Using Microsaccades to Estimate Task Difficulty During Visual Search of Layered Surfaces

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We develop an approach to using microsaccade dynamics for the measurement of task difficulty/cognitive load imposed by a visual search task of a layered surface. Previous studies provide converging evidence that task difficulty/cognitive load can influence microsaccade activity. We corroborate this notion. Specifically, we explore this relationship during visual search for features embedded in a terrain-like surface, with the eyes allowed to move freely during the task. We make two relevant contributions. First, we validate an approach to distinguishing between the *ambient* and *focal* phases of visual search. We show that this spectrum of visual behavior can be quantified by a single previously reported estimator, known as Krejtz's $\mathcal{K}$ coefficient. Second, we use ambient/focal segments based on $\mathcal{K}$ as a moderating factor for microsaccade analysis in response to task difficulty. We find that during the focal phase of visual search (a) microsaccade magnitude increases significantly, and (b) microsaccade rate decreases significantly, with increased task difficulty. We conclude that the combined use of $\mathcal{K}$ and microsaccade analysis may be helpful in building effective tools that provide an indication of the level of cognitive activity within a task while the task is being performed.

***Index Terms*—Visual search, eye tracking, microsaccades, cognitive load, textured surfaces.**

I. Introduction

CONSIDERABLE advances have been made in the technology of eye tracking yielding numerous studies on how humans visually scan a document, image, or display [1]. Simultaneously, there is a developing perceptual science behind the design of visualizations for optimal data or information display. While there is a natural and obvious tie between eye tracking and the science behind the perceptual optimization of visualization design, studies in the important area of visualization psychophysics are fairly rare, especially those considering *cognitive load* of the user. We believe that measuring how visualization and computer graphics are perceived by the user, and especially how they affect task performance, will become increasingly important. In this paper we review the concept of cognitive load in the context of a spatial search task and discuss means of its measurement with an eye tracker.

When considering the design and implementation of a visualization or user interface, the concept of cognitive load is often invoked as one way of thinking about the usability and effectiveness of the design. A classic example of the use of this concept is illustrated by Cumming et al.'s [2] psychophysical investigation of shape-from-texture. Cumming et al. posited that the role of cognitive judgments is minimized by using stimuli in which shape, when portrayed by texture, is constant while the texture, used to portray that shape, varies. Specifically, they investigated how different components of texture (e.g., compression, area, and density) contribute to the reconstruction of three-dimensional surfaces. While they recorded participants' subjective impression of depth, they did not directly substantiate their claim of minimized cognitive judgments. To do so, a measure of cognitive load would be needed. Here we propose and provide initial validation for a novel method of cognitive load measurement derived from the user's eye movements.

Further inspiration for the present work is drawn from the work of Bair et al. [3]–[6] concerning perceptual optimization of textures for layered surface visualization. The problem of visualizing layered surfaces is important in many application areas, including medical imaging, geological imaging, oceanography, and meteorology. Bair et al. [3] used an experimental methodology with a human-in-the-loop genetic algorithm to search the texture parameter space while collecting a database of rated textures. They used manually entered subjective texture ratings to produce populations of highly rated textures over several generations of the algorithm. A metric of cognitive load could potentially augment or replace these subjective inputs, as it would provide a direct measure indicative of task difficulty. The metric could also complement other objective performance measures, such as those of speed and accuracy, as exemplified by Bair and House's [5] collection of users' error rates in estimating layered surface orientation.

A reliable, non-invasive, physiological form of cognitive load measurement has been elusive. The most promising involves the use of an eye tracker, but it is not clear which eye tracking metric is most indicative of cognitive load, e.g., one derived from blink rate, pupil diameter, gaze position (i.e., fixation, saccades, microsaccades), or some combination thereof [7].

Here we develop and evaluate an approach to cognitive

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load measurement in the context of visual search by extending the work of previous investigators from various tasks meant to elicit cognitive load (e.g., mental arithmetic [8]) to a visual search task across terrain-like, textured surfaces. As a means of validation of our cognitive load metric, we chose a feature recognition task wherein we vary task difficulty by manipulating the elevation of a target surface feature. Establishing cognitive load response during a relatively simple task lays the groundwork for future experimentation with more complex stimuli.

Below we describe two studies using the same experimental protocol but conducted separately with two different eye trackers. From these studies we arrive at conclusions pointing to two important contributions to the literature on cognitive load, and particularly the measurement of cognitive load coincident with the conduct of a task.

First, using a conventional, readily available eye tracker, we demonstrate a method to distinguish between ambient and focal segments of the visual search task.

Second, using a high-speed eye tracker, we demonstrate an approach to measuring microsaccades that allows us to examine the response of microsaccades to task difficulty during fixations. Our results indicate that the dynamics of microsaccades change significantly with task difficulty but only within highly focal fixations. This suggests a new method for the measurement of cognitive load during visual search, one that combines traditional positional eye movement metrics with microsaccades.

II. Background: Visual Search and Expected Eye Movement Dynamics

We expect visual search to follow Just and Carpenter's [9] three-stage model of cognitive processing: search $\rightarrow$ decision $\rightarrow$ confirmation, where the latter two steps comprise the decision-making aspect of cognition. Concordantly, we expect that cognitive load measures will manifest significant responses but only during the decision-making aspect of the task, when visual search completes and a decision must be made whether the localized feature is the sought one. Just and Carpenter noted that eye fixation data make it possible to distinguish the three stages of visual performance, although their analysis relied on the relation between fixation duration and angular disparity. While qualitatively effective, the relation provided no easy way of combining fixation duration and disparity into a useful quantity with which to distinguish the cognitive stages.

Since then, several metrics derived from fixations and saccades have appeared to characterize visual performance. Short fixations followed by long saccades are characteristic of ambient processing, while long fixations followed by short saccades are indicative of focal processing [10]. The dynamic pattern of visual attention, attributed to the two ambient/focal modes of information acquisition [11], has been widely referred to as orienting and evaluating [12], noticing and examining [13], exploring and inspecting [14], skimming and scrutinizing [15], or exploring and exploiting [16]. Over the time course of scene perception, fixation durations tend to increase while saccadic amplitudes tend to decrease [17].

Krejtz et al. [18] introduced an estimator, known as Krejtz's $\mathcal{K}$ coefficient, which is computed as a difference between z-scores of saccade amplitudes and fixation durations. Given its definition (see Section IV), $\mathcal{K}<0$ indicates ambient processing during visual search (when relatively short fixations are followed by relatively long saccades), and $\mathcal{K} > 0$ indicates focal processing (when relatively long fixations are followed by short saccades) which we assume takes place during decision making. In the work reported here, we use $\mathcal{K}$ to allow detection of ambient/focal cognitive transitions. Since the ambient phase of a visual search should not be strongly affected by task difficulty, it is only during the focal processing, decision-making stage that we hypothesize to find changes in microsaccade dynamics related to task difficulty. Recently, Krejtz et al. [19] observed a positive relationship between focal fixations and pupil dilation, indicating deeper cognitive processing, during the focal decision-making segment of the visual scan of emotional facial expressions.

A. Eye Tracking Metrics and Cognitive Load

Due to the *eye-mind assumption* posited by Just and Carpenter [20], which states that gaze remains fixed on the stimulus so long as it is being processed, traditional eye tracking metrics have been derived from fixations, e.g., number of fixations and fixation duration. Relationships between fixations and cognitive activity have produced rudimentary theoretical models relating fixations to specific cognitive processes [21].

Because of the long-standing association of the Task-Evoked Pupillary Response (TEPR) with cognitive load [22] it has almost been taken for granted that pupil diameter, as reported by an eye tracker, is synonymous with cognitive load. Consequently, eye trackers are increasingly being used to measure cognitive load due to its recording of pupil diameter as a matter of course [23]–[27]. However, the pupil is sensitive to a number of factors unrelated to cognitive load such as luminance [28] and off-axis distortion [29]. In contrast, eye movements such as fixations, saccades, and microsaccades (see below), are not susceptible to these effects since they indicate position of gaze [30]. Consider, for example, looking at a fixed point. The pupil may constrict or dilate due to changing luminance conditions but gaze will remain fixed (unless potentially perturbed by cognitive load).

Surprisingly, users of eye trackers do not always appreciate the optical distortion of the apparent pupil when the eye moves away from the eye tracker camera's line of sight. Off-axis, the nearly circular pupil is foreshortened into an ellipse. The distortion has been modeled empirically by Mathur et al. [29] as a function of the cosine of the viewing angle of ϕ degrees, i.e. $y(\phi) = R^2 \cos([\phi + 5.3]/1.121)$, where $R^2 = 0.99$, and y is the viewing-angle-dependent ratio of the ellipse major and minor axes. When off-axis, the apparent dimension of the pupil can be diminished by as much as 12% potentially impacting pupil diameter measurement and interpretation.

One eye tracking manufacturer goes so far as to warn the researcher that if pupil size is to be measured, the subject should not move their eyes during trials [31].

