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Citation	The 37th Annual Conference of the Cognitive Science Society (CogSci 2015), Pasadena, CA., 22-25 July 2015.
Issued Date	2015
URL	http://hdl.handle.net/10722/212263
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Eye Movement Pattern in Face Recognition is Associated with Cognitive Decline in the Elderly

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Abstract

The present study investigated the relationship between eye movement pattern in face recognition and cognitive performance during natural aging through modeling and comparing eye movement of young (18-24 years) and older (65-81 years) adults using Hidden Markov Model (HMM) based approach. Young adults recognized faces better than older adults, particularly when measured by the false alarm rate. Older adults' recognition performance, on the other hand, correlated with their cognitive status assessed by the Montreal Cognitive Assessment (MoCA). Eye movement analysis with HMM revealed two different strategies, namely "analytic" and "holistic". Participants using the analytic strategy had better recognition performance (particularly in the false alarm rate) than those using the holistic strategy. Significantly more young adults adopted the analytic strategy; whereas more older adults adopted the holistic strategy. Interestingly, older adults with lower cognitive status were associated with higher likelihood of using the holistic strategy. These results suggest an association between holistic eye movement patterns and cognitive decline in the elderly.

Keywords: eye movement; aging; face recognition; holistic processing; cognitive ability; Hidden Markov Model (HMM).

Introduction

A large amount of research has studied the effect of age on face recognition and revealed that young adults recognize faces better than older adults (Fulton & Bartlett, 1991; Grady, McIntosh, Horwitz, & Rapoport, 2000; Lamont, Stewart-Williams, & Podd, 2005). The differences are suggested to be due to declines in cognitive ability and spatial vision in the elderly (Lott, Haegerstrom-Portnoy, Schneck, & Brabyn, 2005). Lamont et al. (2005) conducted a face recognition experiment with three age groups (18-39 years, 60-75 years and 76-96 years), and concluded that face recognition performance declined with age, in which the oldest group performed the worst. The deficits in face recognition with age were seemingly in consequence of high false alarm rates, instead of low hit rates, produced by older adults (Crook & Larrabee, 1992; Lamont et al., 2005). Nevertheless, it remains unclear why aging is particularly associated with an increased false alarm rate in face recognition.

Previous research has shown that eye movement is related to underlying cognitive processes. Eye movement behavior, such as fixation location and duration, changes as the task, level of difficulty, or stimulus type change (Rayner, 1978). In face recognition, Hsiao and Cottrell (2008) found that two eye fixations were sufficient to recognize a face and the accuracy would not be further improved by allocating more fixations. The two fixations were just around the center of the nose, demonstrating the preferred viewing location phenomenon in face recognition (cf. Rayner, 1978). This location is also shown to be the optimal viewing location for recognizing a face (Hsiao & Liu, 2012). These results suggest that eye movements in cognitive tasks have functional roles in respect of the cognitive task at hand.

However, aging people were shown to have different or atypical eye movements as compared with young adults. For example, healthy older adults fixated more than young adults on the lower half of a face (Wong, Cronin-Golomb, & Neargarder, 2005). Patients with Alzheimer's disease were reported to have less efficient eye movements in facial expression identification (Ogrocki, Hills & Strauss, 2000) and reduced exploratory eye movements on novel images (Daffner, Scinto, Weintraub, Guinessey, & Mesulam, 1992). These atypical eye movement patterns may be reflecting related cognitive deficits/decline in older adults. Nevertheless, the link between particular eye movement patterns and cognitive performance in the elderly remains unclear.

Hidden Markov Model for Eye Movement Analysis

To examine the association between eye movement patterns and cognitive performance in the elderly, methods for identifying and summarizing individual eye movement patterns in both spatial (fixation locations) and temporal (transitions between fixations) dimensions are required. Nevertheless, most of the current eye movement data analysis methods primarily focus on spatial information such as using predefined regions of interest (ROIs). ROI analysis allows easy comparisons on fixation duration and number of fixations in different ROIs. However, it involves subjective definitions of the ROIs and thus is subject to experiment bias. For example, eyes can be defined as two separate ROIs (Barton, Radcliffe, Cherkasova, Edelman, & Intriligator, 2006) or a single ROI (Henderson, Williams, & Falk, 2005). In addition, predefined ROIs are not able to reflect individual differences in ROI choices. More recent eye movement analysis has addressed the problem of subjective ROIs by directly generating ROIs from data. For instance, a fixation heat map is created by plotting the location of fixations and smoothing them with a Gaussian function. Two heat maps can be compared by testing statistically difference between the two maps pixel by pixel (Caldara & Miellet, 2011).

