Individual differences in facial expression recognition ability are linked to differences in the efficiency at using the diagnostic visual information

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Context

- ❖ Ability in facial expression recognition is commonly assumed to be related to the adequacy of visual strategies.
- ❖ It has been recently shown that multiple eye fixation patterns may lead to comparable performances[1].
- ❖ Since eye fixations and visual information utilization are partially dissociated, it remains possible that facial recognition ability is associated with this latter component of visual strategies.
- ❖ The goal of this study was to test this hypothesis by assessing the link between one's facial expression recognition ability and pattern of visual information utilization.

Method

69 White-Westerner participants (34 men: 21.83 years old on average). Stimuli were provided by the Stoic database.

Aim 1: Measuring the facial expression recognition ability

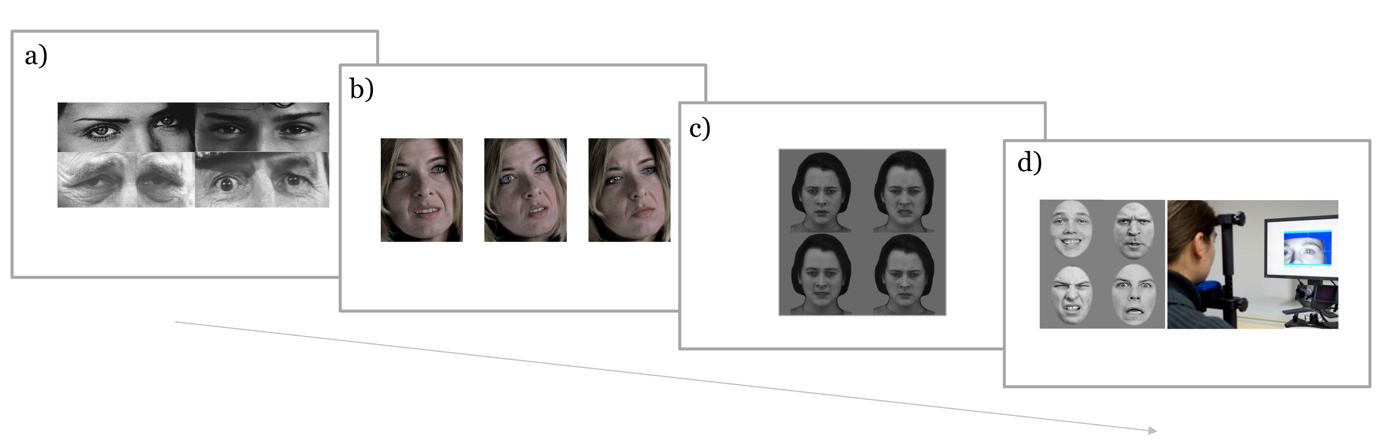

Figure 1. a) Reading the mind in the eyes test [2], b) Films facial expression task [3], c) Facial expression megamix [4], d) Emotion categorization task performed with eye-tracker .

Aim 2: Measuring the visual information utilization pattern

The Bubbles method was used [5]. On every trial (N = 4000/participant), a random sample of visual information contained in a stimulus (here a face expressing either anger, disgust, fear, or joy) was made available (see figure 2). The task consisted of categorizing an emotion between four given alternative choices (anger, disgust, fear, or joy).

