International Journal on Semantic Web and Information Systems
Volume 20 • Issue 1

SSVEP-Enhanced Threat Detection and Its Impact on Image Segmentation

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ABSTRACT

Selective attention, essential in discerning visual stimuli, enables the identification of threats such as snakes—a prime evolutionary influence on the human visual system. This phenomenon is encapsulated in snake detection theory (SDT), which posits that our ancestors' need to recognize these predators led to specialized perceptual abilities. This investigation utilizes steady-state visual evoked potentials (SSVEP) alongside the random image structure evolution technique, which systematically increases visual clarity through the interpolation of random noise, to probe the neural mechanisms underpinning selective attention, with a focus on serpentine forms. These findings underscore snakes' unique perceptual impact due to their curved forms and scaled textures, crucial for quick recognition—advancing image semantic segmentation and recognition tech.. This is particularly relevant for security and wildlife management, showcasing the evolutionary progression and cognitive prowess of the human visual apparatus.

KEYWORD

Image Semantic Segmentation, Selective Attention, Snake Detection Theory, Steady-State Visual Evoked Potentials

1. INTRODUCTION

Selective attention refers to the mechanism by which an individual prioritizes processing specific representations while overlooking other concurrently presented representations (Anderson, 2005). Past studies have identified different kinds of selective attention processes, often defined by the attributes of task-specific stimuli, including their location or substance. Each type of attention mechanism may involve the coordinated effort of multiple brain regions, ultimately leading to changes in sensory representation, memory, cognitive processes, or directed motor program. A prominent

DOI: 10.4018/IJSWIS.336550
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role of attentional processes is the effective discernment and recognition of cues associated with threats. Studies on healthy individuals indicate that cues signaling threats are identified with greater speed and precision compared to neutral ones. These mechanisms, crucial in natural environments, also play a significant role in various technological domains. For instance, they are instrumental in media-based surveillance systems, federated cloud systems, and image encryption methods that utilize quaternion Fresnel transforms (Stergiou, Psannis, Gupta, 2021; Yu et al., 2018). The ability to rapidly respond to visual threats is also evident in recent advancements in image recognition technologies that leverage visual saliency for more effective image retrieval (Wang et al., 2020). For instance, Nhi and Le explored semantic-based image retrieval, emphasizing the role of visual cognition in understanding threats (Nhi and Le., 2022; Memos et al., 2018; Mandle et al., 2022; Chopra et al., 2022). Moreover, the memories linked to these threats tend to be more resilient and less prone to disruption by unrelated information 200909). Advances in image retrieval and style transfer technologies have demonstrated the application of these cognitive principles in artificial systems as well (Qian et al., 2022), suggesting that threat cues are given processing priority, thereby affording organisms strong adaptive capabilities in their environments.

Selective attention plays a pivotal role in enabling organisms to focus on specific stimuli in their environment while ignoring others. This ability has evolved over time to allow species to better detect and respond to potential threats or opportunities, enhancing their chances of survival. A salient example illustrating the evolutionary significance of selective attention is the Snake Detection Theory (SDT) (Murray, & Foote, 1979). The SDT suggests that snakes, due to their efficient hunting techniques and potent venom, posed a significant threat to primate ancestors over millennia. This threat necessitated the evolution of the primate and human visual systems to rapidly and effectively recognize snake presence. In line with this theory, snakes are believed to have exerted selective pressures on the evolution and expansion of primate visual systems. Consequently, this pressure prompted primates to prioritize vision as their primary sensory modality for environmental interaction, further contributing to enhanced visual acuity. Recent studies in image classification and recognition echo these evolutionary trends, underscoring the importance of visual cues in cognitive processing (Chu et al., 2022; Zheng et al., 2022; Wang et al., 2020). As a result of this evolutionary pressure, natural selection would likely favor primates with superior visual abilities, thereby facilitating the detection of snakes concealed in their natural habitats (Öhman, & Mineka, 2001; Isbell, 2006; Lobue, & Rakison, 2013; Shibasaki, & Kawai, 2009; Kawai, & Koda, 2016; He, Kubo, & Kawai, 2014; Soares et al., 2009). Presently, a significant number of individuals maintain an innate aversion to snakes. This pervasive fear is frequently considered a result of evolutionary adaptations. With the rapid advancement in the field of computer vision, the areas of Emotion-based Image Synthesis and Semantic Image Processing have garnered widespread attention and achieved notable successes. Current methods in image and text sentiment analysis often focus on the interplay between image and text modalities, yet they tend to overlook the inconsistencies and correlations within image and text data. This challenge becomes particularly evident in the semantic segmentation of emotional images(Yin, & Chen, 2023). Addressing this challenge may require seeking inspiration from exploring the potential of image generation technology in producing the desired emotional images. This approach could open new avenues for creating visually compelling content that resonates with human emotions and possesses a high degree of realism. For instance, recent studies have quantitatively examined how AI-generated cosmetic packaging designs impact consumer satisfaction and emotions (Chen, Luh, & Wang, 2023). By extending these approaches to emotional images, we could uncover new insights into creating more accurate and emotionally resonant images. However, creating emotionally evocative images with high realism remains a challenge. This is particularly true for negative emotional images, which are characterized by complex structures and rich textural details, such as numerous snake images. This paper introduces an improved experimental paradigm based on Steady-State Visual Evoked Potentials (SSVEP). This approach studies emotional images that effectively capture human selective attention and identifies unique features of negative emotional images. Our research aids in comprehensive behavioral valence measurements for synthesized images and highlights the cognitive importance of primary contours or texture features in visual recognition. These findings will guide future developments in image generation and semantic segmentation, emphasizing key low-level features for generating threat-related images.

In the past decade, significant contributions have been made by numerous researchers in understanding the effects of visual distraction under emotional stimuli on a neural timescale, particularly through the use of steady-state visual evoked potentials (SSVEP). Additionally, various SSVEP-BCI systems have been developed. SSVEP is the brain's response to periodically presented visual stimuli, with its fundamental frequency response matching the frequency of the visual stimulus. Notably, the SSVEP amplitude elicited by objects that receive focused human attention significantly increases compared to those stimuli that are ignored]. In paradigms with competitive stimuli, SSVEP signals and frequency-tagging techniques enable researchers to individually measure the cortical neural group responses associated with simultaneously presented stimuli. Due to its excellent signal-to-noise ratio (SNR), SSVEP offers the possibility of tracking the dynamics of visual cortical changes over extended time scales in single trials. Given the aforementioned advantages of SSVEP in researching selective attention, we utilized the sweep SSVEP paradigm in this study to explore participants' cognitive performance as they observed images of animals with varying threat levels, with the blurriness of these images decreasing systematically over time. This methodology aligns with recent studies emphasizing the importance of semantic features in image analysis and machine learning classifiers (Almomani et al., 2022). To achieve this, we utilized random image structure evolution techniques, enabling a systematic increase in image clarity. Inducing SSVEP involves making the image stream flicker at a fixed frequency, which embeds low-level information into the images. This technique is closely related to our study, where we explore human visual responses to potential threats. The ability to detect and interpret visual cues is crucial in both natural settings and technological applications such as DFT-based image steganography (Jelušić et al., 2022). This approach not only allows us to evaluate detection thresholds based on participants' behavior but also to study specific SSVEP response components in the EEG spectra as the structural visibility of the animal images incrementally improves. Ultimately, this provides a means to assess the human visual system's response capabilities to potential threats, which can be applied to future image semantic segmentation technologies. By focusing attention on specific features within the image, such as the shape and texture of snakes, we gain insights into how humans rapidly and accurately identify these patterns. This knowledge can be translated into algorithms that enhance image analysis technology, particularly relevant for applications in security monitoring, autonomous vehicles, and augmented reality (Memos et al. 2018). These advancements will enable machines to not only 'see' but also 'understand' the content of images, responding and making decisions based on this understanding. Our aim is to learn from the human visual recognition mechanism to improve machine interaction with the real world.