Nevertheless, both of the aforementioned approaches purely focused on spatial information of eye movements without considering temporal information. Some have proposed to use the string-editing method to describe a scan path. A stimulus is divided into several ROIs, each of which is labeled with a letter. Eye movement is then described by a string of letters according to the ROIs visited. Two strings can be compared by computing their Levenshtein distance, which is the number of changes (insertions, deletions and/or substitutions) between two strings (Goldberg & Helfman, 2010). Nonetheless, Levenshtein distance does not precisely reflect the differences in transition between two scan paths. For example, LEAD and HEAD differ in the first character and HEAT and HEAD differ in the last character. However, the Levenshtein distances of both cases are also 1. Another method to examine temporal information is to compare fixation maps at different times (Caldara & Miellet, 2011). For example, the difference between the maps of the first and second fixations can tell us how distributions of fixations change over time. However, these difference maps do not reflect exact transitions between regions, and the resulting different regions are usually scattered and hard to be interpreted.

In view of these drawbacks, Chuk, Chan, and Hsiao (2014) recently proposed a Hidden Markov Model (HMM) based approach to analyze eye movement data. First, an HMM is estimated to represent the eye fixation sequences of an individual. An HMM contains a number of hidden states, and each state represents a different ROI of a face. The fixation locations in each ROI are modeled as a Gaussian distribution. A set of prior probabilities models the initial hidden state (i.e., fixation), while the transition probabilities model the movement from one ROI to another. The HMM parameters are estimated from the individual's eye movements using a variational Bayesian approach, which automatically determines the number of ROIs. Second, a group of individuals' HMMs can be clustered into subgroups via the variational hierarchical EM algorithm (VHEM; Coviello, Chan, & Lanckriet, 2014), and each subgroup can be portrayed by a representative HMM. In this way, common eye fixation strategies among individuals can be discovered from the group data. In addition, the level at which an individuals' eye fixations belongs to a certain HMM (e.g. a representative HMM of a subgroup) is calculated as the log-likelihood of the individuals' fixation sequences under the given HMM.

Thus, the HMM-based approach is particularly suitable for examining individual differences in eye movements and their association with cognitive performances. Here we used this approach to examine the association between eye movement pattern in face recognition and cognitive performance in the elderly. We recruited young and older adults to perform in a standard face recognition memory task while their eye movements were recorded. The HMM-based approach allows us to (1) model eye movements of each individual with an HMM and summarize individual HMMs into representative group HMMs to reveal general patterns in each group, (2) cluster the individual HMMs according to their similarities to discover common patterns, (3) compare recognition performance between people with different eye movement patterns and examine the difference between the two age groups, and (4) examine the association between individual eye movement patterns and their cognitive performance.

Method

Participants

Sixty-eight Chinese participants were divided into two age groups, including 34 young adults aged from 18 to 24 (M=20, SD=2) and 34 older adults aged from 65 to 81 (M=69, SD=8). They all reported right-handedness and with normal or corrected to normal vision. The young adults were recruited from University of Hong Kong and the older adults were recruited mainly from elderly centers. Cognitive functioning of all older participants was assessed using the Montreal Cognitive Assessment (MoCA) Hong Kong version (Wong et al., 2009) and they were all within the normal range, with scores 22 or above out of 30 (i.e., healthy older adults with no cognitive impairment). Informed consent was collected from each participant; the research protocol was approved by the Ethics Review Board at University of Hong Kong.

Materials and Apparatus

Forty Chinese face images were used. They were all frontal view in grayscale, with standardized distances between the eyes and the mouth, and with similar distance between the eyes (less than 0.5 visual degree differences from the average distance). Each face image was cropped according to the original shape of the face such that only the face (without hair) was visible. Eye movements were recorded with Eyelink 1000 eye-tracking system, which was connected to a 17” monitor and a response box. The screen resolution was set to 1024 x 768 pixels and a chinrest was positioned approximately 60 cm in front of the screen.

