Computer Communication & Collaboration (Vol. 5, Issue 1, 2017)
ISSN 2292-1028(Print) 2292-1036(Online)
Submitted on Feb. 10, 2017
DOIC: 2292-1036-2017-01-003-82

Extrafoveal Vision Maximizes the Likelihood to Grab Information in Visual-sequential Search

Giacomo Veneri, Alessandra Rufa (corresponding author)

Visual Applications Lab - University fo Siena

Viale Bracci 2, 53100 Siena, Italy

E-mail: rufa@unisi.it

Abstract: Visual input from the external world is actively sampled for promoting appropriate actions during everyday life. This mechanism is dynamic and not one-shot made, and involves a continuous re-sampling of spatial elements. The Eye-tracking version of the Trail Making Test is a repeated search task in which subject is asked to connect by gaze a logical sequence of numbers and letters. In this task the target of the next fixation changes continuously reproducing an "in-vitro real search". Twenty subjects performed the test and their gaze was registered through an eye-tracking device. Results reported that subjects planned some within-target fixations. To understand this mechanism we propose a probabilistic model and compare the visual search outcome with subjects' exploration; computer generated data reported a strategy similar to the humans strategy. We hypothesized that subjects maximized the probability to catch the target with extra-foveal information, landing in the midst of the whole configuration. We conclude that selective spatial attention is influenced by the likelihood to build an appropriate spatial map.

Keywords: Fixation, Eye-tracking, Probabilistic Model, Visual System, Spatial Map

1. Introduction

The foveo-centric organization of the human visual system reflects the anatomical distribution of the photoreceptors across the retina; these neurons ensure the best resolution in a small central region called fovea (≈1 deg in ray) [28]; outside this region (see also Figure 3), visual resolution decreases sharply. Due to this limit, the human brain has developed fast and accurate eye movements (called saccades; see also Figure 1) for directing the fovea at attention-grabbing regions of the visual field. In other words, each saccade landing point (fixation) is the locus in the space where human vision gathers the most detailed information; far from this location, the items of a scene can be easily localized, but are less distinguished. The analysis of temporal and spatial characteristics of fixations may therefore, indicate how efficiently attention enhances detailed image processing during visual search tasks [13, 20]. Moreover, their localization may be considered an expression of visual exploration strategy depending upon the image features, complexity of the task, cognitive demand and subject's cognitive resources [9,8]. We recently demonstrated [37,33] that the gaze strategy adopted during visual-sequencial search (VSS), which is a complex cognitive task, may be flexibly modified depending upon peripheral vision accessibility [10,11,22,6,24]. These strategies, differ in terms of performance and efficiency as revealed by the distribution of fixation around or into each element of the sequence. In particular, we found that spatial ranking is an efficient strategy adopted by the brain in a logical (alphanumerical) VSS when the peripheral vision is completely available. Indeed, it reduces the neural cost of visual exploration by avoiding unnecessary foveations on targets when peripheral information are already sufficient, and promotes sequential search by facilitating the onset of a new saccade. We proposed that the distance of fixation to next target may be considered an indicator of VSS performance and that the distance of fixation to nearest element (region of interest:ROI) is an indicator of the perceptual abilities of the peripheral vision; both also gives information on the VSS strategy adopted during the tasks. The aim of this study is to validate the spatial ranking strategy: spatial ranking is the act of choosing the most informative location instead of the potential targets (Figure 1). This mechanism may be related to a probabilistic (bayesian) approach. In the current paper, we propose a probabilistic model of fixation distribution, which may account for the extrafoveal information processing during this logical alphanumerical sequencing task. The results of our study demonstrate that the selection of the correct target of the sequence is related to the likelihood that the preceeding saccade will land in a more informative location (distance to nearest ROI), as compared to others.

2 Methods

We used a highly cognitive demanding task, namely the trail making test [3], in which subjects were asked to follow an alphanumeric sequence (*TMT*, Figure 1). The trail making stimulus is a high contrast pop-out image [1] consisting of a sequence of numbers and letters arranged in an unpredictable manner. A distinctive feature of *TMT* is to force the user to change continuously the target and to avoid surrounding distracters (conjunction search). A complete description of the task has been estensively reported elsewere [37].

2.1 Subjects

Twenty sex-matched subjects were enrolled in the study (13 female and 7 male). The mean age was 32 years (range 20-40 years). The subjects, all volunteers, were recruited from students or other people working at the Department of Neurosciences of the University of Siena. The study was performed according to the criteria of the Declaration of Helsinki and was approved by the Local Ethical Committee (Azienda Ospedaliera Universitaria Senese AOUS).

Visual function was tested before the experiment in each subject. Subjects with any history of neurological, visual or psychiatric disorders and pharmacological treatment or substance abuse, which may affect brain activity, were excluded from the study. Subjects with refractive errors ≥3 diopters were also excluded. Three or four sessions and three tasks for each session were planned on different days for each subject. Informed consent was obtained from each subject before the experiment.

