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A methodology for capturing and fusing unconscious cognition with computation

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Abstract

Based on the potential power of human-computer symbiosis, we present a methodology to capture and fuse unconscious cognition with high-powered computer analysis to improve the solution to complex computational problems. Unconscious cognition can be captured using non-intrusive sensors such as eye trackers when stimuli are controlled, and this system's response signal has the resolution to differentiate between conscious deliberate movements from the unconscious. This post-processed response signal, when combined with the power of computation, will provide a dynamic pathway to enable enhanced discovery and understanding in complex problem-solving domains, aiding effective decision-making. A central result of this paper is a methodology that can rank order unconscious cognition responses for prioritization into the computational engine, demonstrated using eye-tracking measurements on visual search.

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Keywords: Human-computer symbiosis; Eye tracking; Unconscious cognition; Visual search; Fuzzy logic; Decision-making

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1. Introduction

Based on the potential power of human-computer symbiosis, we present a methodology to capture and fuse unconscious cognition with high-powered computer analysis to improve the solution to complex computational problems.

A key assumption is that experts who have been trained in specific scenarios, have intuitions that are accurate most of the time. Most researchers and experts agree that intuition is a rapid, associative process that drives judgments without the use of deliberate, conscious reasoning [1, 2]. It is this unconscious, rapidly generated behavior, we intend to capture and aid via computation. Unconscious cognition can be captured using non-intrusive sensors such as eye trackers, and its response signal has the resolution to differentiate deliberate conscious behavior from the unconscious. This post-processed response signal, when combined with the power of computation, will provide a dynamic pathway, to enable enhanced discovery and understanding in complex problem solving-domains aiding effective decision-making. A central result of this paper is a methodology that can rank order unconscious cognition responses for prioritization into the computational engine, demonstrated using visual search eye-tracking measurements.

Our review of the literature and prior research resulted in the identification of two ways to elicit intuitive cognition: 1) force-choice decision tasks, which elicit non-conscious processing [3], and 2) a probable response-time window, which serves as a quantifiable boundary for intuition [4]. Ultimately, this method forces user selection, and creates time-pressure conditions upon which responses arise with minimal influence of conscious reasoning.

As an estimate for a probable response-time window we use knowledge of event-related potential measurements through a dense-array EEG within 280ms [5], which serves as a window in which intuition occurs. This measure also aligns closely with the prominent P300 measure of neurological reactions to a given stimulus [6]. While quantifying intuition like behavior at a neurological level, it is important to note that these measures are event related potentials, and do not represent the added time for motor responses (i.e., the time it takes to respond with a choice after initial perception of stimuli). This is critical for our purposes because our inputs will be generated through user responses, not neurological assessments. Hence, response timings will have to be adjusted for different sensors and measurement setups.

In addition to these force-choice decision tasks and probable response-time window, we signal process the response to employ additional and practical measures of unconscious cognition, namely speed to respond to stimuli and wavering of response, to help rank order the unconscious cognition inputs. We rank order the measured response signals to stimuli using a novel, fuzzy logic-based approach. Preliminary test results using representative test data - images (stimuli) and their corresponding responses – are promising and provide preliminary validation of our research approach.

Finally, we illustrate the potential practical benefits of this research by describing realistic application concepts. The currently chosen experiments are driven by visual search of images for object identification. Openly available image data sets are used to demonstrate how the technology solution combines human unconscious cognition inputs with Artificial Intelligence (AI)-based computational methods, to enable robust problem solving and decision support.

2. Experimental methodology

An eye tracker is a powerful sensor that gives an accurate representation and understanding of an individual's eye movement behavior. The technology has come a long way in the last decade, and it is almost unobtrusive today. It currently has a price point (< USD $100) that could facilitate the deployment of such hardware as standard user interface in computer systems, in the very near future. However, eye trackers are not mind-reading devices. They can tell us where the person looked at, but not why.

Our goal in this research is to measure eye tracking movements of different users on various image stimuli and differentiate movement patterns or behaviors during visual search. We hypothesize that different visual search behavioral patterns are induced due to differing levels of unconscious cognition triggers. While we cannot attribute the eye movement behavior to specific human thought processes, the grading of these unconscious cognition signals could be used as additional inputs in man-machine symbiosis applications.

Fig. 1. Image Stimulus and Eye Track.