Procedure

Participants sat in front of a computer with their head resting on a chinrest such that the eye level of the participants was about the mid-level of the screen. Participants' right eye was tracked throughout the experiment and 9-point calibration was conducted prior to the start of the experiment. In the study phase, participants were instructed to view and remember 20 human face images one at a time at the rate of 5 seconds each. The face was displayed either at the upper center or at the lower center (i.e., 30% upward or downward from the center) of the screen randomly. Participants had to fixate at a cross "x" located at the screen center prior to the presentation of the next image. In the test phase, participants were displayed with 40 face images one at a time, with 20 old images and 20 new images, and asked to judge if they saw the face in the study phase or not. Their responses were recorded via a response box.

Result

Behavioral Performance

The MoCA scores, used for assessing the cognitive ability of the older participants, were between 22 and 30; the mean score was 26.94 with an SD of 1.77. Thus, none of the older participants showed indication of cognitive impairment (>= 22 out of 30, Wong et al., 2009).

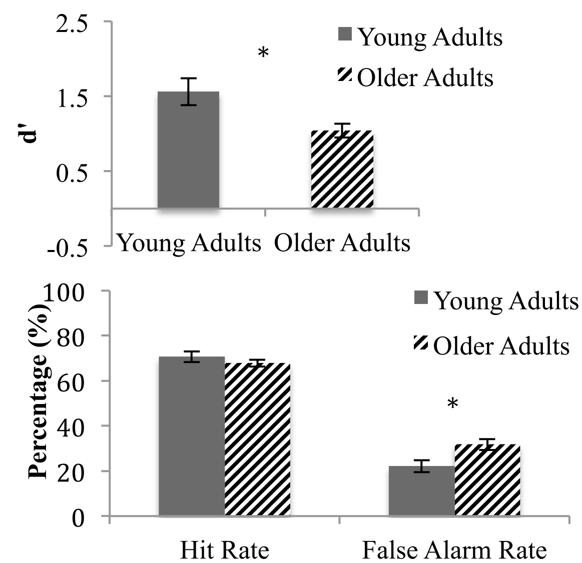
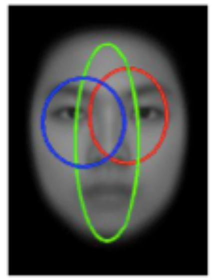


Figure 1: Face recognition performance for young and older adults (* p< .05).

Face recognition performance was measured with the discrimination sensitivity measure *d'*, hit rate, and false alarm rate (Figure 1). Independent t-test showed that the d' of young adults was significantly higher than that of older adults, t(66) = 2.53, p = .01. The false alarm rate of young adults was also significantly lower than that of older adults, t(66) = -2.58, p = .01. However, the hit rate between the two groups showed no significant difference, t(66) = .741, n.s. This result was consistent with previous studies (Crook & Larrabee, 1992).

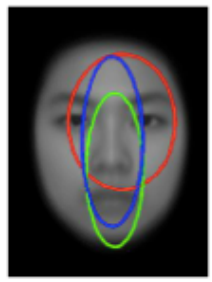
Face Recognition Strategy Used

In order to identify the strategies used by the young and older participants, we first trained one HMM for each participant, as discussed previously. We then learned the representative HMM for young adults by using VHEM to group



Young Adults' Summary HMM

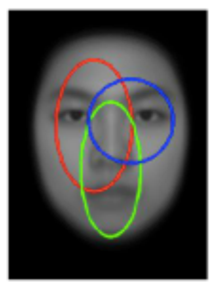
	To red	To green	To blue
Prior values	.20	.72	.08
From red	.52	.24	.24
From green	.19	.72	.09
From blue	.47	.26	.27



Older Adults' Summary HMM

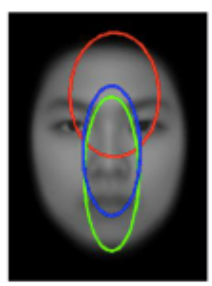
	To red	To green	To blue
Prior values	.17	.51	.32
From red	.66	.19	.15
From green	.31	.25	.44
From blue	.34	.30	.36

Figure 2: The summary HMMs of young and older adults and the corresponding transition probability matrices.