Although numerous metrics related to the pupil diameter exist, including baseline-related difference measures [24], [26], [27], [32], the Low Frequency/High Frequency (LF/HF) ratio [16], and the Index of Cognitive Activity [33]–[35] (measuring pupil oscillation, known as *pupil unrest* [36]), it is not clear which is superior.

Besides pupil diameter, some eye tracking users infer cognitive load from blink rate [26], while others ignore this data. From an eye tracking perspective, blinks are something of a by-product. An eye tracker's main task is to produce an estimate of the user's gaze on the stimulus being viewed. When blinks occur, the eye tracker loses sight of the pupil, and is forced to output some undefined value for gaze position.

Positional eye movements present a number of potential metrics including number of fixations [21], fixation durations [9], [37], and number of regressions [38]. The most recent entrant into this fray are microsaccades, but their effectiveness as indicators of cognitive load has not yet been fully tested. When gaze is fixed and luminance levels maintained consistently, microsaccade magnitude and baseline-related pupil diameter difference measures respond comparably to cognitive load [30]. We review the observed relationship between microsaccades and task difficulty below.

B. *Microsaccades and Task Difficulty*

Along with tremor and drift, microsaccades are a component of miniature, eye movements made during visual fixation [39]–[41]. Although microsaccades have been defined as involuntary, Poletti and Rucci [42] note that the reliance on volition is problematic as the characterization of involuntary microsaccades has origins in experiments where the participant is required to maintain fixation. They bolster the observation made by Otero-Millan et al. [43] that no functional distinction exists between most microsaccades and larger saccades under natural viewing conditions (see also Martinez-Conde et al. [41] who further elaborated on the functional equivalence of microsaccades and saccades, and moreover proposed that microsaccades and saccades are comparably subjected to volitional control).

Using a maintained fixation protocol, Siegenthaler et al. [8] investigated the influence of task difficulty on microsaccades during the performance of a non-visual, mental arithmetic task with two levels of complexity. They found that microsaccade rates decreased and microsaccade magnitudes increased with increased task difficulty. Their hypothesis is that microsaccade generation is affected by working memory performance. In their mental arithmetic study, attention is divided between maintaining fixation and counting tasks, increasing load on working memory. They propose that the more difficult the task (i.e., the higher the working memory load), the more difficult it is to execute the fixation task, producing fewer microsaccades with decreased control over their (e.g., larger) magnitude.

Because it is thought that microsaccades and saccades share a common neural generator [43], [44] (the superior colliculus (SC)), Siegenthaler et al. suggest that different levels of task difficulty induce variations in attentional load, modulating microsaccade parameters via changes in the intensity and shape of the rostral SC activity map. Fluctuations of SC activity at the rostral poles are thought to give rise to microsaccades during fixation.

Siegenthaler et al.'s study carries, by design, a number of noteworthy limitations. Because gaze was induced to remain fixed at a central visual target, reinforced via an aural beep when gaze strayed beyond 3° visual angle, it is not clear whether microsaccades reflect task difficulty when the eyes are free to move beyond the central target.

Similarly, because Siegenthaler et al.'s study was non-visual in nature, it is not clear how well their observations regarding the effect of task difficulty on microsaccade generation generalizes to tasks that include a visual component (e.g., visual search).

We should also note that Siegenthaler et al. stopped short of positing causality between cognitive workload and microsaccades, suggesting the relation should be probed further, especially in ecologically valid scenarios.

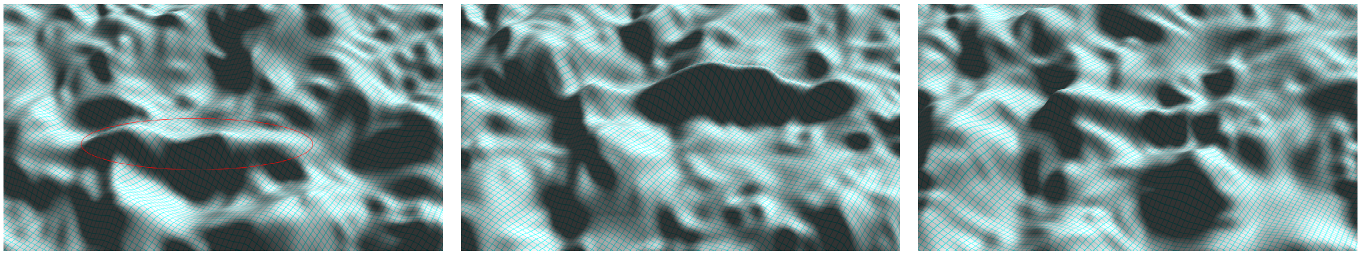
However, evidence for the connection between task difficulty and microsaccades has emerged in other research. A brief review of microsaccade characteristics in visual tasks with unconstrained fixations follows.

Valsecchi et al. [45] reported fewer microsaccades when participants were asked to actively count the occurrences of stimuli in an odd-ball task, suggesting higher-order cognitive processes, like active recognition and stimuli recall, can influence the frequency of microsaccades. The reported microsaccade rate was significantly higher compared to a simple, spatial attention task [45].

Chen et al. [46] showed that increased task difficulty reduces interference caused by peripheral distracters, decreasing the likelihood that distracters will deviate the focus of attention. This may be why visual task difficulty modulates the activity of specific populations of neurons in the primary visual cortex.

Pastukhov and Braun [47] used visual recognition tasks that required different attention loads (e.g., reporting the identity vs. the color of a target letter) and found lower microsaccade rates associated with tasks involving greater loads.

Benedetto et al. [48] used microsaccades in combination with EEG to determine cognitive load during visual search tasks. They recorded exploratory saccades and microsaccades with free head movement during a lane-change task in a simulated driving environment. A simultaneous visual search task was imposed in a dual-task paradigm in which drivers searched for a target among similar distracters on a panel to the driver's right. In the dual-task condi-



(a) Target circled (training). (b) Elevation high (easy). (c) Elevation low (difficult).

Fig. 1. Example stimuli used in both pilot and main studies: visual search of terrain feature during training (a), where the target surface feature was circled by an ellipse; with target elevation high (b), easy task; and target elevation low (c), difficult task. In (b) and (c) the target ridge is in the center of the image.

tion, a significantly increased microsaccade rate was found along with an even larger increase in frequency of large exploratory saccades.

According to Gao et al. [49], non-visual cognitive processing can suppress microsaccade rate. The extent of such suppression is related to task difficulty. In tasks where participants were asked to perform easy and difficult arithmetic, they showed microsaccade rate modulation at different task phases. Microsaccades in the post-calculation phase remained at double the rate obtained within the during-calculation phase, and microsaccade rate in the control condition was much greater compared to post-calculation.

Dalmaso et al. [50] provided evidence that working memory load is reflected in microsaccade rate and magnitude. Microsaccades are apparently associated with cognitive processes as well as with oculomotor responses supporting vision. Results of their two experiments showed that microsaccadic rate drops in the rebound phase of a high demand task (200-400 ms after onset), compared to an easier task. In both experiments visual stimuli were the same. Results showed a reduction in microsaccadic rate in the high-load condition compared to the low-load condition, indicating that microsaccadic generation can be connected with top-down processes, consistent with previous findings [8], [45], [49].

Previous work thus provides converging evidence that task difficulty (mental or cognitive load) can influence microsaccade activity. Our results are in line with these findings.

C. Eye Tracking and Spatial Research

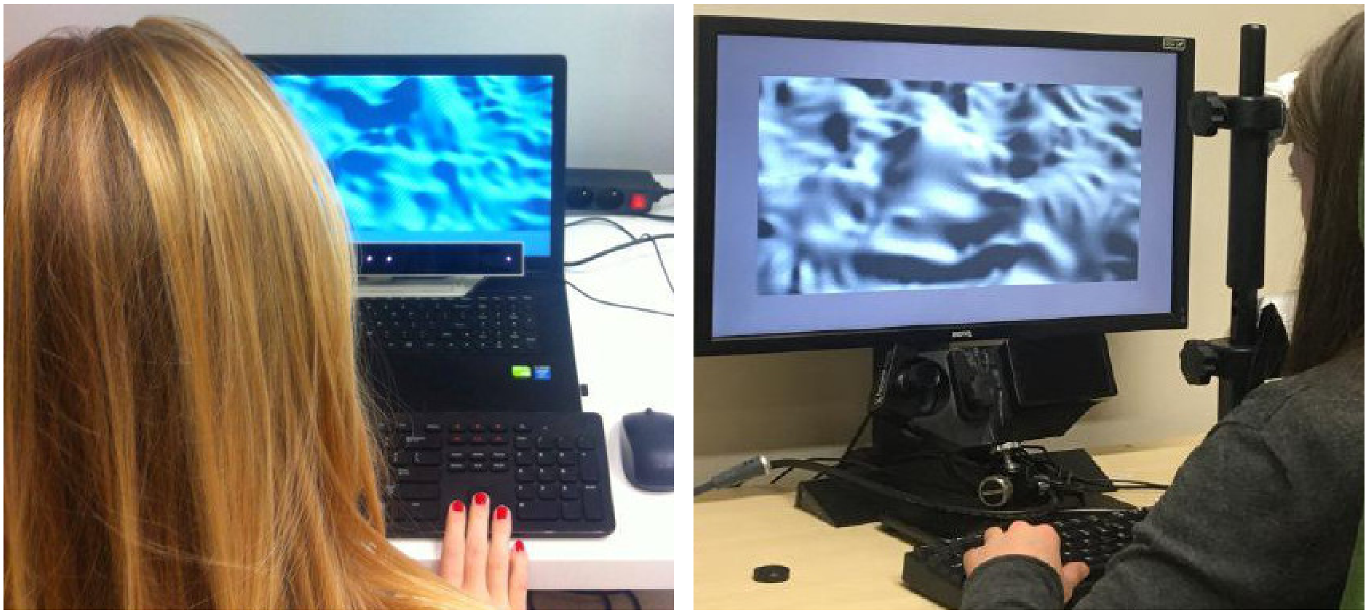
Evaluation of users' cognitive load has been identified as an important factor in the design of geographic visualization and spatial information systems [51]–[55]. As acquisition of spatial information is largely visual in nature, eye tracking has become popular for investigating research questions related to Spatial Cognition, Geographic Information Science (GIScience), Cartography, and related fields [56]. Applications include interaction with geographic information systems, perception of space and the decision-making situations which the space affords, and enhancement or development of new cognitive models of how humans perceive, behave in, and reason about space. Kiefer et al. [56] review eye tracking in spatial cognition, focusing on wayfinding and cartography/geovisualization.

