The Influence of Visual Long-Term Memory on Visual Awareness

Combining a Visual Long-Term Memory Learning Task with the Breaking Continuous Flash Suppression Method.

Bachelor Thesis (KI3V12012)

15 ECTS

Chris Dekker (5556481)

Liberal Arts and Sciences, Major Cognitive and Neurobiological Psychology

Supervisors: Dr. Chris Paffen & Prof. dr. Stefan van der Stigchel

First reviewer: Dr. Chris Paffen

Second reviewer: Dr. Stella Donker

Utrecht University, 17 December 2018

Index

Abstract

Visual information is filtered and selected prior to awareness. Previous studies have shown that the content held in visual working memory (VWM) affects visual awareness and the prioritization of visual information for conscious access. Visual information tends to break through interocular suppression and enter visual awareness faster when it matches the content of VWM than non-matching information. This study investigated whether the content stored in visual long-term memory (VLTM) also affects visual awareness during interocular suppression. To study the influence of VLTM on visual awareness an experiment has been conducted which combined a learning task that utilized the big storage capacity for object details of the human VLTM with the method of breaking continuous flash suppression (b-CFS). First, the participants had to learn 99 images. Second, a b-CFS task took place to measure whether images gained prioritized access to visual awareness when matching certain criteria of information stored in LTM. These images could (a) be identical to a learned image, (b) match a category of a certain learned image, (c) match a learned image with the same identity but depicted in a different state, or (d) be a new image that was not learned. No significant difference was found between the variance of the four conditions or between learned and not learned images. The data suggested that the content stored in VLTM does not directly affect visual awareness during interocular suppression.

Introduction

Only a small part of all the visual information that people are exposed to in their daily environments gives rise to visual awareness and conscious access, as the information in a typical scene greatly exceeds the processing capacity of the visual system (Todd & Marois, 2004). Therefore, the content of visual awareness - awareness of external visual input but also internally generated representations (e.g. mental images) - is of limited capacity and therefore applies a selection stage to filter the vast amount of incoming visual input (Li & Geng, 2008). A modern method to study this selection process, by delaying the time it takes for visual information to enter visual awareness, can be found in breaking continuous flash suppression.

Breaking continuous flash suppression (b-CFS) is a psychophysical method that can be applied to study differences between visual stimuli in their potency to gain access to awareness (Stein, Hebart & Sterzar, 2011). The method is based on a phenomenon in visual perception called binocular rivalry, in which two eyes constantly compete for exclusive visibility or *dominance*. As a result, perception alternates between two different images presented concurrently to each eye (Handa et al., 2004). By applying b-CFS, a visual stimulus can temporarily be erased from visual awareness. One eye gets exposed to a visual stimulus that gradually ramps up in brightness while this visual stimulus simultaneously gets suppressed by the exposure of a visual high-contrast dynamic pattern to the other eye. This renders the image presented to the first eye temporarily invisible, up until a certain point when the image breaks through interocular suppression. The moment an image breaks through suppression is the moment it enters visual awareness and the time it took for the visual stimulus to do so provides a measure of prioritization for conscious access (Stein, Hebart & Sterzar, 2011).

Studies using the method of b-CFS have shown that visual information is prioritized for visual awareness and conscious access when it matches the content of visual working memory (VWM) (Gayet, Paffen & Van der Stigchel, 2013, Van Moorselaar et al., 2017). Visual stimuli tend to break through interocular suppression faster when they match a color category (Gayet, Paffen & Van der Stighel, 2013; Gayet et al. 2016; Van Moorselaar et al., 2017), orientation (Liu, Wang & Jiang, 2013) or a face (Pan et al., 2013) that is actively held in VWM. These studies have shown that visual information is filtered and selected prior to awareness. In the light of these findings, an experiment has been conducted using the b-CFS method to study whether the content of visual long-term memory (VLTM) also affects visual awareness during interocular suppression.

Where working memory is known to persist up to 18-30 seconds (without active rehearsal) and able to store around a maximum of seven “chunks” of information, the amount and persistence of information that can be stored in long-term memory is far less defined and even considered indefinite (Shephard, 1967; Baddeley & Hitch, 1974). The capacity limit of the human VLTM has not yet been found but studies have shown that VLTM has a massive capacity for visual details. Various studies have shown that human participants are able to select the correct picture they have seen after learning 612 or even 2560 images, which they have seen for only a couple of seconds in a single exposure, in a two-alternative choice recognition test with a success rate above 90% (Shephard, 1967; Standing, Conezio & Haber 1970).

