantly and positively associated with the accurate pain categorization. The SF most correlated with performance corresponded to 6 cpf. However, given the atypical shape of the frequency tuning curve (typical SF tuning curves usually look more Gaussian; see [35]), we also measured the ASFM which was found at 11.67 cpf. Interestingly, the atypical appearance of the curve could possibly indicate the existence of two distinct peaks, the first reaching its maximal value at 6 cpf (from 4.5 to ~ 14.6 cpf) and the second reaching its maximal value at 22.7 cpf (from ~ 14.6 to 48.4 cpf). Moreover, the present data are not necessarily inconsistent with previous studies [19]. The bootstrap procedure revealed that LSFs were more useful than HSFs for correct categorization of pain in 9,961 out of the 10,000 classification vectors ($p = 0.036$).

Figure 2. Pain categorization revealed by the Bubble's method. The left panel displays the SF tuning for pain categorization. The black dotted line represents the statistical threshold for significance ($p < 0.05$). The right panel represents an example of a stimulus filtered with the significant SFs associated with pain categorization.

Experiment 2 - Distance for pain categorization

First, unbiased hit rates (see [41] for details) were computed. This measure refers to a modified form of the signal detection sensitivity measure *d'*. It allows us to quantify sensitivity independently of response bias when discriminating a given expression from the remaining expressions. A repeated measures ANOVA on the factor of distance revealed a significant main effect $F(3.33, 63.33) = 337.27$, $p < .001$ ($\eta^2 = .95$) (see Fig. 3). Post hoc comparisons corrected with Bonferroni's method revealed significant differences between the various distances. The three conditions representing the closest simulated distances (1.2, 2.4 and 4.8m) were not significantly different from each other (all *p*'s > 0.45, all Cohen's d <

0.41). However, a significant decrease in performance was observed between 4.8m and 9.6m ($p < .001$, Cohen's d = 1.57). Subsequently, all conditions representing the furthest simulated distances (9.6, 19.2 and 38.4m) showed a large decrease in performance and were all significantly different from each other (all p's < .001, all Cohen's d > 1.57). Since the pyramid toolbox removes one octave of SF information for each iteration, it is possible to infer the relationship between distance and SFs (see the *Methods* section for details). Thereby, the results suggest that removing HSFs (over 32 cpf) does not significantly hinder pain categorization. On the other hand, it is clear that removing MSFs between 16 and 32 cpf and between 8 and 16 cpf significantly decreases performance. As mentioned before, only data regarding pain facial expressions are presented but data on other facial expressions (i.e. anger, disgust, fear, joy, sadness, surprise and neutral) carefully replicate Smith and Schyns (2009) study [16] despite using different stimuli and participants.

Discussion

Studies on low-level visual information underlying the processing of pain facial expressions have led to inconsistent findings. While some are showing an advantage for LSF over HSF [19, 20] others find a preponderance of MSF [14]. The main objective of this study was to reevaluate this question using a method specifically created to investigate the contribution of each SF to performance. Moreover, with a concern for the generalizability of our findings to more ecological conditions, we verified the impact of distance on the ability to categorize the facial expression of pain. More specifically, our results highlight the importance of a wide range of SFs from LSF (4.5 cpf) to relatively HSF (48.4 cpf) when categorizing pain among other basic emotions. Interestingly, the data presented in experiment 1 may suggest the presence of two peaks that could be linked with facial feature processing. Taken in combination with the data presented by Roy et al., [14, 21] it is possible to interpret the first peak as related to the processing of the mouth area in low-to-mid SF, while the second peak could be associated with the frown line in mid-to-high SF. Of course, this interpretation of our data remains speculative and needs to be taken with caution. Finally, categorizing pain among other basic emotions is more accurate when stimuli are in a distance range of 1.2 to 4.8 meters from the observer rendering available a broad range of SFs from low to high. The important decrease in performance between 4.8m and 9.6m emphasizes the crucial role of MSFs between 16 and 32 cpf. Taken together, the results from the SF Bubbles method and the distance experiment highlight the importance of MSF in pain recognition, although an advantage for LSF is found when solely comparing LSF to HSF tuning.

