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Visual Cue Effects on Individual's Response Prediction to Intelligence Questions Using Eye Movement Analysis

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Abstract: *In this study, we examined how to improve learning quality by means of visually guidance to respond intelligence questions. We hypothesised that the visual cues can improve the performance of individual's responses to the questions. Electrooculography (EOG) is used to analyze eye movement patterns of nine subjects while they responded the questions in presence and absence of colors as visual cues. The data were collected in an experimental procedure wherein subjects were trained how to respond sample questions. Sixteen questions were chosen to be presented, half with the presence of visual cues and the other half without any visual cues. The EOG signals were filtered using a band pass filter to remove noise and artifacts. Thirty one features were extracted from horizontal and vertical channels of EOG signals. Afterwards 15 best features were selected using minimum Redundancy Maximum Relevance (mRMR) algorithm. The selected features used for classification using Support Vector Machine (SVM) classifier. Leave-one-person-out technique for validation was used to achieve more reliable results. Visual cues improved the perceptual attention, supported by the higher classification performance of eye movement and higher rate of correct responses in the state of presence of visual cues compared to the absence of them.*

Keywords: *Electrooculography, Eye Movement Analysis, Learning, Attention, Visual Cues.*

I. Introduction

Nowadays the analysis of eye movements is shown to reveal information in relation to cognitive processes [1], [2]. Learning is a cognitive process that is tightly dependent to eye movements in visual perception and attention. Eye movement can represent the quality of learning based on its characteristics such as fixation duration on salient objects in the visual field to uncover the attentional effort made to perceive an image or read a text for example. In this study, we examined whether it is possible to improve learning process by means of visual cues as a learning tool to reduce attentional effort. The visual cue here is referred to visual guidance that directs subjects' attention towards relevant areas of an image to avoid extra effort to browse on unimportant points.

There are several studies that examined or reviewed the effects of visual guidance on learning using eye-tracking. In [3], learning of a piano mechanism illustrated by an animation where the different components of the piano were visually signaled by spreading color cues was studied. They underlined the effectiveness of using colors in directing the attention. In [4] the advantages of using eye-tracking in studying the effectiveness of different types of visual cues and the relevant features from eye movements were discussed.

In this study, we took an experimental approach to investigate the effectiveness of visual cues to respond to intelligence questions. Relevant features from eye movements were extracted to predict the correctness of the answers of subjects to the questions to see how accurate can the features from eye movement capture successful strategies in responding questions versus the unsuccessful attempts.

II. Method

This experiment were performed with nine subjects including four males and five females with the mean age of 25.5 +/- 2.1 years. This experiment were performed in a quiet and dim place. The subjects were sited on a chair in front of a projector screen and their head movement was limited by a chin rest during experiment. The experiment was designed in power point slides and proposed by a video projector. The stimuli included customized version of spatial ability tests described in [6]. We recorded electrooculographic signals from subjects to analyze their eye movements using a Powerlab (26T) device.

Five electrodes were used to record eye movements (two electrode for recording horizontal eye movement, two electrode for recording vertical eye movement and one electrode for ground (see **Fig (1)**)[5].

Fig (1) A: five electrodes, B: a powerlab (26T) device and C: the image demonstrates the placement of the EOG electrodes on the face

The data were collected in an experimental procedure wherein subjects were trained how to solve the incoming problems and answering to the related questions. In the training phase, subjects learned how to solve and give response to a customized version of spatial ability tests such as ' Paper Folding Test' [6], See **Fig (2)**. There were sixteen questions containing eight questions without visual cues and eight questions with visual cues. We used colors as visual cues. **Fig (3)** shows an example of questions without visual cues and **Fig (4)** shows an example of questions with visual cues in this experiment.