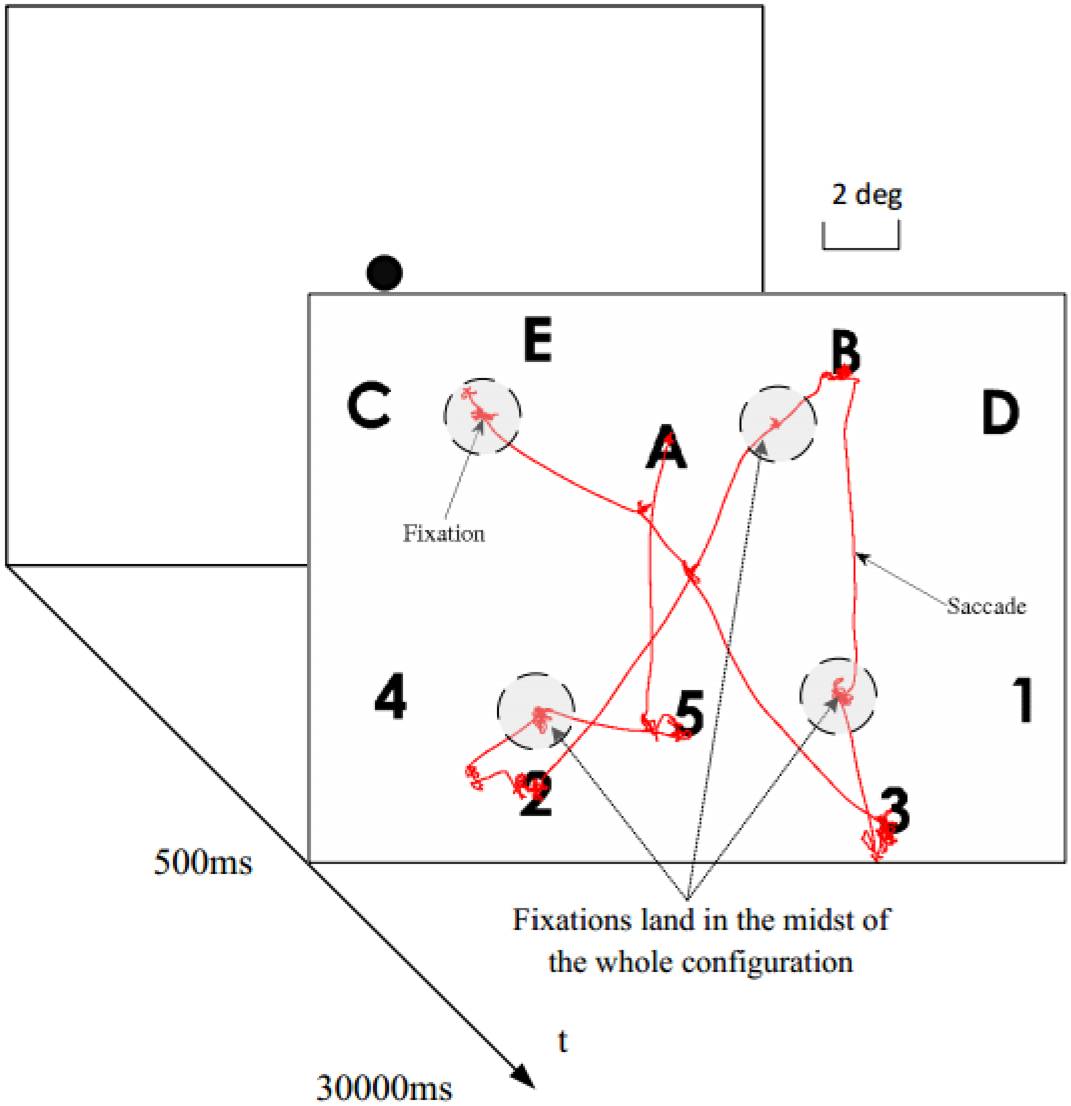


Figure 1: Example of a display shown in the task and: (**a**) Subjects, after a fixation point of 500 *ms*, were asked to follow an alphanumeric sequence (1−*A*−2−*B*−3−*C*−4−*D*−5−*E*) with their gaze: the subject had to look at the symbols. In the proposed modified version of the TMT, the numbers and letters appeared in a pseudo-random distribution (letters on top and numbers on the bottom) on a 1024×768 *px* and 58×31 *cm* black screen for 30000 *ms*. (**b**) *Fixation*, instead of landing at the designated target "E", land in the midst of the whole configuration; this effect suggests a probabilistic spatial ranking.

2.2 Stimulus Display

To perform this task we used the method of the *TMT*, which is a validated neuropsychological battery testing visual spatial abilities and executive functions [3, 37]: in the standard TMT Part B subjects are required to connect by pencil a sequence of numbers and letters. The sequential tracking follows a logical procedure in which each number is connected to the corresponding letter along a crescent order. To test the visual search behavior, we used a modified and simplified version of the standard test, in which subjects were asked to connect, in ascendant order, the correct number with its respective letter, i.e. $1-A-2-B-3-C-4-D-5-E$, by gaze (Figure 1). Formerly learned sequential procedures (particularly numeric and alphabetic sequences) facilitate the performance of this visual search task.

To standardize the bottom-up effect and the size effect due to image features [35], we used a few salient stimuli (luminance $63cd/m2$): five sequential capital letters and five sequential numbers on a black background with luminance of $2.5cd/m2$. The size of each stimulus covered an area of $2.5deg$ of visual angle, which allowed full visibility of the target when centered by the foveal vision [25]. The distance from the center and among symbols displayed in the geometric arrangement of our tasks forced a clear shift of the gaze to look at the correct target. Although, the spatial arrangement of numbers and letters remained the same through tasks, the position of the symbols was randomly changed.

2.2.1 Gaze Recording

The gaze of each subject was recorded while performing the sequence [34]using the ASL 6000 system, which provided the coordinates of the gaze (x,y) and the pupil diameter every 4.167 *ms* (240Hz).

2.3 Analyses

Post-processing: numbers and letters were sampled as pre-defined rectangular *ROI* centered on letters and numbers and having widths and heights set to 3.5×3.5 *deg*. Gaze data point (x,y) at a time t was assigned to ROI_i if $(x,y) \in ROI_i$. The same *ROI* spatial distribution was pre-defined for all tests.

As no explicit feedback was requested to subjects, a post-processing recursive algorithm [39] discovered the sequence followed by subjects to provide an indicator of task performance. Only the tests with an error less than the 20% (at least 8 right steps) were accepted.

Fixations distribution: to analyze subjects' explorations, we evaluated fixations distribution. Fixations (Figure 1) were calculated using a dispersion-based algorithm [29,36]. For each fixation, we evaluated the Euclidean distance from the center of nearest *ROI* (*DN*) and the Euclidean distance to next target (*DT*); these two measures provide a valuable indicator of of visual attention within spatial map allocation (*DN*) and task performance (*DT*) [12, 39, 40,33]. See also Figure 2. On [38] we verified the statistical independence between these two indicators and we provided evidence of their efficacy on evaluating the TMT visual exploration.

Finally, fixations distribution was compared between tests and with a probability map to find the target.