In addition to being associated with arbitrary decisions, the utilization of cutoffs present an important downfall by hindering the possible contribution of a large band of MSF, which, as revealed in this study, are diagnostic for the recognition of pain facial expressions. Indeed, cutoff methods used in previous research hide the complexity of SF information utilization and lead to misleading conclusions. Even though we found consistent results when using the same criterion as past studies for cutoffs of LSF and HSF (i.e. LSFs were more useful than HSFs), this does not mean that LSFs are the most useful SFs for pain facial expression decoding. Needless to say, Wang's [19] study is by no means the only one to use arbitrary cutoffs to separate HSF and LSF (e.g. [22–24]) that are not theoretically driven but rather

informed by methodological issues (e.g. [25, 26] or by concerns for the replication of previous studies [27]. Furthermore, given the central role of MSF in many face perception tasks such as identification [35, 29, 42, 43] and facial expression categorization [44] it is substantial to include them in tasks investigating pain recognition or any other facial expressions. Therefore, it is critical to use methods and experimental paradigms that allow us to investigate the full SF spectrum. SF Bubbles method is effective but other methods such as critical band masking [42, 45] and bandpass filtering [46] are also suitable. Since several existing methods allow us to assess the contribution of each SF to performance, it would be crucial that future studies make use of such methods and avoid arbitrary cutoffs of low and high SFs.

There are some limitations and interesting future directions to be considered. Firstly, one potential limit of the study concerns the choice of stimuli. The stimuli used here came from a validated database [47, 48] composed of photos of 10 different identities successively expressing one of seven emotions (i.e. anger, disgust, fear, joy, sadness, surprise and pain) at a comparable, strong intensity level or displaying a neutral expression. These stimuli consist of facial expressions produced on request (i.e. posed facial expressions) as opposed to spontaneously induced expressions. One could argue that the latter are more ecologically valid and could potentially lead to different results than those obtained in the present study. Interestingly, a group of researchers [49] has shown a high degree of similarity in visual strategies when posed and spontaneous facial expressions are compared. However, they do reveal that there is a higher degree of heterogeneity in the useful facial cues across identities in spontaneous expressions [49]. This implies that different facial features could be more/less useful for different expressors. Given these results, it would be interesting for future studies to compare posed and spontaneous pain facial expressions and to verify whether SF tuning differs across these conditions. It would also be interesting to investigate visual information extraction in terms of facial cues as in Roy and colleagues' study [14] with the Bubbles method but with spontaneous pain facial expressions. Secondly, another potential limit of this study with respect to our choice of stimuli concerns their static display. In everyday life, facial expressions are generated with facial movement and are dynamics. Hence, a more ecological way of investigating pain facial expression recognition would be to use dynamic stimuli. Interestingly, it has been shown that a slight shift toward lower SFs occurs for dynamic expressions (i.e anger, disgust, fear, joy, sadness, surprise) in comparison with static ones [50]. These authors suggest that it is the presence of motion in general that causes this shift in SFs and not motion information *per se*, since a shift to LSFs is also observed when frames of dynamic facial expressions are shuffled. Considering the broad literature supporting the advantage of dynamic facial expression over static ones (e.g. [50, 51]) and the shift toward lower SFs in their processing, it would be interesting to replicate these findings using dynamic pain facial expression.

Altogether, this study not only reconciles data from different groups of researchers, but reveals the SFs useful for pain recognition through different methods. Indeed, results with SF Bubbles are corroborated by another experiment using a completely different methodology (i.e. distance experiment). The convergence of these findings is interesting since it enables greater extrapolation of our results to real life situations that may potentially be tied to evolutionary hypotheses. For example, experiment 2 revealed that pain categorization is more accurate and mostly identical between a perceived distance of 1.2 to

about 4.8 meters which corresponds to all conditions in which all MSFs and LSFs are available. These data are particularly interesting in the context of healthcare, where time and resources may not always be available even though a rapid and accurate assessment of the presence of pain experienced by patients is crucial. These results suggest that healthcare providers could recognize the presence of pain even from the door frame of a patient's room if it is no more than about 5 meters away. Furthermore, this perceptual treatment is compatible with survival mechanisms since in less than a few seconds (i.e. a distance of a few meters), a person in pain will receive assistance.

