

Selective Attention and Consciousness: Investigating Their Relation Through Computational Modelling

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Abstract The present study aimed at investigating the possible connection between conscious awareness and attention through the implementation of a neurocomputational model of visual selective attention. The development of the model was based on recent neurophysiological findings that document the synchronization of neural activity in cortical areas of the brain and the presence of competitive interactions among stimuli at the early stages of visual processing. The model was used to simulate the findings of a behavioural experiment conducted by Naccache et al. in *Psychol Sci* 13:416–424 (2002), which have sparked a debate on the possible links between attention and consciousness. The model reproduced closely the pattern of the behavioural data while incorporating mechanisms that take into account the neural activity representing the early visual processing of stimuli and the effects of top–down attention. Thus, by adopting a computational approach, we present a possible explanation of the findings at the neural level of information processing. The implications of these findings for the relation between attentional processes and conscious awareness are discussed.

Keywords Spiking neural networks · Visual selective attention · Consciousness

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Introduction

An essential aspect of our everyday life is the ability to select from the multitude of signals that are registered by our sensory organs, the information that is most relevant to our current goals. The mechanism that is responsible for filtering out irrelevant stimulation, thus allowing only a fraction of information to be further processed, is known in the scientific literature as selective attention. Selective attention allows us to keep the balance between internal motivations and external stimulation, and it can thus be guided by both top–down or bottom–up mechanisms [1]. Top–down or endogenous attention refers to the volitional modulation of neural activity that corresponds to an object or a location in space on the basis of signals initiated by internal goals that most likely originate in the parietal and frontal lobes of the brain [2]. Exogenous or bottom–up attention on the other hand is a faster and more automatic process that relies on the sensory saliency of stimuli registered by subcortical structures and the primary sensory cortices [1–3].

Although the role of attention as a control system is ubiquitous, to fully understand the functioning of this mechanism one must closely examine its relation with other psychological constructs such as working memory, learning and consciousness. For example, recent scientific studies have suggested that the ability of a person to enhance or suppress information from the environment is closely related to his/her working memory capacity [4]. In addition, attention seems to play a key role in long-term learning aiding the brain to encode and maintain enormous amounts of information throughout the life span. Specifically, attention is believed to be responsible for stabilizing the reorganization of neural pathways, an ability of the brain necessary for acquiring new knowledge [5, 6].

An interesting, albeit controversial, issue concerns the relationship between selective attention and consciousness.

Although psychologists and neuroscientists accept that selective attention and consciousness are related constructs, the exact nature of this relation remains unclear. Some researchers emphasize this close relation and argue that attention is necessary and sufficient for consciousness [7–10], while others posit that since the two constructs are subserved by separate neural processes, they must be regarded as distinct mechanisms [11–13]. The claims that selective attention and consciousness are very similar constructs or even the same is reinforced by the plethora of evidence showing that a person becomes consciously aware of a stimulus when s/he focuses attention on it [14]. Indeed, as shown by many inattentive blindness studies, a stimulus easily evades conscious awareness when no attention is directed at it [15]. On the other hand, evidence from studies using dual task paradigms demonstrates that it is possible to perceive stimuli presented in the peripheral visual field even when spatial attention is endogenously focused on a central task [16, 17]. Also, both forward and backward maskings have been shown to interfere with the visual awareness of a stimulus [18]; thus, masking paradigms have been commonly used to investigate the relation between attention and consciousness [19].

Examining how attention relates to consciousness is not an easy task as the constructs are theoretical and often not concretely operationalized. In the present work, a computational modelling approach has been adopted to examine the relation between these constructs. Computational modelling forces us to provide explicit definitions for attention and consciousness and allows us to pinpoint at the level of neural activity how these constructs might be related. In the present study, we deal with the interaction between attention and consciousness at the level of simple visual stimuli processing. Therefore, we