Possibly the closest similar prior work to ours, in the context of visual search, is the study by Kiefer et al. [55] who examined pupil diameter during visual exploration of common web maps. They considered six different task demands: free exploration, visual search, polygon comparison, line following, focused search, and route planning, and found changes in pupil diameter, compared to the free exploration task, considered as baseline. They interpreted significant differences in mean pupil diameter as differences in cognitive load, indicating low cognitive load during free exploration, relatively medium cognitive load during visual search, polygon comparison, and line following, and relatively high cognitive load during focused search and route planning.

We specifically consider the visual search task, but in comparison to the maps used by Kiefer et al., our textured surfaces are more abstract. There is no particular location, address, or point of interest to find. Instead our search task requires localization of elevated surface features. We assume that this type of task requires greater scrutiny in the decision-making aspect of cognition (vs., e.g., recognition). We further assume that increased task difficulty will require greater focal attention and greater cognitive load.

III. Methodology

Our goal was to investigate microsaccade sensitivity to visual search task difficulty based on stimulus composition. We hypothesized that microsaccadic response to task difficulty will be moderated by the dynamics of the visual search process (interplay between ambient and focal visual information processing). The main study was designed to allow observation of microsaccadic response to task difficulty during the relatively long process of visual search in which the dynamical interplay between ambient and focal eye movements could be measured. We hypothesized microsaccadic response to task difficulty to be found only during the focal, decision-making stage of the visual search task.



(a) Gazepoint apparatus used in pilot study.

(b) EyeLink apparatus used in main study.

Fig. 2. Eye tracking apparatus for pilot and main studies. The pilot study's slower Gazepoint eye tracker (a) was positioned on the laptop used, obscuring the bottom portion of the laptop screen. The main study's faster EyeLink eye tracker (b) required use of a chin rest.

To test the hypothesis two studies were conducted (pilot and main). In the first (pilot) study we focused on testing whether coefficient $\mathcal{K}$ could be used to discern ambient and focal stages of information processing during the visual search task of varied difficulty. The second (main) experiment was designed and conducted to test the microsaccade hypothesis directly.

We ran the pilot study using a slower but more readily available eye tracker. Its slower sampling rate precluded detection of microsaccades. Both pilot and main studies employed the same experimental design and protocol. The main study used a high-speed eye tracker allowing microsaccade detection.

A. Experimental Design

Both study designs were drawn from the series of studies that concerned layered surface visualization explored by Bair and colleagues [3]–[6]. The main independent variable was visual search task difficulty at four levels (low, mid, high, and control). The levels of task difficulty were operationalized by the visual stimuli design varying spatial frequency content (see Fig. 1), yielding trials differing in target elevation (high, mid, low, and target absent), respectively. In order to generate levels of visual search difficulty we followed the visual stimulus design approach of Bair [6]. To simplify the search task, and for maintenance of internal validity, we restricted our stimuli to single-layer textured surfaces. That is, we varied only one aspect of the visual stimuli in order to exclude possible confounding factors. We varied task difficulty by manipulating the elevation of the target surface feature at three elevations: low, mid, and high, corresponding to high, mid, and low levels of difficulty, respectively. A feature-absent surface served as the control condition. The three task difficulty and feature-absent control conditions serve as the independent variable (see below). Both studies employed a factorial within-subjects experimental design with task difficulty acting as the fixed factor at four levels.

B. Stimuli

Fig. 1 depicts example stimuli used in both pilot and main studies. The surfaces are height fields constructed from Gabor bumps to give a terrain-like feel [5], [57], [58]. We use a single surface with grid texture. The surface construction algorithm drew 100 bumps on each surface, randomizing position, amplitude, orientation, cosine period and the Gaussian falloff parameter for each bump. The cosine period varied between 7.5-20% of the surface width, and amplitude varied from 40-70% of the period. The target is a sequence of four perfectly aligned Gabor bumps, as contrasted with the randomly arranged terrain background. The target feature was elevated by scaling the aligned bumps by an incremental gain factor from 2 (low), to 3 (mid), to 4 (high). Five of each of the low, mid, high, and target-absent stimuli images were generated.

Six additional images were produced for training purposes. Five of these had the target visible and circled and the sixth was an example of the target-absent stimulus. All images were originally rendered to 1600×900 pixel resolution. Because the slower eye tracker used a table mount underneath the laptop screen (see Apparatus below), which obscured the bottom 100 pixels of the images, all stimuli for both studies were rescaled to 1422×800 to allow positioning of the stimuli above the bottom "dead zone" in the pilot study. In the main study, the stimuli were centered on the screen (see Fig. 2).

C. Apparatus

For the pilot study, a 60 Hz GP3 eye tracker from Gazepoint[1] was used, connected to a Lenovo laptop with a 17″ screen. Screen resolution was set to 1600×900 and participants (with no chin-rest) were seated approximately 57 cm away from the screen (see Fig. 2a).

For the main study, an Eye Link 1000 eye tracker from SR Research[2] was used, running at 500 Hz, with 17″ screen resolution set to 1600×900. Participants placed their head in a chin-rest approximately 57 cm away from the screen (see Fig. 2b).

A custom 9-point calibration was used for both studies, with the study procedure controlled by PsychoPy software [59].

D. Participants

Participants volunteered for both studies with no compensation. Eleven (11) participants took part in the pilot study with 3 data sets removed due to problems with calibration. The final sample in the pilot study consisted of 5 female and 3 male subjects aged between 23 and 47 years old ($\mathrm{M} = 28.00, \mathrm{SD} = 8.49$). Thirteen (13) participants took part in the main study (7F, 6M, mean age 33.08, $\mathrm{SD} = 10.80$) with 4 data sets removed for similar reasons. The final sample in the main study consisted of 6 male and 3 female participants aged between 24 and 50 years old ($\mathrm{M} = 33.67, \mathrm{SD} = 11.07$).

E. Experimental Procedure

The participants' main task was to indicate whether the specific terrain elevation target was present in the stimuli image by pressing the 'A' key. When they decided that this specific terrain elevation target was not present, they pressed the 'L' key. Participants were instructed to complete their task as quickly and accurately as possible—to do so they were asked to keep their pointing fingers on the 'A' and 'L' keys during the entire procedure.

The experimental procedure consisted of two phases: training and experiment. After signing a consent form and receiving general instructions for the experiment on a computer screen, participants underwent the eye tracker calibration procedure. When calibration succeeded (meaning an average calibration error was lower than 0.5° visual angle) they underwent training by visually inspecting images where the target was highlighted (circled by an ellipse, see Fig. 1a for an example). During the training phase each participant was presented with five such images with the target present and one image shown with the target absent. The goal of this training phase of the experimental procedure was to accustom participants to their task and the experimental setting. Eye tracking data from the training phase are not reported in the results.

Following training (during the experimental trials), each participant was presented with 5 trials of each of the low, mid, high, or control stimuli in randomized order, totaling 20 trials. The experimental trials were preceded by an instruction screen. Eye tracking data recorded during this phase were used for the main analyses presented in the results.

Each trial in the procedure (for both training and experimental phases) started with an empty screen shown for 500 ms followed by a fixation cross of size 1.5° visual angle in both directions, shown in the center of the screen for 1000 ms. The presentation of each stimulus in each trial was self-paced thus each participant took as long as they needed to produce and answer via key press. The total duration of the entire procedure was about 10 minutes. A schematic of the procedure and trial construction are given in Fig. 3.

F. Independent and Dependent Variables

The main fixed factor for the analyses was **task difficulty** at four levels (control, low, mid, and high) operationalized by target elevation (target absent (control), high, mid, and low, respectively).