Conclusion

In sum, this study revealed through two different experiments the SF information involved in pain recognition. The results reconcile previous data from different groups of researchers, and highlight the importance of a broad range of SFs starting from low to relatively high. Most importantly, these findings stress the importance of MSFs in pain recognition and suggest that any method that removes these SFs does not provide a true portrait of visual processing of pain.

Methods

Participants

Twenty healthy adult participants between 18 and 40 years old took part in experiment 1 (10 women; mean age of 26 years-old; SD = 3.4) and another twenty participants took part in experiment 2 (14 women; mean age of 21.45 years-old; SD = 3.52). The sample size for all experiments was chosen based on similar studies (between 3 and 28; e.g. [28, 35, 50]). According to recent studies using the SF Bubble's method [29, 33], the results obtained with this method are generally very robust since they are based on many trials for a single task. For both experiments, participants provided their written and informed consent for participating in the experiments. They all had normal or corrected-to-normal vision as indicated by their score on the Snellen Chart and Pelli-Robson Contrast Sensitivity Chart [52] and were compensated 12$/hour for their participation. All procedures were carried out with the ethics approval of the Université du Québec en Outaouais and all experiments conformed to relevant guidelines and regulations with regard to the use of human participants.

Material and stimuli

The stimuli came from the STOIC validated database [47, 48] composed of photos of 10 different identities expressing seven emotions (i.e. anger, disgust, fear, joy, sadness, surprise and pain) at a strong, comparable intensity level or displaying a neutral expression. These stimuli are the same as the ones used by Wang and coll. [19, 20] and Roy and coll. [14, 21]. They were gray-scaled and their global orientation was normalized. All stimuli were equated in their mean luminance, contrast and SF spectrum using the SHINE toolbox for Matlab [53]. A grey mask with an elliptic hole was applied to each face to hide the hair and ears of the stimuli as well as the background.

Stimuli were displayed on a calibrated LCD monitor with a resolution of 1080p and a refresh rate of 100Hz. The experimental program was written in Matlab (Natick, MA), using functions from the Psychophysics Toolbox [52, 54]. The face width subtended 5.72 degrees of visual angle and the viewing distance was maintained at 46.5cm using a chinrest for the first experiment and 122cm for the second experiment.

Manipulation of spatial frequencies - Bubble's method

To reveal the visual information useful for the recognition of facial expressions the SF Bubble's method was used [29, 35] in the first experiment. The method consists of randomly sampling the visual information contained in a stimulus on a trial-by-trial basis, such that a different subset of this information is rendered available to the participant. For example, in one trial, only MSF may have been sampled while on the next trial both LSF and HSF may have been presented to the participant. Across trials, all combinations of SF were therefore possible. The correlation of the participant's performance on a trial-by-trial basis with the availability of each SF can then be calculated.

The creation of a stimulus with SF Bubbles went as follows (see Fig. 4; for more details about the SF Bubble's method, see [29]). First, the base stimulus was padded with a uniform gray background of twice the stimulus size in order to minimize edge artifacts in the SF domain. Second, the padded stimulus was fast Fourier transformed (FFT) using functions from the Image Processing Toolbox for MATLAB (Natick, MA). To create a random SF filter, a binary random vector of $2wk$ elements was generated (c), where w was the stimulus width (256 pixels) and k a constant that determined the smoothness of the sampling; k was set to 20 for all the experiments reported in this article. The random vector thus had 10,240 elements. The vector contained zeros among which b ones were randomly distributed (with replacement). Parameter b thus determined the number of SF bubbles and was set to 10. To create a smooth filter, the binary vector was convolved with a Gaussian kernel, referred to as a SF bubble (d). The standard deviation of the SF bubble was set to 1.8 cycles per image. The convolution resulted in a "sampling vector" consisting of b randomly located SF bubbles (e). This smoothed vector was then subjected to a logarithmic transformation (f) in order to fit the human visual system's SF sensitivity [55]. The resulting w-element filter was then rotated about its origin to create an isotropic random two-dimensional filter of size $w \times w$ (g). Filtering was carried out by dot-multiplying the two-dimensional filter with the complex amplitude of the padded base stimulus before subjecting the result to the inverse Fourier transform. We constructed the experimental stimuli by cropping the central $w \times w$ pixel region of the filtered image.