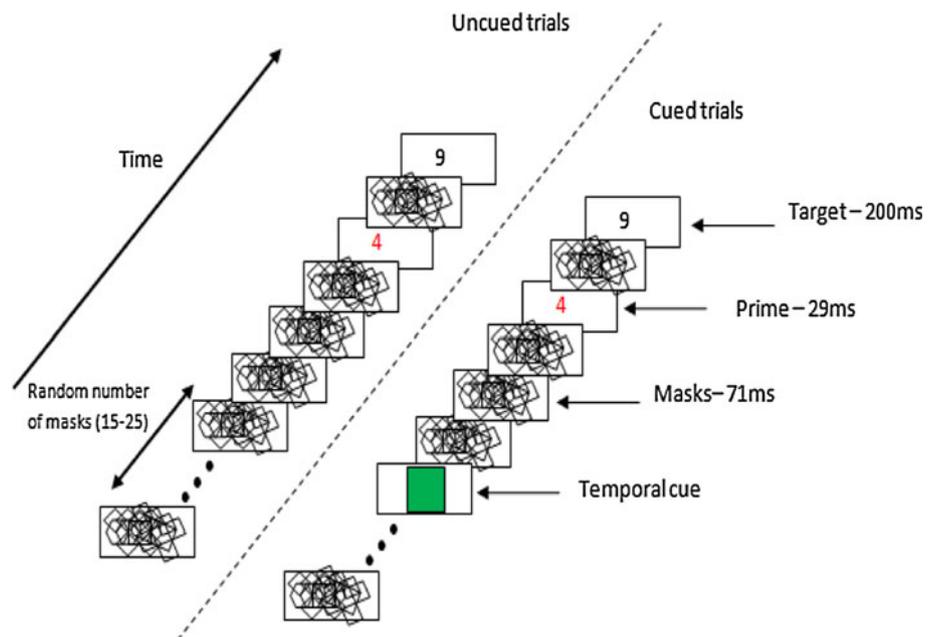
assume that a certain stimulus is consciously perceived, if at least some of its attributes have reached working memory. Thus, in the present research, consciousness is equated with perceptual awareness. Importantly, the model assumes that the experience of being perceptually aware of a stimulus is only achieved if the specific stimulus has gained access to visual working memory. The possible connection between attention and consciousness as it is defined in the present study is investigated through an implemented spiking neural network (SNN) computational model of visual selective attention. The model is used to simulate the findings from a behavioural experiment conducted by Naccache et al. [19]. These findings are described next.

Behavioural Data

In the study by Naccache et al. [19], participants were presented with a number-comparison task in which they were asked to indicate if a presented numeric stimulus (a number between 1 and 9 but excluding 5) was greater or smaller than 5. Shortly before the appearance of the target stimulus, a prime was presented that could be either congruent with the target (both the prime and target are greater or smaller than 5) or incongruent (the prime is greater than 5 but the target smaller or vice versa).

The prime was presented among masking stimuli for only 29 ms and as confirmed by the study, participants were not aware of its presence. In addition to the basic task, a temporal cue was presented in some trials. The cue did not reveal any information about the identity of the target but allowed the participants to anticipate when the target would be presented (Fig 1).

Fig. 1 The experimental setup used by Naccache et al. [19]



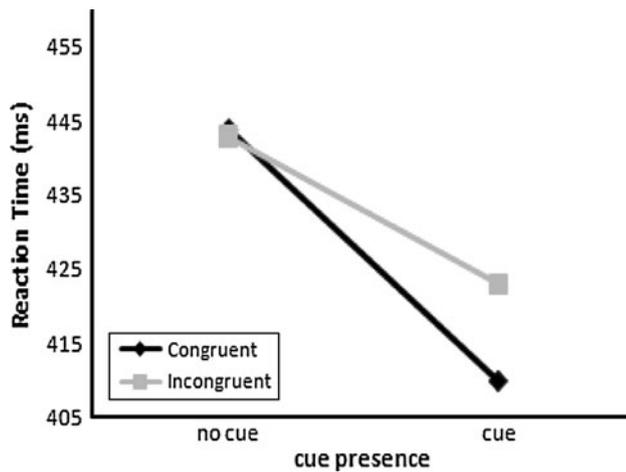


Fig. 2 Basic pattern of findings from Naccache et al. [19]

Results from the study revealed an interaction between cueing condition and target compatibility. Participants were faster responding to a congruent than an incongruent target but only when a temporal cue was provided. When no temporal cue was present, response times for congruent and incongruent targets were about equal. Overall, the temporal cue enhanced performance as response times were faster for cued than non-cued trials. The basic pattern of the findings by Naccache et al. [19] is presented in Fig 2.

