A left eye bias for female faces

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***Abstract*—We investigated whether men and women use different scanning strategies to extract the visual information relevant for the recognition of female and male faces. We used an old-new recognition task during which observers were asked to identify previously learned faces. Data from two groups of observers (male, female) revealed a more accurate, but not faster, recognition of male face stimuli. Interestingly, the fixation maps revealed a consistent left gaze bias for female face stimuli, regardless of the gender of the observer. Altogether, our data show that humans deploy distinct and flexible visual sample strategies to process faces.**

Keywords- face recognition;gender;eye-movements; accuracy;response time.

I. INTRODUCTION

Face recognition is a powerful human skill essential for social interactions. Faces not only provide the core information for identification, but also convey a wealth of other visual signals disclosing cues related to age [e.g., 1] emotional state [2-5], race [6-9], and gender [10, 11].

Understanding how faces are decoded and recognized has been extensively studied over the last decades. Using the *i*Hybrid technique, Miellet et al. (2011) found differences in scanning strategies (i.e., local or global) within the same observer as a function of the landing position of the first fixation [12]. Another recent study demonstrated individual differences in information fixated during face exploration [13]. Similarly, Kanan et al. (2015) reported individual and task-specific eye-movement strategies when observers were asked to evaluate faces on diverse social dimensions [14].

Other studies have revealed that the cultural background, as well as expression-related facial cues, influence face processing strategies. Blais et al. (2008) showed the powerful influence of culture in shaping facial exploration strategies, indicating that face processing is not achieved universally across cultures. More specifically, their findings demonstrate that Western Caucasian observers scan faces using a triangular scanning pattern over the eyes and the mouth for identifying Asian and Caucasian faces, whereas East Asian observers focus comparably more on the central part of the faces, regardless of the race of the face stimuli [15]. Nevertheless, gaze-contingent paradigms have shown that Western and Eastern observers rely on similar facial features to achieve face recognition, but with both a specific information span and a distinct tuning to spatial frequencies [16-19]. This cultural perceptual bias starts early in age [20-22], is resistant to the face inversion effect [23] and is not abolished by social experience [24]. On another line, Jack et al. (2009, 2012) reported cross-cultural tuning in the decoding of facial emotional signals [25, 26], a cultural difference that emerges early in age [27]. Schurgin et al. (2014) evidenced that the visual strategies employed to extract facial information were also modulated by the emotional expressions conveyed by the face stimuli, with observers fixating the eyes more during processing of stimuli displaying "fear" and "sadness", and the mouth when stimuli displayed "happiness" [28].

Besides individual and cross-cultural differences in visual sampling strategies during face processing, other studies have also reported differences as a function of observers' gender. Vassalo et al. (2009) observed that female and male observers scanning strategies differed during perception of emotional expressions: compared to females, males fixated more the nose and mouth [29]. Similarly, in a gender judgement study, Sæther et al. (2009) observed that males fixated more the lower and central parts of the face compared to their female counterparts [30]. However, another study observed differences between male and female observers only when the gender of the face stimuli was task relevant [31], with female and male observers sampling the eye region and cheeks, respectively. Further studies have revealed gender differences in terms of face recognition performance. Specifically, irrespective of the gender of faces presented, women outperformed men [32]. Moreover, female observers demonstrated an own-sex bias, that was not found for male observers [32]. Finally, using a novel data-driven approach enclosing the spatiotemporal nature of gazing behavior, Coutrot et al. (2016) demonstrated gender differences in face

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exploration dynamics. More specifically, they reported an own-sex bias for female observers when looking at female actresses and found that, compared to male observers, females exhibited shorter fixations [33]. However, as acknowledged by the authors, several aspects of their experimental design might have influenced their findings. All the faces presented in their study displayed movies of Western Caucasian actors maintaining a neutral face. As previously reported, this might have influenced facial scanning patterns [25-27] by prompting observers to direct their fixations to specific facial features. Moreover, given the nature of their between-subjects design, both stimulus or observer characteristics might have influenced the results (i.e., participants were tested in only one out of all conditions).

Altogether, these findings point to a *non-universal* facial information extraction pattern, determined by several factors, including amongst others culture. Whether the gender of the observer plays a role in the sampling strategies used to identify female and male faces remains to be clarified. To this aim, we investigated gender differences using a full design, in which female and male observers were asked to recognize were previously encoded female and male faces presented among novel distractor faces (i.e., old-new recognition task). We analyzed observers' eye-movements, as well as accuracy and response times.