Manipulation of spatial frequencies - Distance

In order to examine whether the results obtained with the Bubble's method are consistent with a more ecological method, participants completed a distance task where the distance at which a facial expression can be perceived was manipulated. This method is inspired by the work of Smith and Schyns (2009) [16] who investigated the effectiveness of the transmission of emotion signals over different viewing distances. Here we used this method to reveal how pain facial expressions can be recognized across various distances and therefore at which SF. Indeed, increasing perceived distance between a

stimulus and an observer represents an ecological way to manipulate SF since it decreases the availability of higher SFs. We first created stimuli using the Laplacian Pyramid toolbox [56], a method that recursively removes the highest SFs of an image while down-sampling the residual image by a factor of two in order to create six reduced-size images simulating increasing viewing distances (see Fig. 5). We used the Laplacian Pyramid because it removes one octave of SF between images of different sizes, which corresponds roughly to a similar decrement in spectral energy. Note that there was no loss of face SF information from the filtered original image or the reduced size image, despite the reduction in size. The original image size was 384 x 384 pixels (~ 6.9 cm), which corresponds to 3.26 degrees of visual angle. The impact of distance on SF information acts as a low-pass filter, where the original image contains available SFs (i.e. 128 cpf) and subsequent images respectively contains information under 64 cpf, 32 cpf, 16 cpf, 8 cpf and 4 cpf. The simulated viewing distances corresponded to 1.2, 2.4, 4.8, 9.6, 19.2, and 38.4 meters (or respectively 3.26, 1.63, .815, .41, .20, .10 degree of visual angle).

Procedure

Prior to both experiments, participants were invited to look at the emotional faces displayed on a computer screen. When they felt confident that they could recognize all facial expressions, a practice session began. Each trial began with a fixation cross displayed in the center of the screen for 500ms. One of the 80 stimuli was then randomly selected and presented for 300ms. The next trial began right after the participant's response. Participants responded by pressing one of the eight keyboard keys associated with each emotion. No response time limit was imposed and no accuracy feedback was provided. The main goal of the learning phase was to ensure that participants were able to recognize each facial expression. The learning phase was completed when performance was above 90% correct for two consecutive blocks of 160 trials. Participants then completed either experiment 1 or 2. The only difference between both experiments is that faces filtered with SF bubbles were presented to participants in experiment 1 and faces varying in sizes were presented in experiment 2. The following methodological indications apply to both experiments. On each trial, a fixation point was first displayed in the center of the screen for 500ms and was immediately replaced by the stimulus. The stimulus was displayed for 300ms and was then replaced by a grey screen that remained visible until the participant responded (i.e. which facial expression have been perceived). The next trial began right after the participant's response. Participants responded by pressing specific keys on a keyboard. No response time limit was imposed but the participant was asked to be as fast and accurate as possible. A small amount of white Gaussian noise was added to the stimulus, with the amount of noise manipulated on a trial-by-trial basis using QUEST [57] to maintain performance halfway between chance and perfect performance. Participants completed 26 blocks for a total of 4160 trials per participant in experiment 1 and 15 blocks for a total of 2400 trials per participant in experiment 2. Of course, participants completed the experiments in several sessions and took breaks as needed.

Declarations

Data Availability

The datasets generated during and/or analysed during the current study are available in the OSF repository, https://osf.io/cn9ed/?view_only=6d684d4cf9524c6dbb2fad0fd3643138.