To demonstrate our concept, the first task is to set up visual stimuli that are generic for the average adult, and does not require any specific domain knowledge or training. We also have to ensure that human eye trace behavior is independent of the images that are used. So the goal of experimental design is to present different image categories with different complexity and monitor and differentiate eye trace behavior. We can then argue that the technique will scale in general.

We choose the freely downloadable and categorized Corel image database [7] to assemble a visual stimuli. The visual stimuli for these experiments is a 10*15 grid of 150 butterfly images, randomly assembled from the image database. We call this the background. We replace one of the grid butterfly images with an image of a tiger (Fig. 1). The visual search task is to locate the tiger from among the butterflies. The white track is a typical eye trace from center of screen to the tiger.

The image stimulus is presented to the user for only about 5 seconds maximum and the user has to locate the tiger within this time period. Thus, this is a forced choice task and the user's job is to as quickly as possible, locate the tiger from among the butterflies and stay focused on the tiger once discovered. Whether the user locates the tiger or not, the next visual stimulus image is displayed after the set time interval. The user then initiates the next visual search from where they left off from the previous image stimulus. A maximum of 10 image stimuli are presented for one experimental run (category), so as not to tire the user.

The four image stimuli categories reflecting differing levels of complexity in tracking the target are:

1. Keep the background butterfly *image grid the same* and vary the location of the *same tiger* image at random.
2. Keep the background butterfly *image grid the same* and vary the location of *different tiger* images at random.
3. Reassemble the background butterfly *image grid with different butterfly images* and vary the location of the *same* tiger image at random.
4. Reassemble the background butterfly *image grid with different butterfly images* and vary the location of *different tiger* images at random.

User's eye traces are captured for the four experimental categories above, for ten image stimuli in each category, totaling to 40 measurements. For these initial experiments we had four users with ages ranging from 20 to 60. Hence there were 160 experiments in total for 4 users each with 40 measurements. The goal was to check for differentiable eye trace pattern behaviors while undertaking visual search. The experimental categories cater to differing tiger image contrast with respect to the background butterfly images, presenting different difficulties of search. The four experimental categories get more complicated from 1 to 4 listed above. Irrespective of the complexity of the image stimuli, there are similar patterns of eye trace behavior, across all categories. As the stimuli gets complex there is more searching for the target, and hence a more conscious deliberate response.

The eye is constantly scanning around to help construct a complete picture of what we are looking at. This process is divided into fixation – the pause of the eye movement on a specific area of the visual field and saccades – rapid movements of the eye from one fixation to another. Saccades help stitch the complete scene together. Fixations take place in our foveal vision, which accounts for nearly half of the visual information sent to our brain and is highly detailed and provides complete clarity about what we are looking at [8]. Eye trackers only track an individual's foveal vision, which accounts for less than 8% of our visual field [9].

In the first experimental category, for every new stimulus the background image remained the same and the same known tiger image was randomly moved around. Without going into the details, the eye perceives the difference between the current and previous images and is hence able to detect the new random tiger location with much more ease for the first experimental set as compared to the last category, where the background and the tiger image is new for every new stimulus. What is being detected by the user could be a change or movement of stimulus in the peripheral vision [10] rather than the actual tiger. In this case the visual search is decisive and the eye moves rapidly from start point on image to the target tiger image as seen in Fig. 1. When the stimulus includes changing backgrounds or the tiger image, contrast is too close to those of neighboring butterflies, hence detection becomes difficult and the eye traces a longer path hunting for the tiger. This then becomes a deliberate and conscious search.

Our intent is to develop a robust methodology by signal processing the eye trace signals to differentiate between these two extreme behaviors, a rapid decisive movement versus an indecisive and conscious movement.

3. Results and discussions

We have successfully developed a methodology that can differentiate between the two extreme behaviors in eye traces during visual search – a rapid decisive movement versus an indecisive and conscious search pattern. We can also show that these two behaviors are universal and independent of the variations in stimuli as tested. These behaviors exist on the four categories of images tested. We can further generalize that these results are not dependent on the specific images of the butterflies or tiger as in our experiments.