It should be noted that the difference between congruent and incongruent conditions in the presence of a temporal cue may be attributed to facilitation from the compatible prime, interference from the incompatible prime, or a combination of the two. Regardless of the source of the effect, its mere presence suggests that although the prime was not consciously perceived, it was capable of influencing performance.

Method

The main goal of the present study is to provide an account for the findings of Naccache et al. [19] at the neural level of information processing through a neurocomputational model of selective attention. By using this approach, we attempt to examine how attentional processes may influence behaviour through conscious and non-conscious processes.

Overview of the Proposed Computational Model

The computational model is depicted schematically in Fig 3. The model is comprised of two stages of processing implemented as spiking neural networks. The first stage simulates the initial bottom-up competitive neural interactions among visual stimuli, while the second involves

top-down semantic modulations of neural activity. During the progression of neural activity in the two stages of processing, encoded stimuli compete for access to working memory (WM) through forward, backward and lateral inhibitory interactions which influence the strength of their neural response. This implementation is based on findings showing that competition for neural representation in V1 is initiated when two or more stimuli fall within the receptive fields of the same or nearby cells [20], a phenomenon known as biased competition [21].

It should be also pointed out that throughout the stream of processing top-down signals can interfere and modulate neural activity. In particular, spatial top-down information can interfere with the neural activity in the first stage of processing, while semantic top-down information may exert influence in the second stage of processing.

The model has been previously used in similar form to account for the Attentional Blink phenomenon [22, 23] and the Perceptual Load effects [24]. Without changing its underlying logic, the model is here further extended, refined and polished from its previous implementations and is applied to the task of Naccache et al. [19].

Basic Units of the Model

The SNN of the computational model is comprised of basic integrate and fire models of neurons (*I&F*) as well as coincidence detector (CD) nodes.

The functioning of a basic *I&F* neuron is governed by the membrane equation:

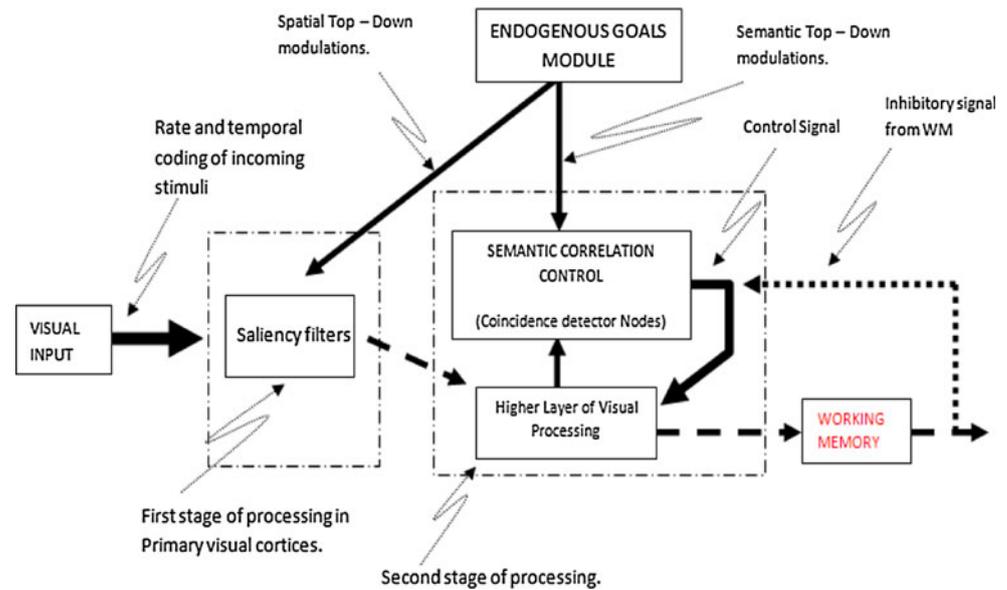
$$\tau_m \frac{dV}{dt} = E_{leak} - V - R_m I \quad (1)$$

In Eq. (1), τ_m is the membrane time constant and V is the membrane potential of each neuron. The membrane potential can be seen as a measure of the extent to which a node is excited. E_{leak} corresponds to a leak current that drives the node's membrane potential towards the resting potential and R_m is the membrane resistance of the neuron. I is the total current, a simple combination of excitation currents that result in a proportional increase of the membrane potential and inhibition currents that drop the membrane potential of the node. As shown in Eq. (1), the total summations of the excitatory and inhibitory currents which reflect the interactions with other neurons are essential for the computation of the membrane potential at each time instance.