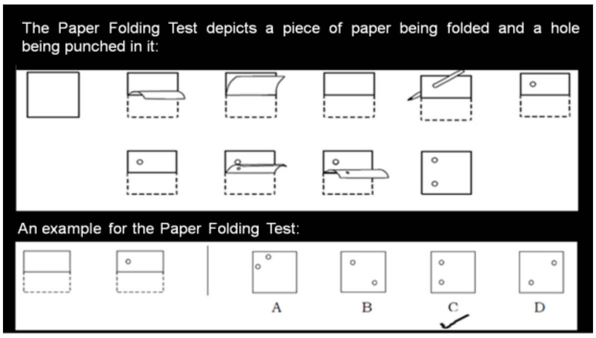

Fig (2) one slide that we proposed in learning phase

Fig (3) an example of questions without visual cues

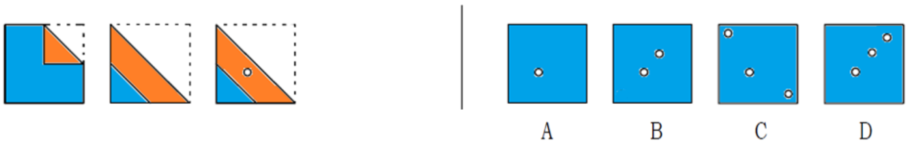

Fig (4) an example of questions with visual cues

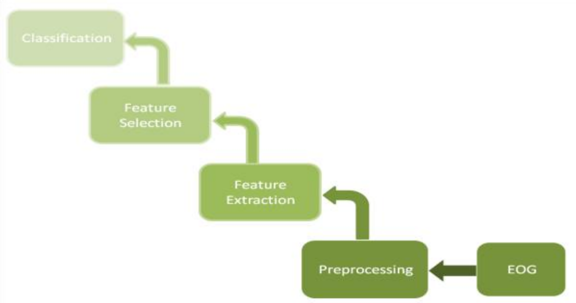

Fig (5) an algorithm based on signal processing techniques was used to analyze EOG signals

A novel algorithm based on signal processing techniques was used to analyze EOG signals [7]. The algorithm has showed in **Fig (5)**. After preprocessing using a band pass filter, 31 features were extracted from horizontal and vertical channel of EOG signals [8]. **Table (1)** shows the features that were extracted. We used minimum redundancy maximum relevance feature selection (mRMR) [9], [10] for discrete variables because of the lower computational costs and thus shorter runtime given the large dataset. The mRMR algorithm selects a feature subset of arbitrary size S that best characterizes the statistical properties of the given target classes based on the ground truth labeling [9],[10]. In contrast to other methods such as the F-test, mRMR also considers relationship between features during the selection [7]. Amongst the possible underlying statistical measures described in literature, mutual information was shown to yield the most promising results and mRMR implementation in this study combines the measures of redundancy and relevance among classes using the mutual information difference (MID).

For classification, we use a linear support vector machine. Our SVM implementation uses a fast sequential dual method for dealing with multiple classes [11], [12]. This reduces training time considerably while retaining recognition performance. These two algorithms are combined into a hybrid feature selection and classification method. In a first step, mRMR ranks all available features. During classification, the size of the feature set is then optimized with respect to recognition accuracy by sweeping S. Consequently, 15 best features were selected using mRMR, see **Fig (6)**.

Table (1) The list of extracted features from horizontal (H) and vertical (V) channels of EOG

Feature No.	Feature Description		
1	Gaze Dispersion	17	Mean of saccade durations in VEOG
2	Gaze numbers	18	Variance of saccade durations in VEOG
3	Saccade numbers in HEOG	19	Maximum of saccade amplitudes in VEOG
4	Mean of saccade amplitude in HEOG	20	Maximum of saccade durations in VEOG
5	Median of saccade amplitudes in HEOG	21	Entropy of HEOG signal
6	Standard deviation of saccade amplitudes in HEOG	22	Entropy of VEOG signal
7	Variance of saccade amplitudes in HEOG	23	Energy of HEOG signal
8	Mean of saccade durations in HEOG	24	Energy of VEOG signal
9	Variance of saccade durations in HEOG	25	Energy of HEOG and VEOG multiplication
10	Maximum of saccade amplitudes in HEOG	26	Autocorrelation of HEOG
11	Maximum of saccade durations in HEOG	27	Autocorrelation of VEOG
12	Saccade numbers in VEOG	28	Cross correlation between HEOG and VEOG
13	Mean of saccade amplitudes in VEOG	29	Mutual information of HEOG with itself
14	Median of saccade amplitudes in VEOG	30	Mutual information of VEOG with itself
15	Standard deviation of saccade amplitudes in VEOG	31	Mutual information of HEOG and VEOG
16	Variance of saccade amplitudes in VEOG		