II. Methods

A. Participants

Sixty-four Caucasian students of the university of Fribourg (32 females with mean age = 21.90 ± 3.07 and 32 males with mean age = 21.56 ± 2.49) participated in our experiment. This study was approved by the local Ethical Committee.

B. Appartus

Stimuli were presented on a VIEWPixx/3D LCD monitor (52.13x29.32 cm) with a refresh rate of 120 Hz and a resolution of 1920x1080 pixels. The images on the screen were 702x688 pixels in size reflecting a visual angle of 14° at a viewing distance of 70 cm. The experiment was implemented in Matlab using the Psychophysics [34-36] and EyeLink Toolbox [37] extensions.

C. Stimuli

We selected a set of 168 black and white Western Caucasian (84 females) faces from the KDEF database [38]. For the aim of this study, we analyzed only the eye movement data of the recognition stage, only for the correct trials.

D. Procedure

Participants sat in a quiet and dimly illuminated room. They were informed that throughout the experiment, they would have to learn and subsequently recognize a series of Caucasian faces. The experiment included 2 blocks. Each one was composed of a learning and a recognition phase. During the learning phase, 14 faces (7 females) were presented one after the other to the participants. Each trial started with a black fixation cross presented for 1000ms followed by a face which was randomly presented for 5s in one of the four quadrants of the screen (Fig. 1). During the recognition phase, a series of 28 faces (14 faces from the learning phase – 14 new faces) were presented. Participants were instructed to indicate as accurately as possible whether each face had been previously seen or not by pressing two labeled keys on a computer keyboard. Stimuli remained on the screen until participants responded (Fig. 1). In both phases, we recorded the eye-movements of observers using the Eye-Link 1000 Desktop Mount system (SR Research Ltd., Ontario, Canada) with a sampling rate of 1000 Hz. At the beginning of the experiment and between each block a 9 nine-point calibration was performed.

III. Data analyses

A. Behavioral Analyses

We performed a generalized linear mixed model with a binomial family [39] to analyze the response times and accuracy of the observers. We considered the gender of the stimuli (GS) and the gender of the observer (GO) as main predictor variables and their

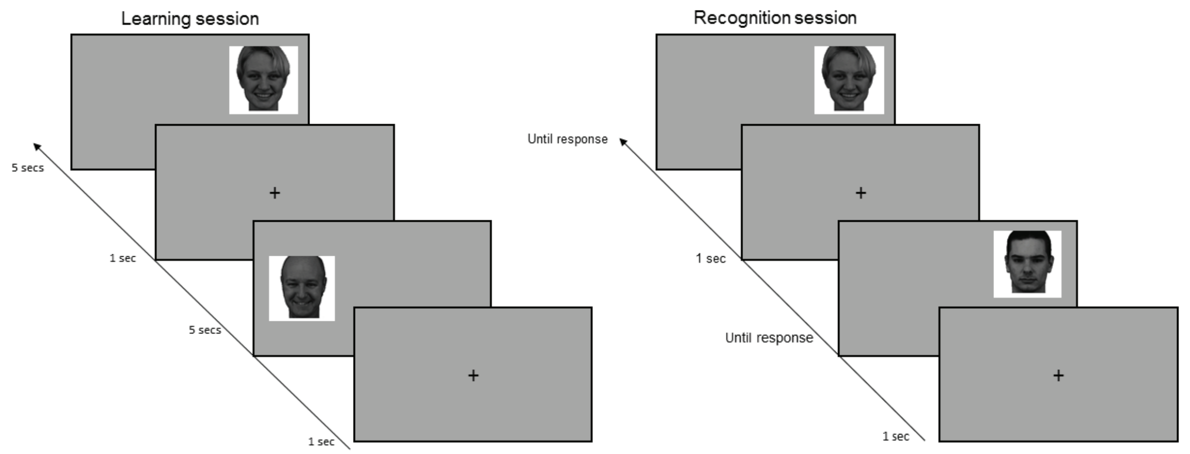

Figure 1. An example of two trials of the experiment with a learning and recognition session. In the recognition session, the first trial is a new face while the second trial is an old face i.e. it has been shown in the learning session.

interaction. To account for the variation among observers, we added the variable observer as a random factor. The model is a 2*2 design and can be expressed as follows:

$$\text{Accuracy} \sim GO*GS + (1|\text{observers}) \qquad (1)$$

Then, we run the models for each predictor (gender stimuli and observers) separately.