The second fixed factor, **time period**, was created to allow analysis of eye movement dynamics, with the time of each individual trial segmented into four equal periods. The last period represented the time interval directly before the decision-making aspect of each trial. The time period thus served as the independent fixed factor in the statistical analyses. Note that the length of each time period is relative to each trial and each participant.

For the analyses of microsaccadic response dynamics to task difficulty in the main study, we used a fixed moderating factor, the **ambient/focal segment**, which reflected ambient/focal eye movements at four levels (extreme-ambient, ambient, focal, extreme-focal). The factor was based on analysis of coefficient $\mathcal{K}$ ($\mathrm{M} = 0.43$, $\mathrm{SD} = 1.27$), i.e., coefficient $\mathcal{K}$ was split into four segments at 1 SD (standard deviation) increments. Thus, $\mathcal{K} < -1$ was labeled as extreme-ambient, $-1 < \mathcal{K} < 0$ ambient, $0 < \mathcal{K} < 1$ focal, and $1 < \mathcal{K}$ extreme-focal. We attribute the ambient/focal label to fixations as each fixation carries its own coefficient $\mathcal{K}_i$, as per (1) below.

The data analyses in the pilot and in the main studies relied on three sets of dependent variables representing different aspects of human reaction to task difficulty:

- behavioral (answer accuracy and its reaction time)
- large eye movements (ambient/focal coefficient $\mathcal{K}$)
- microsaccadic properties (microsaccade amplitude, microsaccade peak velocity, microsaccade rate, and microsaccade amplitude-peak velocity (main sequence) intercept and slope).

The details of eye movement dependent measures are given in Section IV. Note that before the statistical analyses of microsaccadic eye movements the data were filtered based on the following thresholds: $< 2°$ for microsaccade amplitude and < 40 ms for microsaccade duration. Threshold levels were chosen based on procedures described in the literature, in particular those of Otero-Millan et al. [43].

[1] Gazepoint: http://gazept.com.

[2] SR Research: http://sr-research.com.

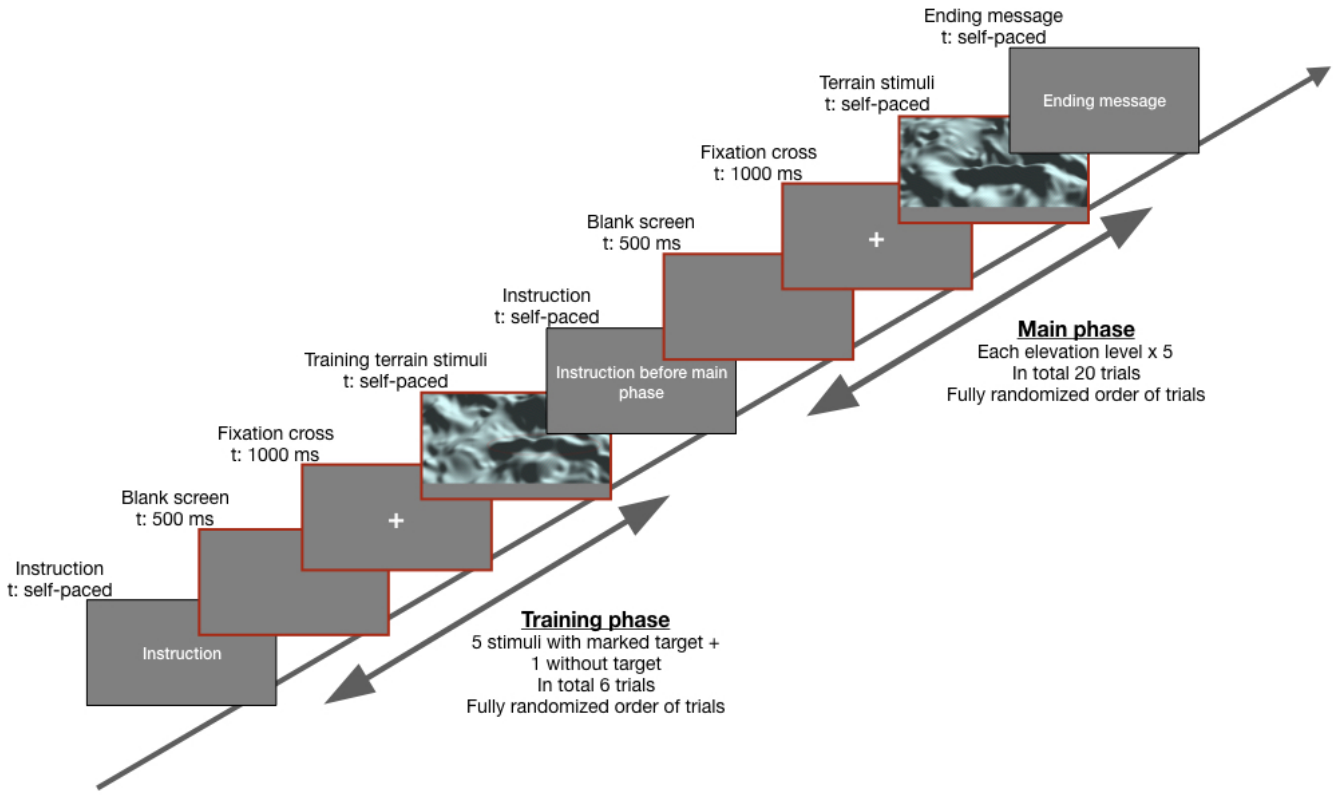


Fig. 3. The schematics of experimental procedure for both pilot and main studies. Training and experimental trails of the procedure are marked in red.

IV. Implementation of Gaze-Based Measures

Analysis of eye movements from both pilot and main studies relies on fixation detection followed by microsaccade detection based on Engbert and Kliegl's [39] algorithm.

Otero-Millan et al. [43] first used this algorithm successfully to detect microsaccades during free-viewing and visual search. Other examples of the algorithm's applicability to free viewing (e.g., of images) also exist [60]–[62]. However, as the algorithm was designed to detect microsaccades, it is somewhat unwieldy for estimation of fixations, in that classification of eye movements as saccades or microsaccades, i.e., during free viewing, is challenging since one cannot distinguish between saccades and microsaccades based on their magnitude [43]. However, Otero-Millan et al. [43], [61] use Engbert and Kliegl's [39] algorithm to identify both saccades and microsaccades, with fixations obtained as a by-product of saccades, defined as microsaccades with magnitude $>1°$ visual angle.

A similar classification strategy is adopted by McCamy et al. [62] who use Engbert and Kliegl's [39] algorithm to identify microsaccades, with fixation periods defined as those during which saccades exceeding 1° were made.

In a slightly different approach, Egaña et al. [60] combine Engbert and Kliegl's [39] algorithm with another algorithm (i.e., developed by SR Research) to detect fixations. We opt for a similar approach, wherein we detect fixations *first*, using a saccade-detection algorithm, and then use Engbert and Kliegl's [39] to detect microsaccades within fixation periods.

Following blink removal (in the pilot study blink data is simply removed, blinks are handled slightly differently when pre-processing for microsaccade detection in the main study), we detect fixations from the unprocessed eye movement data following Nyström and Holmqvist [63], and by using the Savitzky-Golay [64] filter for velocity-based (I-VT [65]) event detection. The Savitzky-Golay filter fits a polynomial curve of order n via least squares minimization prior to calculation of the curve's s^{th} derivative (e.g., 1^{st} derivative ($s=1$) for velocity estimation) [66]. We used a 3^{rd} degree Savitzky-Golay filter of width 7 with velocity threshold of 100°/s, tuned to the sampling rate of our eye tracker.

Following fixation detection, each fixation is annotated with $\mathcal{K}_i$, computed as the mean difference between standardized scores (z-scores) of each saccade amplitude (a_{i+1}) and its preceding i^{th} fixation duration (d_i):

$$\mathcal{K}_i = \frac{d_i - \mu_d}{\sigma_d} - \frac{a_{i+1} - \mu_a}{\sigma_a}, \text{ such that } \mathcal{K} = \frac{1}{n}\sum_n \mathcal{K}_i, \quad (1)$$

where μ_d, μ_a are the mean fixation duration and saccade amplitude, respectively, and σ_d, σ_a are the fixation duration and saccade amplitude standard deviations, respectively, computed over all n fixations found in the given sequence comprising the given scanpath (i.e., spanning the duration of each stimulus presentation). Hence as there are n fixations, there are also n $\mathcal{K}_i$ coefficients, each corresponding to a fixation [18].

Blinks are handled slightly differently in the main study: following Engbert and Kliegl [39], prior to fixation detection, eye movement data is first extracted in a preprocessing step to remove data 200 ms before the start of, and 200 ms following the end of a blink, as identified by the eye tracker. Following this pre-processing step, we then locate fixations within the otherwise unprocessed gaze data as for the pilot study.

When detecting microsaccades, we use the unprocessed eye movement data (unfiltered by the eye tracking software), but only those segments delimited by the start and end of identified fixations. Within these segments, when gaze is fixed on a stationary object during a fixation, microsaccades can be detected in the raw eye movement signal, $\mathbf{p}_t = (x(t), y(t))$, using an adapted version of Engbert and Kliegl's [39] algorithm, detailed below.