A spike will be generated whenever V in Eq. (1) exceeds a specific threshold (V_{th}). Following the emitting of a spike, V resets to its initial condition or resting potential V_{reset} . Finally, an absolute refractory period of 2 ms is applied before V begins to evolve again.

The model also consists of CD neurons which are models of neurons that are sensitive to certain temporal

Fig. 3 The proposed computational model for visual selective attention



input patterns. There is considerable evidence in the literature showing that under certain conditions such as high background synaptic activity, certain neurons such as the pyramidal cells can function as coincidence detectors [25]. The computational implementation of the CD neurons in the traditional view can be made using Eq. (1), provided that the value of the membrane time constant is low. A small membrane time constant results in faster integration and therefore only synchronous (or near synchronous) input spikes can push the membrane potential above the threshold. However, the present computational model is implemented to operate in discrete time with the assumption that each spike has duration of 1 ms and thus the CD nodes are designed in an alternative manner. The implementation of the CD nodes is based on a simple rule that causes them to fire only if a number of their input neurons fire synchronously. Specifically, in the implementation of the model a certain threshold has been set to define the number of synchronous inputs that are necessary to trigger an output response.

First Stage of Processing

The first stage of processing is responsible for the firing rate adjustment of the neurons whose receptive fields correspond to the spatial location of an incoming stimulus. This adaptation is performed in a bottom-up manner based on the saliency of each stimulus. The saliency of a visual location/stimulus describes its ability to attract attention before any influence of top-down semantic factors. Top-down spatial factors (e.g., when cues are used to prime the spatial location of an upcoming stimulus) are allowed to exert an influence at this stage. This is supported by several

studies showing that top-down signals about spatial location can have an effect on the neural activity immediately after the presentation of a stimulus [26], or even before the stimulus appears [27, 28].

Initial representations of stimuli that enter the visual field are created in the model on the basis of a saliency map. The manipulation of visual activity by means of a saliency map in the early stages of visual processing is supported by the finding that in the primary visual cortex and specifically in visual area V1, a neuron's response can be significantly suppressed by contextual inputs that lie outside but near its receptive field [29–31]. Furthermore, the response to a preferred input feature, i.e., in orientation, colour, or motion direction etc., is much more suppressed when there are similar rather than different input features in the nearby context. Specific examples of such iso-feature suppressions include iso-orientation suppression [32], iso-colour suppression [31] and iso-motion-direction suppression [33].

For the current model, we have adopted a saliency map that has been developed by Koch and Ullman [34] in the form of an algorithm. The neuromorphic vision algorithms of the saliency map have been implemented by Walther and Koch [35] into a Matlab toolbox (SaliencyToolbox—<http://www.saliencytoolbox.net>) which outputs saliency values for every spatial location in the visual field.

It should be noted that the importance of saliency in visual perception is a debated issue. On one hand, salient but irrelevant stimuli have been shown to automatically capture attention [36]. On the other hand, in their recent review, Corbetta et al. [37] claim that the behavioural relevance of a stimulus is more important than saliency for the activation of ventral frontoparietal network that is responsible for