Acknowledgments

We are grateful to all the participants who took part in these experiments. The present work was supported by grants from the Natural Sciences and Engineering Research Council of Canada (NSERC) to Daniel Fiset as well as by a Canada Research Chair in Cognitive and Social Vision (#950-232282) held by Caroline Blais. Isabelle Charbonneau is supported by a graduate scholarship from SSHRC. Joël Guérette is supported by a graduate scholarship from FRQSC.

Author Contributions

D.F., S.C., and C.B. conceptualized the study; I.C., C.B., D.F. and F.S. designed the experiments; I.C., J.G. and G.L.-B. conducted the experiments; I.C. and D.F. analyzed the data, created the figures, and wrote the manuscripts draft. All authors reviewed the manuscript.

Competing Interests: The authors declare that they have no competing interests.

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Figures

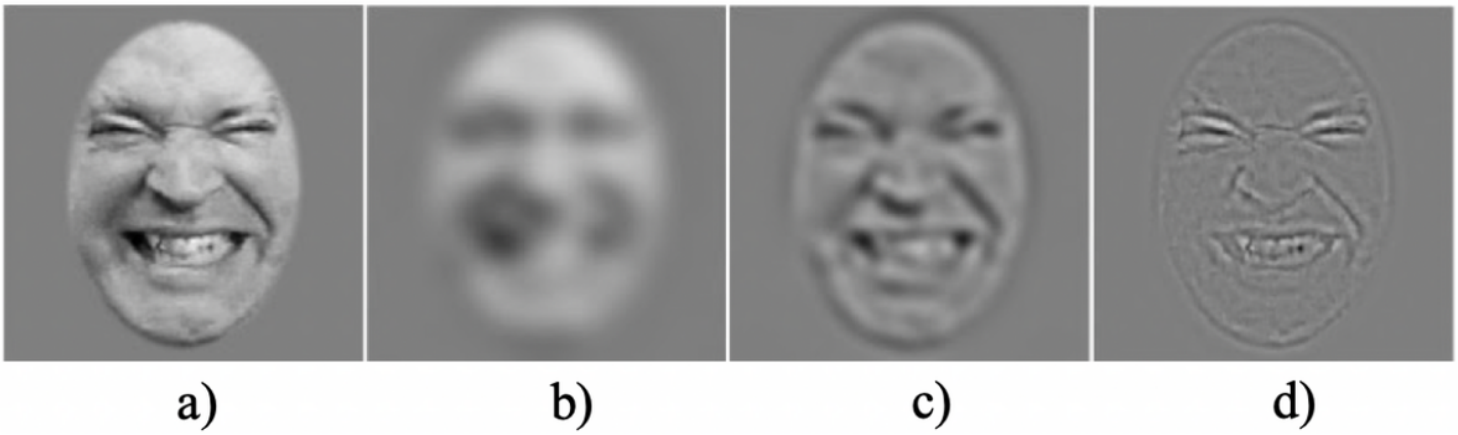

Figure 1

Example Stimuli. Panel a) represents a broadband stimulus, b) a low-pass stimulus (< 8 cpf), c) a band-pass stimulus (between 8 and 32 cpf) and d) a high-pass stimulus (> 32 cpf). MSF as in c) are typically not included in experiments conducted on facial expression processing, including those about pain.