One of the more recent studies to the capacity of VLTM was conducted by Brady et al. (2008). In this experiment participants had to learn 2500 unique images of objects which were, in contrast to previous studies, not embedded in scenes and thus could not be memorized in terms of context. Afterwards, the participants had to pick the image they had seen before in a two forced choice test. The images they had to learn were presented next to a novel image (one that was not seen before), an exemplar image (an object of the same category but with another identity) or a state image (object with the same identity in a different state). Participants were able to select the image they had seen before with a performance rate far above chance (92% novel, 88% exemplar and 87% state). These results do not suggest that people have a photographic memory or can name every image they have seen in a free recall. It does however suggest that a lot of detailed visual information is stored somewhere along the visual processing stream (Brady et al., 2008; Ahissar & Hochstein, 2004).

Here, we conducted an experiment that utilized the storage capacity of VLTM in combination with a b-CFS task in order to study the influence of the content of VLTM on visual awareness. Participants learned a selection of the same images used by Brady et al. (2008) in a similar VLTM learning task, but instead of testing the capacity of VLTM afterwards with a two forced recognition test, the images were presented in a b-CFS setup. Images appeared in four conditions during the b-CFS task: match (these images of objects were learned exactly as they were presented), state (these objects had the same identity as the learned object but were presented in a different state), exemplar (these objects had another identity but were from the same category as the learned object) and novel (these objects were not learned).

Low-level stimuli properties, such as orientation and color, can be processed unconsciously during suppression but it remains unclear to which extent higher-level aspects of visual stimuli, such as familiarity or category membership, can be extracted without awareness under b-CFS viewing conditions (Stein, Hebart & Sterzar, 2011). Ahissar and Hochstein (2004) argued that high-levels are the first levels that are accessed by conscious perception. They proposed the Reverse Hierarchy Theory (RHT), which states that top-down control or guiding mechanisms influence both perceptual learning and conscious perception. According to this theory, visual conscious perception and learning happens first on high levels (e.g. category and gist) and later, if this information does not suffice, progresses backwards to lower input levels that have a better signal to noise ratio (e.g. orientation). When hypothesizing through the lens of this theory, match images would break through suppression first as they match the content of LTM (more information, faster processing). There would be no significant difference between state and exemplar images as they can both be processed based on gist or category. Novel images would take the longest time to break through suppression as they do not match the content of LTM and lower levels of processing would be needed, where receptive fields are more specific to, for example, retinal position and orientation.

Another possibility, according to the novelty/encoding hypothesis, is that novel images receive a preferential treatment over familiar information (Tulving & Kroll, 1995). Studies have shown that the brain is attracted to novelty and found that brain activity, in the cortical and subcortical regions as well as in the temporal lobes and accuracy of recognition is higher for novelty than for comparable familiar information that matches the information of LTM (Li, Miller & Desimone, 1993; Berns, Cohen & Mintun, 1997). Various researchers argued that the novelty/encoding hypothesis only applies to long-term memory and stated that mechanisms responsive to novelty do not affect attentional or working-memory processing of on-line information (Tulving & Kroll, 1995; Berns, Cohen & Mintun, 1997). In the light of this hypothesis, novel images would potentially break faster through interocular suppression than familiar images.

Prioritization of information is an important subject in the field of artificial intelligence. Artificial Intelligence (AI) is the simulation of human intelligence processes by computer systems and machines. These processes include image recognition, navigation, reasoning and self-correction. Prioritization of relevant visual information is crucial for humans to navigate through their everyday environments as human processing capacity for visual information is limited. A better understanding of these processes in humans could help in the development towards a more accurate implementation of human like intelligence processes in an AI system. Prioritization of information is a crucial in, for example, AI systems of self-driving cars. At high speed the AI system needs to respond fast and correctly to relevant information and ignore irrelevant information. Its needs to, for example, make choices about whether the red sign in the distance is a stopping sign or not, and whether or not the sign applies to the road the car is driving on. The system has to make decisions and prioritize relevant information based on the context the information is embedded in.

Method

The experiment consisted of two phases. It started with a learning phase during which the participants learned 99 images of objects followed by a 15-minute break. After this break, the b-CFS phase took place. In this phase new images and counterparts of the learned images were presented to one eye while the image was being suppressed by the presentation of a high-contrast dynamic pattern to the other eye. Participants were instructed to push a button (letter F on a keyboard) when they saw (part of) a target image appear. Pushing the button resulted in a reaction time (RT) that represented the time it took for the image to break through interocular suppression and enter visual awareness.

In the first phase, the participants got to learn 99 images from three different conditions: 33 state, 33 exemplar and 33 match images. These conditions refer to the form in which the counterpart images appeared in the second phase. The second phase, the b-CFS task phase, contained four conditions: state, exemplar, match and novel. State condition images contained pairs of objects that had the same identity, but their counterpart was in a different “state” (for example: image A appeared in the learning phase as an open umbrella and counterpart A’ in the b-CFS phase was the same umbrella but closed). Exemplar images had a counterpart from the same category but with different identities (for example: a black bunny B and a brown bunny B’). Match images were the same in both the learning phase and the b-CFS phase. Novel images were only presented during the b-CFS phase and not learned or seen before. An example of the conditions that appeared in the learning- and b-CFS phase is depicted in Figure (1).