Analytic Strategy's Representative HMM

	To red	To green	To blue
Prior values	.25	.44	.31
From red	.47	.13	.40
From green	.29	.26	.44
From blue	.26	.18	.56



Holistic Strategy's Representative HMM

	To red	To green	To blue
Prior values	.19	.56	.25
From red	.64	.35	.01
From green	.11	.44	.45
From blue	.07	.23	.70

Figure 3: The representative HMMs of the two subgroups, analytic and holistic strategies, and the corresponding transition probability matrices.

their HMMs into 1 cluster, and similarly for older adults. As shown in Figure 2, each HMM included three ROIs as indicated with different colors. The overlapping area of two or more ROIs means that the fixations around that area have similar probabilities of belonging to those ROIs. The prior values in the matrices represented the probability that an initial eye fixation located at each of the ROIs. The rest of the matrix represents the transition probabilities among the three Gaussian components. For example, in the young adults' matrix, the prior value to the red ROI is 0.20 and the probability of changing the eye movement from the green to the blue ROI is 0.09. It could be observed that the ROIs of the older adults' summary HMM were concentrated at the center of the face, with some engagement around the eye region. However, the ROIs of the young adults' summary HMM were more clearly located at different facial features, including the left eye (blue), right eye (red), and nose/mouth (green).

Next, we grouped all the young and older participants' HMMs and applied VHEM to cluster the HMMs into two subgroups (Figure 3). It can be observed that the ROIs of the representative HMM on the bottom were more condensed at the vertical and central location of the face with less engagement on individual features of the face. People using this eye movement pattern are likely to process the face as a whole without detailed encoding of individual features and therefore, here we term it the holistic strategy. In contrast, the ROIs of the representative HMM on the top were more separately located at different areas of the face, indicating more engagement of facial features such as the left eye (red), the right eye (blue) and nose/mouth (green), as compared with the holistic strategy. People using this eye movement pattern are likely to have detailed encoding of individual facial features, and thus here we term it the analytic strategy. Both strategies had their prior fixation mostly located around the face center, which was also regarded as the most preferred viewing location (Hsiao & Cottrell, 2008). However, the subsequent scan paths of the two strategies were quite different. For examples, in the analytic strategy, after viewing the face center (prior prob. = .44), people tended to transit the eye movement to the right eye (prob. = .44), then stayed at this ROI a while (prob. = .56) or transited to the left eye (prob. = .26). In contrast, in the holistic strategy, after viewing the face center (prior prob. = .56), the eye movements stayed around the same ROI (prob. = .44) or moved upward a bit to the upper nose (prob. = .55), or occasionally transited to forehead area (prob. = .11).

We also used VHEM to calculate the probabilities of each participant's HMM belonging to the two strategies, and classify the participants into the analytic or holistic group accordingly. As shown in Table 1, significantly more young adults used the analytic strategy and more older adults used the holistic strategy, $X(2) = 4.77$, $p = .03$ (Chi-square test).

Table 1: The number of young and older adults belonging to the analytic and holistic subgroups.

	No. of young adults	No. of older adults
Analytic subgroup	22	13
Holistic subgroup	12	21

Relationship between Strategy and Recognition Performance/Cognitive Status

To examine the relationship between eye movement strategy and recognition performance, we compared the performance between the holistic and analytic groups with age group as a covariate using ANCOVA. The analytic strategy yielded a higher d', $F(65, 1) = 4.20$, $p < .05$, and lower false alarm rate, $F(65, 1) = 6.21$, $p = .02$, than the holistic strategy. However, the hit rate was not affected by the use of the analytic or holistic strategies, $F(65, 1) = .12$, $p = .73$. The result suggested that the analytic strategy was a more effective strategy in face recognition. In addition, we observed a positive correlation between the log-likelihood of one's eye movement being classified as the holistic strategy and false alarm rate in young adults, $r(34) = .35$, $p = .05$ (Figure 4, top; this correlation was not significant in older adults, $r(34) = .23$, $p = .18$, possibly because of a ceiling effect, i.e., they generally all had a high false alarm rate). In other words, the more holistic strategy a young adult used, the more likely he/she encountered a false alarm situation. This suggested an association between the holistic eye movement strategy and false alarms in face recognition.