The algorithm proceeds in three steps. First, we transform the time series of gaze positions to velocities via a moving average of velocities over 5 data samples,

$$\dot{x}_n = \frac{x_{n+2} + x_{n+1} - x_{n-1} - x_{n-2}}{6\Delta t}, \quad (2)$$

computed separately for $x(t)$ and $y(t)$. As Engbert and Kliegl note, due to the random orientations of the velocity vectors during fixation, the resulting mean is effectively zero. Microsaccades, being ballistic movements creating small linear sequences embedded in the rather erratic fixation trajectory induced by small drifts, can therefore be identified by their velocities, which are clearly separated from the kernel of the distribution as "outliers" in velocity space.

Second, computation of velocity thresholds for the detection algorithm is based on the median of the velocity time series to protect the analysis from noise. A multiple of the standard deviation of the velocity distribution is used as the detection threshold [67],

$$\sigma_x = \sqrt{\langle \dot{x}^2 \rangle - \langle \dot{x} \rangle^2}, \quad \sigma_y = \sqrt{\langle \dot{y}^2 \rangle - \langle \dot{y} \rangle^2}$$

where $\langle \cdot \rangle$ denotes the median estimator. Detection thresholds are computed independently for horizontal η_x and vertical η_y components and separately for each trial, relative to the noise level, i.e., $\eta_x = \lambda\sigma_x$, $\eta_y = \lambda\sigma_y$. Like Engbert and Kliegl [39], we used $\lambda = 6$ in all computations,[3] and we assume a minimal microsaccade duration of 6 ms (three data samples at 500 Hz). Following Engbert [67], as a necessary condition for a microsaccade, we require $\dot{x}$ and $\dot{y}$ fulfill the criterion $(\dot{x}_n/\eta_x)^2 + (\dot{y}_n/\eta_y)^2 > 1$.

Third, Engbert and Kliegl [39] focus on binocular microsaccades, defined as microsaccades occurring in left and right eyes with a temporal overlap. They exploit binocular information by applying a temporal overlap criterion: if a microsaccade in the right eye starting at time r_1 is found that ends at time r_2, and a microsaccade in the left eye begins at time l_1 and ends at time l_2, then the criterion for temporal overlap is implemented by the conditions $r_2 > l_1$ and $r_1 < l_2$. Following Duchowski et al. [69], we omit this step and average both left and right gaze points into a single point as would be looked at by a cyclopean eye, i.e., $(x(t), y(t)) = ([x_l(t) + x_r(t)]/2, [y_l(t) + y_r(t)]/2)$. A plot of the microsaccadic peak velocity/amplitude obtained from data captured in the main study (see below), similar to one shown by Siegenthaler et al. [8], is shown in Fig. 4.

V. Results

In the pilot study, analysis of results examines the use of $\mathcal{K}$ for its suitability in differentiating the dynamics of visual attention, i.e., whether differences in attention, specifically changing from ambient to focal, can be detected under differing levels of task difficulty.

In the main study, the analyses are more concerned with examining response accuracy and response time in the different experimental conditions, i.e., was the target feature correctly identified when it was present (low, mid, and high task difficulty conditions, i.e., high, mid, and low target elevation, respectively) and identified as absent when it was not present (the control condition). Visualization of typical scanpaths recorded during the main study are shown in Fig. 5 using ambient/focal visualization [70].

Main results are based on multi-way within-subject Analyses of Variance (ANOVA) which were followed by post hoc analyses with HSD Tukey method of p-value adjustment for multiple comparisons. The design of each analysis was matched to each tested hypotheses with fixed factors. We also report results of correlation analyses based on Pearson's R coefficient which checks the relation between the main dependent variables. All analyses were conducted in R, the computational language for statistical analyses [71].

A. Pilot Study

A two-way repeated-measures ANOVA on mean $\mathcal{K}$ using task difficulty (at four levels) and time period (also at four levels) as the fixed factors indicates a significant effect of time ($F(3, 21) = 5.19, p = 0.008, \eta = 0.20$) but not of task difficulty ($F(3, 21) = 2.33, p = 0.104, \eta = 0.04$).

[3] Mergenthaler [68] discusses how the choice of λ substantially affects the number of detected microsaccades. As λ increases, the number of detected microsaccades decreases.

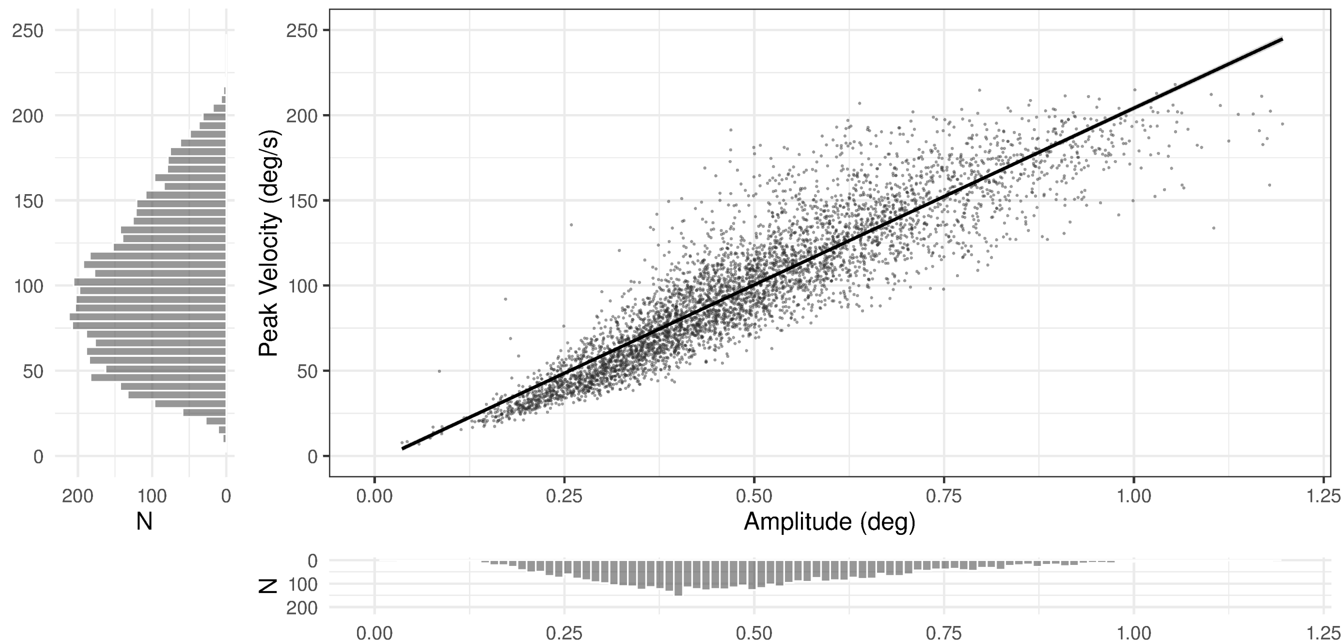


Fig. 4. Plot of peak velocity-amplitude (main sequence) relation of microsaccades detected in the main study.

Post-hoc pairwise analyses with Tukey HSD method of p-value adjustment, show a significant difference between the second and fourth time periods ($p=0.004$), see Fig. 6a. The interaction of condition and time period was not statistically significant, ($F(9,63)=1.68, p=0.113, \eta=0.09$).

Analysis of $\mathcal{K}$ suggests a greater proportion of focal fixations in the low difficulty condition versus the control condition, especially during the latter stages of inspection. Note that in all conditions, $\mathcal{K}$'s zero-crossing likely suggests transition from search to decision-making. The relative level of focal processing may coincide with increased cognitive load, e.g., greater uncertainty, and this is the temporal segment of visual processing when cognitive load measures need to be evaluated.

B. Main Study

The main study results first address performance metrics, i.e., response time and accuracy, followed by process metrics focusing on microsaccades dependent on task difficulty and ambient/focal coefficient $\mathcal{K}$. We start with descriptive statistics of the main dependent variables used in the analyses (microsaccade amplitude, microsaccade peak velocity, microsaccade rate, and coefficient $\mathcal{K}$) along with correlation with Pearson's R coefficient between microsaccade amplitude and peak velocity.

1) Descriptive Statistics and Correlation Tests

The descriptive statistics of the dependent variables considered in the main study are given in Table I. Not surprisingly, Pearson's correlation between microsaccadic amplitude and peak velocity is positive and statistically significant, $R = 0.906$, $t(4887) = 149.71$, $p < 0.001$. This result is consistent with the main sequence relation between these two microsaccadic properties [72].