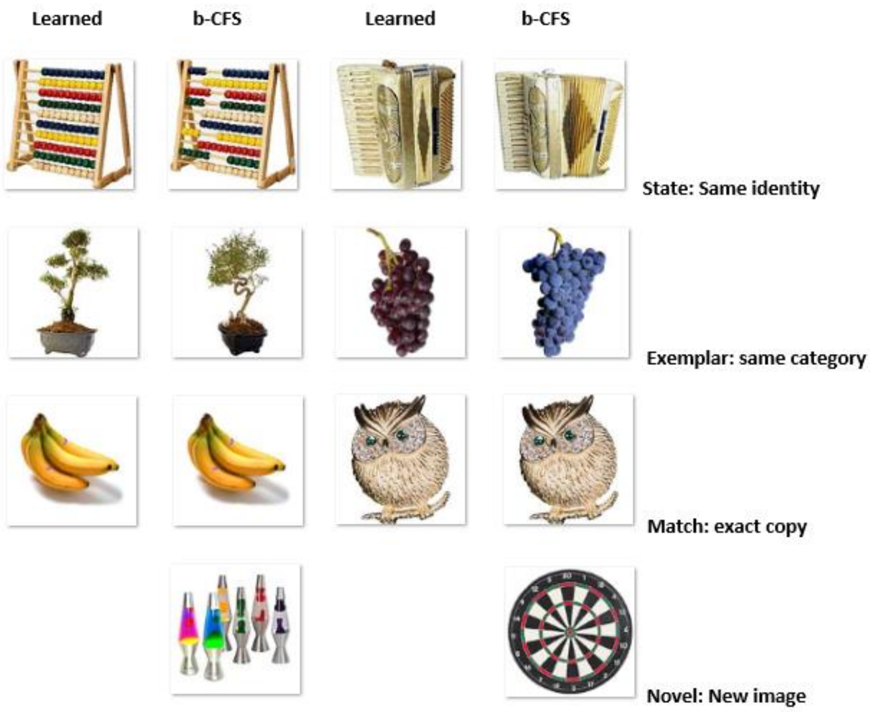

Figure 1: Example of stimuli and conditions for the learning phase and the b-CFS phase. Images were made available for academic use and can be found on the website of The UCSD Vision and Memory lab.

Learning phase

As learning can be regarded as an attention driven process (Bourbon-Teles et al., 2014), the experiment started with a learning phase in the form of a Repeat-Detection task. This method allowed us to probe online memory capacity and maintain the attention of the participants during the trials. Each image was presented for 5s followed by an 800ms fixation cross. Participants were instructed to only push a button (letter F on a keyboard) whenever they saw an image that appeared on screen for the second time. State, exemplar and match (the "probe images") appeared twice during the task. The learning phase also contained 102 filler images that only appeared once and did not return in the b-CFS phase. Pushing the button (F) when a probe image was presented for the first time or when a filler image was presented, resulted in a *non-correct* hit. Not pushing the button when a probe image was presented for the second time also resulted in a non-correct hit.

Participants were split up into group A and B. The stimuli content of the learning phase is depicted in table 1. The images were randomly shuffled into the stimuli pool of group A or group B. During the task the images appeared in a random order and were presented to both eyes at the same time. The task was split up into three blocks and took around 35 minutes. At the end of each block participants could choose to take a short break or resume the task. Each participant got to see a total of 300 images of which 99 were presented twice.

Group A stimuli content	**Group B stimuli content**
33 State A	33 State B
33 Exemplar A	33 Exemplar B
33 Match A	33 Match B
102 Filler	102 Filler

Table 1: Learning phase. Repeat detection task. Overview of the content of the stimuli pools of version A and B. State, exemplar and match condition images appeared twice; filler stimuli only once. Participants got to see a total of 300 images (99x2 + 102 = 300).

b-CFS phase

During the b-CFS task, a medium high-contrast dynamic pattern mask (10Hz) was presented to the dominant eye while an image presented to the supressed non-dominant eye was ramped up from 0 to maximum contrast in 1000ms. Participants were told to push a button (letter F on a keyboard) whenever they saw an image appear. If they did not press a button, the trial took 5,3s. After both actions (hit or no hit), a short 500ms mask was presented to both eyes to wipe the after image from sensory memory. After this, a short 500ms fixation cross was presented to both eyes on a white background followed by a new trial. The b-CFS task was split up into four blocks. In between these blocks, participants could choose to take a short break. Each trial block contained 20% catch trials, which were empty trials put in place to prevent participants from just keep pushing the button aimlessly. Each participant performed a total of 160 trials of which 132 contained an image.