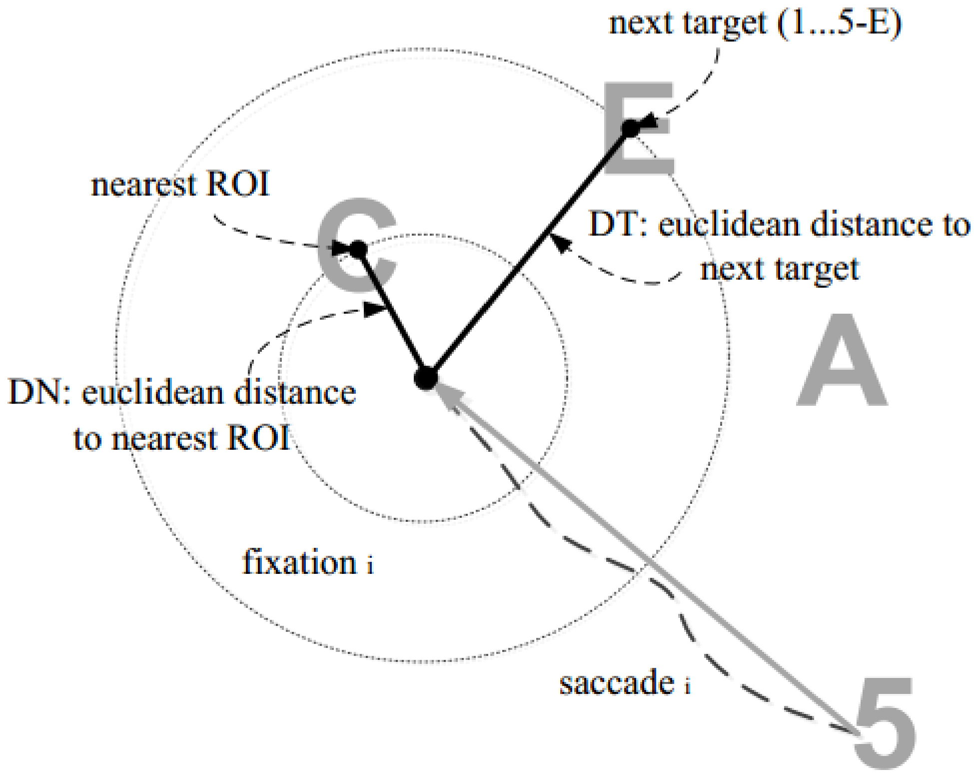


Figure 2: Distance (euclidean) to nearest *ROI* provided a method to globally evaluate fixations distribution over the scene: high values meant sparser fixations. Distance (euclidean) to next target *DT* provided a method to evaluate execution task: low values meant high performance.

2.4 Probabilistic model implementation - PM

We defined a potential target probability for each (x,y) point, estimating the likelihood to find one or more potential targets (letter or number) conditioned to the target distance.

Bayesian approach: the fundamental idea of the Bayesian approach to perceptual computations is that the information provided by a set of sensory information about the real world is represented by a conditional probability density function over the set of unknown variables (the posterior density function) [32, 27, 2].

A Bayesian perceptual system would represent the perceived depth of an object, as a conditional probability density function $P(T|I)$, where I is the available scene's information. Bayesian formulation estimates the position of an object T from sensory information I (visual, auditory, grasping) [19]:

$$P(T|I)=P(I|T)\cdot P(T)/P(I) \qquad (1)$$

where $P(I|T)$ specifies the relative likelihood of perceiving the given data for different values of T; $P(T)$ is the prior probability of different values of T. In our task, assuming no-bias due to memory

[18], the symbols have the same dimension and the same probability to be seen, $P(T)=1/N=1/10$ and $P(I)=K$, where K is a constant. Then the probability density to direct the gaze to a target T is proportional to the probability to perceive information I looking for T ($P(I|T)$). In other words, the probability to find a target is proportional to *ROI* availability nearby the fovea.

Likelihood function: in our implementation, each *ROI* was a potential target (T). We defined the following bi-dimensional formula:

$$P(\alpha,\beta,x,y) = \begin{cases} 1, & \text{if } d_{tgt_i}(x,y) < \alpha \\ 0, & \text{if } d_{tgt_i}(x,y) > \beta \\ a \cdot d_{tgt_i}(x,y) + b, & \text{otherwise} \end{cases} \tag{2}$$

where d_{tgti} (x,y) is the euclidean distance to i-th potential target (tgt_i); α is the minimum distance where (x,y) falls into the target; β is the maximum distance when the target was too far, and was empirically set to 5·α as suggested by the study of [28] about visibility (Figure 3); $a=1/(\alpha-\beta)$ is the slope and $b=\beta/(\beta-\alpha)$ is the intercept of the linear function probability as proposed by [6].

Then, for each target:

$$\Pi(\alpha,\beta,x,y) = 1/N \cdot \sum_{\forall target} P_{tgt_i}(\alpha,\beta,x,y) \tag{3}$$

N=10 numbers of target here reported only for completeness. Since $P_{tgti}(\alpha,\beta \mid x,y)$ cannot be greater than 1, we set α=1 *deg*≈ fovea size. The equation is the probability union to find a potential target within α *deg* conditioned from the target distance.

According to Eq. 3 we developed an artificial exploration (visual ranking Map *PM*) where fixations were placed on (x_f,y_f) with probability $\prod(\alpha,\beta,x_f,y_f)$.