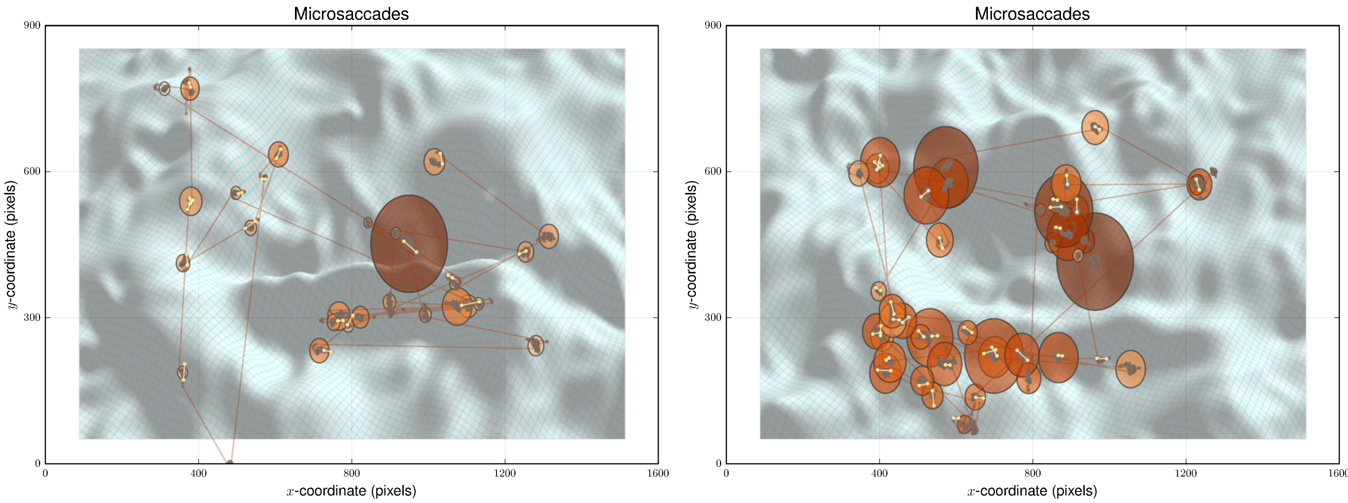
The correlation between microsaccade amplitude and ambient/focal coefficient $\mathcal{K}$ was not significant, $R = -0.005$, $t(4887) = 0.342$, $p = 0.733$. Similarly, Person's correlation showed no relationship between microsaccadic peak velocity and coefficient $\mathcal{K}$, $R = -0.006$, $t(4887) = 0.393$, $p=0.694$. The lack of correlation between microsaccadic properties and ambient/focal coefficient ensures that treating the latter as a factor in analyses of variance will not bias results.

2) Ambient/Focal Eye Movement Dynamics

Similar to the pilot study, a two-way repeated-measures ANOVA of mean $\mathcal{K}$ using task difficulty and time period as the fixed factors was conducted showing consistency with pilot study results. The analysis revealed a main effect of time period, $F(3,24) = 8.77$, $p < 0.001$, $\eta^2 = 0.12$. Post-hoc comparisons showed that in the first time period eye movements begin in focal mode (M = 0.12, SE = 0.04), become ambient in the second period (M = −0.22, SE = 0.04), and then slowly become more and more focal in the third (M = −0.04, SE = 0.05) and fourth periods (M = 0.14, SE = 0.05).

The analysis also showed a main effect of task difficulty. $F(3,24) = 8.43$, $p < 0.001$, $\eta^2 = 0.18$ Interestingly, participants in the control (target absent) condition used significantly ($p<0.02$) more ambient eye movements than in the high, mid, and low difficulty conditions, see Table I for descriptive statistics.

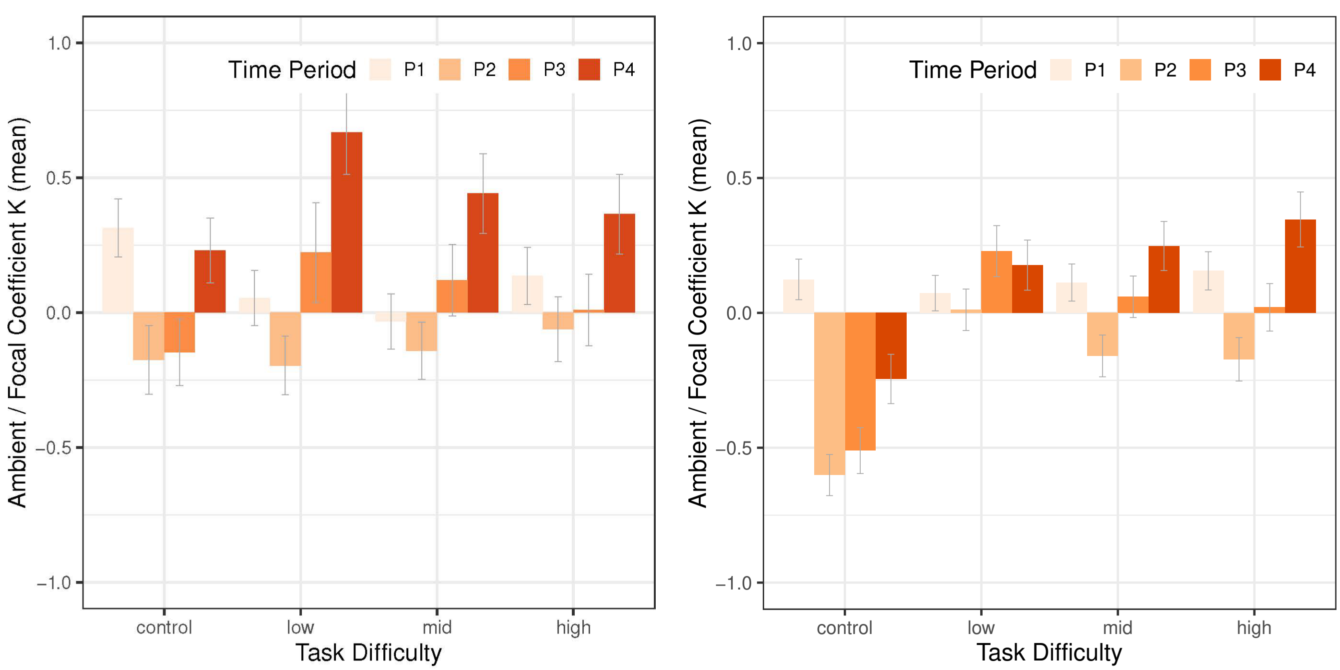
The effect of time period was moderated by task difficulty, resulting in a significant interaction effect, $F(9,72) = 2.88$, $p=0.006$, $\eta^2=0.09$. Although the pattern of means is similar to the main effect of time period in all conditions, a significant ($p<0.001$) change from focal eye movements in the first period (M = 0.12, SE = 0.08) to ambient in the



(a) Easy (high elevation) task.

(b) Difficult (low elevation) task.

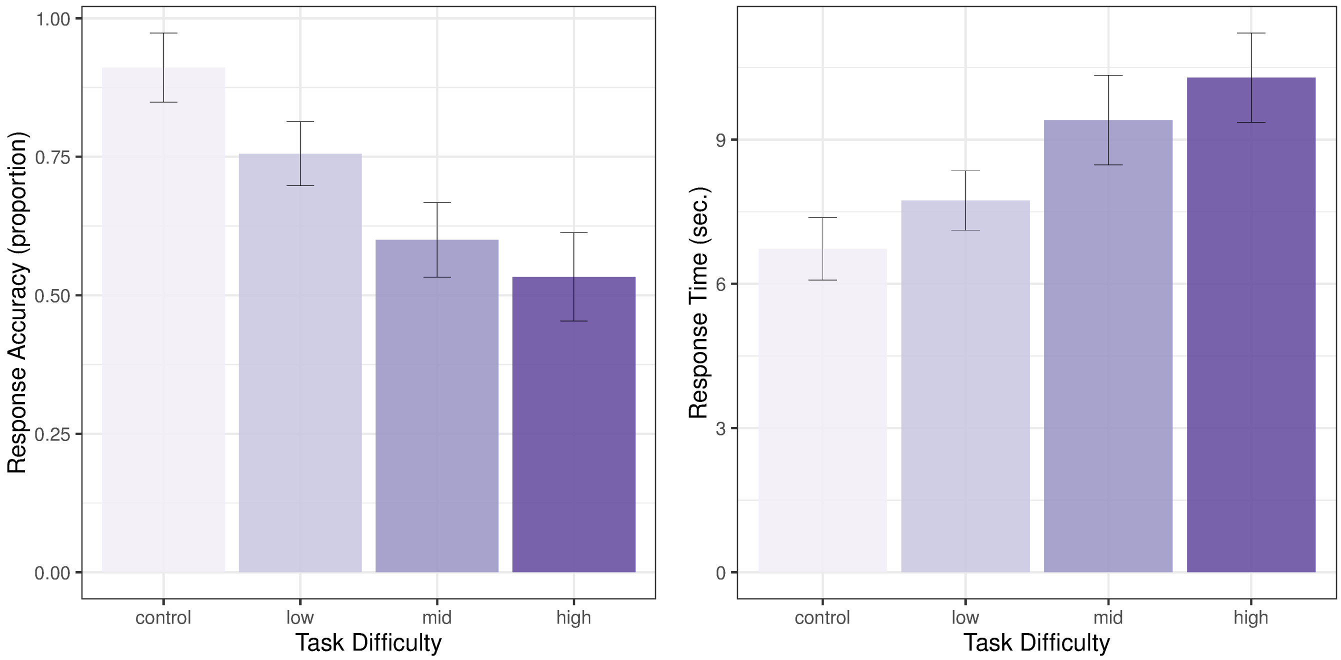
Fig. 5. Ambient/focal fixation visualization [70] of a typical participant's scanpath in the main study during easy (a) and difficult tasks (b). Focal fixations are drawn with a deeper shade of the color palette than ambient fixations. Raw (unprocessed) gaze points are shown in a dark grey color. Microsaccades are highlighted in a brighter yellow. Note that in the easy task the target is fairly quickly located with fairly short and relatively ambient fixations needed for the recognition decision. In the difficult task, however, the situation appears to call for a relatively larger number of longer, and more focal fixations to make the decisions. Scanpath plots are shown from the same individual.