Similarly, we applied a linear mixed model to explore the reaction time (RT) of observers of correct trials. RT that were higher than 5 seconds (2.69%) were discarded to decrease the influence of outliers, which represent all values higher than 2.5*SDs from the mean. The gender of stimuli (GS) and of observers (GO) were considered as explanatory variables with their interaction terms. The observers were treated as a random factor. This can be written as follows:

$$RT \sim GO*GS + (1|\text{ observers}) \qquad (2)$$

We also run the models for each predictor (Gender stimuli and observer) separately.

All models were fitted in R [40] using the lmerTest package [41].

B. Eye-Movements Analyses

We applied the adaptive velocity based algorithm developped by Nystrom & Holmqvist [42] to retrieve fixations and saccades from the raw data. Fixations that felt outside the stimuli were discarded. We then used a statistically data-driven method built in iMap4 [43] to compute fixation duration maps. The resulting maps (conditions*xSize*ySize) were then smoothed with a two-dimensional Gaussian Kernel function at 1° of visual angle by choosing the estimated option. This method consists in computing for each condition and observer, the expected values across trials. Finally, the maps were normalized by dividing them with the sum duration of each trial. Furthermore, we performed a pixel-wise Linear Mixed Model (LMM) on the

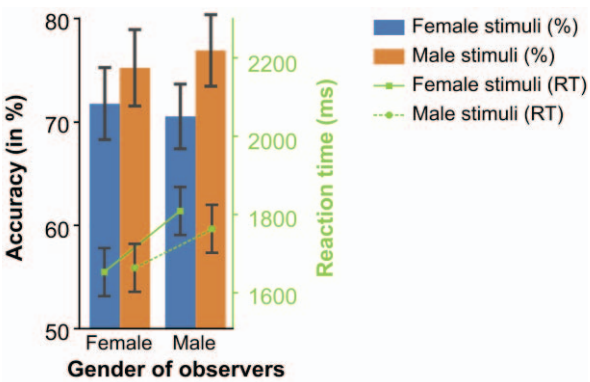

Figure 2. Accuracy Left: Average of the percentage of correct responses; right: reaction time (ms) for both group of observers and gender of stimuli. Error bars indicate 95% confidence intervals.

smoothed normalized fixation maps by considering the fixation duration (Y) as a response variable and the gender of stimuli (GS) and observers (GO) as predictors with their interaction factor. Thus, the full design model can be expressed as follows:

$$\begin{aligned} Y_{(x,y)} \sim\ & 1 + GS + GO \\ & + GS*GO + (1|\text{observers}) \\ & 1<x<xSize,\ 1<y<ySize \end{aligned} \qquad (3)$$

To control for the Type 1 error, a multiple comparison corrections was assessed by using a bootstrap spatial clustering method (option: cluster size. A post-hoc analysis was conducted within the significant area.

We furthermore performed a linear mixed model to investigate the differences between the average fixation duration (DurFix) of observers when female and male stimuli were presented. The model can be written as follows:

$$\text{DurFix} \sim GO*GS + (1|\text{ observers}) \qquad (2)$$

where GO and GS is the gender of observers and stimuli, respectively.

IV. Results

A. Behavioral

The results from the fitted full model (equation 1) showed no main effects of predictors and their interaction. However, running the model with only the gender of stimuli as explanatory variable, revealed a significant main effect [$F(1,64) = 11.40$, with p-value<0.001]. Both female and male observers performed better when they were exposed to male stimuli (M = 76.06, 95% CI [73.27 78.52]) compared to female stimuli (M=71.15, 95% CI [68.86,73.38]) with a z-value equal to 3.37 (p-value <0.05), suggesting that the accuracy of observers is slightly higher when the gender of stimuli is a male. This is illustrated in Fig. 2.

The results from the general linear mixed model (equation 2) and from the models where each predictor was independently included, presented no main effects ($F(1,2567) = 0.18$, p-value >0.05), see Fig.2. This latter result reflects that the reaction time of observers was not affected by the gender of stimuli or by the one of observers.