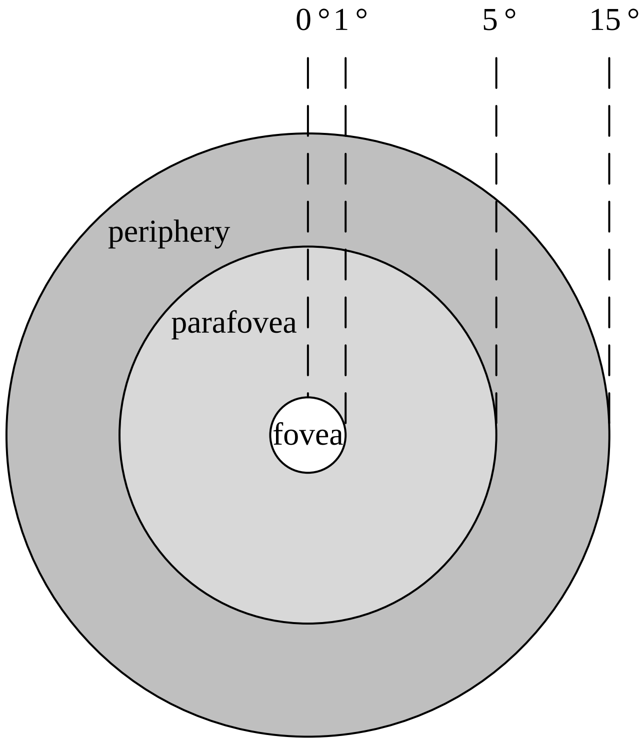


Figure 3: The visual acuity represents the eye ability to recognize fine details of an object, i.e. the clearness of vision; it is calculated as the inverse of the minimum angular dimension that an object must have to be correctly perceived. The highest visual acuity (1deg) can be found at the level of fovea centralis, which is a depression in the surface of the retina, approximately 1.0 mm in diameter at 0deg eccentricity, containing the higher peak cone density in the photoreceptor layer. Therefore, foveal vision is characterized by high color sensitivity and discrimination ability. Moving away from the fovea, visual acuity decreases quickly, in relation with the reduction of the cones photoreceptors and the increase of retinal rods density, which ensure a surveillance function (good perception of movement of the objects but absence in color and details sensitivity).

2.5 Computer-generated Data

Synthetic data was generated through an algorithm, allocating fixations according to a bi-dimensional (*x*,*y*) probability function: an artificial map (*PM*) was generated giving, to each location *x*,*y* of image, a probability conditioned to the *ROI*s distance.

In other words, we may construct *PM* giving to each point (*x*,*y*) the belief of selecting one or more *ROI*s, proportional to the distance from *ROI*s. The idea was proposed by [17, 12] and [6]: authors argued that the probability to move to the target was proportional to the target distance.

PM was compared with subjects' fixations distribution.

2.6 Statistical Analysis

Statistical analysis has been performed by Holm-Sidak test comparing subjects' performances and *PM* over the measure *DN*. Descriptive statistics are given as the means ±standard deviation or median (25-75% interquartile range) as appropriate. $p<0.05$ was considered significant.

3 Results

3.1 Model's Response

We generated data of the model varying α and β=*k*·α. Figure 4 reports the *DN* measure. Since α is the minimum distance where (*x*,*y*) falls into the target, we set α=1*deg*≈ fovea size; β is the maximum distance when the target is too far to be considered, and it should be greater than α; therefore, *k* must be greater than 1. Accordingly to the study of visibility, the fovea's capability decreases abruptly [13,40]; we set *k*=5≈ parafovea size, in other words a target is ignored when the distance from the center of the fovea is 5*deg*. Figure 4 shows, also, the degraded response of the model when two or more symbols are available at fovea (α=3÷5); in this case two or more ROIs fall into the fovea and the model is not able to distinguish the target seen.

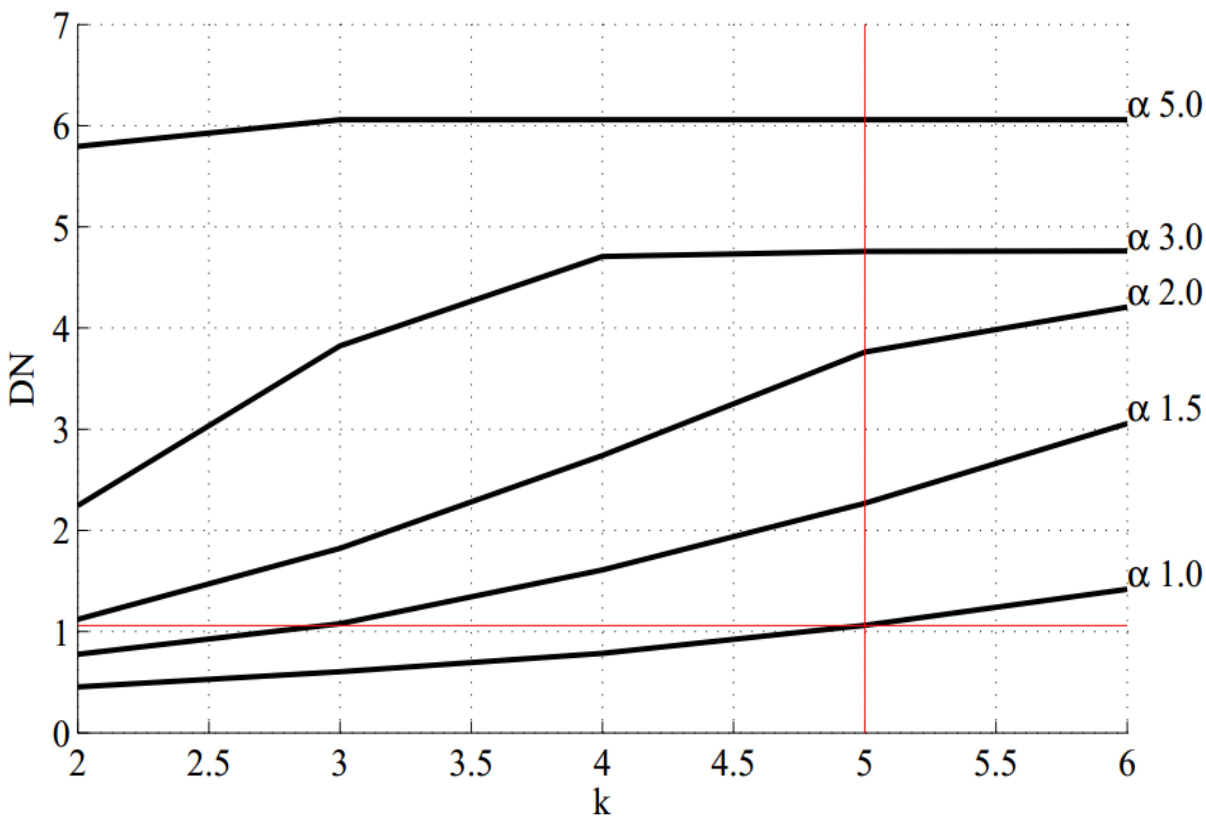


Figure 4: DN response of the model varying α and β=*k*·α. We set α=1*deg*≈ fovea size, and β=5·α≈ parafovea size.

