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RESEARCH ARTICLE

Investigation of eye movement pattern parameters of individuals with different fluid intelligence

Bahman Abdi Sargezeh[1,2] · Ahmad Ayatollahi[2] · Mohammad Reza Daliri[1]

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Abstract

Eye movement studies are subject of interest in human cognition. Cortical activity and cognitive load impress eye movement influentially. Here, we investigated whether fluid intelligence (FI) has any effect on eye movement pattern in a comparative visual search (CVS) task. FI of individuals was measured using the Cattell test, and participants were divided into three groups: low FI, middle FI, and high FI. Eye movements of individuals were then recorded during the CVS task. Eye movement patterns were extracted and compared statistically among the three groups. Our experiment demonstrated that eye movement patterns were significantly different among the three groups. Pearson correlation coefficients between FI and eye movement parameters were also calculated to assess which of the eye movement parameters were most affected by FI. Our findings illustrate that saccade peak velocity had the greatest positive correlation with FI score and the ratio of total fixation duration to total saccade duration had the greatest negative correlation with FI. Next, we extracted 24 features from eye movement patterns and designed: (1) a classifier to categorize individuals and (2) a regression analysis to predict the FI score of individuals. In the best case examined, the classifier categorized subjects with 68.3% accuracy, and the regression predicted FI of individuals with a 0.54 correlation between observed FI and predicted FI. In our investigation, the results have emphasized that imposed loads on low FI individuals is greater than that of high FI individuals in the cognitive load tasks.

Keywords Eye movement · Fluid intelligence · Comparative visual search · Individual categorization · Predicting fluid intelligence

Introduction

There are many ways to define intelligence. Raymond Cattell has proposed two types of cognitive abilities for understanding the intelligence: fluid intelligence (FI) and crystalized intelligence (Cattell 1963). The former is defined as the capacity of human ability to solve new problems regardless of any knowledge from the past, and the latter is defined as knowledge-based ability that depends on education and experience. Some psychological studies have demonstrated the dependence of brain functioning on intelligence. As a result, it has been illustrated that intelligence has a significant correlation with working memory capacity, speed of information processing (Conway et al. 2002), (Fry and Hale 2000), and inspection time (Nettelbeck et al. 1986).

Human retina is the nerve layer that creates impulses which move to the brain through optic nerve; hence, the retina is considered as part of the central nervous system (Tuladhar et al. 2014). Three main areas control eye movements in the frontal lobe: the frontal eye field, the supplementary eye field, and the dorsolateral prefrontal cortex (DLPFC) (Pierrot-Deseilligny et al. 2003, 2004). Moreover, there is a significant correlation between FI and the activity in DLPFC (Gray et al. 2003). Accordingly, the relationship between DLPFC and eye movements as well as the relationship between DLPFC and FI motivated us to investigate the eye movement patterns of individuals having different FI scores.

The human's eyes are controlled by intricate cerebral networks (Leigh and Zee 2015; Duchowski 2007). The

✉ Mohammad Reza Daliri
daliri@iust.ac.ir

[1] Neuroscience and Neuroengineering Research Lab., Biomedical Engineering Department, School of Electrical Engineering, Iran University of Science and Technology (IUST), 16846-13114 Narmak, Tehran, Iran

[2] Electronics Engineering Department, School of Electrical Engineering, Iran University of Science and Technology (IUST), 16846-13114 Narmak, Tehran, Iran

neurological characteristics of the brainstem (Jellinger 2009) and the cortical activity affect eye movements. Maghanathan et al. illustrated that fixation duration and pupil size depend on dynamic memory load (Meghanathan et al. 2015). Their stimuli were comprised of three different levels of task difficulty. They reported that fixation duration and the pupil size increase with increasing the task difficulty level. It means that the capacity of memory load affects the eye movement patterns. In a study conducted by Coco et al., the relationship between brain activity and eye movement patterns was investigated in three different tasks: namely, visual search, scene description, and object naming (Coco and Keller 2014). The authors were able to categorize the tasks using the features extracted from eye movement patterns.

In addition, Van Der Meer et al. have indicated that intelligence quotient (IQ) and pupil dilation are related (Van Der Meer et al. 2010). They used geometric analogies, designed in three different levels of task difficulty, as stimuli to investigate the relationship between pupil dilation and individuals' IQ. The results showed that pupil dilation is larger in high IQ individuals compared to those with low IQ while solving the geometric analogies problems. In a study performed by Hayes et al., eye movements of participants were recorded, while they were solving the Raven's Advanced Progressive Matrices (RAMP) (Hayes and Petrov 2015). Similar to Van Der Meer et al. (2010), they have also described that those subjects who solved more questions of RAMP than others had more pupil dilation. Like Hayes and Petrov (2015), Hayes et al. (2011) also recorded participants' eye movements during solving RAMP questions. They demonstrated a correlation between the Raven scores and eye movement data. Furthermore, they predicted the Raven score of individuals by sequential eye movement analysis. In addition, some eye movement parameters of individuals with different IQ scores were investigated during the observation of complex pictures task (Nesbit 1981). The authors found that low IQ individuals produced greater fixation duration as compared to high IQ individuals. In contrast, the number of fixations was more numerous in high IQ individuals than those of low IQ.

Eye movement parameters have not been widely investigated to study the relationship between eye movements and intelligence. To the best of our knowledge, this is the first study trying to examine eye movement patterns of individuals with different FI and predict the FI score of individuals using eye movement parameters. Thus, this approach is more comprehensive than preceding studies.

Comparative visual search (CVS) tasks have been used here and pairs of indoor scenes were simultaneously presented side-by-side during eye movement recording. There were one-to-three added/deleted objects in one of the pairs of images in which the method is called addition/deletion approach. Besides addition/deletion method, two other ways of performing a CVS task were proposed in (Galpin and Underwood 2005): (1) object substitution, an object in the first image is substituted for another object of the same category in the second image; (2) location change, an object is moved horizontally in one of the images. Based on the comparative study in (Galpin and Underwood 2005), addition/deletion method outperforms the others, in terms of detection accuracy and reaction time. Therefore, we have used addition/deletion approach.

Materials and methods

Participants

Forty-four subjects (age 24–33 years, mean 26.25 years, 18 females) participated in the experiment. Twenty-nine participants had normal vision and the others had corrected-to-normal vision with glasses. Three subjects were excluded from analysis because of their noisy eye movement data and the results of 41 participants (15 females) are reported here. All participants were students at the Iran University of Science and Technology.

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all the individual participants included in the study.

FI test

The R. B. Cattell test (Cattell 1963) has been used to evaluate the FI of participants. There are four subtests which contribute to the standard and full Cattell test. The first one is completing a sequence of drawings, the second one is classification subtest where respondents are supposed to pick a drawing which is different from others, completing a matrix like pattern, and the third one is related to the geometric drawing. Note that the FI test was given before the main task. After performing the R. B. Cattell test, participants were divided into three groups based on FI scores. Table 1 provides the full details of groups.