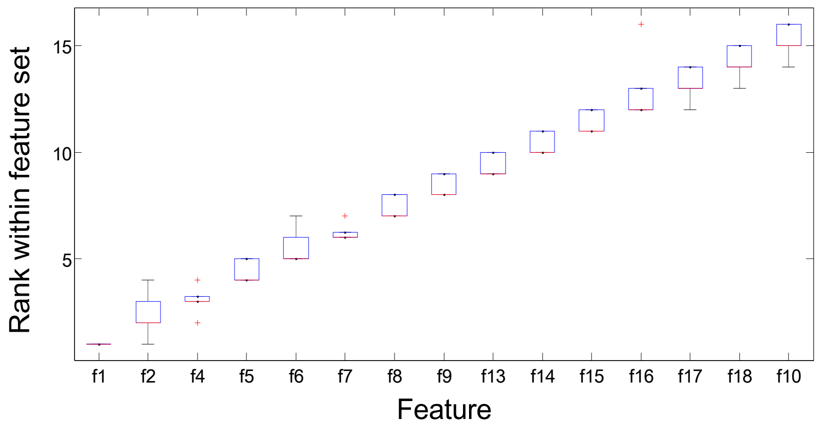

Fig (6) rank within feature set with using mRMR

III. Result

We used leave-one-person-out cross-validation technique for classification to achieve more reliable results. Taking advantage of this technique the results show that the mean classification performance was 77.7% (TPR=74.4%, FPR=29.8%) in questions without visual cues, see **Fig (7)**, and 87.5% (TPR=88.1%, FPR=18.8%) in questions with visual cues see **Fig (8)** .In **Fig (7)** and **Fig (8)** we used two criterion true positive rate (TPR) and false positive rate (FPR) for classification valuation. **Table (2)** shows visual cues effect on learning in this experiment.

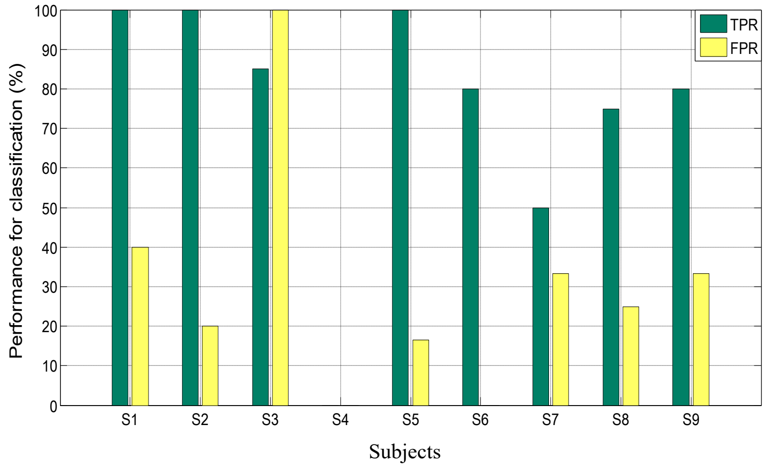

Fig (7) Classification performance in the absence of visual cues

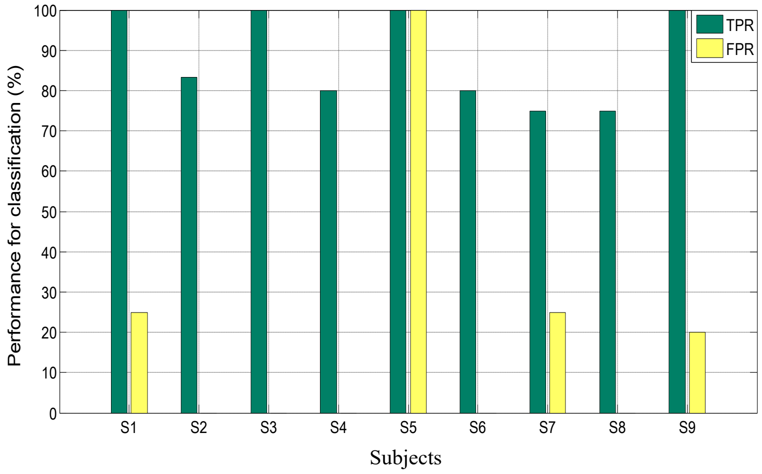

Fig (8) Classification performance in presence of visual cues

Table (2) Number of correct responses of the subjects to the questions in the two states of with and without visual cues

Subjects	S1	S2	S3	S4	S5	S6	S7	S8	S9	average
Correct response without Visual cues	3	3	7	2	2	5	2	4	5	3.6
Correct response with Visual cues	4	6	8	5	7	5	4	4	3	5.1

IV. Conclusion

Classification performance increased in the state of with visual cues compared to without visual cues. Visual cues also increased correct responses. The visual cues guided the subjects to important points, and prevented distractions remarkably. The visual cues may enhance synchrony in eye movement which is reflected in the classification performance of eye movements. All this supports the importance of visual cues to improve learning. The high performances in the prediction of the correctness of responses implies the possibility to recognize successful attentional strategies from failures to solve the proposed questions. The differences between the classification performances to compare the two states of the presence of visual cues versus the absence of visual cues confirms the hypothesis that the visual cues which here were color signals makes relevant changes in the patterns of eye movements.

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