Most people have the tendency to prefer visual input from one eye to the other, this is called ocular dominance. The dynamic mask was presented to the dominant eye in each trial because the total duration of exclusive visibility of the dominant eye is longer than that of the non-dominant eye (Handa et al., 2004). Ding et al. (2018) recommended that eye dominance should be determined using pretrials of the same task that will be used in the main experiment, as b-CFS might reflect a different form of eye dominance than onset and ongoing rivalry. In accordance with this information, eye dominance for each participant was determined in a short b-CFS task before the primary task. This task followed the same procedure as the main b-CFS task using 12 unique images. Each image was presented twice to each eye and the task also contained 20% catch trials. The eye to which presentation of the target resulted in the lowest RT, and thus shortest suppression duration, was considered the dominant eye.

Strong suppression of the non-dominant eye can be obtained by a high contrast mask (Kim & Blake, 2005). The maximum contrast for a b-CFS task can be obtained by using a high-contrast (black and white) dynamic pattern mask and by presenting the target stimuli on a gray background (e.g. Gayet et al., 2016). Because all images used in this experiment were embedded in a white background, they also had to be presented on a white background (64.2 cd/m^2) instead of a gray one (31.9 cd/m^2) in order to prevent them all from appearing as a big white square during the b-CFS task. Presentation of the images on a white background led to very strong suppression by a high-contrast dynamic pattern mask (black and white, >99% Michelson contrast), rendering almost all images invisible during test trials. Therefore, a medium high-contrast mask was used, for which the contrast was lowered by 50%, resulting in a dark- and light gray mask (50% Michelson contrast).

The b-CFS phase contained the stimuli content depicted in Table 2. The match conditions of both groups were counterbalanced to make up for individual differences between the images: the novel condition of B was the match condition of A and vice versa. This was done because the memorability for each used image was not (yet) estimated during this experiment, meaning that there was a possibility that one pool of images contained a higher total of better memorable images than the other.

Group A b-CFS stimuli content	**Group B b-CFS stimuli content**
33 State A’	33 State B’
33 Exemplar A’	33 Exemplar B’
33 Match A	33 Match B
33 Novel (= Match B)	33 Novel (= Match A)

Table 2: b-CFS phase stimuli content. Match images are exact copies of learned images and novel images are not learned in the first phase. Match images from group A are novel images for group B and vice versa.

Participants

Twenty participants (7 males and 13 females; age 19-31 years) completed both phases of the experiment and reported normal or corrected-to-normal vision. The participants were randomly appointed to group A or group B (ten participants in each group). All participants passed the TNO test for stereoscopic vision and Ishihara’s tests for colour vision. Each participant’s eye dominance was determined in the practice pre-b-CFS phase. All participants signed a consent which was approved by the Scientific and Ethical Review Committee. Participants were offered €7 per hour in exchange for their participation.

Apparatus and stimuli

All phases of the experiment were conducted on an Apple Mac mini with a 2,6Hz Intel Core i5 processor and an Intel Iris 1536MB graphics card running on macOS Sierra version 10.12.4 using an Iiyama G-Master GB2488HSU monitor (1920x1080 pixels; 100Hz refresh rate) and an Apple keyboard. MATLAB 2017a with Psychophysics Toolbox 3 was used to program, run and register the input data of the experiments. During trials the room was completely dark apart from the light coming from the monitor. A pair of displays were used to present the images to both eyes through a mirror stereoscope on a chin rest which kept the viewing distance at an effective 47cm distance from the monitor.

To facilitate binocular fusion during the b-CFS task the images (depicted in 2,56cm x 2,56cm) and masks were presented inside a circular area with a diameter of 7,5° surrounded by a black frame (<1cd/m^2) presented to each eye. Images containing the target stimuli inside the circles were presented on a white background (64,2 cd/m^2) and ramped from 0 to maximum brightness in 1000ms. Images were presented for a maximum of 5,3s in absence of input (a button push) from the participant. The masks used during the b-CFS trials were created by filtering pink (1/f) noise using a rotationally symmetric Gaussian low-pass filter ($\sigma = 3,5$) and making the resulting image dark- and light gray (50% Michelson contrast). On every trial 20 new masks were generated which were presented for 10 frames each (10 Hz). Instructions were depicted in black Arial font (<1cd/m$^{2)}$ with a size of 20.

The gathered stimuli used in this experiment were a selection from the images of objects used in the experiment and corresponding article *Visual long-term memory has a massive storage capacity for object details (2008),* which were made available for use and can be found on the website of The UCSD Vision and Memory lab directed by Dr. Timothy Brady. All gathered stimuli were embedded in a white background (64,2 cd/m^2) so they could not be memorized by context. The stimuli used in this experiment were selected based on several visual and semantic characteristics and properties. Images that were too small, only black and white or had a poor contrast on a white background were considered not fit for use in the b-CFS setup as their visual properties could potentially lower the chance of the images to break through interocular suppression (Handa et al., 2004; Yang & Blake, 2012). Stimuli with well-known images of pop culture were also rejected (although an image of SpongeBob and Superman were used in the pre b-CFS task in which eye dominance was determined), as for these images it might be hard for the participant to remember whether the stimulus was probed during the learning phase or not due to their familiarity. Images of objects with human faces were also not used in the experiment, as human faces do have a record as strong attractors of visual attention, making it hard to conclude whether the image broke through the b-CFS mask because of the visual properties of the object itself or the face on it (Theeuwes & Van der Stigchel, 2006). Each image or pair of images had a unique category to minimize the chance of interference between the image categories. A total of 312 unique images were used, of which 12 were only used in the practice phase.