Table 1 Means, ranges, and standard deviations of FI score of the three groups of subjects

FI group	Number	FI range	Mean FI	SD FI
Low FI	8	73–100	91.2	9.1
Middle FI	23	101–125	115.1	5.7
High IQ	10	126–155	137.7	10.3

Stimuli

Forty-six images of change blindness data set (Sareen et al. 2016) were selected—publicly available in http://search.bwh.harvard.edu/new/CBDatabase.html—to prepare stimuli. The size of each image was 1024 × 768 in pixel. A copy of each image was placed beside the original image, and then, one-to-three changes, in addition\deletion condition, were created in the pairs of images. It means that there were one-to-three differences between the two almost identical images arranged side by side. The size of stimuli was 2126 × 768 in pixel; however, we resized stimuli to 1920 × 768 in pixel for a better presentation in the monitor. Figure 1 shows a stimulus in which there are two differences between a pair of side-by-side images.

Procedure

In this study, a visual search task has been utilized. Participants were asked to find the number of differences in the two side-by-side images. For diminishing the adverse effects of participants' fatigue, we presented the stimuli in two blocks each of which consisted of 23 trials. After finishing the eye movement recording of the first block, participants rested for 10 min. It is worth noting that, before the main task, participants had been taught how to address the differences in the stimuli, by performing six trials as training. In addition, they were informed that there are one-to-three differences in each display.

At the beginning of each trial, a gray screen with a fixation point in its center was shown. Participants were simultaneously supposed to gaze on the fixation point and press the space bar to start the task before each trial.

The visual search display was shown for a duration of 20 s after pressing the space bar. After this period, a message was presented at the center of the display: ''how many differences did you see between the two images?'' Left, down, and right arrow keys were used for responding to one-difference, two-difference, and three-difference, respectively. This message disappeared either after report of participants or after 2 s, and then, the new trial was initiated.

Eye movement recording

Before the beginning of each block, nine-point calibration and validation procedures were carried out. The validation errors of eye tracker were graded in three levels, that is, GOOD, errors are acceptable; FAIR, errors are moderate and calibration should be improved; POOR, which means that errors are too high for useful eye tracking. As a result, when the grade was not "GOOD," the calibration was repeated. In addition, the drift correction was performed before each trial to ensure the right calibration until the end of each block. When drift was larger than 1°, the calibration procedure was carried out again. In the default mode, the left eye of subjects was tracked, but when good calibration was not obtained, the right eye of the participant was tracked. For 2 of 41 subjects whose data were finally confirmed, the right eye was tracked. It should be noted that the saccade velocity and acceleration thresholds were defined as 30°/s and 8000°/s^2, respectively (Chuk et al. 2017).

The apparatus utilized to record the eye movements of individuals in this experiment was the desktop system of the Eye Link 1000 plus eye tracker (SR research, Canada). The sampling rate of the eye tracker was adjusted to 1000 Hz in the monocular Pupil-CR recording mode.

A chinrest was used to reduce participants' head movement. Participants' distance from the monitor screen was set to be 60 cm. A 24-inch LCD monitor with the resolution of 1920 × 1080 pixels was used to show stimuli.

Fig. 1 Sample of stimulus in which there are two differences between the side-by-side images. The differences are distinguished with red circles

Preprocessing of eye movement data

The initial fixation point is a coercive point that occurs unconsciously (Momtaz and Daliri 2016) and it may be different in low as well as high FI individuals, and therefore, the initial fixation duration was considered as a feature. Furthermore, to calculate the mean of fixation duration, all fixation durations except the initial duration and those occurring immediately after eye blinks were averaged.

Experimental results

We extracted participants' eye movement parameters and compared them among the three groups statistically. We found out that the eye movement parameters depended on individuals FI score. Wilcoxon rank-sum test and one-way analysis of variance (ANOVA) were applied to parameters to investigate whether significant differences exist among the three groups or not. Next, participants' eye movement patterns were entered into a classifier to categorize the subjects into three classes (high FI, middle FI, and low FI) and to carry out a regression analysis to predict the FI score of individuals.

Table 2 Percentage of correct answers for the CVS task obtained from 41 subjects

FI group	All trials
Low FI	54.08
Middle FI	48.39
High FI	52.61
All subjects	50.53

For each participant, we just analyzed those stimuli which were answered correctly (the percentage of correct answers for the CVS task is illustrated in Table 2). For the correct answers of three groups, we found no significant difference (ANOVA: $F_{(2,40)} = 1.72$, $\rho > 0.1$).

Differences of eye movement patterns in participants with different FI score

Eye movement patterns present useful information about the human's cognition (Yarbus 1967; Gaarder 1975). To compare eye movement patterns among the three groups, we extracted some features such as fixation duration, number of fixations, fixation distance, saccade peak velocity, spatial density, ratio of total fixation duration to total saccade duration (RFDSD), scanpath length, and the number of saccades occurring between the two scenes (NSBS). The mean of each parameter was calculated for each image, and variations of these values are shown in Fig. 2 with the mean (M) and the standard deviation (SD).

Fixation duration provides the temporal information of eye movements. Longer fixation duration means that the subject spends more time for interpreting or relating the objects (Irwin and Carlson-Radvansky 1996). In this experiment, low FI individuals demonstrated longer fixation duration ($M = 217.85$ ms, $SD = 23.37$) than both