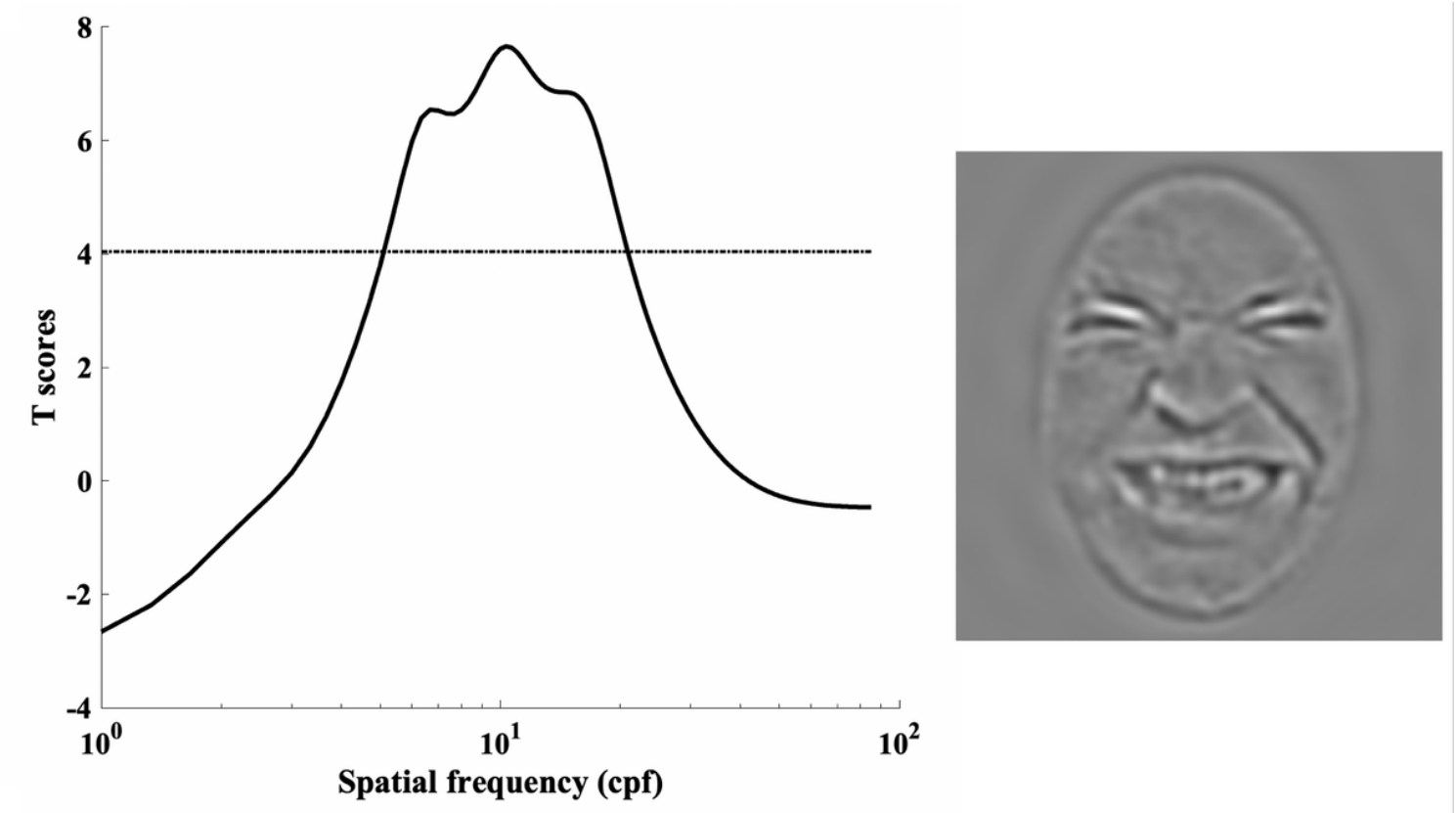

Figure 2

Pain categorization revealed by the Bubble's method. The left panel displays the SF tuning for pain categorization. The black dotted line represents the statistical threshold for significance ($p<0.05$). The right panel represents an example of a stimulus filtered with the significant SFs associated with pain categorization.

