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Abstract

Aging is associated with more nose-focused face scanning pattern and reduced pattern consistency during face recognition, and both effects are correlated with performance reduction. We investigated whether these changes are related to sensorimotor (increased saccade noise) or cognitive (declined memory of visual routines) declines by simulating both mechanisms in a Deep Neural Network + Hidden Markov Model (DNN+HMM) architecture that learns facial representations and oculomotor routines for face recognition simultaneously. Results showed that increasing saccade noise reduced scanning pattern consistency without making the pattern more eyes- or nose-focused, whereas reducing visual routine accuracy to simulate memory decline led to more nose-focus scanning pattern without affecting pattern consistency. Both effects were correlated with reduced recognition accuracy, consistent with human data. Our results thus suggested that changes in face scanning pattern and consistency are dissociable consequences of distinct mechanisms underlying aging-related decline in face recognition ability, with important implications for intervention strategies.

Keywords: Cognitive Aging; Deep Neural Networks; EMHMM; Face Recognition

Instruction

Face recognition is among the most vital social cognitive abilities. People with face recognition deficits such as prosopagnosia can experience severe psychosocial difficulties including anxiety and social isolation. (Yardley et al., 2008). The development of this ability across age is shown to follow an inverted-U shape. In a web-based study (N=4,143 and age: 10-70 years), it was found that participants' face recognition ability peaked in the 20s and declined after 50s (DeGutis et al., 2023). Lab-based experiments showed consistent results: compared to young adults, healthy older adults exhibited increased face identification errors and longer response times (Fulton & Bartlett, 1991; Boutet & Faubert, 2006; Edmonds et al., 2012; Chan et al., 2018; Zheng et al., 2025). Since decreased face recognition performance emerges in older adults with normal visual acuity (Lott et al., 2005), it has been assumed that changes in recognition performance and associated changes in eye movement behavior mainly result from age-related decline in cognitive ability. However, the specific mechanisms underlying these age-related changes remain unclear (Plude & Doussard-Roosevelt, 1989; Geerligs et al., 2014; Zhuravleva et al., 2014; Quigley & Müller, 2014; Huddleston et al., 2014).

Across a wide range of tasks, aging produces systematic and multifaceted changes in eye-movement behavior, reflecting declines in sensory, motor, and cognitive components of oculomotor control. Older adults' basic tracking mechanisms such as smooth pursuit and optokinetic responses become less effective (Paige, 1994; Seferlis et al., 2015; Zackon & Sharpe, 1987; Fozard & Gordon-Salant, 2001), and pursuit initiation becomes slower and more variable (Knox et al., 2005). Saccadic eye movements are particularly sensitive to aging: older adults exhibit slower initiation reduced peak velocities, and increased latency (Munoz et al., 1998; Klein et al., 2000; Peltsch et al., 2011; Noiret et al., 2017; Huaman & Sharpe, 1993). These changes extend to daily-life behavior, such as having fewer and smaller saccades during locomotion and real-world exploration (Dowiasch et al., 2015; Thomas et al., 2017), long fixation duration during online navigation (Beattie & Morrison, 2019), and longer fixations and more regressions when reading (Kemper & Liu, 2007) or performing visual search (Veiel et al., 2006). In addition, older adults have greater eye movement errors than young adults, such as having more frequent direction errors in anti-saccade tasks (Klein et al., 2000; Peltsch et al., 2011; Noiret et al., 2017) and exhibiting worse precision in localizing visual targets at peripheral visual areas through fixations (Dobreva et al., 2012).