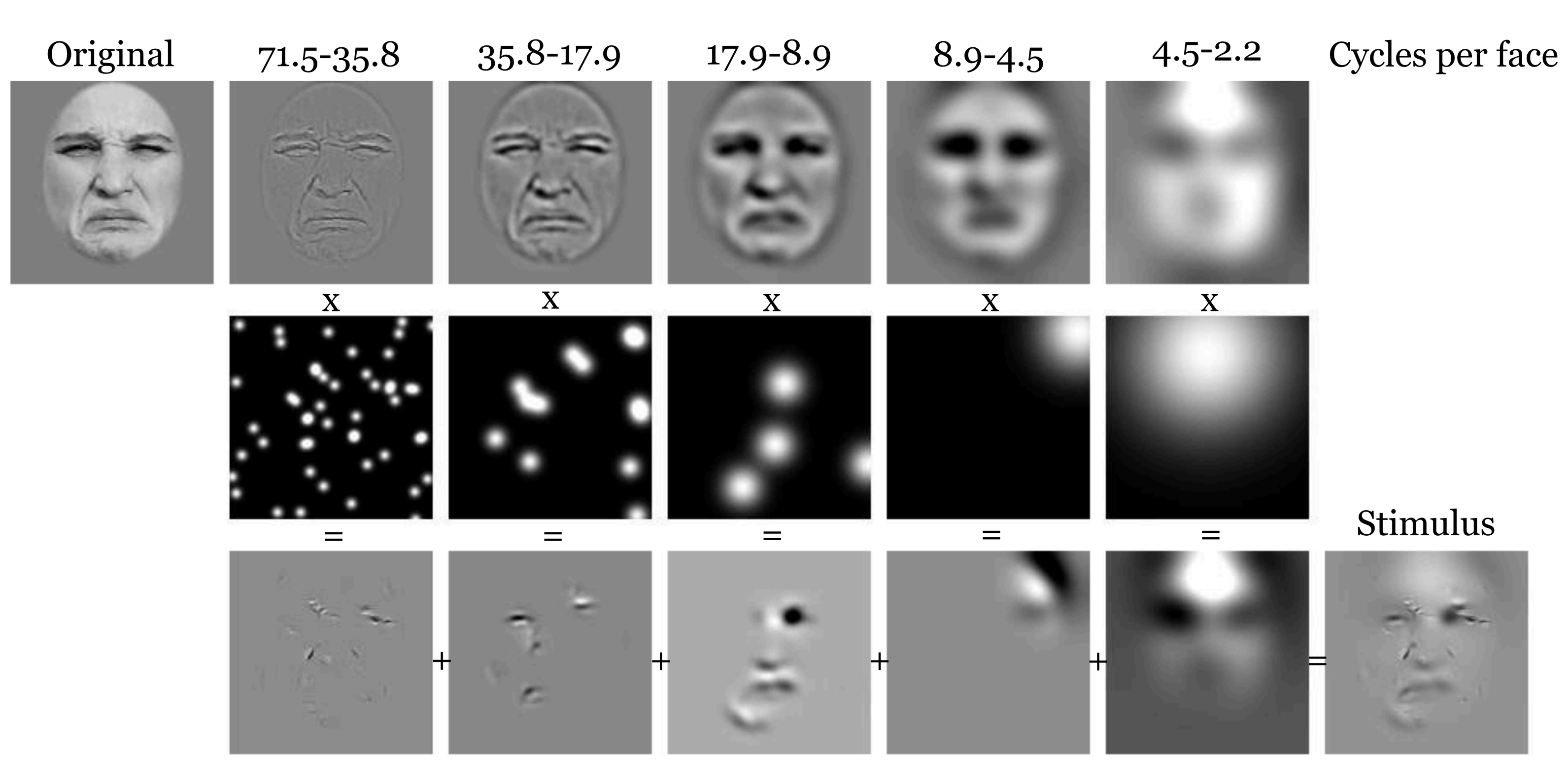

Figure 2. Procedure to create a bubblized stimulus.

Analyses and results

Emotional expression recognition ability. A principal component analysis (PCA) was conducted on the five ability measures and the two extracted components were used as ability indexes (see figure 3).

Component Matrix[a]

	Component 1	Component 2
Balanced integration score	,842	-,200
Number of bubbles	-,637	-,351
Reading the mind in the eyes test	,423	,147
Facial expression megamix	-,059	,810
Films facial expression task	,292	,641

Extraction Method: Principal Component Analysis. Rotation Method : Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Figure 3. Principal components extracted.