Results

Five participants were excluded from analyses (participant 1, 10, 12, 17 and 20). One participant was excluded because of problems with the save files containing the learning phase data and another one because of a low score (<90%) in the learning phase (89% correct hits). Another participant was excluded for cheating the b-CFS task as the participant was excessively blinking the entire task which led to extremely high results (100% hit rate for each condition and RTs close to 1s, which is also the time it took for the presented images to reach maximum brightness). Furthermore, two datasets were excluded because of a low hit rate (= percentage of correct hits <87%) in the b-CFS phase, of which one participant had an average hit rate of 75% and the other one had an average hit rate of 79%.

Learning phase

Most participants performed very well in the learning phase. All total scores (N=15) were above 90% correct hits with a mean score of 95,7 and median of 96%. The highest score was 99% and the lowest 91%. Match condition images were recalled with a mean correctness percentage of 92% (*SD=0,06*), state with 88% (*SD=0,08*) and exemplar with 90% (*SD = 0,11*). A repeated measures ANOVA was conducted which showed a significant difference between the variance of the learning score conditions [$F(2,18) = 3{,}5$, $p = 0{,}044$ with $\alpha = 0{,}05$] with a large effect [$\eta 2 = 0{,}605$]. This significant difference between the three conditions may indicate that some of the images in certain condition pools had weaker visual properties and memorability, as the participants did not know that the images belonged to a certain condition during the task.

b-CFS phase

Results from the b-CFS trials (N = 15) are depicted in Table 3. Values depicted under ‘mean’ represent the mean of the medians of each condition without the inclusion of non-hits. Total hit rates (= percentage correct presses when an image was presented) varied between 87% and 99% with a mean of 93%. The state condition had a mean hit rate of 87%, exemplar 85%, match 92% and novel 94%. Catch trials were rarely hit and when it happened it occurred only once in the participants' 160 trials (apart from one single data set that was already excluded from analyses).

	Mean	Std. Deviation	N
State	1,8686	,4594	15
Exemplar	1,8673	,3978	15
Match	1,7706	,3868	15
Novel	1,7756	,4704	15

Table 3. Mean RT of the medians and standard deviation for each condition (N=15) without inclusion of non-hits.

Use of the median instead of the mean is often preferred in b-CFS analyses because most RTs can be found on the X-axis in the first half of each trial after the stimulus reached maximum brightness (in this case between 1 and 2,5 seconds). Using the mean instead of the median would therefore result in less accurate total values as one outlier would more heavily impact the end results. Because medians are used, the RTs of non-hits (max RT of 5,3s) can also be included. This will slightly increase the RTs of participants and conditions with relatively lower hit rates. The mean of the medians with inclusion of non-hits are depicted in Table (4) for each condition. This data is used for further analyses.

	Mean RT	Std. Deviation	N
State	1,9429	,5242	15
Exemplar	1,9862	,4664	15
Match	1,8362	,4120	15
Novel	1,8317	,4983	15

Table 4. Mean RT of the medians and standard deviation for each condition (N=15) with inclusion of non-hits.

A repeated-measures ANOVA was conducted over the four conditions [$F(3,42) = 2,778$, $p = 0,053$]. Although close to an α of 0,05, the differences in variance are not significant and have a small effect size [$\eta 2 = 0,166$], from which can be concluded that there is no significant difference between the RTs over the four conditions. This suggests that storing an image in visual long-term memory in terms of category, identity, and exact match may not necessarily influence whether the object is prioritized for visual awareness and conscious processing.

Both match and novel images have similar mean RTs and no significant difference in variance, suggesting that learned images may not necessarily break through suppression faster than new images when presented during interocular suppression. To test whether it makes a difference whether images are learned and stored in VLTM, a paired samples t-test was conducted using the images from the match/novel pool. Images from the match/novel pool occurred in both trials of group A and B as they were counterbalanced. This means 33 novel images from group A are the 33 match condition images of group B and 33 other images are novel for B and the match condition images for A. These 66 individual images have RTs in a learned and not-learned condition. A paired samples t-test between not learned ($M = 1,94$, $SD = 0,59$) and learned images ($M = 1,93$, $SD = 0,63$) showed no significant difference between the conditions [$t\ (65) = 0,83$, $p = 0,934$ with $\alpha = 0,05$]. Simply storing visual information of objects in VLTM therefore did not enhance the speed with which the visual stimulus entered visual awareness and broke through interocular suppression.