3.2 Execution of Task performed by subjects

All subjects performed the tests correctly completing the alphanumeric sequence (1−*A*−2−*B*−3−*C*−4−*D*−5−*E*) within the given time. Studying the distribution of fixations (Figure 6(b)) we observed that subjects performed fixations around a *ROI*: we evaluated the number of fixations preceding a saccade directed into *ROI*, and we found the 54% of fixations of *TMT* respectively, anticipated a fixation inside *ROI*.

We evaluated the correlation between *DT* and *DN* and we found an inverse correlation: ($R^2=0.29, p\approx 0.01$; see Figure 5). This result suggested that subjects used extra-foveal information to allocate a more efficient spatial map and used a spatial ranking of the elements of the scene at each fixation to make the future gaze shift more consistent with sequencing order. Our findings suggested that this strategy improved performance.

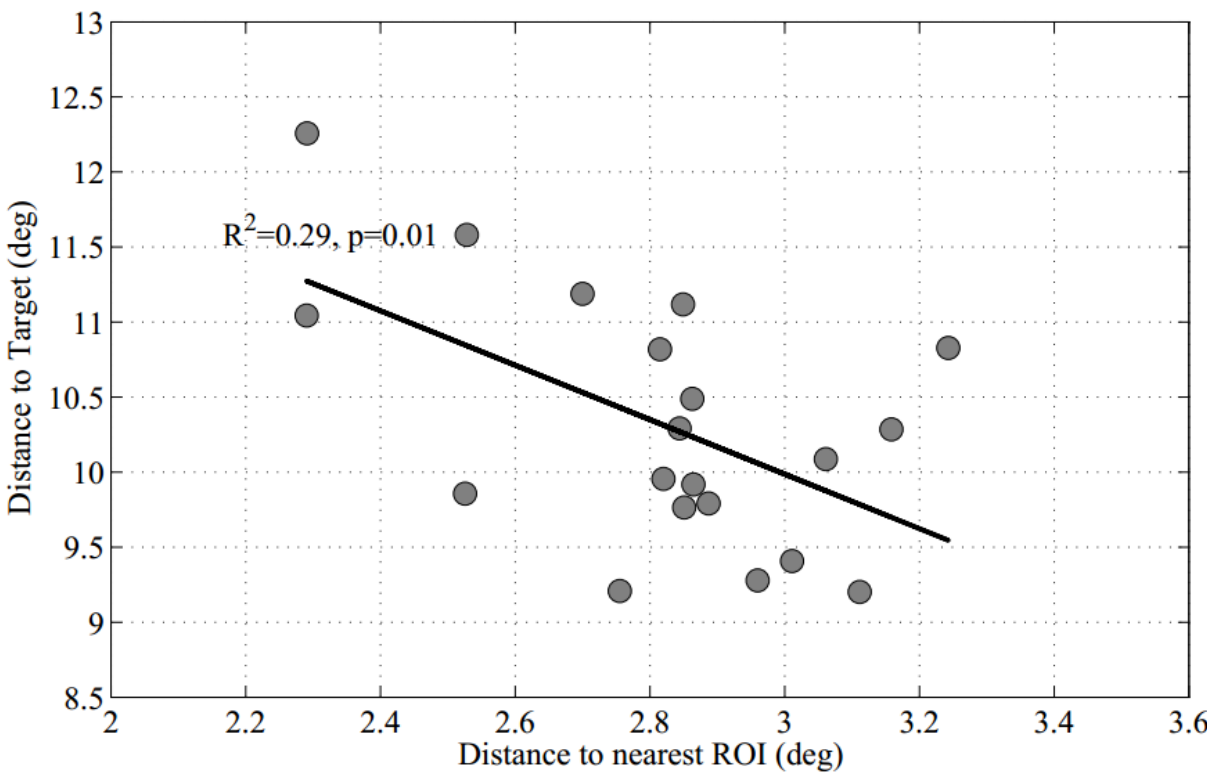
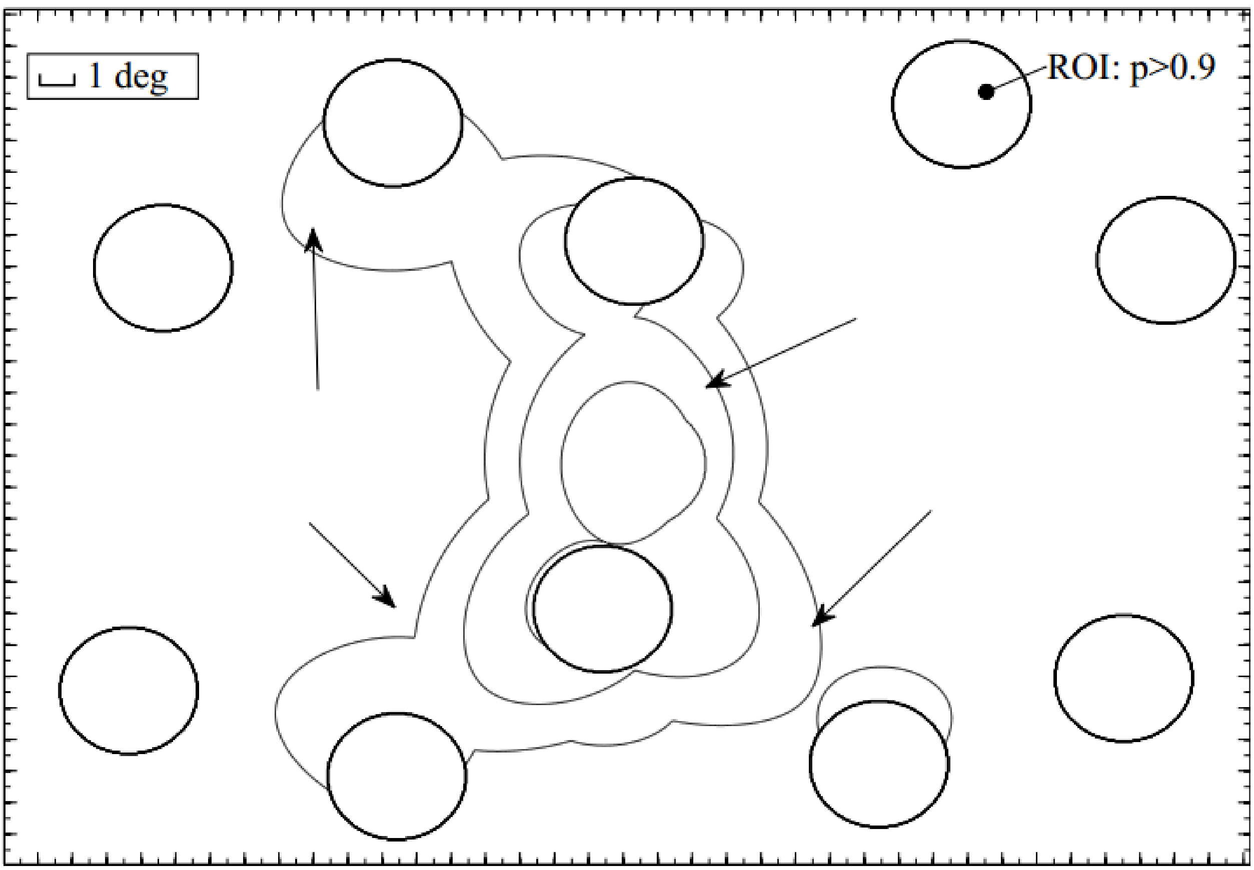