Eye trace for every image stimulus start at different locations depending on where the eye was at the previous stimulus. In Fig. 1 the eye trace started at the center of the screen as it was the first image displayed. In Fig. 2(a) the eye trace started where the eye was looking at the end of the previous image stimuli. Hence we have to normalize eye traces to compare responses across different stimuli. Fig. 2(b) shows the normalized eye trace for that in Fig. 2(a). The starting point is always normalized to (0, 0) and the end point to (1, 1) so that all in-between points are scaled to these end points. In practice we take the mean of a group of points at start and end respectively, to ensure statistical stability of end points. The straight line connecting the end points is just for reference.

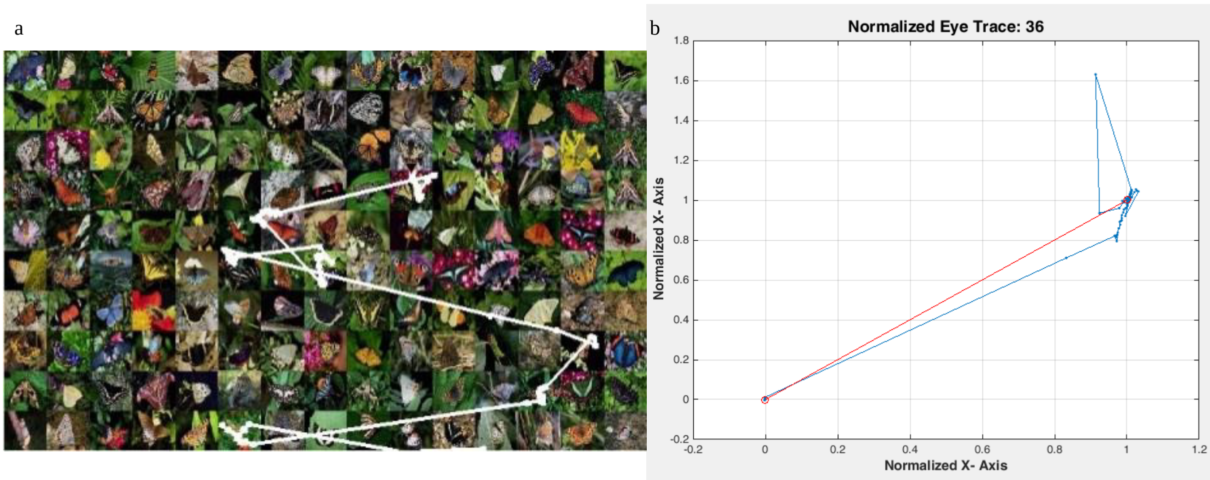

Fig. 2. (a) Conscious Visual Search; (b) Normalized Eye Trace.

One of the key results of this work is to design a computational routine that can distinguish between a deliberate conscious wavering search similar to Fig. 2(a) and that of an unconscious not so wavering search path as in Fig. 1. All eye trace responses for stimuli images such as shown in Fig. 1 and Fig. 2(a) are first normalized as shown in Fig. 2(b). We then extract features from this normalized signal. The features of interest are based on knowledge of intuitive like behaviors such as 1) wavering and 2) reaction time.

Specifically, wavering can be computed as the total path traversed by the eye trace in the normalized plot. Since the distance between start and end is normalized to unity, the length of path is an indicator of how much longer it took vis-à-vis, a straight line path, the shortest distance between start and end points.

Reaction time can be represented using various features. We use average velocity around start point and end points to be a proxy for reaction. A deliberate move would involve high start velocities. However, a lower end velocity around points clustering towards a target end point, would be an indicator of having reached the search goal. Note that this does not ensure the participant has found the search goal, but only that the eye has settled on some region of interest on the image stimulus. In addition to start and end velocities, we use the average velocity of the entire trace and its average acceleration as additional proxies for reaction. Given these five input features 1) *Waver* 2) *VelRatioStart* - average velocity at start point 3) *VelRatioEnd* - average velocity at end point 4) *VelRatio* - average trace velocity and 5) *AccnRatio* - average trace acceleration, we can build a rule engine that predicts if the eye trace is a deliberate unconscious response - *UCog* or not. The output of the Fuzzy computation *UCog* tends to unity as the eye trace is classified as an unconscious response.