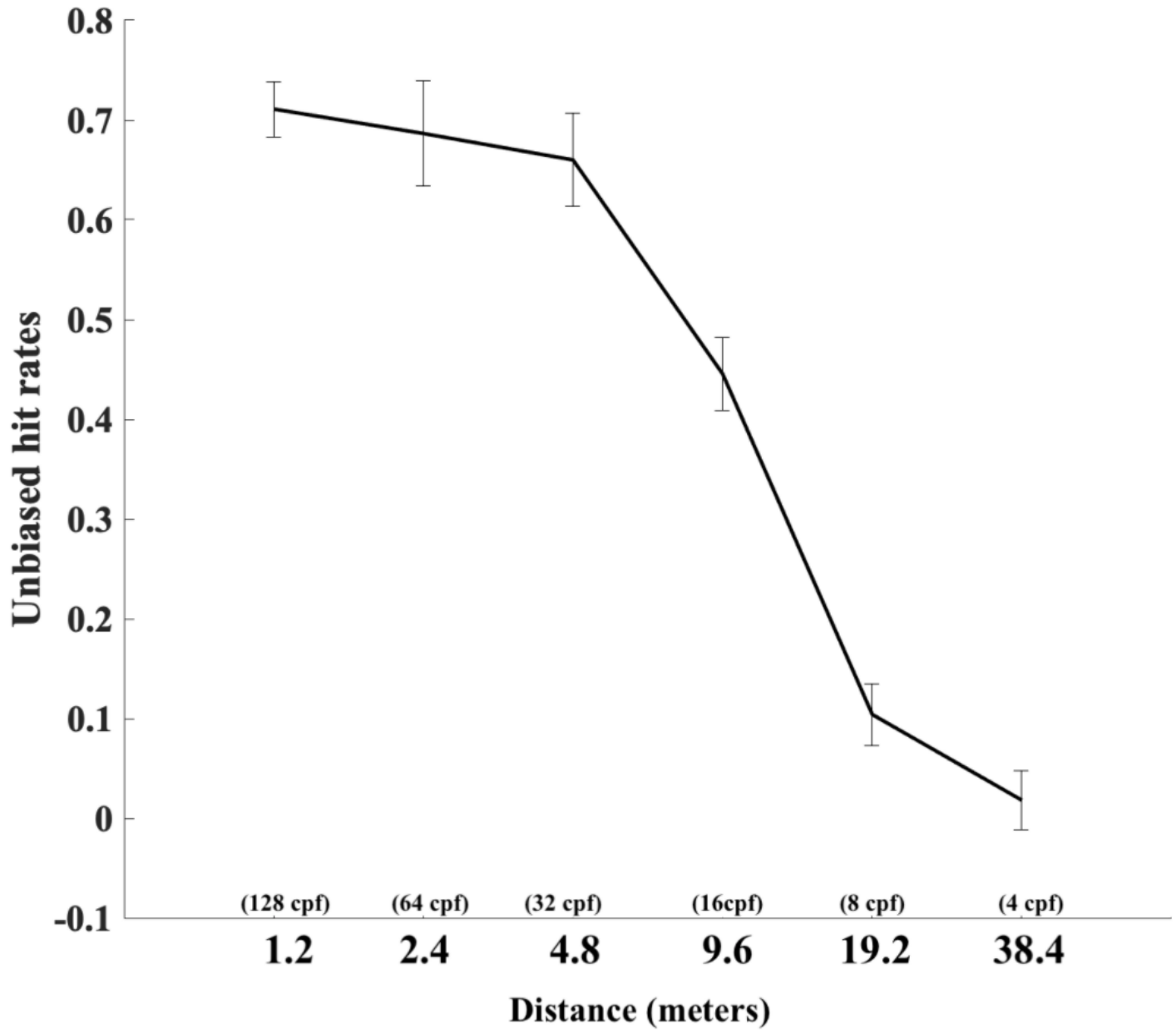

Figure 3

Distance for pain categorization. Unbiased hit rates for pain categorization as a function of viewing distance. The equivalence in cycles per face (cpf) is presented in parenthesis. Error bars represent the standard error.