Instead of being stored in VLTM or not, images might break through suppression faster based on individual visual properties like color, contrast and size. Earlier research on binocular rivalry found that visually strong stimuli break through suppression faster than weaker stimuli (Handa et al.,2004). Reaction times (median of the RT with inclusion of non-hits) for each of the 132 individual images that appeared in the b-CFS trials of group A (N=8) were sorted from shortest to longest RT and depicted in Figure (2).

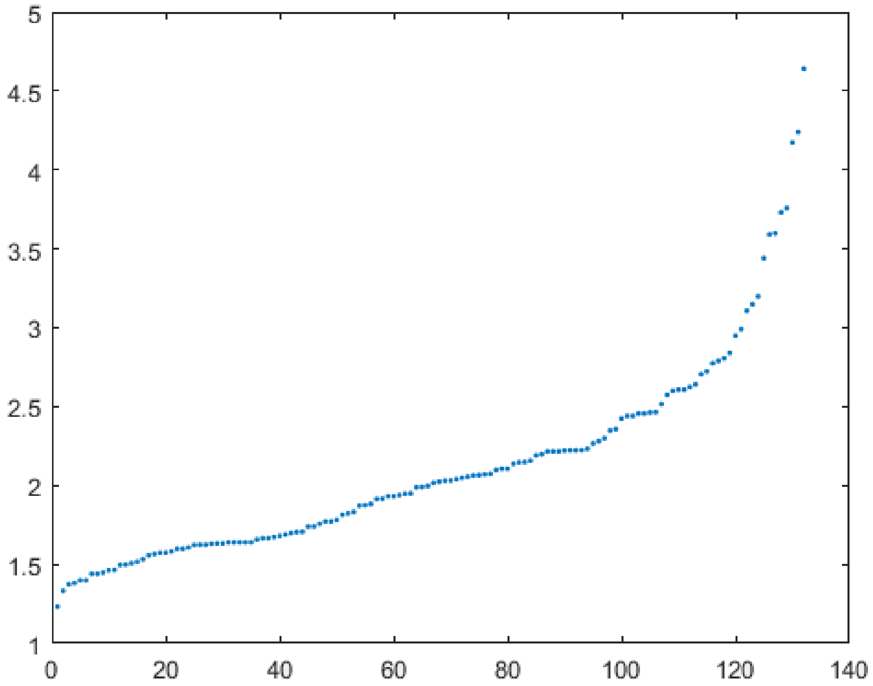

Figure 2: RT on the Y- axis and number of images on the X-axis. Each dot represents the median of the RT of an individual image. The images are sorted from shortest to longest RTs.

The graph shows that the RTs, and thus the potency to gain access to awareness, varied a lot between individual images. Some images broke through suppression very fast around 1,3 and 1,5s. Other images broke through suppression a lot slower around 3 and even 4s. It is possible that these differences originated from the visual properties of the objects as there was no significant difference found between learned and not-learned images in terms of RT. The data does not suggest that the content of VLTM has no effect at all on visual awareness. It might be possible that visual stimuli are more prioritized for conscious access based on their visual properties rather than if the visual content matches the content stored in VLTM. The differences in RTs between the images, while also regarding the significant difference found between the variance of the conditions in the learning phase, suggest that the used images might not have been exactly equal in terms of potency to break through interocular suppression.

Discussion

Visual information is not prioritized for conscious access when it matches the content of VLTM according to the obtained experimental data. Images did not break through interocular suppression faster when matching the content of VLTM in terms of category, identity or exact match. Novel images also did not break through interocular suppression faster than learned images.

The data does not contradict the shared believe between various researchers (e.g. Tulving & Kroll, 1995; Berns, Cohen & Mintun, 1997) that the novelty/encoding hypothesis, which states that novel information gets processed faster than familiar information, only applies to LTM and can operate independently of awareness. The obtained data suggests that the content of LTM may not necessarily directly influence visual awareness as there was no significant difference found in RTs between novel and learned images. The novelty/encoding hypothesis might possibly not be applicable to a b-CFS paradigm, as the content of VLTM did not influence visual awareness and possibly therefore novel images did not break through interocular suppression significantly faster than learned images. Whether a visual object is considered novel or not can often depend on the context the object is embedded in, as familiar objects from the past can appear in contexts that are novel in the present. The images of objects used in current experiment were not embedded in a context. Future research might test the novelty/encoding hypothesis using the b-CFS method with objects embedded in several different contexts.