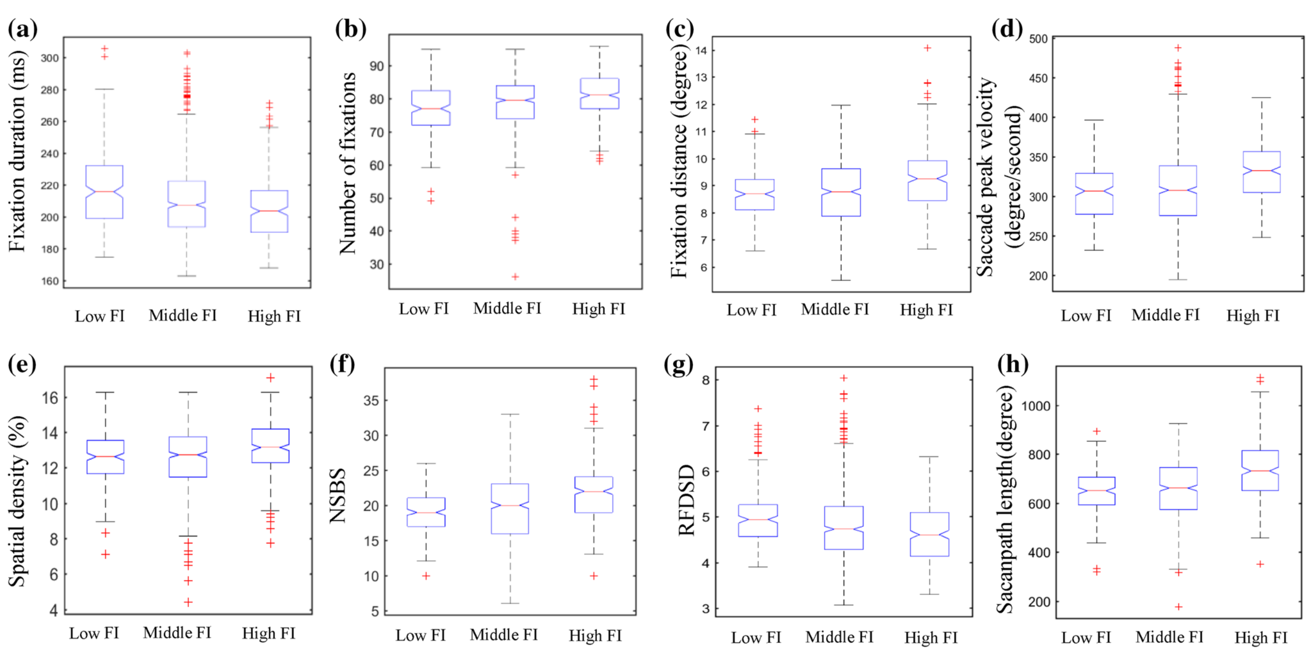


Fig. 2 Box plot of eye movement parameters for the three groups: **a** fixation duration, **b** the number of fixations, **c** fixation distance, **d** saccade peak velocity, **e** spatial density, **f** NSBS, **g** RFDSD, and **h** scanpath length

middle FI individuals ($M = 211.53$ ms, SD = 25.82; ANOVA: $F_{(1,747)} = 9.47$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$) and high FI individuals ($M = 204.63$ms, SD = 19.35; ANOVA: $F_{(1,768)} = 44.86$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$). Likewise, the fixation duration of middle FI individuals was longer than that of high FI individuals (ANOVA: $F_{(1,800)} = 14.62$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$). As a matter of fact, low FI subjects spent longer time to process the components of stimuli than high FI subjects (Fig. 2a).

The number of fixations indicates the number of components processed by the subject. Low FI individuals generated a smaller number of fixations ($M = 76.8$, SD = 7.3) as compared to both middle FI individuals ($M = 78.12$, SD = 8.95; ANOVA: $F_{(1,747)} = 4.1$, $\rho < 0.05$; Wilcoxon rank-sum test: $\rho < 0.01$) and high FI individuals ($M = 80.78$, SD = 6.78 ; ANOVA: $F_{(1,768)} = 37.23$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$). In similar fashion, the number of fixations of middle FI individuals was less than that of high FI individuals (ANOVA: $F_{(1,800)} = 18.06$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$). Indeed, higher FI individuals interpreted more objects than lower FI individuals (Fig. 2b).

Fixation distance, which gives the information about spatial features of eye movement, is the Euclidean distance between preceding and following fixations (Burch 2017). In general, fixation distance is slightly larger than saccade amplitude, since saccades do not include sub-threshold velocity parts of the eye movement. It represents the rapidity of the subject's scanning for finding differences. Smaller fixation distance is produced if the location of objects misleads the subject. In this study, high FI individuals produced higher fixation distance ($M = 9.2$ degree of visual angle, SD = 1.12) as compared to both middle FI individuals ($M = 8.7$ degree of visual angle, SD = 1.23; ANOVA: $F_{(1,800)} = 46.16$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$) and low FI individuals ($M = 8.7$ degree of visual angle, SD = 0.91; ANOVA: $F_{(1,768)} = 41.33$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$). On the other hand, there was no significant difference between the fixation distance of middle FI and low FI individuals (ANOVA: $F_{(1,747)} = 0$) and they were close to each other. In point of fact, higher FI subjects scanned the scene quicker than lower FI subjects (Fig. 2c).

Saccade peak and average velocity are especially valuable for neuro-psychophysical tasks. Saccade peak velocity has been proposed as an eye movement index in brain cognition (Hutton 2008). In this study, saccade peak velocity was greater in high FI individuals ($M = 331.08$ degree of visual angle in per second, SD = 34.52) in comparison with both middle FI individuals ($M = 309.38$ degree of visual angle in per second, SD = 48.12; ANOVA: $F_{(1,800)} = 42.48$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$) and low FI individuals ($M = 304.76$ degree of visual angle in per second, SD = 35.43; ANOVA: $F_{(1,768)} = 65.67$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$). There was no significant difference between the middle FI and low FI individuals (ANOVA: $F_{(1,747)} = 1.58$), in spite of the fact that the saccade peak velocity of middle FI individuals was greater than that of low FI individuals. The box plot of the saccade peak velocity is depicted in Fig. 2d for the three groups.

Spatial density represents the spatial distribution of fixation points. To calculate the spatial density, we divided the display into an evenly spaced 30×16 grids, with each cell covering 64×48 pixels. Then, the total number of cells containing at least one fixation point was divided by the total number of grid cells (480) (Goldberg and Kotval 1999). Bigger spatial density demonstrates extensive search, and smaller spatial density demonstrates more directed search without attention to temporal fixation point (Cowen et al. 2002). High FI individual produced 1% larger spatial density ($M = 13\%$, SD=1.52) as compared to both middle FI individuals ($M = 12\%$, SD = 1.69; ANOVA: $F_{(1,800)} = 25.36$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$) and low FI individuals (M = 12%, SD = 1.52; ANOVA: $F_{(1,768)} = 15.22$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$). The spatial density of middle FI and low FI subjects was really close to each other, and there was no significant difference between them (ANOVA: $F_{(1,747)} = 0.28$). As a result, higher FI individuals searched a wider location of stimuli to find differences in comparison with lower FI individuals (Fig. 2e).

We computed the NSBS to obtain the relative organization and amount of visual search between the two scenes; more NSBS means greater amount of visual search. High FI individuals performed more NSBS ($M = 22.2$, SD = 4.7) as compared to both middle FI individuals ($M = 19.77$, SD = 4.65; ANOVA: $F_{(1,800)} = 47.88$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$) and low FI individuals ($M = 19.05$, SD = 3.13; ANOVA: $F_{(1,768)} = 69.16$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$). The NSBS of middle FI individuals was slightly greater than that of low FI individuals. There was no significant difference between them by Wilcoxon rank-sum test ($\rho > 0.05$). Rather, they were significantly different by ANOVA ($F_{(1,747)} = 4.23$, $\rho < 0.05$). Figure 2f presents the box plot of the NSBS for the three groups.

To compare the time which was taken for processing the components (total fixation duration) with the time taken for searching added/deleted objects (total saccade duration), we calculated the RFDSD. Greater RFDSD value implies more processing or less search activity (Goldberg and Kotval 1999). In this experiment, the RFDSD was significantly greater in low FI subjects ($M = 5$, SD = 0.64) than both middle FI subjects ($M = 4.8$, SD = 0.77; ANOVA: $F_{(1,747)} = 10.2$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$) and high FI subjects ($M = 4.64$, SD = 0.62; ANOVA: $F_{(1,768)} = 37.81$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$). In addition, there was a significant difference between middle FI and high FI individuals (ANOVA: $F_{(1,800)} = 9.29$, $\rho < 0.01$;

Wilcoxon rank-sum test: $\rho < 0.05$). This demonstrates that lower FI individuals spent more time on processing components, while higher FI individuals spent more time on searching added/deleted objects (Fig. 2g).