The mechanisms underlying age-related changes in eye movement have been explored. These include multiple oculomotor factors, such as visual-vestibular interactions (Paige, 1994), optomotor controls (Seferlis et al., 2015; Klein et al., 2000) and neural controls of eye movements (Zackon & Sharpe, 1987; Munoz et al., 1998; Peltsch et al., 2011). These factors directly impact the execution of eye movements. Additionally, cognitive factors such as memory have been shown to influence eye movement behavior, as evidenced by the associations between eye movement pattern changes and variations in memory task performance. For instance, Ryan et al. (2022) proposed that age-related declines in memory may lead to altered visual exploration patterns, which can be suboptimal and hinder effective information binding into memory. Wynn et al. (2018) found that as compared with young adults, older adults had greater

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fixation reinstatement during memory retrial, and the relationship between fixation reinstatement and detection accuracy in older adults was stronger, indicating a link between age-related memory decline and changes in eye movement behavior. Since aging causes both oculomotor deterioration and cognitive decline, disentangling their contributions to eye movement behavior changes through experimental approaches poses significant challenges. However, it may be facilitated by computational modelling.

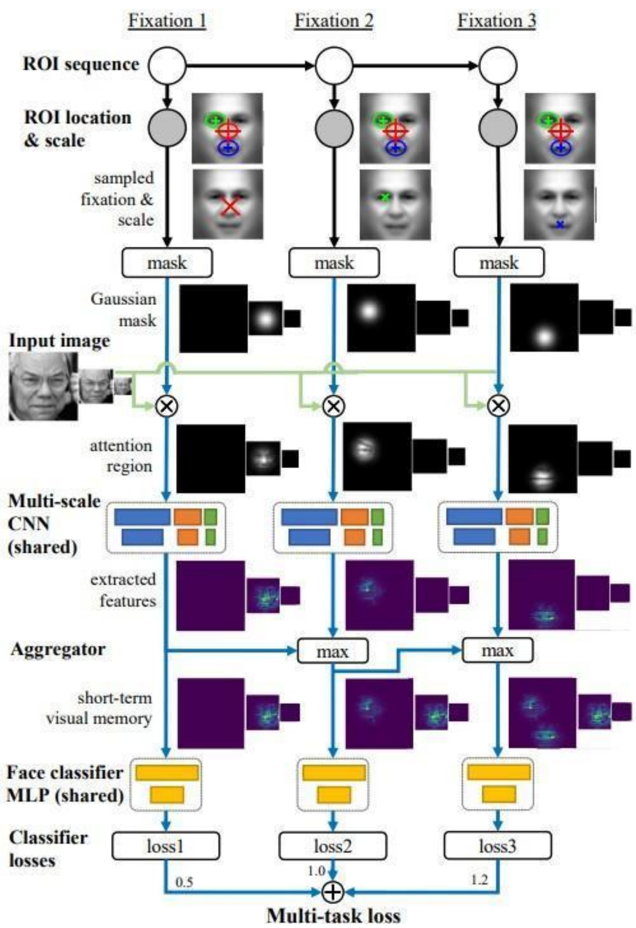

Figure 1: The structure of the DNN+HMM model for face recognition.

Across adulthood, aging gradually reshapes the eye-movement strategies used to recognize faces. Many studies showed that older adults allocate less attention to the eyes and more to the mouth or lower facial regions during face processing, suggesting a broad reorganization of perceptual priorities (e.g., Grainger & Henry, 2020; Chaby et al, 2017; Circelli et al., 2013; Sullivan et al., 2007; Wong et al., 2005; Pavic et al., 2021). Older adults also tend to exhibit increased visual exploration, yet these fixations are distributed differently, sometimes favoring peripheral or non-diagnostic face regions (Williams et al., 2016; Mazloum-Farzaghi et al., 2023; Liu et al., 2018; Wynn et al., 2020). Notably, recent studies employing Eye Movement analysis with Hidden Markov Models (EMHMM; Chuk et al., 2020), a machine-learning-based approach, have demonstrated two major types of aging effects on eye movements during face recognition. First, Hsiao et al. (2022) observed a developmental change in the consistency of eye movement behavior in children, where children use a more consistent sequence of fixations across trials with age. In contrast, Zheng et al. (2025) found that older adults exhibit decreased scan-path consistency, indicating a reversal of this trend in adults. Second, the spatiotemporal patterns of regions of interest (ROIs) change markedly: older adults exhibited more nose-focused eye movement patterns, whereas younger adults were more eye-focused (Chan et al., 2018). Importantly, both aging effects were significantly correlated with poorer recognition accuracy and cognitive decline, as measured using cognitive tasks including the DalCAB (Jones et al., 2016), the Tower of London (Culbertson & Zillmer, 1999), and the Trail Making Tests (Reitan, 1958). In a recent EEG study with young adult participants, it was found that effects in eye movement patterns and consistency during face recognition involve different mechanisms. Specifically, eye movement pattern was associated with EEG decoding accuracy, indicating its relevance to neural representation quality, whereas eye movement consistency was correlated with the latency of peak decoding accuracy, suggesting its association with the efficiency of neural representation (Liu et al., 2025). However, the mechanisms underlying the aging effects on these two aspects of eye movement behavior during face recognition remain unclear.