2. RELATED WORK

In exploring Selective attention, behavioral psychologists have developed a variety of experiments, many involving visual search tasks, which are intended to evaluate visual cognition when visibility is impaired. One prominent method is the continuous flash suppression (CFS) technique, which incrementally degrades visual clarity (Gomes et al., 2018). In parallel, research in image watermarking and encryption highlights the complexity of visual processing in digital domains (Li et al., 2019; Yu et al., 2018). Findings from these studies have shown that participants can swiftly identify snake images by discerning low spatial frequency information (Kawai, & He, 2016). This observation suggests that the superior colliculus (SC)-pulvinar pathway, leading to the amygdala, may play a pivotal role in the mechanisms for rapid fear detection. Building upon this premise, other experiments have incorporated the Random Image Structure Evolution technique. This technique, which perturbs image phases to produce blurred visual perceptions, has shown remarkable results. This method perturbs image phases to produce blurred visual perceptions. Remarkably, results have revealed that humans can still accurately identify snake images even in these compromised visual conditions . Collectively, these experimental findings provide preliminary behavioral evidence in support of the Snake Detection Theory (SDT). While behavioral experiments have shed significant light on the heightened visual sensitivity of primates, including humans, towards snakes, they are not without their constraints. Solely depending on behavioral data is fraught with complications. For instance, these results can be influenced by individual biases, strategies, or other cognitive factors, potentially clouding our understanding of the true biological mechanisms at play. Moreover, there's the risk that behavioral responses might not capture the full spectrum of nuanced neural activities elicited by varied visual stimuli, thus curtailing a comprehensive understanding of the specialized sensitivity mechanisms. In light of these considerations, the scientific community increasingly acknowledges the pivotal role of electrophysiological evidence in corroborating the Snake Detection Theory (SDT)(Van Le et al., 2013; Le et al., 2014; Le et al., 2016; Van Strien, Franken, Huijding, 2014).

Building on this, numerous studies employing early posterior negativity(EPN) measures have provided compelling evidence in support of the Snake Detection Theory. The Early Posterior Negativity(EPN) is a distinctive component of the Event-Related Potential(ERP). It is intricately linked to the emotional processing of stimuli, with a notable emphasis on handling aversive visual stimuli. As such, researchers commonly utilize ERP measurements to systematically assess the interplay between emotion and attention across various stages of cognitive processing (Schupp et al., 2006). Consistent with the Snake Detection Theory(SDT), it's been observed that snake imagery induces a considerably more pronounced EPN response than other animal images, drawing attention to the unique sinuous form of snakes as a possible catalyst for this amplified reaction (Strien et al., 2014; Van Strien, & Isbell, 2017). Further emphasizing the evolutionary importance of snakes, one investigation postulated that the instant visual attention garnered by snake images is an innate response, rather than merely a reaction to reported fear, especially when compared to reactions towards spider images Validating this hypothesis, subsequent research revealed that, in contrast to spiders, snakes invariably command heightened attention (Tsuchiya, & Koch, 2005). Adding another layer of intrigue, the unique scale patterns distinctive to snake skin, scarcely seen elsewhere in nature, have been associated with stronger EPN responses further highlighting the inbuilt vigilance and detection mechanisms tailored for these reptiles. While early posterior negativity (EPN) measures have provided significant insights into the Snake Detection Theory, the inherent limitations of transient ERP methodologies cannot be overlooked. The inherent low signal-to-noise ratio of the transient ERP method demands the recording and averaging of numerous trials to yield consistent transient ERP responses that differentiate specified images from control stimuli across a group of participants. This challenge is magnified when attempting to discern such differences within the data of a singular observer, let alone when focusing on distinct groups such as infants, children, or clinical populations (Tsuchiya, & Koch, 2005). Our research aims to achieve a more nuanced understanding of human perception toward threatening stimuli. To this end, we intend to employ brain-computer interface (BCI) technology, focusing particularly on steady-state visual evoked potential (SSVEP) features. The selection of the sweep SSVEP is based on its capability to capture the variations in visuocortical shifts at individual trial levels. Additionally, its connection with BCIs is noteworthy, as they usually offer improved bit rates and stability (Öhman et al., 2012). These characteristics position the sweep SSVEP as an especially suitable tool for addressing the dynamics of attentional bias in the context of Snake Detection Theory (Coelho et al., 2019).

3. MATERIALS AND METHODS

3.1. Participants

From the School of Mechatronic Engineering and Automation, six individuals participated in the study. Participants received academic credits or literature gifts for their involvement. The study included six participants: five men and one woman, all right-handed, with an average age of 23.95 years (standard deviation = 1.51). Based on their own declarations, none had any history of psychiatric illnesses, nor were they under medications impacting the central nervous system. Participants were instructed to rest adequately, avoid strenuous physical activities, and abstain from caffeine, nicotine, or any substances affecting the central nervous system before each testing session. Comprehensive details about the experimental procedure were provided, and participants gave their written consent. The study strictly adhered to the ethical guidelines outlined in the Declaration of Helsinki (1964).

3.2. Random Image Structure Evolution

Random Image Structure Evolution is considered a type of image morphing or degradation process, primarily used to create a series of transitional images between two grayscale images, smoothly transitioning in structure from a starting image to an ending one. This smooth transition effect of the images is achieved by manipulating the phase of the images in the frequency domain (Fourier space), which is commonly used in visual science research to study perceptual and cognitive processes. (Figure 1 had been presented)

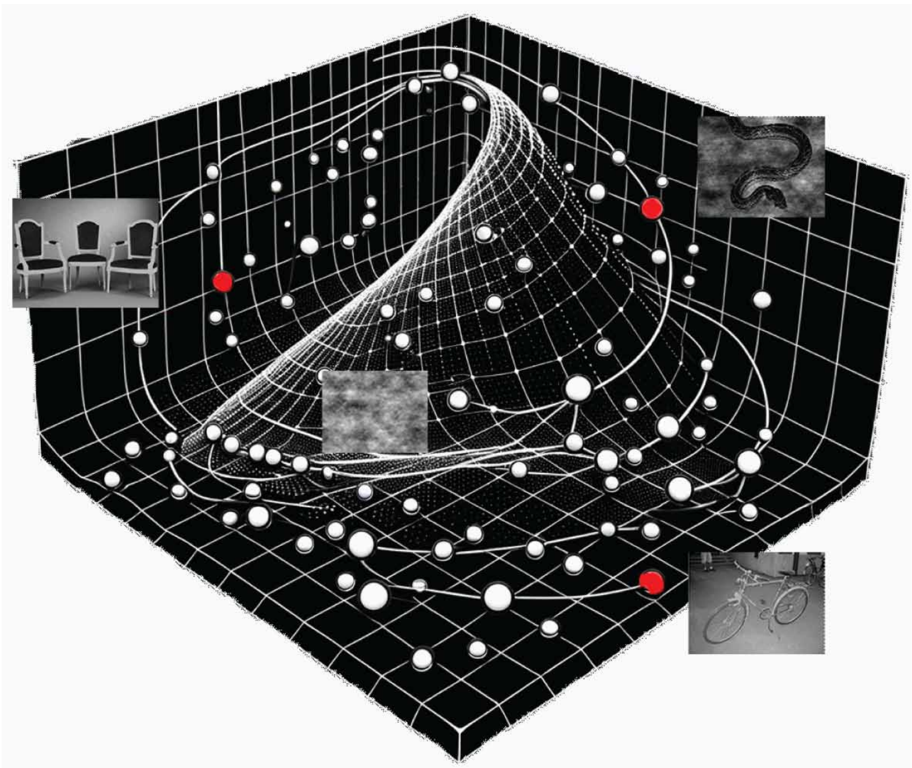
The specific steps are as follows: First, the code converts the input starting and ending images into smoothly transitioning in structure, then performs a two-dimensional Fourier transform (FFT) on both the starting and ending images, extracting the phase angle and amplitude of these two images. The angle difference between the starting phase and the ending phase is calculated, and an interpolation method is used to create a series of phase angles. These phase angles smoothly transition from the phase of the starting image to that of the ending image, combining each phase angle with the amplitude of the ending image to form a complex image representation. Each complex image undergoes an inverse Fourier transform, generating the actual image sequence. These images gradually transform from the starting image to the ending image. This process enables localized structural randomization within a small range. The original image can depict anything of interest, such as objects, faces, scenes, abstract shapes, etc. In addition to being computationally straightforward, this method also precisely maintains global luminance properties such as brightness and color histograms, thereby avoiding confounding experimental results with variations in these low-level attributes.

In the schematic shown in Figure 1, any image is represented as a point within a high-dimensional ‘image space.’ In recognition studies, the specific images of objects and scenes form a sparse subset within this space, similar to the small spheres in the diagram. Typically, inferring high-level visual processes from responses measured at only a few of these points is challenging. RISE was developed to address this challenge by exploring perception along continuous trajectories within this image space. These trajectories intersect points of interest, creating sequences that represent well-controlled visual transformations. This method facilitates a more comprehensive understanding of visual processing.