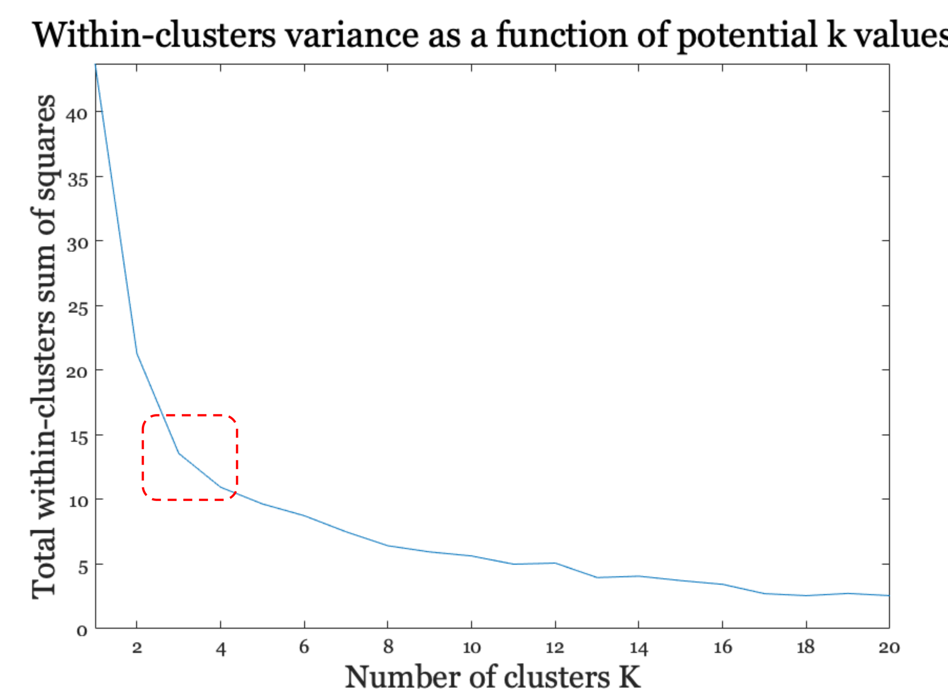

Figure 4. The optimal number of clusters was determined by assessing the within-clusters variance by running a *k*-means analysis for each possible appropriate *k* values.

Utilization patterns. In order to define their utilization pattern, a vector representing the proportion of used information in three regions of interest (ROI) (eyes, nose, and mouth) was calculated for each participant across all emotions. They were submitted to a *k*-means analysis (see figure 4), and three general patterns were revealed (see figure 5).