Building on previous findings on age-related deterioration in oculomotor function and memory and the two different aspects of eye movement behavior relevant to face recognition performance, we propose two mechanisms may account for aging-related changes in eye movement during face recognition: increased saccade noise due to deteriorated oculomotor function, and decreased visual routine accuracy due to deteriorated memory function. In this study, we aimed to investigate the effects of these two factors on eye movement patterns and consistency during face recognition, as well as their relationship with face recognition performance, using computational modeling. This approach allows us to manipulate these two aging-related factors separately and examine their effects on eye movement behavior and recognition performance, as these factors cannot be easily controlled in human subject studies. Specifically, we leveraged a Deep Neural Network + Hidden Markov Model (DNN+HMM) approach that has been shown to effectively simulate simultaneous learning of visual representations and eye-movement routines in face recognition (Hsiao et al., 2020, 2022). The DNN+HMM is able to account for differential effects of eye movement pattern and consistency on face recognition performance in children and adults observed in human data: Eye movement consistency, rather than pattern, predicted face recognition performance in children, whereas eye movement patterns, rather than consistency, were associated with face recognition performance in adults (Hsiao et al., 2020, 2022). Additionally, this model is able to account for the positive correlation between holistic processing and eye-focused eye movement pattern/recognition performance observed in human data, demonstrating great cognitive plausibility for face recognition tasks (Xing et al., 2024).

Methods

Description of the Model

As illustrated in Figure 1, the DNN+HMM model contains multiple layers (from top to bottom) representing a sequential processing hierarchy that mimics attention-guided human visual perception, learning, and decision-making. At the beginning, an HMM generates a sequence of ROIs, each consisting of a pixel fixation location and an attention window scale, according to its initial probabilities, transition matrix, and Gaussian emission densities. A larger window corresponds to a lower spatial frequency (SF) to simulate a more global attention associated with fixations in the ROI. The different window scales are implemented through an image pyramid, where the smallest image corresponds to the largest window scale. Next, centered at its fixation location and with image size selected according to the window scale, the attention region for each ROI is simulated as a 2D Gaussian mask. Subsequently, the masked input images are fed into a multi-scale Convolutional Neural Network (CNN), and then aggregated over the ROI sequence, by which the visual short-term memory (VSTM) is formed. After the first fixation, the VSTM is updated by taking the element-wise maximum between the previous VSTM feature map and the feature map of the current fixation. Finally, a shared multilayer perceptron (MLP) decodes the VSTM and makes a prediction about the presented face identity. During training, a weighted loss summed over the ROI sequence enables the HMM to learn the optimal ROI sequence while the CNN learns the optimal perceptual representation at the same time.