(a) Pilot study.

(b) Main study.

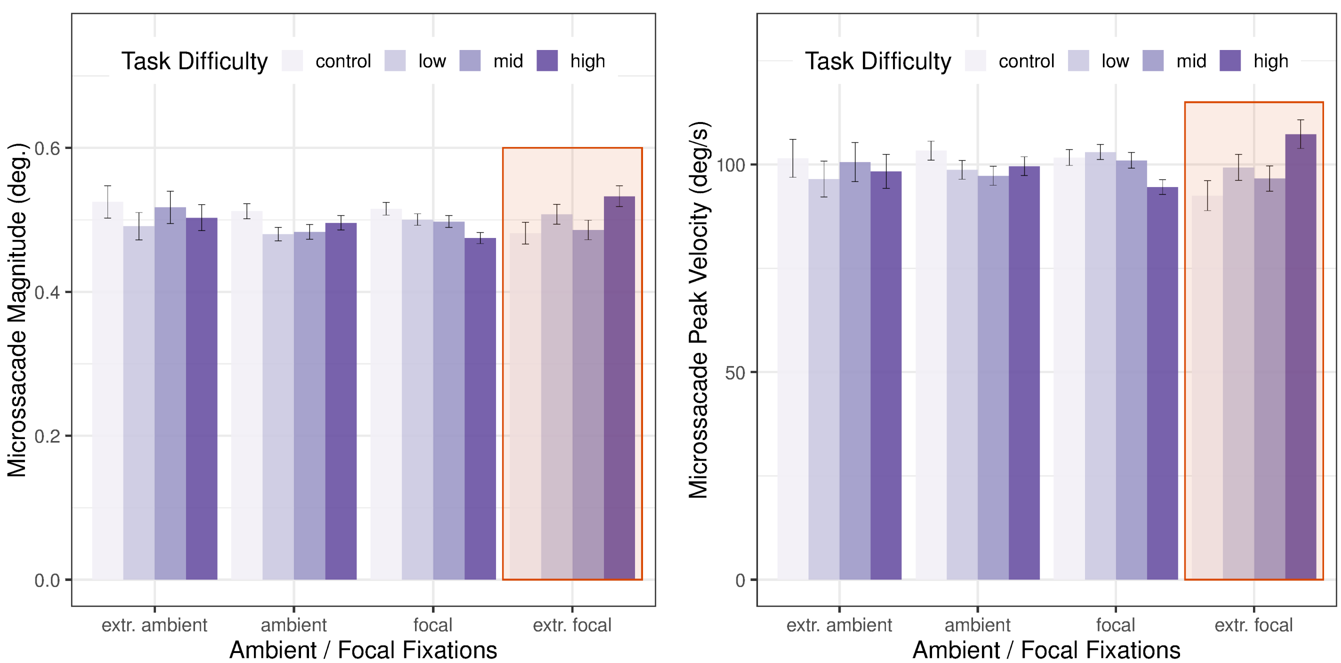
Fig. 6. Mean ambient/focal $\mathcal{K}$ over 4 time periods in different conditions. Whiskers indicate $\pm$1SE.



(a) Accuracy of responses.

(b) Decision time of correct responses.

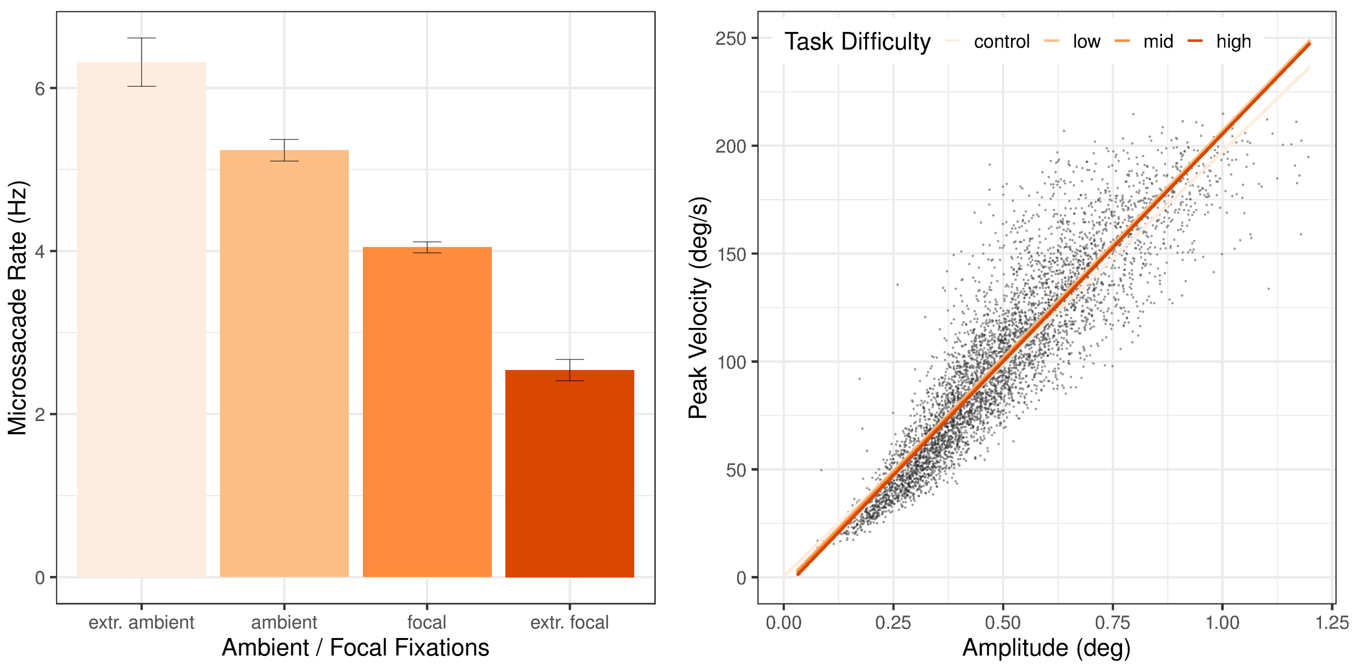
Fig. 7. Accuracy of responses and the decision times of correct responses in the main study. Whiskers indicate ±1SE.



(a) Microsaccade magnitudes.

(b) Microsaccade peak velocity.

Fig. 8. Microsaccadic responses dependent on task difficulty and ambient/focal fixations in the main study. Whiskers indicate ±1SE.



(a) Microsaccade rate.

(b) Microsaccade magnitude and peak velocity relationship.

Fig. 9. Comparison of microsaccade rate and magnitude–peak velocity relationship (main sequence) between experimental conditions in the main study. Whiskers indicate ±1SE.

second period (M $= -0.60$, SE $= 0.08$) was observed only for the control condition (target absent). When performing this task, participants' eye movements remain ambient through the last time period, see Fig. 6b.

3) Response Accuracy and Reaction Time

Two one-way analyses of variance were conducted in order to compare response accuracy and reaction time, dependent on task difficulty.

Analysis of accuracy revealed a significant main effect of task difficulty $F(3, 24) = 6.21$, $p = 0.003$, $\eta^2 = 0.24$, see Fig. 7a. The accuracy of detecting the absence of the target (control condition) was significantly ($p < 0.02$) higher than the task at mid and ($p < 0.01$) high difficulties with the latter producing the lowest accuracy, see Table I for descriptive statistics.

One-way ANOVA of decision time was conducted for only those trials where an accurate answer was given; trials with incorrect decisions were removed. Analysis approached the canonical level of significance of task difficulty, $F(3, 18) = 2.80$, $p = 0.069$, $\eta^2 = 0.09$, see Fig. 7b. Mean time to decide was longer approaching the canonical level of significance ($p = 0.071$) at high task difficulty than in the control condition (target absent), see Table I for descriptive statistics.

Both analyses of response accuracy and decision time (of correct responses) suggest that the high and mid task difficulties were more difficult for participants than either of the control (target absent) or low difficulty conditions.

4) Microsaccadic Response, Task Difficulty, and $\mathcal{K}$

To compare microsaccadic response to task difficulty, two two-way (4×4) within-subject analyses of variances were conducted with microsaccade rate and magnitude as dependent measures. In the analyses the two fixed factors were task difficulty (control or low, mid, or high) and mode of attention (ambient/focal).