B. Eye-Movements

Our results showed that, on average, observers performed between 6 and 7 fixations. Running the linear mixed model on the mean fixation duration (in ms) revealed a main effect of the gender of stimuli [$F(1,126) = 7.67$, with p-value<0.05], with lower fixation durations for female faces. However, this effect was too small to be considered with $\beta_{female\_stimuli} = -3.8$ (ms), 95% CI [-0.0066 0.0011].

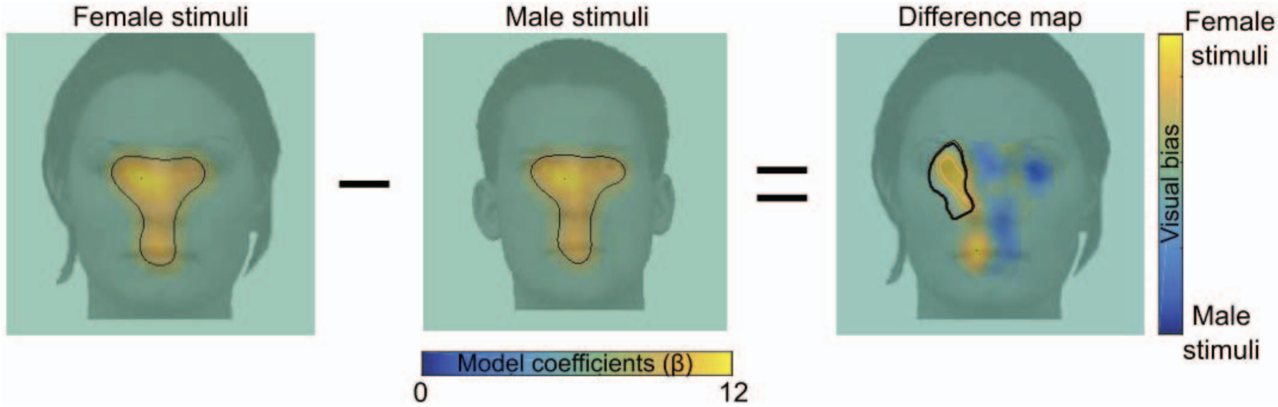

Figure 3. Fixation maps showing the visual bias for observers during face recognition. The significant areas are marked with a black line.

The iMap4 output of the linear mixed model of the full model (equation 3) revealed a significant effect of gender on the left eye region. By performing the linear contrast between female and male stimuli we obtained the following: $F(1,124)=1.375$ at the local maximum within the significant cluster with a beta contrast equal to 1.37, 95% CI [0.55, 2.19]; and $F(1,124) = 3.92$, $p<0.05$ at the local minimum within the significant cluster with a beta contrast equal to 0.62, 95% CI [0.00, 1.25]. In line with the main effect, post-hoc within the significant cluster showed that both groups of observers displayed a longer fixation for female stimuli than male stimuli (female observers: female-male 95% CI [9.13, 12.8], male observers: female-male 95% CI [9.38 15.52]) with an effect size of r equal to 0.20.

Altogether, these results suggest that *all* observers tended to look more at the left eye when a female stimuli was presented during recognition (see Fig. 3).

V. Conclusion

Here, we investigated whether the gender of the observer plays a role during recognition of male and female face stimuli, by using an old-new face recognition paradigm. Behaviorally, both groups of observers exhibited similar response times, and were more accurate for male stimuli. This latter result differs from the results reported by Rehnman and Herlitz (2007), revealing that female observers remembered better faces than male observers, with even higher scores when female stimuli were presented [32].

With respect to eye-movements, both female and male observers exhibited a left eye bias for female face stimuli. This observation partly coincides with the results of a previous study [33], which reported the same bias, albeit only for female observers. This result is nevertheless interesting, as both paradigms relied on fundamentally different designs and task constraints. However, at this stage any interpretation of this effect is speculative, as it could be attributed to a stimulus effect and not to gender *per se*. We thus believe that further investigations are necessary to assess the solidity of this finding and to identify the mechanisms that are at the root of this perceptual bias. One future direction would consist in testing East Asian observers with a similar paradigm in order to verify the universality of this phenomenon. Nevertheless, altogether the present data show that the face system is rooted into different visual sampling strategies for processing male and female faces.

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