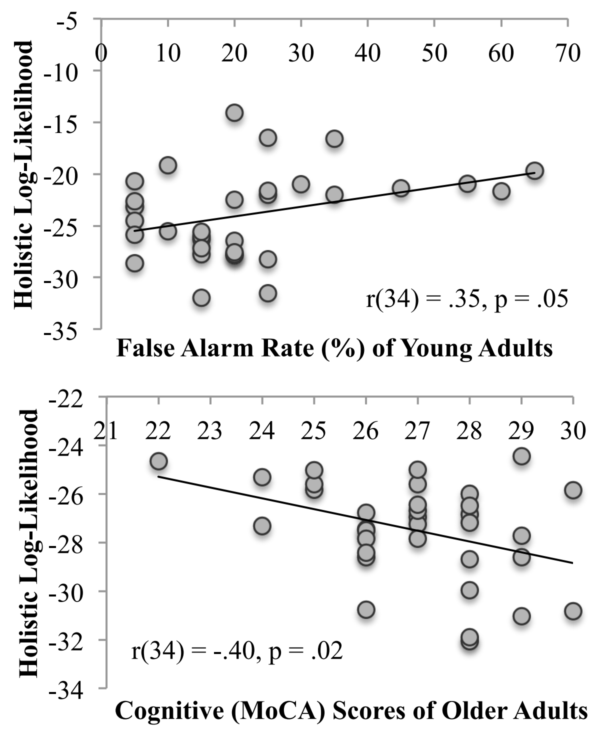


Figure 4: Correlation of false alarm rate and log-likelihood of being classified as using the holistic strategy in young adults (top) and correlation of cognitive status and log-likelihood of being classified as using the holistic strategy in older adults (bottom).

For older adults, we also examined the correlations among their MoCA scores, log-likelihoods of their eye movements being classified as the holistic/analytic strategy, and face recognition performance. We found that the MoCA score was correlated with the strategy used. More specifically the lower the MoCA score was, the more likely the eye movement pattern was classified as holistic, $r(34) = -.40$, $p = .02$ (Figure 4, bottom). Concerning the face recognition performance, the MoCA score was positively correlated with hit rate, $r(34) = .34$, $p = .05$, and marginally correlated with d', $r(34) = .30$, $p = .08$. However, it did not correlate with false alarm rate, $r(34) = .06$, $p = .75$. Age of older adults showed no significant correlation with any of the strategies used, d', hit rate, and false alarm rate. This suggested cognitive status in older adults was associated with eye movement pattern and face recognition performance.

Discussion

The current study aimed at investigating eye movement patterns of young and older adults in face recognition and their association with cognitive performances. We first observed that the face recognition performance of young adults was higher than that of older adults. Although there was no difference found in the hit rate between the two age groups, the false alarm rate was significantly higher in the older group than in the younger group, suggesting that lower accuracy observed in older adults could be attributed to the confusion of the new faces from the old faces. Similar results were also reported in previous research (e.g. Crook & Larrabee, 1992; Fulton & Bartlett, 1991). Our further analysis showed that older adults' d' and hit rate significantly decreased with their cognitive status as measured by the MoCA, but not their age. This result is inline with what reported in previous research showing that face recognition impairment was associated with cognitive status decline (Lott et. al., 2005).