Experimental Design

We trained 80 models with different initializations, representing 80 individuals. These models were trained and validated using grayscale images from the 100 most frequent people (3,651 images) in the aligned Labelled Faces in the Wild dataset (LFW-a, Wolf et al., 2010) with a split ratio of 9:1. Throughout the experiments, each image was scaled to 64 pixels wide. Each model consists of three ROIs, as suggested by previous studies, which are sufficient for face recognition and appropriate for HMM analysis (Hsiao & Cottrell, 2008; Chuk et al., 2014, 2017). Three SFs 8, 16, and 32 cycles/face were deemed optimal for face recognition (Costen et al., 1996), which correspond to three attention window sizes: 32, 16, and 8 pixels (visual angle: 4°, 2°, and 1°), respectively. The SD of each Gaussian mask was initialized at half of its size plus 1 pixel (0.125°). For each SF, there were two CNN layers of 3×3 filters with 8 and 16 channels, respectively, and both layers used ReLU activation functions. Last, each MLP had two layers, containing 40 and 100 neurons, and activated by ReLU and softmax, respectively. During training, the Adam optimizer was used, and the cross-entropy loss was applied to each MLP's prediction, in which the first fixation was weighted the most, simulating face identification with as few fixations as possible.

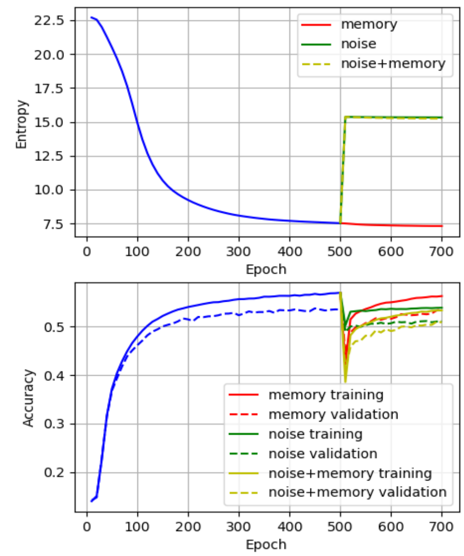

Figure 2: Mean entropy and accuracy across models with respect to number of training epochs in all conditions.

The experiments consisted of two stages. In Stage 1, models were trained for 500 epochs to simulate the normal development of face recognition behaviors. Next, in Stage 2, we simulated the increased saccade noise by increasing the SD of all ROI's Gaussian emission in the HMM by 5 pixels (0.625°) and the decreased accuracy of visual routine due to memory decline by randomly shifting ROI centers from their locations at epoch 500 based on a 2D Gaussian distribution ($\mu = 32, \sigma = 10.6$) respectively. The size of attention window of each ROI remained unchanged. This stage consisted of three simulations. In the first and second simulations, we applied increased saccade noise and decreased visual routine accuracy separately, and in the third simulation, both changes were applied. In each simulation, all the models were trained for another 200 epochs, during which models learned to adapt to these changes. We denoted these three changes to the models by "noise", "memory", and "noise+memory", respectively, in the subsequent paragraphs. Note that human's cognitive functions typically decline gradually with age, and the cognitive systems adapt to these changes at the same time. Here we simplified this process in our simulation by delivering these changes to the models as a one-time perturbation at the beginning of Stage 2. Then, we investigated how the models adapted to these changes by comparing their performance and eye-movement behavior at the 500th and the 700th epochs. Specifically, eye-movement consistency was assessed using the HMM's overall entropy (Cover & Thomas, 2006). The eye-movement pattern was assessed using the EMHMM method, in which all individual HMMs were clustered to discover two representative patterns, A and B. Next, for each HMM, we calculated AB scale as (A - B)/(|A| + |B|), where A and B referred to the model's data log-likelihood given pattern A and pattern B HMMs, respectively, and used it to quantify each model's similarity along the contrast between patterns A and B. Both measures have been used in a series of studies (Chan et al., 2018; Hsiao et al., 2020; Hsiao et al., 2022).