To compute scanpath length, we summed saccade amplitude for each stimulus; then, we averaged across all the stimuli. Longer scanpath length shows that a subject searches extensively and scans the stimuli quickly. High FI individuals produced longer scanpath length ($M = 735.91$, SD = 124.09) than both middle FI individuals ($M = 658.83$, SD = 117.55; ANOVA: $F_{(1,800)} = 72.93$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$) and low FI individuals ($M = 647.6$, SD = 89.84; ANOVA: $F_{(1,768)} = 74.69$, $\rho < 0.01$; Wilcoxon rank-sum test: $\rho < 0.01$). In contrast, even though longer scanpath length was generated in middle FI subjects in comparison with low FI subjects, there was no significant difference between them (ANOVA: $F_{(1,747)} = 1.55$, $\rho > 0.05$). Figure 2h shows the box plot of the scanpath length for the three groups.

To obtain more information about fixation duration, the number of fixations, fixation distance, and saccade peak velocity, the visual search duration of each trial was divided into 20 bins (each bin is equal to 1 s and divining is carried out at the time of performing the CVS task). For each subject, the mean of the aforementioned parameters was computed in each bin, and then, they were averaged across the individuals in each group. Figure 3 shows the mean and the standard error of the mean of calculated parameters during the visual search. An interaction was observed between the visual search time and the aforementioned parameters.

Fixation duration was increased with increasing visual search time. During the first seconds, subjects searched the scene, without processing the components. After 5 s, individuals started to interpret the objects to find differences. The fixation duration of high FI subjects was significantly less than that of low FI subjects regarding the overall time of visual search (ANOVA: $F_{(1,39)} = 22.83$, $\rho < 0.0005$; Wilcoxon rank-sum test: $\rho < 0.0005$; considering the Bonferroni correction). In addition, it was significantly less than the fixation duration of middle FI individuals at the first 15 s, but they were close to each other at the last 5 s. Considering the Bonferroni correction, there was no significant difference

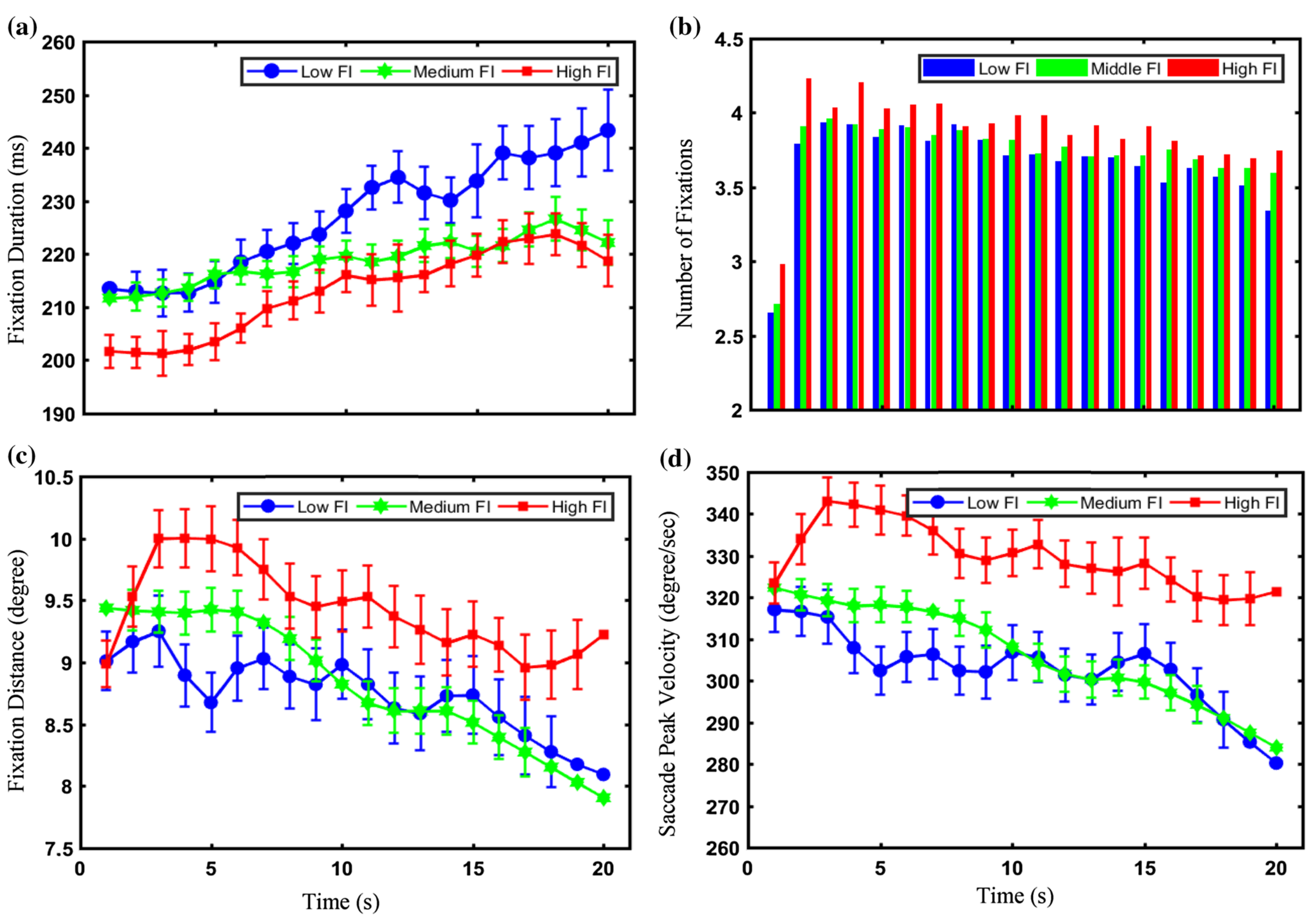


Fig. 3 Eye movement patterns averaging in 1-s intervals: **a** fixation duration, **b** the number of fixations, **c** fixation distance, and **d** saccade peak velocity. The error bars indicate standard error of the mean

between them, even though they were significantly different before the correction (ANOVA: $F_{(1,39)} = 8.37$, $\rho = 0.006$; Wilcoxon rank-sum test: $\rho = 0.02$). Despite the fact that the fixation duration of low FI and middle FI individuals was close to each other at the first 6 s, the fixation duration of low FI individuals was greater than that of middle FI individuals at other times. However, considering the Bonferroni correction, they were significantly different not by Wilcoxon rank-sum test ($\rho = 0.01$), but rather by ANOVA test $F_{(1,39)} = 10.52$, $\rho < 0.0025$).

Unlike fixation duration, the number of fixations was reduced during the CVS task. The trend of fixation duration and number of fixations proved that the number of components processed by participants decreased and the time for processing components was increased as the CVS task goes on. Considering the Bonferroni correction, there was no significant difference between the number of fixations of high FI and low FI individuals by the ANOVA test ($F_{(1,39)} = 5.95$, $\rho = 0.019$). However, they were significantly different by Wilcoxon rank-sum test ($\rho < 0.0025$).