Figure 5: Correlation between *DT* and *DN*: correlation ($R^2 = 0.29$, $p \approx 0.01$) with negative slope between the distance to next target (*DT*) and distance to nearest *ROI* (*DN*) suggested that fixations allocation near ROIs improved performance on target finding.

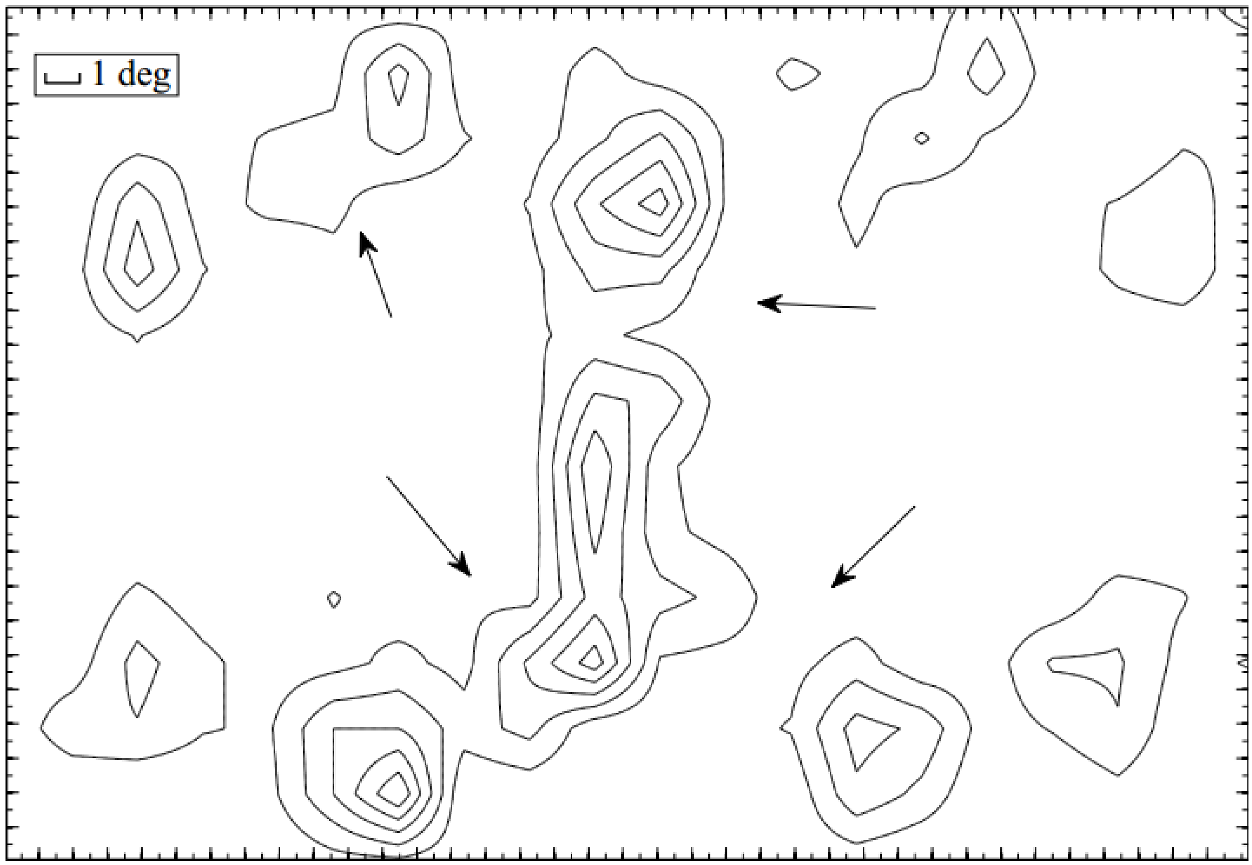
3.3 Model and subjects' exploration comparison

Table 1: Results: mean value and standard deviation (in brackets) of tests.

Indicators	TMT	PM
Distance to nearest ROI (deg)	1.07 (±0.17)	1.06 (±0.33)



(a) PM



(b) TMT

Figure 6: Fixations distribution maps of computer-model and subjects: (**a**) probability map (*PM*) to find a close target within a region with radius =3 *deg*; on the symbols (*ROI*) the probability of finding the target is greater than 90%; (**b**) fixations distribution of subjects which performed the test *TMT*.