Analyses of microsaccade rate revealed a significant main effect of $\mathcal{K}$, $F(3, 24) = 80.00$, $p < 0.0001$, $\eta^2 = 0.67$. Pairwise comparisons showed that all means were sig-

TABLE I

Descriptive statistics of dependent variables used in the main study. The table gives overall and condition-specific (task difficulty) means and their standard deviations (in parentheses).

Variable	**Overall**	**Control**	**High**	**Mid**	**Low**
Microsacc. Amplitude (deg)	0.497 (0.193)	0.509 (0.190)	0.492 (0.194)	0.493 (0.194)	0.495 (0.195)
Microsacc. Peak Velocity (deg/s)	99.667 (43.991)	100.820 (41.961)	98.366 (44.602)	99.022 (44.008)	100.627 (44.875)
Microsacc. Rate (Hz)	4.542 (3.536)	4.732 (3.473)	4.472 (3.393)	4.478 (3.399)	4.513 (3.839)
Microsacc. Amp.–Peak Vel. Intercept	-3.907 (10.515)	-1.817 (12.617)	-6.226 (9.094)	-3.102 (10.794)	-3.958 (9.310)
Msacc. Amp.–Peak Vel. Slope	208.172 (26.009)	201.172 (26.009)	212.611 (20.929)	207.645 (22.380)	211.618 (15.774)
Ambient-Focal Coefficient ($\mathcal{K}$)	0.00 (1.45)	-0.306 (1.590)	0.089 (1.723)	0.065 (1.551)	0.122 (1.680)
Response Accuracy (prop)	0.700 (0.460)	0.911 (0.419)	0.533 (0.080)	0.600 (0.452)	0.756 (0.058)
Correct Answers Response Time (sec)	8.359 (5.103)	6.728 (3.607)	10.290 (4.363)	9.405 (4.834)	8.020 (3.501)

nificantly different from each other with $p < 0.01$. The highest microsaccade rate was observed during extreme-ambient fixations (M = 6.32, SE = 0.30) and the lowest rate during extreme-focal fixations (M = 2.43, SE = 0.13). Mean microsaccade rates during ambient (M = 5.22, SE = 0.13) and focal fixations (M = 4.05, SE = 0.07) were in between the two extremes, see Fig. 9a. Neither main effect of task difficulty $F(3, 24) = 1.12$, $p = 0.36$, $\eta^2 = 0.02$, nor interaction effect (of task difficulty and $\mathcal{K}$), $F(9, 72) < 1$, $p = 0.91$, $\eta^2 = 0.02$, was statistically significant.

The analysis of microsaccade magnitude revealed a significant interaction effect of task difficulty and $\mathcal{K}$ split into four levels, $F(9, 72) = 2.27$, $p = 0.027$, $\eta^2 = 0.06$. Pairwise comparisons, where $\mathcal{K}$ split into four levels was treated as the moderating factor, showed that microsaccade magnitudes differed between task difficulties only during extreme-focal fixations. Microsaccade magnitude was significantly greater ($p < 0.05$) at high task difficulty (M = 0.53, SE = 0.01) than either at mid task difficulty (M = 0.49, SE = 0.01) or control (M = 0.48, SE = 0.02), see Fig. 8a.

All other pairwise comparisons lacked statistical significance ($p > 0.1$). Neither main effect of task difficulty $F(3, 24) = 1.06$, $p = 0.38$, $\eta^2 = 0.02$, nor of $\mathcal{K}$ $F(9, 72) < 1$, $p = 0.63$, $\eta^2 = 0.01$, was significant.

As expected, in line with the above findings, microsaccadic peak velocity, treated as a dependent variable in the same ANOVA design, reached significance, $F(9, 72) = 2.62$, $p = 0.011$, $\eta^2 = 0.08$. Pairwise comparisons, where $\mathcal{K}$ split into four levels was treated as the moderating factor, showed that microsaccade peak velocity differed between task difficulty only during extreme-focal fixations. Peak velocity was significantly greater ($p < 0.05$) at high task difficulty (M = 107.33, SE = 3.46) than either at mid task difficulty (M = 96.64, SE = 3.04) or control (M = 92.49, SE = 3.60), see Fig. 8b. All other pairwise comparisons lacked statistical significance ($p > 0.1$). Neither main effect of task difficulty $F(3, 24) < 1, p = 0.59$, $\eta^2 = 0.009$, nor of $\mathcal{K}$ $F(9, 72) < 1, p = 0.99$, $\eta^2 = 0.0006$, was significant.

We compared the linear model parameters of the microsaccadic main sequence, i.e., the peak velocity-magnitude relation, between differing levels of task difficulty, as this relation may be expressive of trial difficulty [72]. A linear model was fit to the main sequence of each participant in the main study during each task difficulty yielding the intercept and slope as dependent measures.

ANOVA of the intercept as dependent variable showed no significant main effects of task difficulty $F(3, 24) = 2.17$, $p = 0.12$, $\eta^2 = 0.09$, ambient/focal fixations, $F(3, 24) < 1$, $p = 0.45$, $\eta^2 = 0.002$, or of interaction of these two factors, $F(9, 72) < 1, p = 0.90$, $\eta^2 = 0.004$, see Table I for descriptive statistics.

However, in line with the results of Di Stasi et al. [72] and our predictions, the analysis of slope revealed a statistically significant main effect of task difficulty $F(3, 24) = 3.89$, $p = 0.021$, $\eta^2 = 0.21$, see Fig. 9b. Pairwise comparisons revealed that the main sequence slope is significantly ($p < 0.02$) steeper when participants searched at low task difficulty (high elevation features) compared to the target-absent trials (control condition). The difference between slopes of the target-absent and difficult tasks (low elevation feature searches) approached the canonical level of significance ($p = 0.08$), see Table I for descriptive statistics. No other pairwise comparisons showed significant differences. Neither main effect of ambient/focal fixations $F(3, 24) < 1$, $p = 0.51$, $\eta^2 = 0.003$, nor interaction effect of both fixed factors was significant $F(9, 72) < 1$, $p = 0.85$, $\eta^2 = 0.007$.

VI. Discussion

Performance measures (decision time and response accuracy) appear to confirm the relative task difficulties of the visual search tasks. The task with highest difficulty was the search task for the target at low elevation, which took the longest to complete and for which accuracy was lowest at about 50%. The control (target absent) task appears to have been the easiest, yielding highest accuracy and lowest response times (see Fig. 7). Interestingly, the control task was mainly composed of ambient fixations (see Fig. 6), possibly due to the task requiring no decision as to whether the fixated target was in fact the sought one. That is, deciding that the target is absent precludes a further decision of whether what is being fixated is or is not the target. In this situation therefore, we argue, examining cognitive load makes little sense. Indeed, within fixations that are not extremely focal ($\mathcal{K} > 1$), no cognitive load, as would be indicated by microsaccadic response, was detected (see Fig. 8). Further examination of microsaccadic response suggests that: (a) microsaccade magnitude increases with task difficulty within focal search, as delineated by $\mathcal{K}$, and (b) microsaccade rate decreases with increased focal attention, as delineated by $\mathcal{K}$.

The combined use of $\mathcal{K}$ and microsaccade analysis potentially indicates cognitive activity within visual search if the implied causality of (or perhaps logical biconditionality between) microsaccadic response and cognitive load can be assumed. Increased microsaccade magnitude coupled with decreased microsaccade rate imply increased cognitive load but only during the focal component of visual search. Indeed, Loughnane et al. [73] showed that microsaccade rate decreases during decision-making.

In contrast, in a free-viewing visual search protocol, Privitera et al. [74] found that fixations on targets generated more microsaccades and more microsaccades were generated for those targets that were more difficult to disambiguate. However, they noted that microsaccades reflected the saliency of the object of interest and that their finding was consistent with cognitive load inherent in the process of recognition.

Providing a somewhat neutral viewpoint, Strauch et al. [75] suggest that microsaccade rate does not predict choice, e.g., decision-making, but indicates a key press. However, they did report initial microsaccade suppression at stimulus onset in a Go/NoGo decision task and suggested that microsaccade rate in decision making has not been purposefully investigated. The implications of our findings are important as they suggest a novel means of estimating cognitive load during unconstrained visual search of abstract stimuli. The use of $\mathcal{K}$ to delineate ambient/focal fixations allows objective analysis of visual behavior via microsaccadic response *within focal fixations*. The $\mathcal{K}$ coefficient in effect allows exclusion of ambient fixations, which are used during search of candidate search targets but not during target discrimination [18]. Without this delineation, microsaccadic response to task difficulty is obscured. By combining two measures of positional eye movements, we are able to objectively discern task difficulty *vis-à-vis* cognitive load during visual search.

The chief limitation of the use of microsaccadic response is the need for a high sampling rate, i.e., > 300 Hz, well beyond the capability of commonly available eye trackers.

VII. Conclusion

We add to the investigation of microsaccade dynamics results from a cognitive visual search task of a textured, Gabor surface. We found microsaccadic response to task difficulty during the focal, decision-making stage of the visual search task, as delineated by the ambient/focal $\mathcal{K}$ coefficient. Our results may suggest a potentially new method for the measurement of cognitive load during visual search, combining traditional positional eye movement metrics with microsaccades.

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