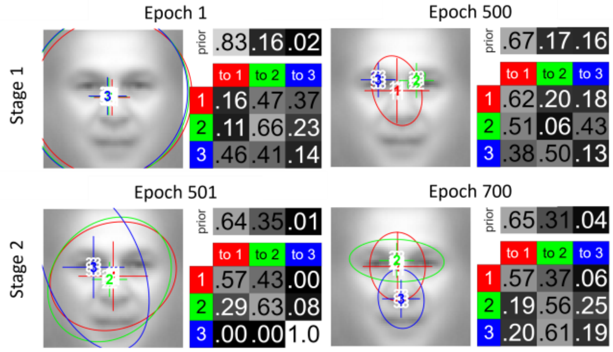

Figure 3: Eye-movement pattern changes in Stages 1 and 2 for the "noise+memory" condition, by summarizing all individual HMMs into a single representative HMM at different stages. In each model, ellipses show ROIs as 2-D Gaussian emissions, and the transition matrix summarizes the transition probabilities among the ROIs. The cross represents the attention window size, where larger windows correspond to lower SFs. Priors show the probabilities of the first fixation of a sequence landing in the corresponding ROIs.

Results

General Performance

Figure 2 shows mean training and validation accuracies and model entropy with respect to epoch number in Stages 1 and 2 for the three conditions. The models' performance in face recognition gradually enhanced as demonstrated by the mean accuracy profiles in both training and validation, and they converged before epoch 500. In Stage 2, the models' accuracy reduced after the perturbation applied in all three conditions, and such reduction was mitigated through further training from epochs 501 to 700. In addition, increasing ROI's SD ("noise") led to higher inconsistency in eye movements, as indicated by increased mean entropies after epoch 500 in both "noise" and "noise+memory" conditions (Figure 2). In contrast, the overall entropy did not increase after randomizing the ROI centers (decreased visual routine accuracy) in the "memory" condition. As for eye-movement patterns, they changed throughout epochs across Stages 1 and 2, especially after epoch 501 when the perturbations were applied. Figure 3 shows how eye-movement pattern was impacted by the perturbation in the "noise+memory" condition, and how further training changed eye movement patterns.

In the subsequent sections, we compared the model's behavior at epoch 500 vs. epoch 700 in each of the three conditions. In each condition, we clustered all individual HMMs at these two epoch numbers to discover two representative patterns A and B and used them to quantify the model's eye movement pattern using AB scale.

Table 1: *Mean (std) AB Scales of epochs 500 and 700*

Conditions	Mean (std) AB Scales	
	Ep500	Ep700
Noise	-0.069 (0.031)	-0.065 (0.029)
Memory	0.023 (0.011)	-0.024 (0.01)
Noise + Memory	0.023 (0.012)	-0.106 (0.006)

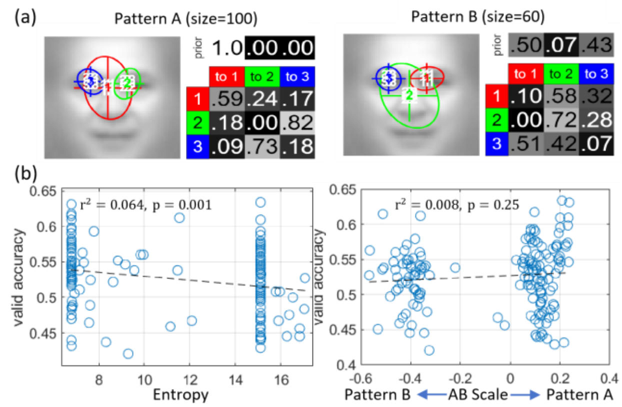

Figure 4: Results of the condition "noise": (a) HMMs of Pattern A and B.(b) Correlation between validation accuracy and entropy/AB scale.