We use the Fuzzy logic Toolbox in Matlab® [11] using the Mamdani Method to implement common sense, human interpretable, intuitive rules based on the above five input features, to compute the output *UCog*. The Fuzzy Inference Rules shown in Fig. are easily interpretable. If eye trace input feature, *Waver* is low then *UCog* – the output of the Fuzzy computation indicating unconscious cognition is high and vice versa. As explained earlier higher velocity at start indicates deliberate moves and lower velocity at end indicates settling down to some region, both indicative of high *UCog*. The six rules shown in Fig. are self-explanatory and have produced good outputs.

To evaluate the performance of the fuzzy classifier we had to manually annotate all the 160 experiments to look for eye traces and evaluate if the trace represented a pattern similar to Fig. 1 or Fig. 2(a). The error was then computed as the difference between the fuzzy output and the human evaluation. Fig. 4 shows the errors in the fuzzy computational engine. The accuracy is about 90% across the entire experimental set.

We can further improve the accuracy of this fuzzy engine. However, the purpose of this work was to demonstrate a methodology to capture behavior from eye traces that can augment computation. We have demonstrated that computing human behavior signals from eye traces is feasible. The next step is to use this input to augment applications.

1. If (Waver is LOW) then (UCog is HIGH) (1)
2. If (Waver is HIGH) then (UCog is LOW) (1)
3. If (Waver is MED) then (UCog is MED) (1)
4. If (VelRatioStart is HIGH) and (VelRatioEnd is LOW) then (UCog is HIGH) (1)
5. If (VelRatioStart is LOW) and (VelRatioEnd is HIGH) then (UCog is LOW) (1)
6. If (VelRatio is LOW) and (AccnRatio is LOW) then (UCog is LOW) (1)

Fig. 3. Fuzzy Inference Rules.

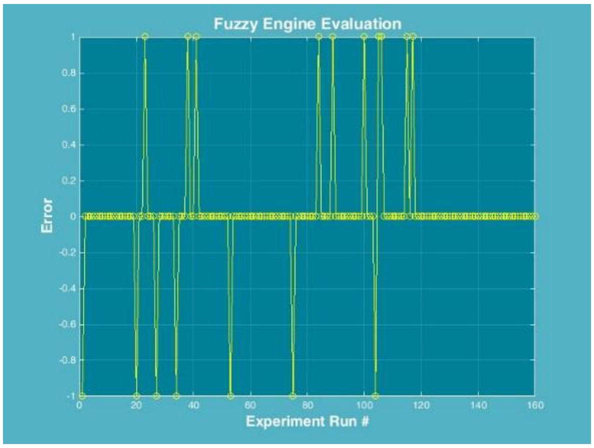

Fig. 4. Fuzzy Rule Evaluation.

4. Potential applications and future R&D

In the next phase of our work we are developing applications driven by the fuzzy engine using our technology called "*Virtual Hyperlink*". We call it virtual as there is no hyperlink marked as such.

The first one is a browsing application, where when a user's attention jumps rapidly to another region on the screen, additional details of artifacts at the end point of the eye track is presented to the user as a non-intrusive pop up window that fades away when the focus of the eye is changed. If the eye focus lingers on the pop up window, the user can explore further details, provided the computational engine has access to relevant information to display.

A second application is for image exploration. Image analysts who have to review a large number of images without a specific directed search intent other than to look for domain specific anomalies, can leverage the *Virtual Hyperlink* technology. Their next image presented to the analyst will be based on their eye trace signal behavior on the current image stimulus. Images similar to regions in the image that command their attention will be fed to them at a higher rate for evaluation. This could be thought of as a *visual directed search*. The analyst looks for artifacts of interest and the computation engine delivers images with similar artifacts back to the analyst. Focusing on a different artifact set will then drive the computation engine in the new chosen direction.

5. Conclusions

We have demonstrated a methodology to capture unconscious cognition using eye tracking signals on image stimuli, post-processed by a fuzzy logic engine based on intuitive rules of behavior. Unconscious cognition can be captured using non-intrusive sensors such as eye trackers when the stimulus is controlled and its response signal has the resolution to differentiate the conscious from the unconscious. Using four different categories of image sets across four different users we show that two distinct eye trace behaviors can be detected 1) an unwavering quick and direct path towards object of interest and 2) a wavering slower undecided long path searching for a target. These behaviors are observed irrespective of the complexity of the visual search problem.

We then describe two computer applications to improve the solution to complex computational problems by fusing computational power with such human behavior responses.

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