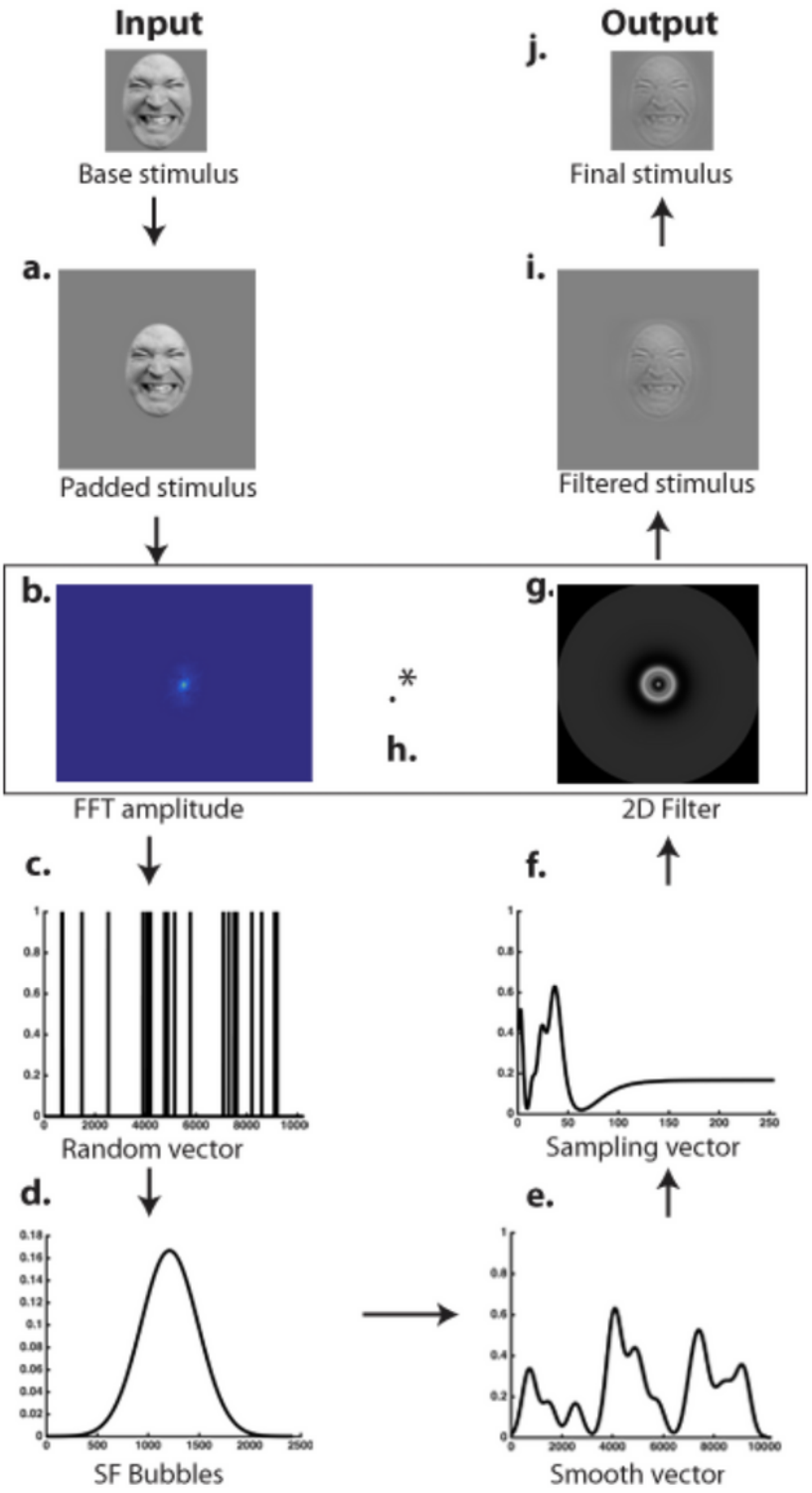

Figure 4

Creation of a bubblized stimulus using the SF Bubble's technique (see text for details).

Figure 5

Example stimuli. Faces stimuli were created with the Laplacian Pyramid toolbox [4] simulating increasing viewing distances (i.e. images from left to right represent 3.26, 1.63, .815, .41, .20, .10 degree of visual angle or a simulated distance of 1.2, 2.4, 4.8, 9.6, 19.2, and 38.4 meters).