3.3. Stimuli Generation

In our study, we converted high-resolution images of four animal groups (snakes, birds, cats, and fish) to grayscale while maintaining consistent luminance across all images (Figure 2). Every animal in the source photos was distinctly presented, with the main subject at the center of the picture. These images were standardized to dimensions of 675 × 532 pixels and were displayed on a 24-inch LCD screen placed about 60 cm from the participants, producing a viewing angle of 16.5 × 12.1°. The collection of images was derived from the source photos through the application of the Random Image Structure Evolution (RISE) approach (Kawai, & He, 2016). The RISE sequences alter only the spatial structure of the original images by modifying their random phase spectrum; the amplitude spectrum,

Figure 1. Random image structure evolution (RISE) graphical example



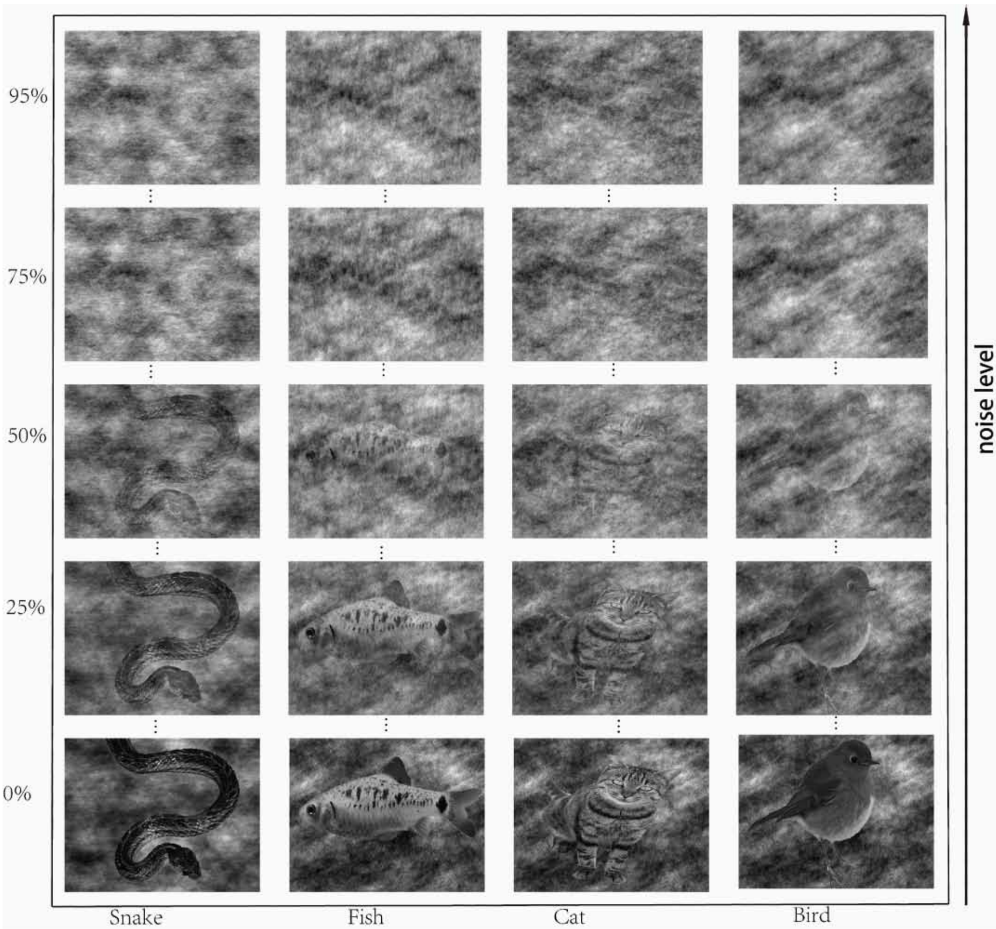
luminance, and contrast remain unchanged. Each sequence covered a range from 95% to 0% of the original phase spectrum interpolation ratios, decreasing in 5% increments, yielding 20 images per sequence. A 100% interpolation ratio corresponds to a completely random phase spectrum, while 0% maintains the original phase spectrum. This method allows for a gradual transition in image clarity, from less to more distinct. Notably, our RISE sequences featured a consistently scrambled background to prevent any background-induced inconsistencies, ensuring that the participants' focus stayed on the stimuli.

Figure 2 illustrates the progressive clarification of stimuli depicting four types of animals: snakes, fish, cats, and birds. It shows a transition from the least clear representation (almost random noise) to increasingly distinct and recognizable forms.

Figure 3 illustrates the procedure of collecting electrophysiological data from the occipital lobe of the human brain, specifically from electrode positions O1, O2, and Oz. The Brain-Computer Interface (BCI) Device acquires neural signals, which are then digitized and transmitted to an upper-level computer system, such as a laptop. The laptop processes these signals to analyze and display the grand-averaged frequency spectra and spectrograms. This process showcases the progression of visual stimuli from initial noise patterns to a recognizable snake image, while the corresponding neural responses are recorded and visualized, providing insights into the cognitive processing of potential threats. The two graphs on the right side of the figure depict the amplitude-frequency relationship and the changes in brain activity over time, respectively, offering a comprehensive overview of the brain's dynamic response to visual stimuli.

Figure 4 provides a schematic illustration of the RISE sequence coherence sweep SSVEP paradigm. In this approach, an image with randomized phase cycles between a stimulus that transitions

Figure 2. Progressive visual clarity of threat and non-threat animal stimuli

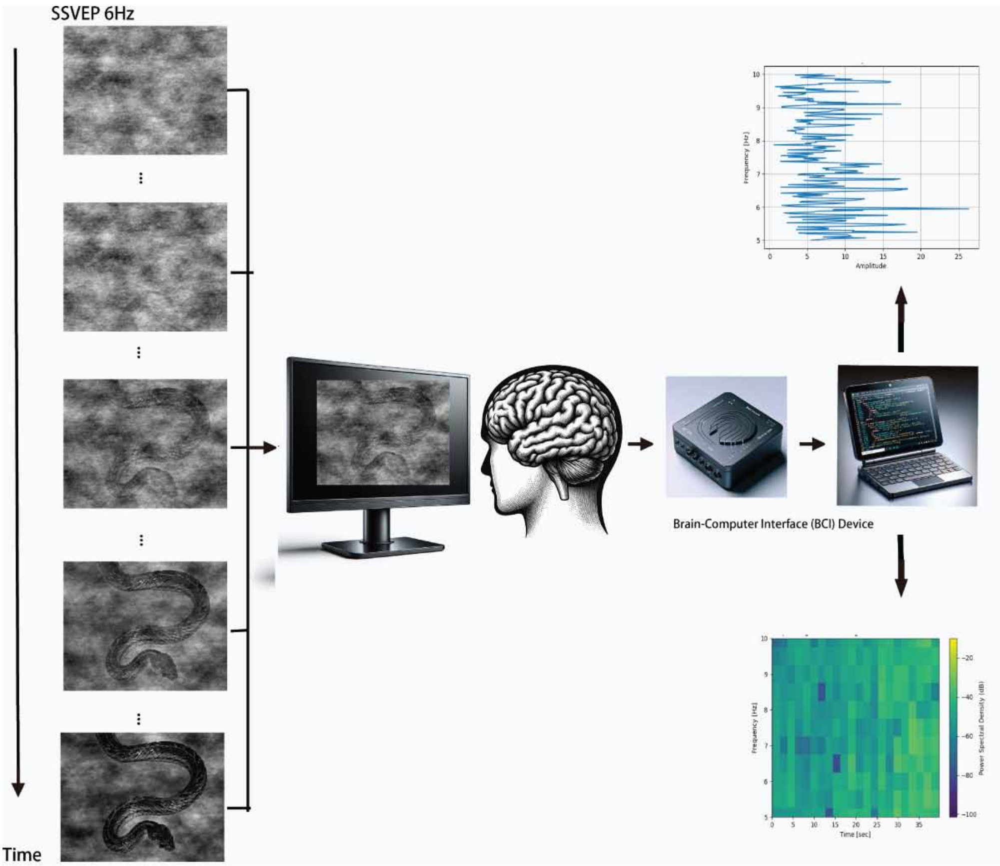


from a scrambled representation of an animal to a fully coherent form. This oscillation occurs at a frequency of 6 Hz, spanning a total of 40 seconds during the stimulation period. Initially, the image displaying the face possesses a spectrum that is almost entirely randomized in phase. As the experiment progresses, the level of phase-scrambling is incrementally reduced in uniform steps. Three of these steps are depicted for clarification. Black bars and corresponding square symbols signify images that are fully randomized, whereas the gray counterparts represent those with partial randomization. Lighter shades within these gray icons and bars indicate lesser degrees of scrambling.

3.4. Experimental Paradigm

In our experiment, we conducted four 40-second sessions for each animal category. In these sessions, images progressively emerged from an almost indiscernible 1% coherence state. This trial design was repeated 20 times, with some sessions incorporating blank control images without any animal patterns. Images with animal patterns alternated with a black background at a frequency of 6Hz. Figure 2 illustrates the early sequence of images during the image stream presentation. Within a single session, 20 images at different perturbation levels were displayed. Within a single session, 20 images at different perturbation levels were displayed. Figure 4 shows a sample progression of these images, illustrating how the depictions of snakes evolved from initially indiscernible to clearly distinguishable.