In our study, we studies the influence of time on fixation distance. Variations in fixation distance during the CVS task would likely be related to changes in the NSBS. Reduction in fixation distance as the CVS task goes on demonstrated that the NSBS decreased. The emergence of a difference between the fixation distance of high FI and middle FI individuals occurred after 2 s from the beginning of the task and remained until the end of search. They also were significantly different from each other with considering the Bonferroni correction (ANOVA: $F_{(1,39)} = 17.98$, $\rho < 0.0005$; Wilcoxon rank-sum test: $\rho < 0.0025$). The fixation distance of high FI individuals was greater than that of low FI individual in overall time of CVS task, and also a significant difference was observed between them according to the Bonferroni correction (ANOVA: $F_{(1,39)} = 42.81$, $\rho < 0.0005$; Wilcoxon rank-sum test: $\rho < 0.0.0005$). Although the fixation distance of middle FI was greater than that of low FI individuals at the first 10 s, there was no significant difference between them and they became close to each other at the remaining time of the CVS task (ANOVA: $F_{(1,39)} = 0.49$, $\rho = 0.48$).

Changes in saccade peak velocity are inevitable consequences of the changes in saccade size as the trial goes on—a relationship known as the "main sequence" (Bahill et al. 1975). Decreasing of the saccade peak velocity with passing the time can also result from fatigue (Hirvonen et al. 2010). Saccade peak velocity in high FI individuals was significantly greater—considering the Bonferroni correction—than both low FI individuals (ANOVA: $F_{(1,39)} = 101.15$, $\rho < 0.0005$; Wilcoxon rank-sum test: $\rho < 0.0005$) and middle FI individuals (ANOVA: $F_{(1,39)} = 54.66$, $\rho < 0.0005$; Wilcoxon rank-sum test: $\rho < 0.0005$) in overall time of visual search. On the other hand, saccade peak velocity of low FI and middle FI individuals was close to each other and there was no significant difference between them (ANOVA: $F_{(1,39)} = 1.13$, $\rho > 0.29$).

Pearson correlation coefficients between eye movement parameters and FI

FI is a continuous score; therefore, we assessed its influence on eye movement parameters as a continuous variable. The Pearson correlation coefficients (PCC) explain the linear correlation between two variables. We calculated the value of PCC between eye movement parameters (mentioned parameters in "Differences of eye movement patterns in participants with different FI score") and the FI score of individuals to investigate which of eye movement parameters are mostly affected by FI score.

PCC can be computed as follows:

$$\text{PCC} = \frac{\sum_{n=1}^{N} (\mathbf{x}_n - \bar{x})(\mathbf{l}_n - \bar{l})}{\sqrt{\sum_{n=1}^{N} (\mathbf{x}_n - \bar{x})^2 (\mathbf{l}_n - \bar{l})^2}}, \quad (1)$$

where $\mathbf{x}$ and $\bar{x}$ are the supposed parameter and the mean of that parameter over N subjects, respectively. In addition, $\mathbf{l}$ and $\bar{l}$ are the FI score and the mean of FI score over N subjects.

The value of PCC between FI score and each parameter is presented in Table 3. Saccade peak velocity obtained the greatest positive correlation (0.26 PCC). Positive correlation means higher FI score individuals produced greater eye movement parameters than lower FI score individuals. Conversely, the RFDSD acquired the largest negative correlation (− 0.17 PCC). Negative correlation means lower FI score individuals generated greater eye movement parameter than higher FI score individuals. These findings confirm the results obtained in "Differences of eye movement patterns in participants with different FI score".

Table 3 PCC between the eye movement parameters and the FI score of individuals

Parameters	PCC
Fixation duration	− 0.08
Number of fixations	0.06
Fixation distance	0.16
Saccade peak velocity	0.26
Spatial density	0.03
RFDSD	− 0.17
Saccade length	0.16
NSBS	0.16

Table 4 Extracted features from eye movement pattern of individuals

Features	Mean	SD
Fixation duration	*	*
Initial fixation duration	*	
Minimum fixation duration	*	*
Maximum fixation duration	*	*
Saccade peak velocity	*	*
Saccade amplitude	*	*
Saccade angle	*	*
Saccade duration	*	*
Fixation location in *X*-direction	*	*
Fixation location in *Y*-direction	*	*
The number of fixations	*	
Fixation distance	*	*
The NSBS	*	
Spatial density	*	

Table 5 Confusion matrix for three classes

Actual classes	Predicted classes		
	Class A	Class B	Class C
Class A	TPA	Eab	Eac
Class B	Eba	TPB	Ebc
Class C	Eca	Ecb	TPC

Categorization of individuals with various FI score using eye movement pattern

As discussed above, eye movement patterns of individuals with various FI scores can be different from each other. We tried to categorize the individuals with various FI using eye movement patterns. To do so, 24 features were extracted from subjects' eye movement data (illustrated in Table 4).

To reduce the data redundancy and improve the data integrity, each feature was normalized using the z-score method as follows:

$$\check{\mathbf{X}} = \frac{\mathbf{x} - \bar{x}}{\boldsymbol{\sigma}}, \quad (2)$$

where $\mathbf{x}$ and $\bar{x}$ are a training feature and its mean, respectively. $\boldsymbol{\sigma}$ represents the SD of training feature and $\check{\mathbf{X}}$ expresses normalized feature. It is worth noting that test data set was normalized using the $\bar{x}$ and $\boldsymbol{\sigma}$ obtained from training data set.

Apart from confusion matrix, to illustrate the obtained results, we calculated and reported accuracy, recall, specificity, precision, and F1 score, as well. Because the number of classes was more than two, confusion matrix was computed using one versus all methods. Table 5 shows the confusion matrix for the three-class classification in which the total number of true positives (TP) for each class is indicated with TP, e.g., $TP_{\text{class (A)}} = TPA$. The total number of false negatives (FN) for a given class is the sum of all the values of corresponding row subtracted by TP, e.g., $FN_{\text{class (A)}} = Eab + Eac$. Similarly, the total number of false positives (FP) for a class is the sum of all the values of corresponding column subtracted by the TP, e.g., $FP_{\text{class (A)}} = Eba + Eca$. The total number of true negatives (TN) for a certain class is the sum of all columns and rows excluding that class's column and row, e.g., $TN_{\text{class(A)}} = TPB + TPC + Ebc + Ecb$.

Accuracy measures the overall ability of a classifier in the correct classification of samples. Furthermore, recall and specificity indicate the ability of a classifier in correct classification of positive and negative samples, respectively (Baratloo et al. 2015). Recall, specificity, precision and F1 score can be calculated for each class using the following formulas:

$$\text{Recall} = \frac{TP}{TP + FN},$$

$$\text{Specificity} = \frac{TN}{TN + FP},$$

$$\text{Precision} = \frac{TP}{TP + FP},$$

$$\text{F1} - \text{Score} = \frac{2TP}{2TP + FP + FN}.$$

In the above equations, TP is the number of test samples categorized correctly in positive class, FP represents the number of samples recognized wrongly as positive class, TN is the number of test samples that are correctly classified in negative class, and FN represents the number of test samples that are wrongly known as negative class. It is notable that we utilized one vs all methods, so positive class shows one of the aforementioned three classes and the negative illustrates two other remained classes.