Research has shown that strong visual properties can enhance the speed in which a visual object breaks through interocular suppression (Handa et al., 2004; Yang & Blake, 2012). It might be possible that visual stimuli are more prioritized for conscious access based on their visual properties rather than if the visual content matches the content stored in VLTM. It is however too early to tell as the data did show big differences in RTs between the images and there was a significant difference between the conditions regarding the learning scores, which may suggest that the images were unequal in terms of strength of their visual properties. Memorability scores were not estimated for the used images, rendering the quality of the images in each condition unequal in terms of potency to break through interocular suppression. Image memorability is an intrinsic property of an image that can reliably be estimated with the use of machine learning algorithms and state-of-the-art Convolutional Neural Networks (CNNs) to quantify deep memorability features (Zhou, 2017; Khosla, 2015). At the time this experiment took place there were no available databases with images like the one made by Brady et al. (2008) that included memorability scores of images of isolated objects that were not embedded in a scene or context. Further research could use images provided with memorability scores to even out the quality of the images used in each condition.

Absence of memorability scores and differences between the visual properties of the used images may suggest that the data does not provide sufficient evidence to make any statements about the four conditions and how their visual properties affect the speed in which they enter visual awareness when presented in a b-CFS setup. The results were not in favour of the reverse hierarchy theory proposed by Ahissar and Hochstein (2004), which states that learned images enter conscious perception first at high hierarchical processing levels (e.g. category and gist). Having learned an image in terms of category, identity or exact match did not enhance the speed in which the image entered visual awareness according to the results of the b-CFS experiment. Further research that includes the use of images provided by memorability scores might give more insight in the influence of top-down processing mechanisms on visual awareness. Another aspect of LTM research to take into account is that most used images contain objects that are probably known concepts to a healthy participant at the age of 19-31 and that it is almost impossible to know what information is stored in ones LTM and how this information might affect ones results in a learning and/or b-CFS task. A novel condition image might for example contain a well-known concept for a participant and thus could possibly also be processed directly by higher level processing mechanisms in the light of the reverse hierarchy theory.

It might be possible that content stored in VLTM first needs to be activated by attentional drive from WM systems in order to affect visual awareness (Ruchkin et al.,2003). Earlier research showed that visual information matching the content held in WM is prioritized for visual awareness and conscious access (Gayet, Paffen & Van der Stighel, 2013; Liu, Wang & Jiang, 2013; Pan et al., 2013; Gayet et al. 2016; Van Moorselaar et al., 2017). Research on LTM found that LTM systems associated with the posterior cortical processors provide the necessary representational basis for WM (Ruchkin et al.,2003). Various models have also been proposed over the years which state that information can be retained from VLTM into working memory (Baddeley, 2000). It could be possible that external visual information gains prioritization for visual awareness and conscious access when it matches specific visual information that is actively retained from VLTM into VWM. Further research can potentially emphasize on active retention from VLTM and how it affects visual awareness.

Conclusion

Visual information when presented in a b-CFS setup is not prioritized for visual awareness and conscious access when it only matches the content of visual long-term memory. No significant difference was found between novel and learned images regarding the time it took for these images to break through interocular suppression and enter visual awareness. The novelty/encoding hypothesis might not be applicable to a b-CFS paradigm. Further research would be needed, in which all used images are provided with memorability scores, in order to gain more insight in the influence of top-down processing and guiding mechanisms on visual awareness during interocular suppression.

References

Ahissar, M. & Hochstein, S. (2004). The reverse hierarchy theory of visual perceptual learning. Trends in Cognitive Sciences. Vol. 8 No. 10 October 2004. Doi:10.1016/j.tics.2004.08.011

Baddeley, A. (2000). The episodic buffer: a new component of working memory? Trends in Cognitive Sciences. Volume 4, Issue 11, 1 November 2000, Pages 417-423. https://doi.org/10.1016/S1364-6613(00)01538-2

Baddeley, A. D., & Hitch, G. (1974). Working Memory. Psychology of Learning and Motivation, 47–89. doi:10.1016/s0079-7421(08)60452-1

Berns, S. G., Cohen, D. & Mintun, M. A. (1997). Brain Regions Responsive to Novelty in the Absence of Awareness. Science Vol 276, 23 May 1997. doi: 10.1126/science.276.5316.1272

Bourbon-Teles, T. Bentley, P. Koshino, S. Shah, K. Dutta, A. Malhotra, P. Egner, T. Husain, M. & Soto, D. (2014). Thalamic Control of Human Attention Driven by Memory and Learning. Current Biology Volume 24, Issue 9, 5 May 2014, Pages 993-999. https://doi.org/10.1016/j.cub.2014.03.024

Brady, T. F., Konkle, T., Alvarez, G. A., & Oliva, A. (2008). Visual long-term memory has a massive storage capacity for object details. Castelhano M. Proceedings of the National Academy of Sciences of the United States of America, 105(38), 14325–14329. http://doi.org/10.1073/pnas.0803390105

Ding, Y., Naber, M., Gayet, S., Van der Stigchel, S. & Paffen, C.L.E. (2018) Assessing the generalizability of eye dominance across binocular rivalry, onset rivalry, and continuous flash suppression . Journal of Vision June 2018, Vol.18, 6. doi:10.1167/18.6.6