We analysed subjects' fixations' distribution of *TMT*, and a probability map developed through the two-dimensional likelihood function *PM* to find a target nearby (see 2.4 for the implementation), and we did not find significant difference (Table 1) of *DN* ($t(19)=-0.366, p=0.989$). Therefore, the model might simulate the ongoing *TMT* exploration performed by the subjects; results reported by the two systems, subjects (1.07 ±0.17) versus computer generated data (1.06 ±0.33), suggested a similar behavior (mean squared error *MSE*=0.15). A qualitative analysis of the two maps, Figure 6(a) and Figure 6(b), showed a good overlap.

4 Discussion

Subjects performing a logical visual sequential search task, look insistently at the locations around the targets but not exactly into the target. This gaze behavior, called spatial ranking, was previously observed during an alphanumeric-visual-sequential search and attributed to the ability of the visual system to optimize the perceptual information of extrafoveal vision, when detailed information on the nature of the target are unnecessary. A similar behavior was observed in complex scene exploration when uncertainty on target choice needs to be solved by pooling pieces of information of the scene collected extrafoveally in favor of one among several options [21]. However, the spatial ranking strategy, by highlighting peripheral vision discrimination, specifically works on visual sequential search for prioritizing the next target of the sequence and facilitating the onset of a new saccade. In this study, we provided further demonstrations on the effectiveness of the spatial ranking as an efficient and optimal strategy adopted by the brain in visual sequencing. In this respect the inverse correlation between DT (distance to target), an indicator of efficiency ("lower is better"), and DN (distance to the nearest number or letter, which is a fixation' distribution indicator), suggests that an "averaged spatial ranking" improves performance and might be considered an optimization of the gaze distribution during visual sequencing for many reasons. The first reason is that it allows the system to enrich of new details the already collected information about the spatial distribution of different elements of the sequence; it enables the brain to continuously prioritizing the next element of the sequence; it increases the capacity of information sampling before deciding the direction of gaze and; finally, it reduces the cost of unnecessary explorative saccades. Therefore, we concluded that the spatial ranking is an optimization mechanism rather than a simple motor control error procedure [12, 6, 24,39].

To understand "How" it works, here we have assumed that humans visual search, acts like a probabilistic estimator to plan the saccades' landing point. In the last two decades various studies have developed some stochastic model [26,16,31,14,23,4,8,15,24,33] to explain human visual search. Evidences from sensorimotor[19], psychological [5,30] and neurophysiological studies [7,30] suggested a Bayesian inference on visual attention; therefore, we compared the exploration map of TMT data (Figure 6(b)) with a two-dimensional probability map looking for one or more close target for each location (Section 2.4, *PM*). Our probability map, based on distance from target shows a significant overlap with the spatial ranking strategy of visual sequencing search performed by subjects (Figure 6(a)); then, subjects explores regions around ROIs because this mechanism maximizes the probability of finding the target. Furthermore, they tend to direct their gaze close to ROIs since at each fixation a spatial ranking of the scene allows updating the localization of the next target of the sequence across the entire scene. In conclusion, the spatial ranking strategy allows to minimize the consequences of decisional mistakes during visual sequential search by maximizing the properties of extrafoveal vision and indicates an optimization of gaze behavior.

References

[1]. BALUCH, F., AND ITTI, L. Mechanisms of top-down attention. *Trends in Neurosciences 34*, 4 (2011), 210–224.

[2]. BAYS, P. M., AND WOLPERT, D. M. Computational principles of sensorimotor control that minimize uncertainty and variability. *J Physiol 578*, Pt 2 (Jan 2007), 387–396.

[3]. BOWIE, C. R., AND HARVEY, P. D. Administration and interpretation of the trail making test. *Nat Protoc 1*, 5 (2006), 2277–2281.

[4]. CAIN, M. S., VUL, E., CLARK, K., AND MITROFF, S. R. A bayesian optimal foraging model of human visual search. *Psychol Sci 23*, 9 (Sep 2012), 1047–1054.

[5]. CHIKKERUR, S., SERRE, T., TAN, C., AND POGGIO, T. What and where: a bayesian inference theory of attention. *Vision Res 50*, 22 (Oct 2010), 2233–2247.

[6]. COHEN, E. H., SCHNITZER, B. S., GERSCH, T. M., SINGH, M., AND KOWLER, E. The relationship between spatial pooling and attention in saccadic and perceptual tasks. *Vision Research 47*, 14

(Jun 2007), 1907–1923.

[7]. DOYA, K., ISHII, S., POUGET, A., AND RAO, R. P., Eds. *Bayesian Brain: Probabilistic Approaches to Neural Coding*. MIT, 2006.

[8]. ECKSTEIN, M. P., DRESCHER, B. A., AND SHIMOZAKI, S. S. Attentional cues in real scenes, saccadic targeting, and bayesian priors. *Psychol Sci 17*, 11 (Nov 2006), 973–980.

[9]. FECTEAU, J. H., AND MUNOZ, D. P. Salience, relevance, and firing: a priority map for target selection. *Trends Cogn Sci 10*, 8 (Aug 2006), 382–390.

[10]. FINDLAY, J. M. Global visual processing for saccadic eye movements. *Vision Research 22*, 8 (1982), 1033–1045.

[11]. FINDLAY, J. M., AND BLYTHE, H. I. Saccade target selection: Do distractors affect saccade accuracy? *Vision Research 49*, 10 (Jun 2009), 1267–1274.

[12]. FINDLAY, J. M., BROWN, V., AND GILCHRIST, I. D. Saccade target selection in visual search: the effect of information from the previous fixation. *Vision Research 41*, 1 (Jan 2001), 87–95.

[13]. GEISLER, W. S. Contributions of ideal observer theory to vision research. *Vision Research 51*, 7 (Apr 2011), 771–781.

[14]. HACISALIHZADE, S. S., STARK, L., AND ALLEN, J. Visual perception and sequences of eye movement fixations: a stochastic modeling approach. *Systems, Man and Cybernetics, IEEE Transactions on 22*, 3 (May 1992), 474–481.