Figure 3. Experimental setup for SSVEP paradigm and brain response measurement



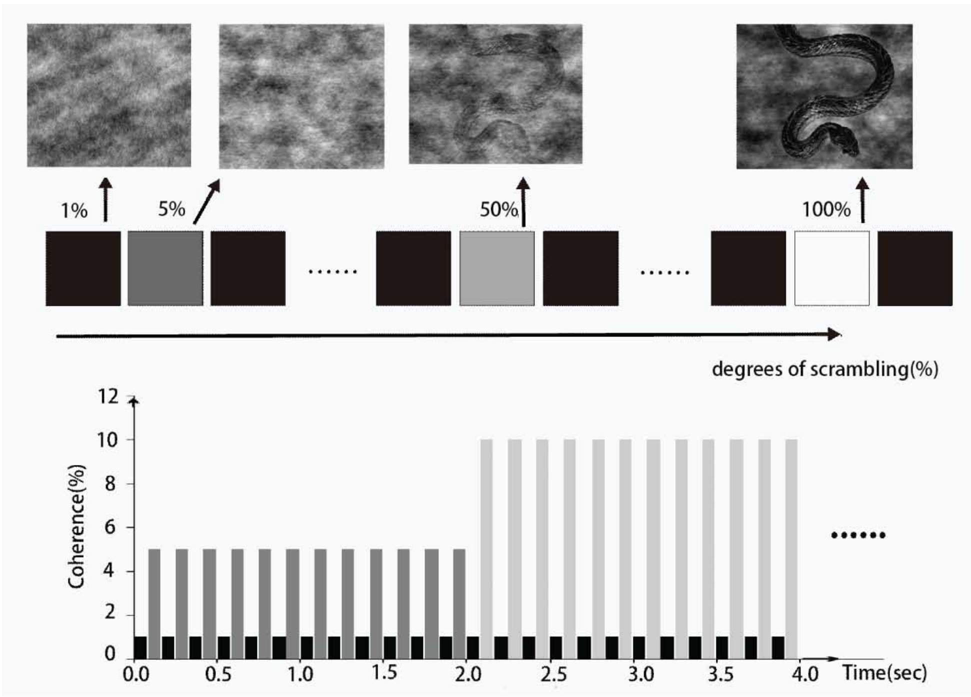
Each perturbed image was displayed for 2 seconds, with 12 of these images interleaved with images at 1% coherence. To reduce the transient visual evoked potential (VEP) resulting from initial contrast variations, each perturbation sequence began with a 2-second presentation of the primary image from the perturbation set, facilitating a transition to a steady state. The experiment included three non-snake pattern images to diminish participants' anticipatory perceptions and speculation of threatening stimuli. Participants were tasked to press a designated key upon recognizing an image and to refrain from pressing if no clear image was discernible. A pre-session key response test was conducted to ensure a conditioned reflex. Participants were informed about the possible appearance of specific animal species and that the sequence would continue until all 20 images were displayed, regardless of correct identification.

Figure 5 shows Sample Progression in a Random Image Structure Evolution (RISE) Sequence for Depictions of Snakes. The sequence encompasses 20 images, beginning with an interpolation ratio of 95% and decrementing in 5% intervals. Over the course of the sequence, the visual clarity transitions from chaotic to readily distinguishable.

3.5. Data Recording and Analysis

In our study, we used an EEG recording system equipped with the Texas Instruments ADS1299 chipset, which includes an eight-channel high-precision amplifier specifically designed for EEG data acquisition. EEG data was recorded from three electrodes (O1, Oz, O2) in the occipital region,

Figure 4. Stages of image coherence in SSVEP stimulus presentation



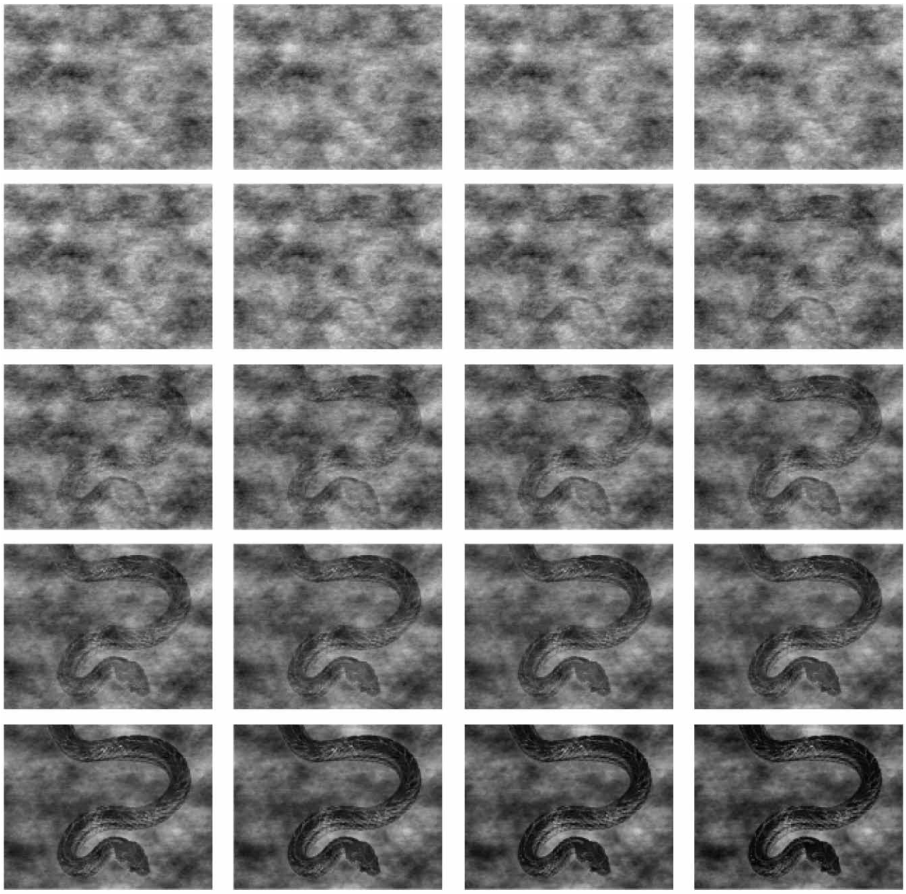
following the 10-20 system, with a sampling rate of 250Hz, using the prefrontal electrode (Fpz) as our reference. We applied a 4th-order Butterworth band-pass filter to the signal data, limiting the frequency range between 1 Hz and 40 Hz, as it captures the pertinent SSVEP details. This process aids in eliminating interference from DC drift and other high-frequency disruptions. For data analysis, a sliding window of 2 seconds with a 90% overlap was used, and the temporal variations of the spectral power at 6 Hz were evaluated using the Fast Fourier Transform (FFT). The spectral power sequences were then z-score normalized, and a grand average was performed across all participants and for the O1, Oz, and O2 channels. We utilized polynomial regression to deduce the general trend of spectral power over time. The optimal order for this regression was identified when the root mean square error (RMSE) for the polynomial regression fell below 0.9 times α . In this context, α represents the RMSE for a first-order polynomial regression. Ultimately, we settled on a 5th-order regression. In the end, we compared the results from the regression with the behavioral data from participants' keypress actions, both qualitatively and quantitatively. Subsequently, to assess the correlation between the regression results and behavioral data, the Pearson correlation coefficient was calculated in this study.

The Short-Time Fourier Transform (STFT) was utilized to analyze the EEG signals in the time-frequency domain. The STFT is a sequence of Fourier Transforms performed on a small window that slides over the signal. It is defined as:

$$STFT\left\{x\left(t\right)\right\}\left(f\,\tau\right)=\int_{-\infty}^{\infty}x\left(t\right)w\left(t-\tau\right)e^{-j2\pi ft}dt \tag{1}$$

where x(t) is the signal, w(t) is the window function centered around zero, f is the frequency, and τ is the time around which the window is centered. This approach enables the observation of the

Figure 5. RISE sequence: Clarity transition of snake



signal's frequency content as it evolves over time. The window function w(t), typically a Gaussian or a Hamming window, is used to localize the signal in time. The choice of window size influences the time-frequency resolution trade-off in the STFT analysis.

3.6. SSVEP SNR Calculation

In the SSVEP paradigm, we computed the SNR of the data preceding and following each recognition task button press. Initially, the signal spectrum was estimated using the Fourier transform in tandem with the Welch method. The Signal-to-Noise Ratio (SNR) was subsequently calculated by contrasting the power spectral densities. The SNR formula employed in this paper is expressed as:

$$SNR = 10\log_{10}\left(\frac{S_{signal}\left(f_0\right)}{S_{noise}\left(f\right)}\right) \tag{2}$$

In this equation, $S_{signal}(f_0)$ represents the mean power spectral density of the signal, while $S_{noise}(f)$ denotes the mean power spectral density of the noise. f_0 is the anticipated frequency of the signal, and f_0 encompasses noise frequencies ranging from 1Hz up to half the sampling rate.