Gayet, S. Paffen, C. L. E. Van der Stigchel, S. (2013) Information Matching the Content of Visual Working Memory is Prioritized for Conscious Access. Psychological Science. 11 October 2013. Doi:10.1177/0956797613495882

Gayet, S., Van Maanen, L., Heilbron, M., Paffen, C.L.E. & Van der Stigchel, S., (2016). Visual input that matches the content of visual working memory requires less (not faster) evidence sampling to reach conscious access . Journal of Vision September 2016, Vol.16, 26. doi:10.1167/16.11.26

Handa, T. Tomoya, C. Mukuno, K. Uozato, H. Niida, T. Shoji, N. Simizu, K. (2004) Effects of Dominant and Nondominant Eyes in Binocular Rivalry. Optometry and Vision Science: May 2004 - Volume 81 - Issue 5 - p 377-383 doi: 10.1097/01.opx.0000135085.54136.65

Khosla, A. Raju, A. S. Torralba, A. Oliva, A. (2015). Understanding and Predicting Image Memorability at a Large Scale. The IEEE International Conference on Computer Vision (ICCV), 2015, pp. 2390-2398. Doi:10.1109/ICCV.2015.275

Kim, C. Blake, R. (2005). Psychophysical magic: rendering the visible 'invisible'. Trends in Cognitive Sciences. Volume 9, Issue 8, August 2005, Pages 381-388. https://doi.org/10.1016/j.tics.2005.06.012

Li. Q, Geng. H. (2008). Progress in cognitive neuroscientific studies of visual awareness. Progress in Natural Science. Volume 19, Issue 2, 10 February 2009, Pages 145-152 doi.org/10.1016/j.pnsc.2008.06.013.

Li, L. Miller, E. K. Desimone, R. (1993) The representation of stimulus familiarity in anterior inferior temporal cortex. Journal of Neuropsychology. Volume 69 Issue 6. 1 June 1993. Pages 1918-1929. https://doi.org/10.1152/jn.1993.69.6.1918

Liu, D., Wang, L., and Jiang, Y.(2013). Working memory modulates unconscious visual processing. Journal of Vision. 13, 802. Doi:10.1167/13.9.802

Pan, Y., Lin, B., Zhao, Y. and Soto, D. (2013). Working memory biasing of visual perception without awareness. Doi: 10.3758/s13414-013-0566-2

Ruchkin, D. S. Grafman, J. Cameron, K. Berndt, R. S. (2003). Working memory retention systems: A state of activated long-term memory. Behavioral and brain sciences (2003) 26, 709-777. Doi-org.proxy.library.uu.nl/10.1017/S0140525X03000165

Standing, L., Conezio, J., & Haber, R. N. (1970). Perception and memory for pictures: Single-trial learning of 2500 visual stimuli. Psychonomic Science, 19(2), 73–74. doi:10.3758/bf03337426

Shepard, R. N. (1967). Recognition memory for words, sentences and pictures. Journal of Verbal Learning and Verbal Behavior, 6, 156-63. https://doi.org/10.1016/S0022-5371(67)80067-7

Stein, T., Hebart, M. N. & Sterzar, P. (2011). Breaking continuous flash suppression: a new measure of unconscious processing during interocular suppression? Frontiers in Human Neuroscience. 20 December 2011. Doi:10:3389/fnhum.2011.00167

Todd, J. & Marois, R. (2004) Capacity limit of visual short-term memory in human posterior parietal cortex. Nature volume 428, pages 751-754 (15 April 2004). DOI:10.1038/nature02466

Theeuwes, J. & Van der Stigchel, S. (2006) Faces capture attention: Evidence from inhibition of return, Visual Cognition, 13:6, 657-665, DOI: 10.1080/13506280500410949

Tulving, E. Kroll, N. (1995). Novelty assessment in the brain and long-term memory encoding. Psychonomic Bulletin & Review. September 1995, Volume 2, Issue 3, pp 387-390. doi: 10.3758/BF03210977

Van Moorselaar, D., Gayet, S., Paffen, C.L.E., Theeuwes, J., Van der Stigchel, S. & Olivers, C. N. L. (2018). Competitive interactions in visual working memory drive access to awareness. Cortex Volume 102, May 2018, Pages 6-13. https://doi.org/10.1016/j.cortex.2017.03.026

Yang. E, Blake. R, (2012). Deconstructing continuous flash suppression. Journal of Vision March 2012, Vol.12, 8. doi:10.1167/12.3.8

Zhou, B. Lapedriza, A. Khosla, A. Oliva, A. Torralba, A. (2017). Places: A 10 Million Image Database for Scene Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence. Volume: 40 , Issue: 6 , June 1 2018. pp 1452 – 1464. Date of Publication: 04 July 2017 Doi:10.1109/TPAMI.2017.2723009.