To understand the association between eye movement and cognitive performances, we used an HMM-based approach (Chuk et al., 2014) to describe and compare individual eye movement patterns. We discovered two distinct eye movement strategies that differed in both the spatial and temporal perspectives by clustering all participants' HMMs into two subgroups according to their similarities – analytic and holistic strategies. Between the two strategies, we found that face recognition performance was better in the analytic group than in the holistic group. In addition, among young adults, the higher the likelihood of their eye movement pattern being classified as a holistic pattern was, the higher their false alarm rate was. This result suggests the association of holistic eye movement patterns and high false alarm rates. Concerning the nature of false alarms, Davies, Shepherd, and Ellis (1979) revealed that increasing the degree of similarity between the studied and new faces also increased the false alarm rate. In other words, the false alarm rate could be reduced by carefully encoding the studied faces that were helpful in distinguishing the studied face from the new faces that may possibly look similar to the studied faces. As proposed by Lamont et al. (2005), participants should have sufficient distinctive facial features available in memory to make a judgment. Accordingly, the association between holistic patterns and high false alarm rates may be because in holistic strategies, important facial features such as the eyes are not foveated, leading to insufficient encoding of distinctive facial features for distinguishing studied faces from new faces and thereby resulting in a higher false alarm rate. As shown in Figure 3, the ROIs of the holistic HMM were centrally located with less engagement in featural processing. Thus, featural information of the studied faces might be more easily confused with new faces. In contrast, the ROIs of the analytic HMM were located on distinctive facial features and consequently promoted more featural processing to support face recognition, resulting in a smaller false alarm rate. Thus, eye movement strategies may affect the effectiveness of the encoding process and consequently affect recognition performance. Our results suggest that analytic strategies are more effective in reducing the false alarm rate as well as the recognition performance.

We also found that young adults were more likely to use an analytic strategy while older adults were more likely to use a holistic strategy. In addition, in the older group, people with lower cognitive status had higher likelihood of being classified as using holistic strategy. Thus, one's cognitive status may be a critical variable affecting the use of eye movement strategies. It is possible that the decreased cognitive status lowered the cognitive resources such as processing speed (Kail & Salthouse, 1994) and impaired executive functions (Grady, 2002), which may influence abilities to plan eye movements for face recognition. Grady (2002) carried out a meta-analysis to examine age-related differences in face recognition via neuroimaging studies, and concluded that the prefrontal cortex was involved in face recognition and the activation of the prefrontal cortex was higher in older adults than in young adults in performing face recognition. In addition, the activation in the prefrontal cortex of older adults was higher when the task required more cognitive load, suggesting that the increased activation in the prefrontal lobe was an indication of greater demands on the executive functions. In other words, decreased cognitive status may be highly associated with decreased executive functions, and our data suggested it is reflected in participants' (holistic) eye movement patterns.

Yarbus (1965) showed that people exhibited different eye movements at the same target image depending on what they expected to see. It suggests that our planning ability, as part of our executive functions, is essential for effectively encoding necessary information in cognitive tasks. By comparing the two strategies discovered in the current study, the analytic strategy may require more cognitive resources and involve more sophisticated eye movement planning – in addition to potentially viewing the whole faces from a central fixation, participants formed ROIs on distinctive facial features and had more diverse and effortful scan paths over these ROIs when processing faces. In contrast, the holistic strategy involved less planning by simply looking around the center of faces (potentially getting a holistic view of the face), with less switching among ROIs, suggesting less featural processing. In short, people with lower cognitive status, may have less effective executive functioning in planning eye movements for encoding faces, and consequently are more likely to adopt a simpler, holistic strategy in viewing faces.

Our results suggested associations among cognitive status, recognition performance, and eye movement pattern. This result has very important implications on ways to improve the elderly's quality of life. For example, this association suggests the potential use of eye movements to detect early signs of cognitive decline and neurodegenerative changes in the elderly. Possible training/intervention programs on eye movement planning may be used to enhance their cognitive performance. Future work will examine these possibilities with a larger older adult sample including those with mild cognitive impairment and Alzheimer's patients.

Conclusion

In summary, through analyzing eye movement data with our HMM-based approach, we revealed several important effects that are able to enhance our understanding of the mechanism underlying behavioral differences in face recognition between young and older adults. We found that young adults tend to use an analytic strategy whilst older adults tend to use a holistic strategy. In addition, holistic strategies in face recognition are associated with higher false alarm rates and lower cognitive status, whereas analytic strategies yielded a higher face recognition performance than holistic strategies. These findings were not possible with traditional eye movement analysis methods that do not take individual differences in both temporal and spatial dimensions of eye movements into account.

Acknowledgments

We thank Mr. Tim Chuk for his technical support in using the HMM-based model, and Ms. Alison Hui in data collection. We are also grateful to the Research Grant Council of Hong Kong (project code 17402814 to J.H. Hsiao and CityU 110513 to A.B. Chan) and Health and Health Services Research Fund (#09100911 to Tatia M. C. Lee).

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