4. RESULTS

4.1. Confirmation of Successful SSVEP Induction

To ascertain if the image sequence produced through our random image structure evolution method successfully triggered the SSVEP, we computed the grand average of the spectral power from the EEG recordings taken during the image sequence display (shown in Figure 6) Spectral analyses revealed distinct peaks at the 6 Hz stimulation frequency. From the SSVEP signals collected during the image sequence stimuli of various animal patterns, we processed and derived spectrograms. These spectrograms, which depict the grand average variations in spectral power, are presented in Figure 6 respectively. In the initial segments of the spectrograms, we observed minimal fluctuations. However, the latter segments unequivocally demonstrated that in all four experiments, the spectral power at the stimulation frequency exceeded that of other frequency bands. Based on this data, we inferred that the rapid-paced image sequence, crafted using our random image structure evolution method, effectively induced the SSVEP response.

Figure 6 illustrates the grand-averaged frequency spectra and spectrograms, derived from EEG data gathered during the continuous presentation of a RISE sequence. This sequence transitions from a state of disorganization to one of clear discernibility in 20 incremental steps. The figure is composed of two panels representing different aspects of the data obtained from the RISE sequence playback: Panel (A) exhibits the grand-averaged frequency spectra, while Panel (B) displays the corresponding spectrograms.

4.2 Comparison of SSVEP and Psychophysical Detection Thresholds for Various Animal Images

The regression results of the grand-averaged temporal power changes at 6 Hz frequency during the presentation of flickering RISE sequences of four categories of animals are displayed in Figure 7. Notably, the graph illustrates two distinct phases, along with the average amplitude and the corresponding timestamps for each phase. The observed upward trend and eventual peak of the SSVEP signal elicited by the RISE sequences of the four animal categories can be attributed to the progressively increasing image recognizability perceived by the participants. The escalation in the SSVEP amplitude likely stems from heightened attention and cognitive processing as participants successfully identified the animals in the images, leading to a gradual increase in the SSVEP amplitude and its eventual peak.

Figure 7 shows Chart Normalized cumulative amplitude difference for the RISE sequences of four categories of animals used in the study. The SSVEP data from various types of experiments

Figure 6. EEG frequency analysis of snake image recognition

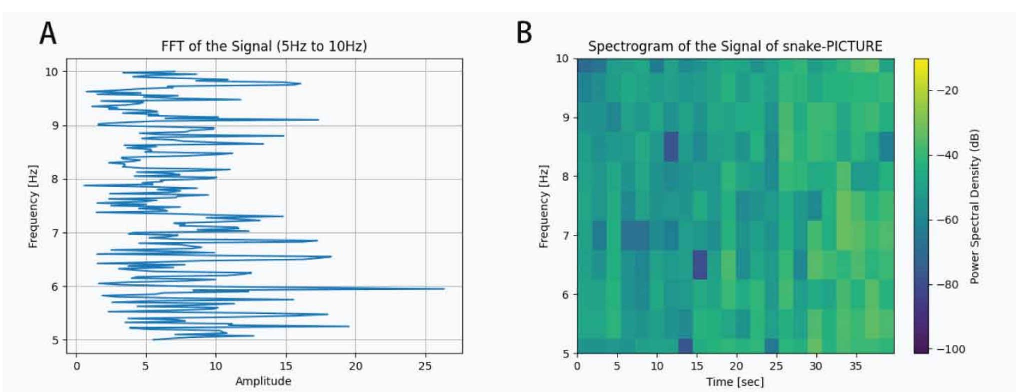
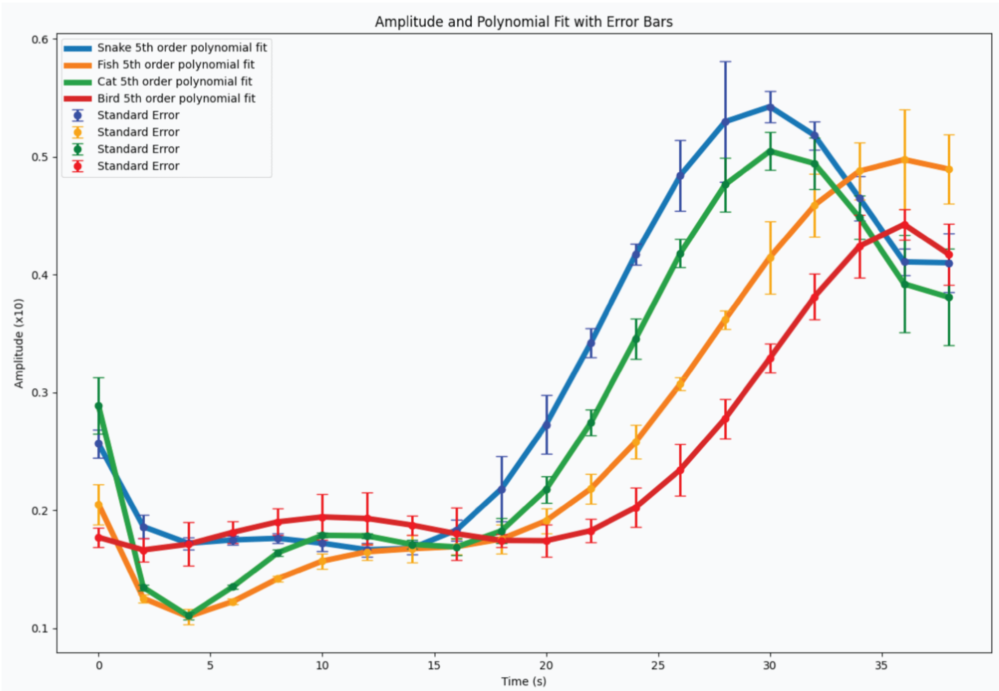


Figure 7. Comparative SSVEP amplitude responses to animal stimuli over



have been subjected to fifth-order linear regression processing. Amplitude of the SSVEP response at 6Hz as a function of coherence. Error bars represent 1 standard error of the mean across participants.

The response speed to animal images (snake, fish, cat, bird) is shown in Figure 8. We used Spearman's correlation analysis to investigate the link between recognition speed and amplitude trends. Our results show a significant positive correlation for snake patterns (coefficient 0.948, $p < 0.05$), indicating that quicker responses to snake images coincide with increasing amplitudes. Fish patterns also displayed a strong correlation (coefficient 0.952, $p < 0.05$). For cat and bird images, the correlations were also positive, albeit with a slightly slower response speed (cat: coefficient 0.895, $p = 0.016$; bird: coefficient 0.846, $p = 0.034$). This indicates that participants generally reacted more slowly to these images, and the increase in SSVEP amplitude occurred later compared to the other stimuli.

Table 1 summarizes participants' behavioral latencies and average SSVEP response times for each animal category. The data, measured in seconds with standard error, indicate varying response times based on the stimulus type, hinting at different cognitive processing speeds and levels of neural engagement for each category. These findings point to heightened sensitivity to specific stimuli, reflected in faster recognition speeds and corresponding amplitude increases, although the exact mechanisms remain to be further explored.

Figure 8 illustrating the average behavioral animal image detection response time for each category of animal image. Each box represents the interquartile range of response times, with the median indicated by the line within the box. Dots represent individual participants' response times for each animal image.

Table 1. The table presents participants' behavioral response latencies and average Steady-State Visual Evoked Potential (SSVEP) response times when identifying four different targets: snakes, fish, cats, and birds. Both the behavioral response latencies and SSVEP response times are measured in seconds, with the standard error of the mean indicated by the ± values alongside the averages.