[15]. HAJI-ABOLHASSANI, A., AND CLARK, J. J. A computational model for task inference in visual search. *J Vis 13*, 11 (2013).

[16]. HAYHOE, M., AND BALLARD, D. Modeling task control of eye movements. *Current Biology 24*, 13 (2014), R622–R628.

[17]. HE, P. Y., AND KOWLER, E. The role of location probability in the programming of saccades: implications for "center-of-gravity" tendencies. *Vision Research 29*, 9 (1989), 1165–1181.

[18]. HOROWITZ, T. S., AND WOLFE, J. M. Visual search has no memory. *Nature 394*, 6693 (Aug 1998), 575–577.

[19]. KNILL, D. C., AND POUGET, A. The bayesian brain: the role of uncertainty in neural coding and computation. *Trends Neurosci 27*, 12 (Dec 2004), 712–719.

[20]. KOWLER, E. Eye movements: The past 25Â years. *Vision Research In Press, Corrected Proof* (2011), –.

[21]. KRISHNA, B. S., IPATA, A. E., BISLEY, J. W., GOTTLIEB, J., AND GOLDBERG, M. E. Extrafoveal preview benefit during free-viewing visual search in the monkey. *J Vis 14*, 1 (2014).

[22]. MELCHER, D., AND KOWLER, E. Shapes, surfaces and saccades. *Vision Research 39*, 17 (Aug 1999), 2929–2946.

[23]. MERK, I., AND SCHNAKENBERG, J. A stochastic model of multistable visual perception. *Biol Cybern 86*, 2 (Feb 2002), 111–116.

[24]. MORVAN, C., AND MALONEY, L. T. Human visual search does not maximize the post-saccadic probability of identifying targets. *PLoS Comput Biol 8*, 2 (Feb 2012), e1002342.

[25]. MURPHY, H. A., DUCHOWSKI, A. T., AND TYRRELL, R. A. Hybrid image/model-based gaze-contingent rendering. *ACM Trans. Appl. Percept. 5*, 4 (2009), 1–21.

[26]. NAJEMNIK, J., AND GEISLER, W. S. Optimal eye movement strategies in visual search. *Nature 434*, 7031 (Mar 2005), 387–391.

[27]. NAJEMNIK, J., AND GEISLER, W. S. Eye movement statistics in humans are consistent with an optimal search strategy. *Journal of Vision 8*, 3 (2008), 1–14.

[28]. PROVIS, J. M., DUBIS, A. M., MADDESS, T., AND CARROLL, J. Adaptation of the central retina for high acuity vision: cones, the fovea and the avascular zone. *Prog Retin Eye Res 35* (Jul 2013), 63–81.

[29]. SALVUCCI, D. D., AND GOLDBERG, J. H. Identifying fixations and saccades in eye-tracking protocols. In *ETRA '00: Proceedings of the 2000 symposium on Eye tracking research & applications* (New York, NY, USA, 2000), ACM, pp. 71–78.

[30]. SERRE, T., KOUH, M., CADIEU, C., KNOBLICH, U., KREIMAN, G., AND POGGIO, T. A theory of object recognition: computations and circuits in the feedforward path of the ventral stream in primate visual cortex, 2005.

[31]. SPRAGUE, N., BALLARD, D., AND ROBINSON, A. Modeling embodied visual behaviors. *ACM Trans. Appl. Percept. 4*, 2 (July 2007).

[32]. VAN BEERS, R. J., BARADUC, P., AND WOLPERT, D. M. Role of uncertainty in sensorimotor control. *Philos Trans R Soc Lond B Biol Sci 357*, 1424 (Aug 2002), 1137–1145.

[33]. VENERI, G., FEDERICO, A., AND RUFA, A. Evaluating the influence of motor control on selective attention through a stochastic model: The paradigm of motor control dysfunction in cerebellar patient. *BioMed Research International 13* (2014), 10–1155.

[34]. VENERI, G., FEDERIGHI, P., ROSINI, F., FEDERICO, A., AND RUFA, A. Influences of data filtering on human-computer interaction by gaze-contingent display and eye-tracking applications. *Computers in Human Behavior 26*, 6 (2010), 1555 – 1563.

[35]. VENERI, G., FEDERIGHI, P., ROSINI, F., FEDERICO, A., AND RUFA, A. Spike removal through multiscale wavelet and entropy analysis of ocular motor noise: A case study in patients with cerebellar disease. *Journal of Neuroscience Methods 196*, 2 (Mar 2011), 318–326.

[36]. VENERI, G., PIU, P., ROSINI, F., FEDERIGHI, P., FEDERICO, A., AND RUFA, A. Automatic eye fixations identification based on analysis of variance and covariance. *Pattern Recognition Letters 32*, 13 (2011), 1588 – 1593.

[37]. VENERI, G., PRETEGIANI, E., FARGNOLI, F., ROSINI, F., VINCIGUERRA, C., FEDERIGHI, P., FEDERICO, A., AND RUFA, A. Spatial ranking strategy and enhanced peripheral vision discrimination optimize performance and efficiency of visual sequential search. *European Journal of Neuroscience* (2014), n/a–n/a.

[38]. VENERI, G., PRETEGIANI, E., ROSINI, F., FEDERIGHI, P., FEDERICO, A., AND RUFA, A. Evaluating the human ongoing visual search performance by eye tracking application and sequencing tests. *Computer Methods and Programs in Biomedicine 107* (Mar 2012), 468–477.

[39]. VENERI, G., ROSINI, F., FEDERIGHI, P., FEDERICO, A., AND RUFA, A. Evaluating gaze control on a multi-target sequencing task: the distribution of fixations is evidence of exploration optimization. *Computers in Biology and Medicine 42/2* (2011), 235–244.

[40]. VENINI, D., REMINGTON, R. W., HORSTMANN, G., AND BECKER, S. I. Centre-of-gravity fixations in visual search: When looking at nothing helps to find something. *J Ophthalmol 2014* (2014), 237812.