Effects of Increased Saccade Noise

Using EMHMM, all individual HMMs at epoch 500 and those at epoch 700 in the "noise" condition were clustered to discover two representative patterns A and B (Figure 4a). Pattern A demonstrates an eye-focused pattern: a scan path mostly starts at the bridge of the nose between the two eyes, and then transits among the bridge of the nose, left eye, and right eye. In comparison, pattern B demonstrates a nose-focused pattern: a scan path transits first from either the left or the right eye to the center of the nose, and then most likely stays around the nose. These two patterns differed significantly according to KL divergence estimates (Chuk et al., 2008): the eyes-focused group's data log-likelihood given the eyes-focused HMM was higher than that given the nose-focused HMM, $t(99) = 25.37$, $p < 0.0001$, $d = 2.54$; similarly for the nose-focused group, $t(59) = 27.09$, $p < 0.0001$, $d = 3.5$. This result was consistent with previous findings from both human data and model simulations on face recognition tasks (Chan et al., 2018; Hsiao et al., 2020; Hsiao et al., 2022). No significant difference in AB scale was observed between epoch 500 and epoch 700, $t(79) = -1.133$, $p = 0.261$, and models in two clusters as represented by patterns A and B remained unchanged between these two epochs, as shown in Tables 1 and 2, respectively. Besides, the validation accuracy did not significantly correlate with AB scale $r^2 = 0.008$, $p = 0.25$. However, a significant increase in entropy was observed after increasing the ROIs' SD, with a higher entropy at epoch 700 than at epoch 500, $t(79) = -83.65$, $p < 0.0001$ (Figure 2). Furthermore, among these models, high entropy was associated with lower validation accuracy, $r^2 = 0.064$, p = 0.001, consistent with previous studies on children (Hsiao et al., 2022). These results suggest that increasing saccade noise in the models at a well-trained stage leads to higher eye-movement inconsistency but does not change the eye-movement pattern in face recognition.

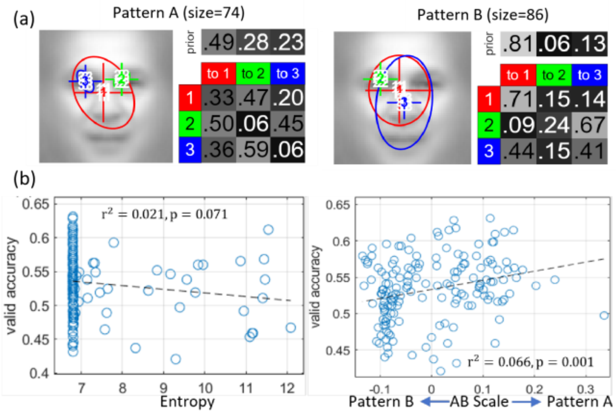

Figure 5: Results of the condition "memory": (a) HMMs of Pattern A and B. (b) Correlation between validation accuracy and entropy/AB scale.

Table 2: *Counts of models from epochs 500 and 700 in two clusters represented by patterns A and B*

Conditions	Counts of Models			
	Ep500-A	Ep700-A	Ep500-B	Ep700-B
Noise	50	50	30	30
Memory	45	29	35	51
Noise + Memory	40	1	40	79

Note. A=Pattern A; B=Pattern B.

Effects of Reduced Visual Routine Accuracy

Similarly, all individual HMMs at epoch 500 and those at epoch 700 in the "memory" condition were clustered to discover two representative patterns A and B (Figure 5a), which demonstrated eyes-focused and nose-focused patterns respectively. These two patterns differed significantly: the eyes-focused group's data log-likelihood given the eyes-focused HMM was higher than that given the nose-focused HMM t(73)=7.983, p<0.0001, d=0.928; similarly for the nose-focused group t(85)=22.32, p<0.0001, d=2.41. Moreover, unlike the "noise" condition, herein HMMs in epoch 700 had a significantly smaller AB scale (more nose-focused) than those in epoch 500, t(79)=-4.278, p <0.0001, and the count of models being clustered to pattern B was significantly higher in epoch 700 than that in epoch 500, χ^2(1, N = 80) = 5.657, p = 0.017, as shown in Tables 1 and 2, respectively. The correlation between AB scale and validation accuracy was also significant, $r^2 = 0.066$, p=0.001: the more eye-focused, the higher the accuracy (Figure 5b). However, there was no significant difference between HMMs' entropies between epochs 500 and 700, t(79)=1.33, p=0.187 (Figure 2), neither the correlation between entropy and validation accuracy, $r^2 = 0.021$, p=0.071 (Figure 5b). These results suggest that introducing memory loss as reduced visual routine accuracy to the models at a well-trained stage shifts the eye-movement pattern towards nose-focused in face recognition, but does not lead to higher eye-movement inconsistency.