Figure 8. Distribution of response times to animal image stream stimuli

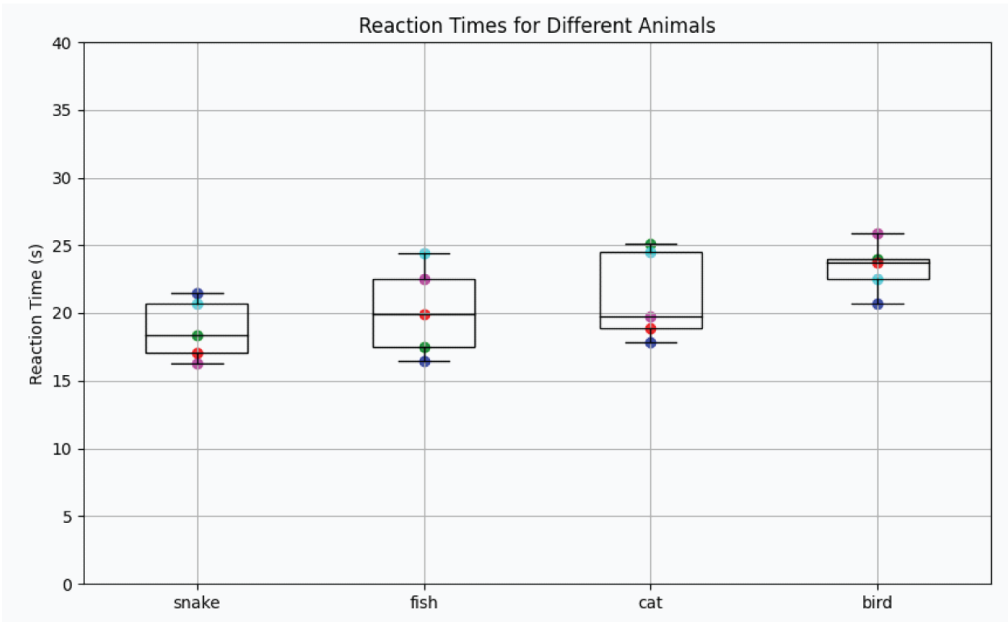
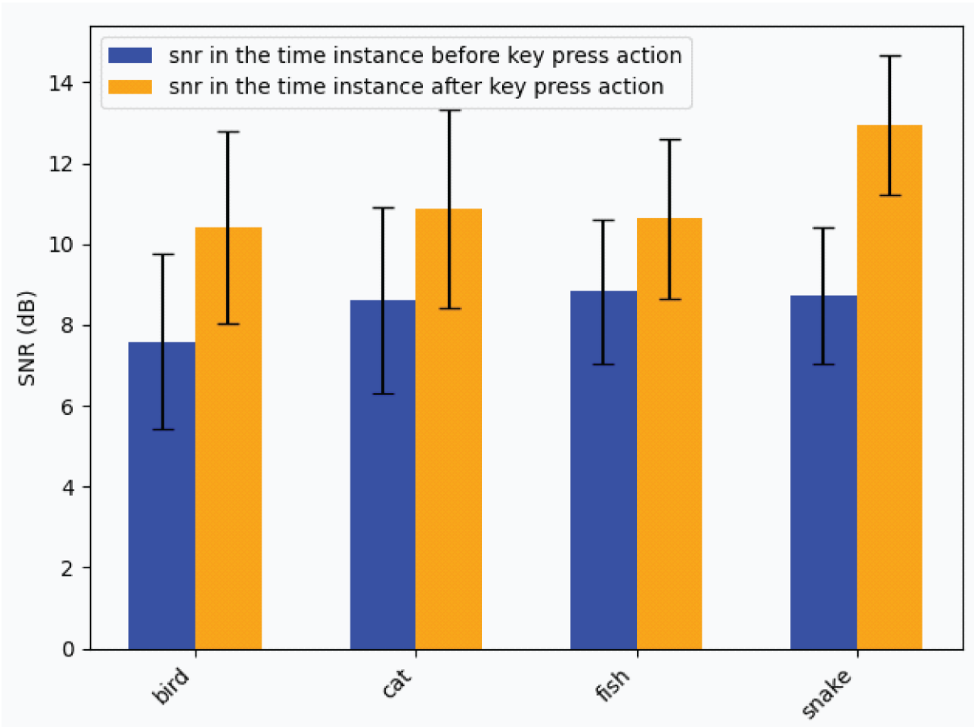


Table 1. Behavioral and SSVEP response times by animal stimulus

Target	Behavioral Response Latencies(sec)	Average SSVEP Response Time(sec)
Snake	9.372 ±0.919	14.843 ±1.01
Fish	10.099 ±1.365	18.843 ±1.995
Cat	10.592 ±1.369	18.189 ±0.734
Bird	11.671 ±0.790	21.625 ±2.327

An analysis of variance (ANOVA) was used to evaluate the SSVEP Signal-to-Noise Ratio (SNR) data. Compared to images with a high degree of perturbation, the capabilities of Brain-Computer Interfaces (BCIs) are enhanced when individuals are exposed to flickering stimuli of images with a lower degree of perturbation. This enhancement is evidenced by an increase in both the amplitude of Steady-State Visual Evoked Potentials (SSVEPs) and the Signal-to-Noise Ratio (SNR) after participants press a button to indicate recognition of the image content. However, trends in SSVEP amplitude ($F = 11.856$, $p < 0.05$) and SNR ($F = 13.560$, $p < 0.05$) vary depending on the type of image stimulus. The most significant increases in SSVEP amplitude and SNR are observed when the perturbation level of threatening images is reduced, suggesting a heightened engagement or sensitivity to these stimuli. The variance data for the SNR of the SSVEP following a button press showed no significant differences for other non-threatening stimuli. This indicates that the SNR in SSVEP stimuli can be influenced by the intensity of the stimulus and the clarity of cognitive pattern recognition, as illustrated in Figure 9.

Figure 9. Signal-to-Noise Ratio (SNR) analysis of the SSVEP response



5. DISCUSSION

This research seeks to corroborate the theory that the human visual system exhibits a heightened sensitivity to snake images, especially in visual search tasks where image clarity is reduced. Previous studies have explored human proficiency in recognizing snakes in suboptimal visual conditions and investigated the role of low spatial frequencies in fear detection (Lobue & Rakison, 2013; Kawai & He, 2016). To further explore the brain's electrophysiological response to rapid recognition of different animal patterns, we refined our experiments based on Signal Detection Theory (SDT). To ensure consistency and comparability, the types of animal patterns embedded in our SSVEP stimuli were consistent with those used in previous studies (Kawai, & He, 2016), which featured snakes, fish, birds, and cats as psychological stimuli. Specifically, we chose snake patterns and compared them with other emotionally neutral images of fish, cats, and birds. In our experiments, we introduced a 6Hz alternating image stream in completely scrambled images, transitioning from 100% to 0% coherence to capture the brain's 6Hz SSVEP response. We hypothesized a quicker ascending trend in SSVEP signals for snake patterns compared to other animals, observable in the EEG's time domain. Steady-State Visual Evoked Potential (SSVEP) is an electrophysiological measurement technique, widely employed to investigate attention to external visual stimuli (Norcia et al., 2015; Vialatte et al., 2010). Our study found that during continuous stimuli presentation, the brain's response amplitude and SNR to SSVEP stimuli are modulated upon cognitive recognition. These observations concur with previous research, underscoring that distinct cognition of patterns augments attention to SSVEP stimuli. Investigations into the neural underpinnings of conscious perception predominantly demonstrate that neural responses are heightened upon stimulus recognition (Sadr, & Sinha, 2004). Furthermore, the concept of RDF query path optimization in Semantic Web and Data-Intensive Cloud Computing contexts offers an interesting parallel to our study(Ilyas et al., 2022). Just as

RDF query optimization requires intricate processing to efficiently retrieve relevant data, our research into SSVEP signals and visual perception involves complex cognitive processing for accurately identifying and responding to visual stimuli. This similarity highlights how advanced computational techniques can mirror human cognitive processes, underscoring the potential for cross-disciplinary insights between cognitive neuroscience and computational technology. Previous studies on RISE sequences show that viewers can quantitatively assess the perceptual onset and offset points of an object's appearance and disappearance within the sequence. The initial metric, termed the 'perceptual onset point', marks the spot in the beginning phase of the RISE sequence where the viewer starts to accurately discern the emerging object. The latter metric, referred to as the 'perceptual offset point', signifies the point in the concluding phase of the RISE sequence after which the viewer ceases to recognize the primary image. The Scanning SSVEP curves from our study also display a perceptual onset point, dividing into two distinct phases. We also observed a slight delay in behavioral confirmation compared to EEG signal transitions, which can be attributed to an inherent visual processing pathway in the human brain (Kawai, 2019).

Initially, visual stimuli are captured by the retina and relayed to the brain. This information travels via the optic nerve and progresses to the lateral geniculate nucleus (LGN), before finally arriving at the primary visual cortex (V1), which serves as a central hub for processing visual information. From V1, visual information follows two primary pathways: the dorsal stream, which handles spatial location and motion ('where' pathway), and the ventral stream, focusing on object shape and color ('what' pathway). Here, we illustrate the ventral processing stream that begins at V1 and involves V2, V4, and terminates in the inferotemporal cortex. Known as the 'content pathway' or 'Who/What pathway,' this stream is crucial in object recognition tasks, including facial recognition. SSVEP signals are primarily acquired from the V1 cortex, but comprehensive object recognition requires the integrated processing of both V1 and V2 cortices. This accounts for the observed delay between alterations in SSVEP amplitude and the initiation of behavioral responses. (Isbell, 2006; Morand et al., 2000).