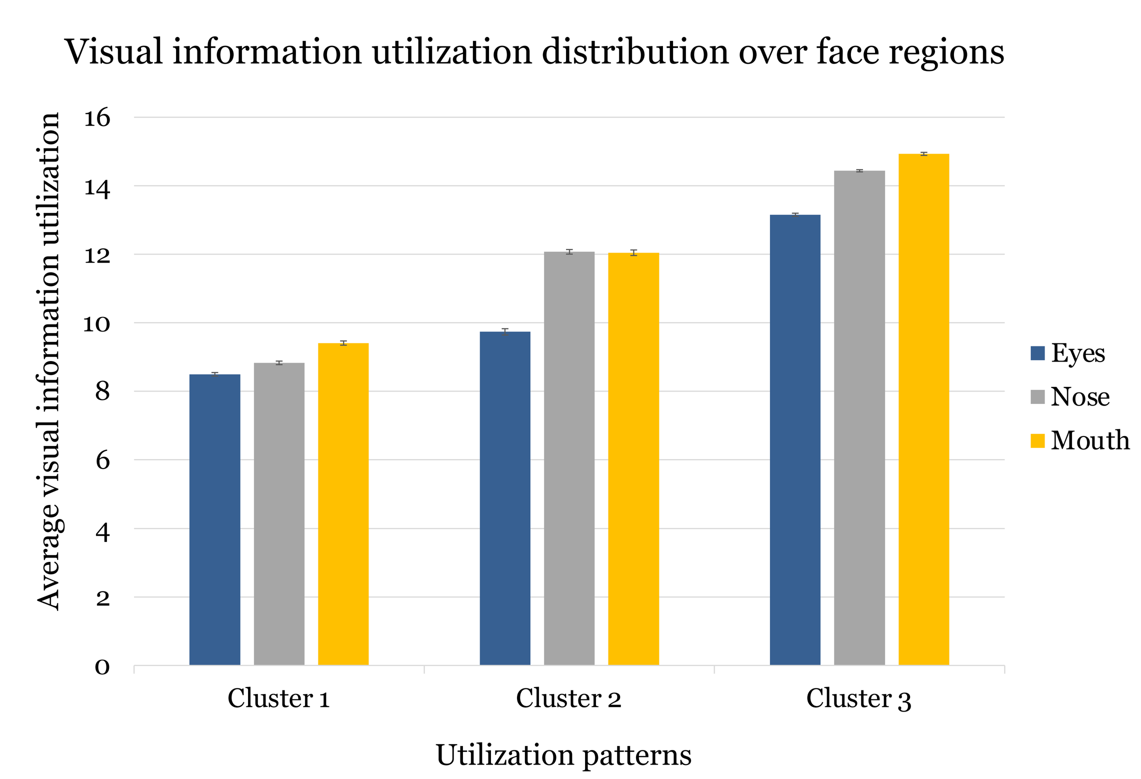

Figure 5. The proportion of average utilization in each ROI, according to the pattern. The error bars represent the standard error.

Classification images. An average classification image (CI) was obtained for each cluster of participants by calculating a weighted sum of the bubble masks presented in the experiment, using the z-scored accuracies as weights (see figure 6). A statistical threshold was calculated using a Cluster test [6] (T_{crit} = 2.3; k = 2911; p < 0.05).

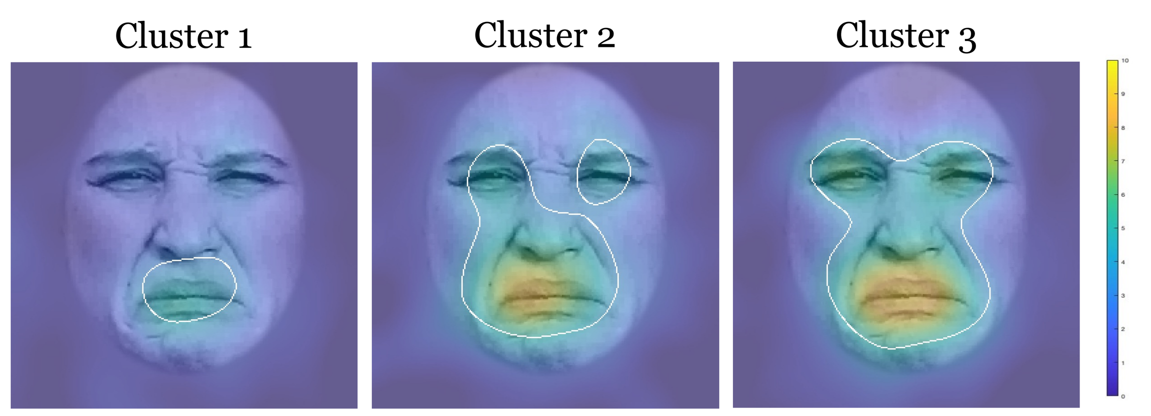

Figure 6. Maps of z scores illustrating the association between the utilization of the visual information contained in various regions of the face and trial-by-trial accuracy. Significant regions are circled in white.

No significant effect was found with the two ability indexes extracted from the PCA. However, two one-way ANOVAs were conducted and revealed a significant impact of utilization pattern on the Films facial expression task results (F(2, 66) = 3.97, p = .02, w^2 = 0.13), and the average number of bubbles needed to complete a successful categorization (F (2, 42.42) = 5.60, p =.007, w^2 = 0.12). Post hoc analysis confirmed a significant difference between clusters 1 and 3, the latter exhibiting an improved performance for both tasks (p = .02, p = .02).

Discussion and conclusion

- ❖ Three main patterns of visual information utilization emerged from our data;
  - ❖ All clusters favored the extraction of information contained in the mouth, followed by the nose and eyes region.
  - ❖ A gradient of efficiency was revealed, suggesting an increase in the efficiency at using all ROI across groups: cluster 1 showed a poorer utilization, and cluster 3 had the most effective strategies.
- ❖ The ability at recognizing emotional facial expressions varied as a function of these utilization patterns;
  - ❖ The cluster with the least efficient visual strategies showed the lowest ability, while the one with the most efficient strategies showed the highest ability.
- ❖ Taken together, these results support the existence of an association between facial expression recognition ability and visual information utilization patterns.

References

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