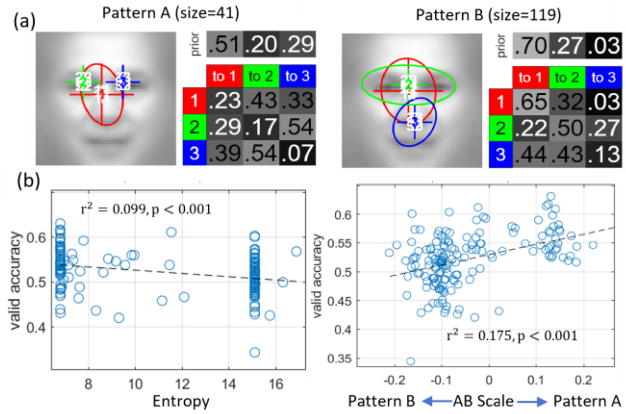

Figure 6: Results of the condition "noise+memory": (a) HMMs of Pattern A and B. (b) Correlation between validation accuracy and entropy/AB scale.

Combining Effects of Increased saccade Noise and Reduced Visual Routine Accuracy

In this condition, we added both perturbations to the model and, using the same EMHMM analysis, examined whether changes in both eye-movement consistency and pattern could be observed. HMMs were clustered and revealed eyes-focused and nose-focused patterns, with a significant difference according to KL divergence estimates (Data from Pattern A: t(118) = 23.85, p < 0.0001, d = 2.19; data from Pattern B: t(40) = 8.443, p < 0.0001, d = 1.32; Figure 6a). HMMs in epoch 700 had a significantly smaller AB scale (more nose-focused) than those in epoch 500, t(79) = -9.56, p < 0.0001, and the count of models being clustered to pattern B was significantly higher in epoch 700 than that in epoch 500, χ^2(1, N = 80) = 47.354, p < 0.0001, as shown in Tables 1 and 2, respectively. Consistent with the "memory" condition, the correlation between AB scale and validation accuracy was significant $r^2 = 0.175$, p < 0.001, indicating a higher performance in more eye-focused models (Figure 6b). Additionally, consistent with the "noise" condition, a significant increase in entropy was observed from epochs 500 to 700 after increasing the ROIs' SD, t(79) = -62.75, p < 0.0001 (Figure 2), and validation accuracy was negatively correlated with entropy $r^2 = 0.099$, p < 0.001 (Figure 6b). These results suggest that, with both memory loss and increased saccade noise at a well-trained stage, the models could exhibit a shift from eye-focused towards nose-focused scan-path, together with a higher inconsistency, during face recognition.

Discussion

Here we examined aging-related changes in performance and eye-movement behavior in face recognition through computational modeling. Specifically, we increased saccade noise and decreased visual routine accuracy to simulate aging-related decline in oculomotor control and in memory function respectively. These were implemented using DNN+HMM (Hsiao et al., 2022) by increasing the SD of the ROIs and by adding noise to the central location of the ROIs in the HMM, respectively. We examined whether these manipulations could account for the shift towards a more nose-focused pattern (Chan et al., 2018) and reduced eye movement consistency (Zheng et al., 2025) observed in older adults.

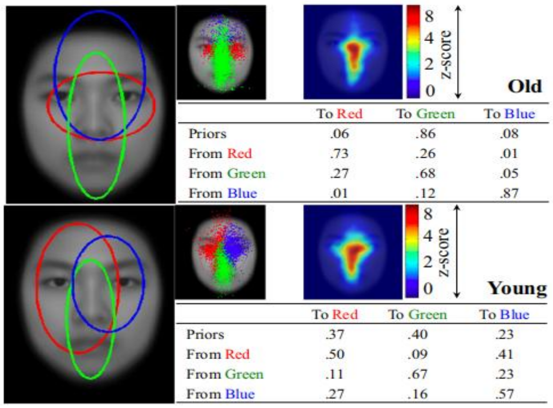

Figure 7: Representative HMMs of young and older adults' eye-movement patterns during face recognition from human data (adapted from Chan et al., 2018).