Unscrambled images, when contrasted with their fully scrambled counterparts, produced SSVEP signals characterized by a significantly elevated amplitude and an enhanced signal-to-noise ratio. This underscores the effectiveness of low-level visual cues in capturing human attention, as reflected in the heightened SSVEP responses (James et al., 2000). Our behavioral experiments revealed participants' proficiency in accurately identifying snake images at scrambling levels ranging from approximately 50% to complete clarity. Conversely, participants took longer to recognize images of other animals compared to snake images. These experimental observations are consistent with the findings of Nobuyuki (Van Le et al., 2013). These patterns may originate from more fundamental visual processing mechanisms. Studies in non-human primates suggest the existence of specialized neurons in the superior colliculus of subcortical regions, which might be adapted for identifying snake-specific features, influencing early visual object processing. Furthermore, the distinct scales and patterns of snake skin could activate specific neurons in the visual cortex. Due to their sensitivity to specific directional lines or rhomboidal patterns, these neurons may facilitate the quick detection of snakes as potential threats (Lobue, 2014).

Earlier SSVEP studies suggest that the distinct curvilinear shape characteristic of snake stimuli may contribute to the heightened SSVEP response observed for snake images. Notably, both snake and worm images elicited more robust SSVEP responses than beetle images, indicating a more pronounced attentional capture for curvilinear organisms. However, the response to snake images exceeded that for worm images, implying the presence of additional threat-related cues in snakes, apart from their curvilinear shape. Future research is needed to ascertain whether the unique scale patterns of snake skin can independently intensify SSVEP responses, and if these patterns transmit more immediate threat signals compared to just curvilinear shapes (Beligiannis, & Van Strien, 2019). In the context of image semantic segmentation technology and information systems, these findings have significant implications. The heightened SSVEP responses to snake images, particularly due to their curvilinear shapes and distinctive scale patterns, suggest a specialized focus for developing advanced image recognition algorithms. Integrating these biological insights into algorithmic design can enhance semantic segmentation models, enabling more effective identification and prioritization of such distinct features. This enhancement could be pivotal in applications requiring rapid and accurate identification of specific patterns or threats, such as in automated surveillance systems, wildlife monitoring, and even in medical imaging where recognizing particular shapes and textures can be crucial. The integration of these perceptual cues into information systems promises to enhance their sensitivity and accuracy, aligning more closely with human cognitive processing and threat detection capabilities.

6. CONCLUSION

In summary, this research investigates the dynamics of visual attention, particularly in response to varying threat levels represented by animal images, using steady-state visual evoked potentials (SSVEP). Key findings of our study demonstrate that human attention, when specifically focused on certain stimuli, notably enhances SSVEP amplitude, underscoring a strong neural response to such targeted objects. This observation is particularly evident when participants engage with images that progressively clarify from blurry to distinct forms, such as images of snakes and other animals. A major impact of this research lies in its contribution to cognitive neuroscience, offering deeper insights into the mechanisms underlying selective attention and threat detection. The research offers evidence supporting the notion that the human visual system is finely tuned to identify and react to potential threats, a feature that likely has evolutionary roots. Our study presents a promising avenue for integrating SSVEP-based assessments into the development of advanced image semantic segmentation and information systems. Real-time tracking of emotional arousal via SSVEP responses introduces an innovative approach to customize image segmentation algorithms, allowing them to adapt to users' cognitive states. This could revolutionize user interfaces by enabling systems to dynamically adjust visual content based on the viewer's emotional cues, thereby improving the relevance and impact of the displayed information. Looking forward, the interplay between cognitive state assessments and image processing can be leveraged to create more intuitive and responsive information systems. These systems could use the insights gleaned from SSVEP responses to prioritize or alter the display of content, ensuring that users are presented with imagery that aligns with their current emotional and cognitive states. Moreover, this technology holds potential for enhancing the accuracy of threat detection in security systems, assisting in medical diagnostics by highlighting areas of concern in medical imagery, and providing more immersive experiences in virtual and augmented reality platforms.

As we continue to bridge the gap between human cognitive processes and machine learning algorithms, the integration of SSVEP markers into semantic segmentation tools will not only make these systems more efficient but also more empathetic to the human experience. This integration of human neuroscience and artificial intelligence marks the advent of a new era in image processing and information technology.

ACKNOWLEDGMENT

Author Contributions: S.G.: conceptualization, methodology, writing—original draft, writing—review editing. Y.C.: methodology, writing—original draft, writing—review editing. J.M., X.D. and X.F.: software, validation. All authors have read and agreed to the published version of the manuscript.

DATA AVAILABILITY

The data in this study are available from the corresponding author on reasonable request.

CONFILICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING STATEMENT

This research was supported by National Key Research and Development Program of China (2022YFF1202500, 2022YFF1202504).

REFERENCES

Almomani, A., Alauthman, M., Shatnawi, M. T., Alweshah, M., Alrosan, A., Alomoush, W., Gupta, B. B., Gupta, B. B., & Gupta, B. B. (2022). Phishing Website Detection With Semantic Features Based on Machine Learning Classifiers: A Comparative Study. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–24. doi:10.4018/IJSWIS.297032

Anderson, A. K. (2005). Affective influences on the attentional dynamics supporting awareness. *Journal of Experimental Psychology. General*, *134*(2), 258–281. doi:10.1037/0096-3445.134.2.258 PMID:15869349

Beligiannis, N., & Van Strien, J.W. (2019). Blurring attenuates the early posterior negativity in response to snake stimuli. *International journal of psychophysiology: official journal of the International Organization of Psychophysiology*.

Chen, T., Luh, D., & Wang, J. G. (2023). Analyzing AI-Generated Packaging's Impact on Consumer Satisfaction With Three Types of Datasets. *International Journal of Data Warehousing and Mining*, *19*(1), 1–17. doi:10.4018/IJDWM.334024

Chopra, M., Singh, S. K., Sharma, A., & Gill, S. S. (2022). A Comparative Study of Generative Adversarial Networks for Text-to-Image Synthesis. *International Journal of Software Science and Computational Intelligence*, *14*(1), 1–12. doi:10.4018/IJSSCI.300364

Chu, J., Zhao, X., Song, D., Li, W., Zhang, S., Li, X., & Liu, A. (2022). Improved Semantic Representation Learning by Multiple Clustering for Image-Based 3D Model Retrieval. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–20. doi:10.4018/IJSWIS.297033

Coelho, C. M., Suttiwan, P., Faiz, A. M., Ferreira-Santos, F., & Zsido, A. N. (2019). Are Humans Prepared to Detect, Fear, and Avoid Snakes? The Mismatch Between Laboratory and Ecological Evidence. *Frontiers in Psychology*, *10*, 10. doi:10.3389/fpsyg.2019.02094 PMID:31572273

Gomes, N., Soares, S. C., Silva, S., & Silva, C. F. (2018). Mind the snake: Fear detection relies on low spatial frequencies. *Emotion (Washington, D.C.)*, *18*(6), 886–895. doi:10.1037/emo0000391 PMID:29265840

He, H., Kubo, K., & Kawai, N. (2014). Spiders do not evoke greater early posterior negativity in the event-related potential as snakes. *Neuroreport*, *25*(13), 1049–1053. doi:10.1097/WNR.0000000000000227 PMID:25026534

Ilyas, Q. M., Ahmad, M., Rauf, S., & Irfan, D. (2022). RDF Query Path Optimization Using Hybrid Genetic Algorithms: Semantic Web vs. Data-Intensive Cloud Computing. *International Journal of Cloud Applications and Computing*, *12*(1), 1–16. doi:10.4018/IJCAC.2022010101

Isbell, L. A. (2006). Snakes as agents of evolutionary change in primate brains. *Journal of Human Evolution*, *51*(1), 1–35. doi:10.1016/j.jhevol.2005.12.012 PMID:16545427

James, T. W., Humphrey, G. K., Gati, J. S., Menon, R. S., & Goodale, M. A. (2000). The effects of visual object priming on brain activation before and after recognition. *Current Biology*, *10*(17), 1017–1024. doi:10.1016/S0960-9822(00)00655-2 PMID:10996068

Jelušić, P. B., Poljicak, A., Donevski, D., & Cigula, T. (2022). Low-Frequency Data Embedding for DFT-Based Image Steganography. *International Journal of Software Science and Computational Intelligence*, *14*(1), 1–11. doi:10.4018/IJSSCI.312558

Kawai, N. (2019). The Underlying Neuronal Circuits of Fear Learning and the Snake Detection Theory (SDT). *The Fear of Snakes*.