We utilized SVM with linear kernel function (the best kernel examined) to categorize individuals in the three classes. Due to a few number of subjects, leave-one-out cross validation was used to evaluate the model.

To improve the performance of classifier, some of the features were selected based on the obtained value of PCC between the features and subjects' FI score. We selected features with higher absolute values of PCC (see Fig. 4). This process was performed on the training data.

Figure 4 presents the mean of evaluation criteria across the three groups according to the different number of features. The best performance was achieved by 17 features selected based on the value of PCC between the feature and subjects' FI. Recall (Fig. 4a) and specificity (Fig. 4b) had the value of 63.6% and 82.27%, respectively. Precision (Fig. 4c)

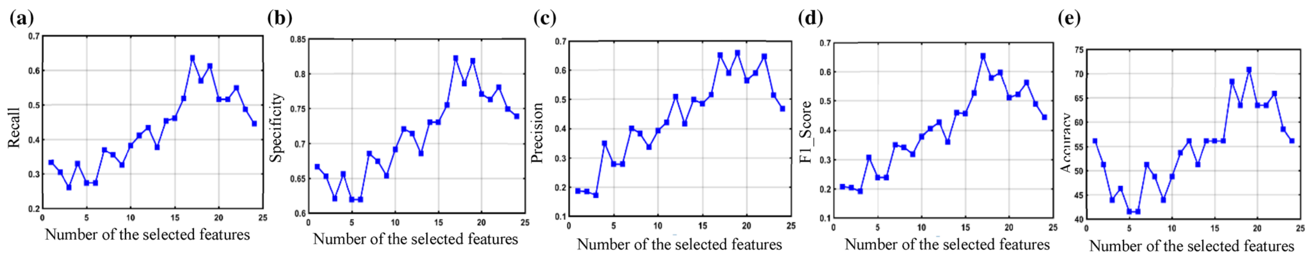


Fig. 4 Performance measure of individual categorization (*y*-axes present evaluation criteria and *x*-axis demonstrates the number of selected features based on the value of PCC between the feature and subjects' FI) by linear SVM; **a** recall, **b** specificity, **c** precision, **d** F1 score, and **e** accuracy

Table 6 Confusion matrix for three classes (low FI, middle FI, and high FI) using the 17 features selected based on the value of PCC between FI score of subjects and the feature

Actual classes	Predicted classes		
	Low FI	Middle FI	High FI
Low FI	5	2	1
Middle FI	0	18	5
High FI	2	3	5

Table 7 Obtained recall, specificity, precision, F1 score, and accuracy using the 17 features selected based on the value of PCC between FI score of subjects and the feature

Metrics	Groups			Mean (%)
	Low FI	Middle FI	High FI	
Recall (%)	62.2	78.26	50	63.6
Specificity (%)	93.94	72.22	80	82.27
Precision (%)	71.43	78.26	45.45	65.05
F1 score (%)	66.67	81.82	47.62	65.37
Accuracy (%)	–	–	–	68.3

and F1 score (Fig. 4d) presented the value of 65.05% and 65.37%, respectively. The classifier has achieved the accuracy of 68.3% using the 17 selected features, but the best accuracy (70.73) was obtained when 19 features were selected. The obtained confusion matrix and evaluation criteria using the 17 selected features are shown in Tables 6 and 7, respectively.

It is worth noting that recall, specificity, precision, and F1 score were separately computed for each class, and then, they were averaged across the three classes. To illustrate the effect of each feature in categorization of individuals, we calculated the repetition number of the selected features (17 features) which was obtained from leave-one-out cross-validation strategy, Fig. 5 depicts it in the histogram format. The histogram elucidates that the 12 features—means of the NSBS, minimum fixation duration, maximum fixation duration, saccade amplitude, saccade peak velocity, saccade duration, fixation distance, and fixation location in *Y*-direction as well as SDs of fixation duration, saccade peak velocity, saccade angle, and fixation location in *X*-direction—were selected in all iterations of leave-one-out cross validation. This shows that these features had a major role in the classification of individuals. For clarification, we evaluated the performance of the classifier using the 12 mentioned features (reported in Table 8).

Predicting the FI score of individuals using eye movement pattern

As illustrated in the previous section, the level of an individual FI can be determined using eye movement patterns. Furthermore, we predicted FI score of individuals by SVR with polynomial kernel function (the best kernel examined). Due to the fact that the FI score of most individuals was between 100 and 125, we randomly selected 11 subjects from this range to prevent overfitting. The total number of subjects whose FI score was predicted by SVR was 29 in the range of 73–155.

We applied the 24 features mentioned in Table 4 to SVR for predicting the FI score of individuals. Z-score method has been used to normalize the features, and we selected the features having the great absolute value of PCC with the FI score of subjects (explained clearly in the previous section).

Leave-one-out cross validation was used to validate the performance of SVR. Three evaluation criteria were also used to measure the performance of the model: PCC, the coefficient of determination (R^2), and minimum absolute error (MAE) between the observed FI score and the predicted FI score. Figure 6 illustrates the obtained evaluation criteria for SVR regarding to the different number of the features selected based on the value of PCC between the feature and subjects' FI score. The maximum performance of SVR was obtained using the 16 selected features. PCC and R^2 had the value of 0.54 and 0.29, respectively, and MAE had the value of 13.7 (summarized in Table 9). Figure 7 shows the repetitions number of the selected features