Our simulation results showed that increasing saccade noise led to lower eye movement consistency with no significant change in eye movement pattern. In contrast, reducing visual routine accuracy led to a shift towards a more nose-focused eye movement pattern without a significant change in eye movement consistency. When both factors were applied, we observed both a shift towards nose-focused pattern and lower eye movement consistency. In addition, the changes in eye movement pattern and consistency were both correlated with reduced recognition performance. These results demonstrated differential mechanisms underlying aging-related changes in eye movement behavior: The decreased eye movement consistency may be related to decline in oculomotor control that leads to increased saccade noise, whereas the shift towards a more nose-focused pattern may be related to decline in memory function that leads to inaccurate memory of learned visual routines. Computational modeling provides a better control over variables than human studies, allowing us to tease apart the influence from saccade noise and memory of the visual routine.

In our study, a perturbation was applied at epoch 500 to test two possible aging-related factors, saccade noise and impaired memory of visual routines, to simulate aging related changes in face recognition. Thus, epochs 500-700 simulated how the model adapted to these perturbations at an old age. Our simulations were able to account for the results and effects observed in previous studies that compared eye movement behaviors between young and older adults. For example, Figure 7 demonstrates the representative HMMs of young and older adults during face recognition from human data (Chan et al., 2018). The older adults' HMM reveals a nose-focused pattern, whereas the young adults' HMM reveals an eye-focused pattern. Consistently in our study, after visual routine accuracy was reduced at epoch 500, as shown in Table 1 and Figures 5-6, epoch 700 had a lower AB score than epoch 500, indicating a more nose-focused pattern at an older age. Furthermore, in the human data (Zheng et al., 2025) older adults' face recognition performance was lower than young adults, whereas their eye movement entropy was higher. Our simulations accounted for these findings: After gaze noise was increased at epoch 500, as shown in Figures 2, 4, and 6, epoch 700 had higher fixation entropy than epoch 500, and the models' accuracy became significantly lower with higher entropy.

In our computational model, the shift toward a more nose-focused pattern may be caused by the different sensitivities of ROIs based on their used window scale. After the ROIs centers are perturbed, the ROIs associated with small window scales likely will not remain over their diagnostic features (e.g. eyes) anymore, whereas ROIs associated with large window scales may still see part of their diagnostic features. Therefore, after the perturbation, the ROIs with large window scales remain useful for recognition and are subsequently enhanced during training – this leads to more nose-focused strategies using large-scale windows.

Note however that in reality, both increase in saccade noise and memory decline develop gradually with respect to age, in contrast to a one-time perturbation as implemented in the current simulations. Here we implemented this protocol in order to examine how the models recovered from or adapted to these perturbations and whether the resulting behaviors could account for human data. Future work will examine whether a more realistic implementation of aging processes by continuously and gradually increasing the amount of perturbations can better account for human data.

In conclusion, through computational modeling, we demonstrate that the two eye movement behavioral markers of aging-related changes in face recognition, decreased eye movement consistency and a shift toward nose-focused eye movement pattern, are dissociable consequences of distinct aging-related deficits rather than a monolithic decline. By injecting saccade noise and memory decline as discrete, late-stage perturbations in the model, we showed that increasing saccade noise degrades eye movement consistency without altering patterns of eye movements, whereas misremembering the learned eye movement patterns re-weighs feature salience toward the nose while sparing trial-to-trial consistency. Computational modeling allows better controls over variables than human subject studies, leading to these important discoveries. These findings not only enhance our understanding of the mechanisms underlying aging-related decline in face recognition ability, but also have important implications for intervention strategies.

Acknowledgments

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