Kawai, N., & He, H. (2016). Breaking Snake Camouflage: Humans Detect Snakes More Accurately than Other Animals under Less Discernible Visual Conditions. *PLoS One*, *11*(10), 11. doi:10.1371/journal.pone.0164342 PMID:27783686

Kawai, N., & Koda, H. (2016). Japanese monkeys (Macaca fuscata) quickly detect snakes but not spiders: Evolutionary origins of fear-relevant animals. *Journal of Comparative Psychology*, *130*(3), 299–303. doi:10.1037/com0000032 PMID:27078076

Le, Q. V., Isbell, L. A., Matsumoto, J., Lê, V. Q., Hori, E., Tran, A. H., Maior, R. S., Tomaz, C., Ono, T., & Nishijo, H. (2014). Monkey Pulvinar Neurons Fire Differentially to Snake Postures. *PLoS One*, *9*(12), 9. doi:10.1371/journal.pone.0114258 PMID:25479158

Le, Q. V., Isbell, L. A., Matsumoto, J., Lê, V. Q., Nishimaru, H., Hori, E., Maior, R. S., Tomaz, C., Ono, T., & Nishijo, H. (2016). Snakes elicit earlier, and monkey faces, later, gamma oscillations in macaque pulvinar neurons. *Scientific Reports*, *6*(1), 6. doi:10.1038/srep20595 PMID:26854087

Li, D., Deng, L., Gupta, B. B., Wang, H., & Choi, C. (2019). A novel CNN based security guaranteed image watermarking generation scenario for smart city applications. *Information Sciences*, *479*, 432–447. doi:10.1016/j.ins.2018.02.060

Lobue, V. (2014). Deconstructing the snake: The relative roles of perception, cognition, and emotion on threat detection. *Emotion (Washington, D.C.)*, *14*(4), 701–711. doi:10.1037/a0035898 PMID:24708497

Lobue, V., & Rakison, D. H. (2013). What we fear most: A developmental advantage for threat-relevant stimuli. *Developmental Review*, *33*(4), 285–303. doi:10.1016/j.dr.2013.07.005

Mandle, A. K., Sahu, S. P., & Gupta, G. P. (2022). CNN-Based Deep Learning Technique for the Brain Tumor Identification and Classification in MRI Images. *International Journal of Software Science and Computational Intelligence*, *14*(1), 1–20. doi:10.4018/IJSSCI.304438

Memos, V. A., Psannis, K. E., Ishibashi, Y., Kim, B. G., & Gupta, B. B. (2018). An efficient algorithm for media-based surveillance system (EAMSuS) in IoT smart city framework. *Future Generation Computer Systems*, *83*, 619–628. doi:10.1016/j.future.2017.04.039

Morand, S., Thut, G., Peralta, R. G., Clarke, S., Khateb, A., Landis, T., & Michel, C. M. (2000). Electrophysiological evidence for fast visual processing through the human koniocellular pathway when stimuli move. *Cerebral Cortex (New York, N.Y.)*, *10*(8), 817–825. doi:10.1093/cercor/10.8.817 PMID:10920053

Murray, E. J., & Foote, F. (1979). The origins of fear of snakes. *Behaviour Research and Therapy*, *17*(5), 489–493. doi:10.1016/0005-7967(79)90065-2 PMID:508228

Nhi, N. V., Le, T. M., & Van, T. T. (2022). A Model of Semantic-Based Image Retrieval Using C-Tree and Neighbor Graph. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–23. doi:10.4018/IJSWIS.295551

Norcia, A. M., Appelbaum, L. G., Ales, J. M., Cottereau, B. R., & Rossion, B. (2015). The steady-state visual evoked potential in vision research: A review. *Journal of Vision (Charlottesville, Va.)*, *15*(6), 4. doi:10.1167/15.6.4 PMID:26024451

Öhman, A., & Mineka, S. (2001). Fears, phobias, and preparedness: Toward an evolved module of fear and fear learning. *Psychological Review*, *108*(3), 483–522. doi:10.1037/0033-295X.108.3.483 PMID:11488376

Öhman, A., Soares, S. C., Juth, P., Lindström, B., & Esteves, F. (2012). Evolutionary derived modulations of attention to two common fear stimuli: Serpents and hostile humans. *Journal of Cognitive Psychology*, *24*(1), 17–32. doi:10.1080/20445911.2011.629603

Qian, W., Li, H., & Mu, H. (2022). Circular LBP Prior-Based Enhanced GAN for Image Style Transfer. *International Journal on Semantic Web and Information Systems*, *18*(2), 1–15. doi:10.4018/IJSWIS.315601

Reynolds, J. H., & Heeger, D. J. (2009). The Normalization Model of Attention. *Neuron*, *61*(2), 168–185. doi:10.1016/j.neuron.2009.01.002 PMID:19186161

Sadr, J., & Sinha, P. (2004). Object recognition and Random Image Structure Evolution. *Cognitive Science*, *28*(2), 259–287. doi:10.1207/s15516709cog2802_7

Schupp, H. T., Flaisch, T., Stockburger, J., & Junghöfer, M. (2006). Emotion and attention: Event-related brain potential studies. *Progress in Brain Research*, *156*, 31–51. doi:10.1016/S0079-6123(06)56002-9 PMID:17015073

Shibasaki, M., & Kawai, N. (2009). Rapid detection of snakes by Japanese monkeys (Macaca fuscata): An evolutionarily predisposed visual system. *Journal of Comparative Psychology*, *123*(2), 131–135. doi:10.1037/a0015095 PMID:19450020

Soares, S. C., Esteves, F., Lundqvist, D., & Ohman, A. (2009). Some animal specific fears are more specific than others: Evidence from attention and emotion measures. *Behaviour Research and Therapy*, *47*(12), 1032–1042. doi:10.1016/j.brat.2009.07.022 PMID:19695561

Stergiou, C. L., Psannis, K. E., & Gupta, B. B. (2021). InFeMo: Flexible big data management through a federated cloud system. *ACM Transactions on Internet Technology*, *22*(2), 1–22. doi:10.1145/3426972

Strien, J. W., Eijlers, R., Franken, I. H., & Huijding, J. (2014). Snake pictures draw more early attention than spider pictures in non-phobic women: Evidence from event-related brain potentials. *Biological Psychology*, *96*, 150–157. doi:10.1016/j.biopsycho.2013.12.014 PMID:24374241

Tsuchiya, N., & Koch, C. (2005). Continuous flash suppression reduces negative afterimages. *Nature Neuroscience*, *8*(8), 1096–1101. doi:10.1038/nn1500 PMID:15995700

Van Le, Q., Isbell, L. A., Matsumoto, J., Nguyen, M. N., Hori, E., Maior, R. S., Tomaz, C., Tran, A. H., Ono, T., & Nishijo, H. (2013). Pulvinar neurons reveal neurobiological evidence of past selection for rapid detection of snakes. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(47), 19000–19005. doi:10.1073/pnas.1312648110 PMID:24167268

Van Strien, J. W., Franken, I. H., & Huijding, J. (2014). Testing the snake-detection hypothesis: Larger early posterior negativity in humans to pictures of snakes than to pictures of other reptiles, spiders and slugs. *Frontiers in Human Neuroscience*, *8*, 691. doi:10.3389/fnhum.2014.00691 PMID:25237303

Van Strien, J. W., & Isbell, L. A. (2017). Snake scales, partial exposure, and the Snake Detection Theory: A human event-related potentials study. *Scientific Reports*, *7*(1), 7. doi:10.1038/srep46331 PMID:28387376

Vialatte, F. B., Maurice, M., Dauwels, J., & Cichocki, A. (2010). Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives. *Progress in Neurobiology*, *90*(4), 418–438. doi:10.1016/j.pneurobio.2009.11.005 PMID:19963032

Wang, H., Li, Z., Li, Y., Gupta, B. B., & Choi, C. (2020). Visual saliency guided complex image retrieval. *Pattern Recognition Letters*, *130*, 64–72. doi:10.1016/j.patrec.2018.08.010

Yin, X., & Chen, L. (2023). Image and Text Aspect Level Multimodal Sentiment Classification Model Using Transformer and Multilayer Attention Interaction. *International Journal of Data Warehousing and Mining*, *19*(1), 1–20. doi:10.4018/IJDWM.333854

Yu, C., Li, J., Li, X., Ren, X., & Gupta, B. B. (2018). Four-image encryption scheme based on quaternion Fresnel transform, chaos and computer generated hologram. *Multimedia Tools and Applications*, *77*(4), 4585–4608. doi:10.1007/s11042-017-4637-6

Zheng, Z., Zhou, J., Gan, J., Luo, S., & Gao, W. (2022). Fine-Grained Image Classification Based on Cross-Attention Network. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–12. doi:10.4018/IJSWIS.315747

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