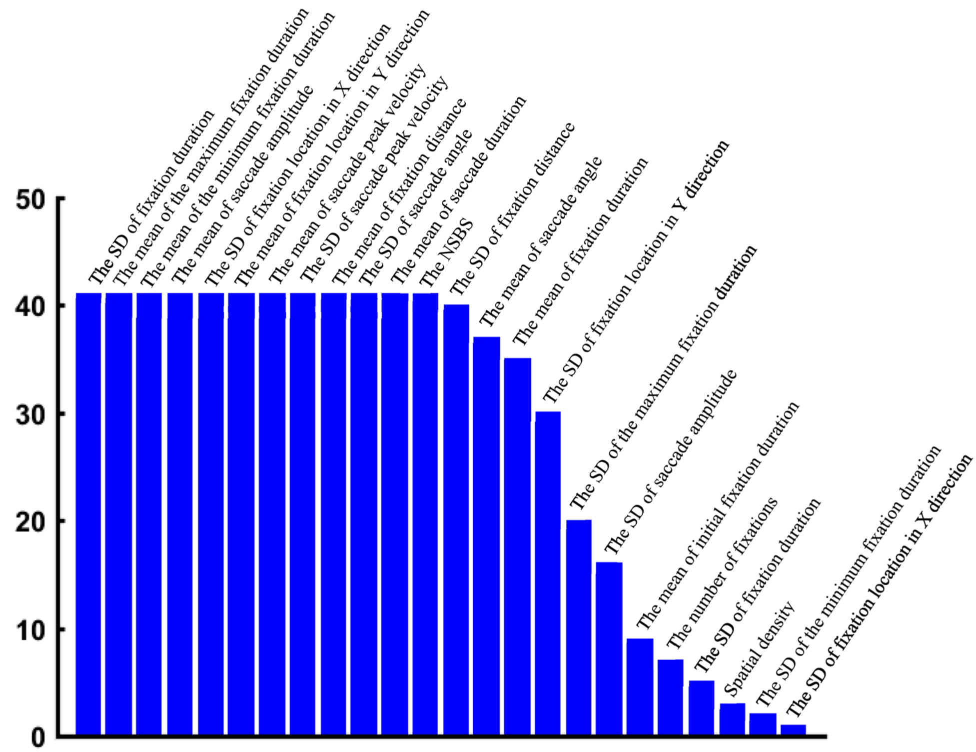


Fig. 5 Repetition histogram of the 17 features selected according to the value of the PCC between subjects' FI score and the feature in the categorization of individuals using linear SVM. The name of the selected feature is shown above the bar and the vertical axis demonstrates the number of folds—in leave-one-out cross validation—that the feature was selected

Table 8 Performance of the classifier using the 12 features selected in all iterations of leave-one-out cross validation

Evaluation criteria	Performance (%)
Recall	58.4
Specificity	78.8
Precision	63.73
F1 score	59.28
Accuracy	65.85

(16 features) which was obtained from leave-one-out cross-validation strategy in histogram format. From the histogram, it is apparent that the nine features—means of the NSBS, saccade amplitude, saccade peak velocity, saccade duration, and fixation distance as well as the SDs of the minimum fixation duration, saccade peak velocity, saccade angle, and fixation location in *X*-direction—were selected in all folds. This shows that these features were more important in the predication of participants' FI.

In addition to the preceding approach, only nine features, selected in all folds of leave-one-out cross validation, were applied to linear SVR (presented the best performance) for predicting participants' FI score. As a result of

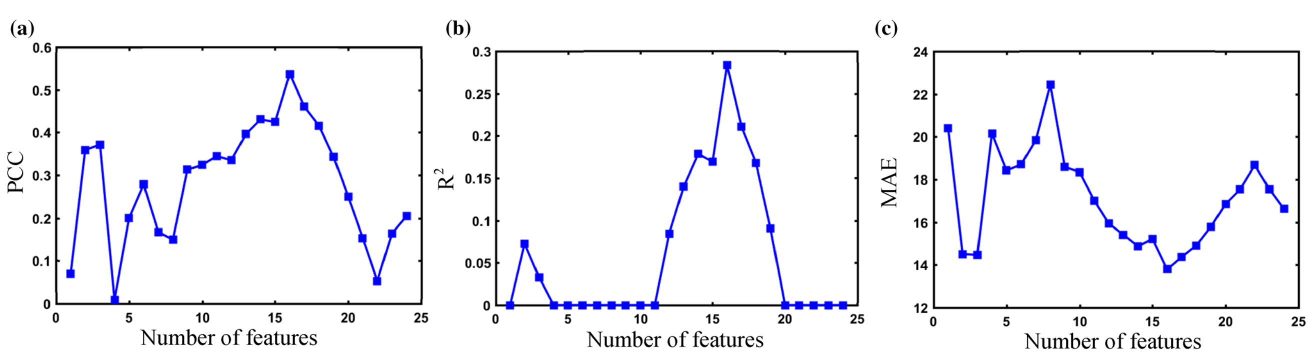


Fig. 6 Performance of SVR according to the different number of selected features using the absolute value of PCC between the feature and FI score of subjects. The horizontal axis shows the number of features that used in SVR and the vertical axes illustrate the value of obtained evaluation criteria between observed FI and predicted FI: **a** PCC, **b** R^2, and **c** MAE

Table 9 PCC, R^2, and MAE obtained using the 16 features selected based on the value of PCC between FI score of subjects and the feature

Criteria		
PCC	R^2	MAE
0.54	0.29	13.7

Table 10 PCC, R^2, and MAE obtained from linear SVR using the nine mentioned features which were selected in all folds of leave-one-out cross validation

Criteria		
PCC	R^2	MAE
0.53	0.28	12.3

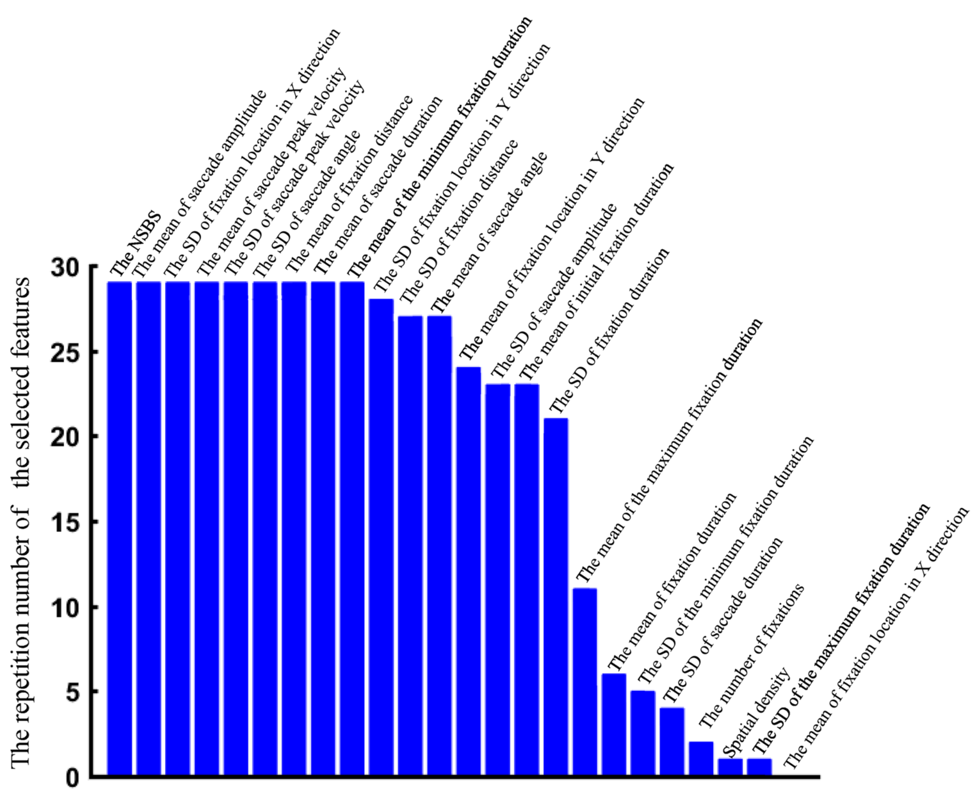
this procedure, the FI score of subjects was predicted with 0.53 of PCC, 0.28 of R^2, and 13.3 of MAE between the observed FI score and the predicted FI score (as summarized in Table 10).

Discussion

In this paper, we investigated whether or not FI of individuals can affect eye movement patterns during the CVS task. In the CVS task, the subjects did not have any prior knowledge about differences in two images, until one makes a series of comparative object-to-object fixations—looking first at an object in one image and then searching the corresponding region in the other image to find out whether they are identical or not (Underwood et al. 2008). These consecutive shifts between the left and right images increase working memory load (Pomplun et al. 2001). Working memory load, information processing, and intelligence are closely related to each other (Van Biesen et al. 2017). Therefore, the differences in the eye movement patterns of individuals having different FI might be observable while performing the CVS task.

The cognitive studies which investigated the eye movement patterns of individuals have noted that they consistently produce different eye movement patterns (e.g., fixation duration and saccade amplitude) according to culture (Rayner et al. 2007; Alotaibi et al. 2017), age (Kirkorian et al. 2012; Munoz et al. 1998), as well as gender (male and female) (Garza et al. 2016; Cazzato et al. 2010). Most of the previous studies investigating the eye movements patterns of individuals with different intelligence only reported the influence of intelligence on pupil dilation (Van Der Meer et al. 2010; Hayes and Petrov 2015; Dix and Meer 2015). While solving Raven's matrices, scan patterns of individuals with different intelligence were analyzed to predict Raven score of subjects (Hayes et al. 2011). Recently, scan patterns of individuals who had different cognitive capacity were investigated during scene viewing (Hayes and Henderson 2017). These earlier findings encouraged us to examine the effect of individual FI on eye movement parameters at the time of performing the CVS task. Even though the influence of IQ on eye fixation duration and the number of eye fixations were previously investigated (Nesbit 1981),

Fig. 7 Repetition histogram of the 16 features selected according to the higher absolute value of PCC between FI score and the feature in the prediction of subjects' FI using polynomial SVR. The name of each selected feature is shown above the bar and the vertical axis demonstrates the number of folds that the feature was selected



we systematically studied eye movement parameters, that is, fixation duration, number of fixations, fixation distance, saccade peak velocity, spatial density, the RFDSD, scanpath length, and the NSBS.

Eye fixation location might depend on the observed scene, since people usually look at the objects that they want to process (Just and Carpenter 1980). A greater spatial density indicates that more regions of scene are processed by subjects. Besides, the number of fixations demonstrates the amount of search. From the spatial density and the number of fixations, it can be inferred that higher FI individuals interpreted larger areas and performed widespread search in the CVS task in comparison with lower FI individuals.

A region of a scene is selected as a target for fixation and through moving eyes the representation of visual space in parietal cortex is updated (Colby and Goldberg 1992). Besides, people typically gaze on components in which they want to obtain information from (Just and Carpenter 1980). Hence, the time taken in fixation and saccade state may provide useful information about the processing time of observed components. Several studies have consistently revealed that visuospatial processing only just happens during the eye fixation. It means that visuospatial processing is diminished during saccade (Irwin and Brockmole 2000, 2004). Our findings—the mean of fixation duration as well as the RFDSD—suggest that lower FI individuals spent more time on processing the objects compared to higher FI subjects who rapidly processed the components. The previous results of psychology studies confirm this finding (Conway et al. 2002; Fry and Hale 2000). They demonstrated that higher FI individuals are faster in information processing than lower FI individuals.

In eye movement studies, the workload is distinguished according to some factors such as fixation duration, fixation distance (or saccade amplitude), and saccade peak velocity. It has been proven that increasing the workload makes longer fixation duration (Meghanathan et al. 2015) and smaller fixation distance (or saccade amplitude) (Van Orden et al. 2001). Besides, greater workload usually reflects the task difficulty in eye movement studies, Just et al. explained that long fixation duration conveys the difficulty in exploiting information from the scene (Just and Carpenter 1976). Our results have shown that increasing in workload was more common in low FI individuals than high FI individuals, meaning lower FI subjects needed to work a lot for finding differences between the pairs of scenes than higher FI individuals. It may be due to the fact that lower FI subjects found the task more difficult than higher FI subjects.

Unlike fixation duration or fixation distance, saccade velocity is not voluntarily controlled (Leigh and Zee 2015). It depends on neural activity (Itoh 2002), and hence, it may be a more effective parameter than gaze parameters in cognitive engagement (Rowland et al. 2005). Several studies have shown that activation of omnipause neurons (OPNs) increases saccade velocity (Henn et al. 1984; Soetedjo et al. 2002). Our study demonstrated that lower FI individuals produced slower saccade peak velocity than higher FI individuals. This may be due to the low activity of OPNs in lower FI individuals in comparison with higher FI individuals. Furthermore, Di Stasi et al. examined saccade main sequence parameters (duration, average velocity, and peak velocity) at different workload levels. They demonstrated that saccade peak velocity decreases with increasing the workload (Di Stasi et al. 2010). Like fixation duration and fixation distance, our finding on saccade peak velocity demonstrated that the workload which was imposed on subjects during the CVS task was more in lower FI subjects in comparison with higher FI subjects.

On the other hand, we observed no significant difference among the three groups in responding to questions which were asked in the CVS task. About 50% of trials were correctly answered by all the participants in the CVS task.

Even though our results have demonstrated a relationship between eye movement patterns and FI in the CVS task, they have several limitations. First limitation of our study is that we just analyzed eye movement patterns of participants performing the CVS task, and other tasks (e.g., reading) or conditions in which there is no specific task (e.g., free viewing) were not examined. Therefore, the research findings may be generalized only to visual search task. The other possibility is that individual differences in gender or age may affect eye movement patterns of individuals, while we only considered the FI of individuals.

For future studies, a number of promising approaches can be suggested to overcome the limitations of our current research. First, analyzing the eye movement patterns of individuals, while they are not performing explicit task (e.g., free viewing) may be advantageous to evaluating whether eye movement patterns are different across individuals with different FI or not. Second, analyzing the eye movement patterns of elementary school students, who have identical age, with different FIs may be useful to improve the reading and the learning studies in eye movement studies.

Conclusion

To sum up, we examined eye movement patterns of individuals who had different FI score. Individuals' FI were evaluated using the Cattell test, and they were divided into three groups: low FI ($FI < 100$), middle FI ($100 < FI < 125$), and high FI ($FI > 125$). We demonstrated that fixation duration, number of fixations, fixation distance, saccade peak velocity, spatial density, the RFDSD, scanpath length, and the NSBS were significantly different among the three groups while performing the CVS task. We also computed the value of PCC between eye movement parameters and the FI of individuals. It was shown that saccade peak velocity and the RFDSD had the largest positive and negative value of PCC with FI score, respectively. Next, we categorized individuals according to their FI score into the three groups using 24 features of eye movement patterns. Linear SVM classifier obtained 68.3% accuracy, 63.9% recall, 82.27% specificity, 65.5% specificity, and 65.37% F1-Score. Finally, the FI score of individuals was predicted with 0.54 PCC, 0.29 R^2, and 13.7 MAE between the predicted FI and the observed FI score using polynomial SVR.

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