stimulus-driven attention. Cobetta et al. argue that exogenous orienting (i.e., orienting towards salient but non-relevant stimuli) activates a dorsal frontoparietal network that is involved in goal-directed attention. While it is not clear whether the temporal cue in the paradigm used by Naccache et al. [19] qualifies as a non-relevant stimulus, it should be noted that saliency values are used in the model only to establish the initial firing rates of the neurons that correspond to visual stimuli. Subsequently, top-down factors, which presumably define behavioural relevance, are allowed to exert influence on neural activity. Moreover, the use of saliency value to generate the initial representation of each incoming stimulus in the model is based on the assumption that different possible factors contribute to the saliency of a stimulus at a different levels in the visual hierarchy. For example, luminance contrast appears to be the initial variable on which saliency computation is based, since it is the first type of information extracted by our visual system in the retina. In higher levels of processing in the visual cortex, other feature dimensions such as orientation, colour and motion are encoded and thus contribute to the visual saliency of a stimulus. At even higher levels in the visual pathway, “features” with increased level of complexity (e.g., semantic contrast) may influence visual saliency. VanRullen [38] suggested that each level in the visual hierarchy processing builds its receptive field selectiveness based on the output of the preceding layers. Thus, although the receptive fields of neurons in the higher layers of the visual pathway will be activated based on top-down activity, information about local contrasts from all previous layers is still maintained and should therefore be included in the computations.

In the current model, the saliency of each stimulus is conveyed in the neural processing through the initial firing rate of the input neurons that correspond to each incoming stimulus. Neural representations are created as streams of spikes using, for each stimulus, 12 input neurons whose receptive fields are assumed to be associated with the location of the stimulus in the visual field. Specifically,

each pixel of the output saliency map image is assumed to belong to the corresponding area of the visual image. Subsequently, the pixel values are used to establish the initial firing rate of the input neurons according to the saliency map (that is created by the Saliency Toolbox) and described by the simple transformation equation:

$$FR_{S_i} = \alpha(\max(P_j)) + \beta \sum_{j=1}^n P_j \quad (2)$$

where FR_{S_i} is the firing rate for each of the 12 input neurons that correspond to the receptive field of stimulus S_i , $(\max(P_j))$ is the maximum pixel value between the pixels that correspond to the spatial location in which stimulus S_i appeared, and $\sum_{j=1}^n P_j$ is the total summation of these pixels. The maximum value of the pixels for each stimulus is used as it captures the general saliency of the stimulus while the summation value reflects the size of the stimulus. Summation was used to encode size as, for the sake of simplicity, the model always uses 12 neurons to encode every incoming stimulus regardless of its size. The terms α and β are weighting constants used for normalization (Fig. 4).

The spike trains of input neurons are generated in the model by a series of binary events (0 or 1) denoting, respectively, the absence or presence of a spike or action potential. The number of time bins that a spike train contains, has been set to signify the duration of appearance of the stimulus. For instance, if a stimulus appears within the visual field for 100 ms then the neurons whose receptive fields correspond to its spatial location will generate spike trains with 100 time bins.

Input neurons are connected in a feed-forward manner to the SNN of the first stage of processing. In the case that two or more stimuli appear simultaneously or in very close temporal proximity in the same or a nearby receptive field, then competition about which stimulus will access working memory begins. Based on their saliency or “strength”, stimuli will exert inhibitory influence to each other (Fig 5).

Fig. 4 An example of spike train initialization for each input neuron

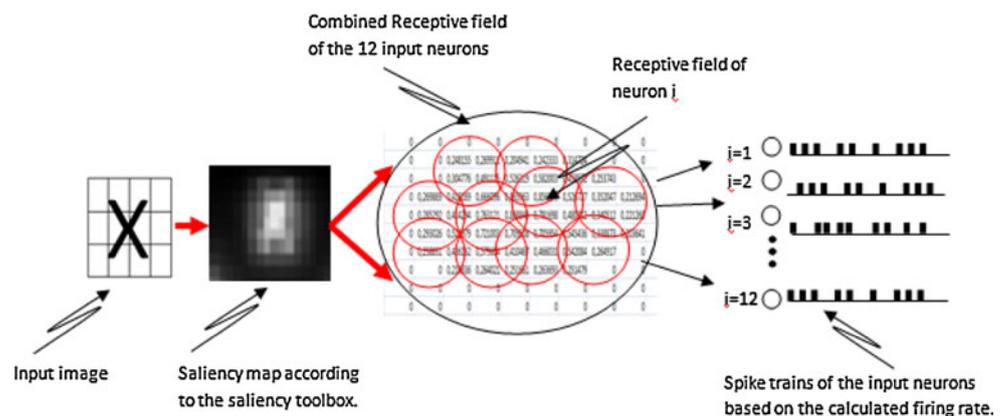
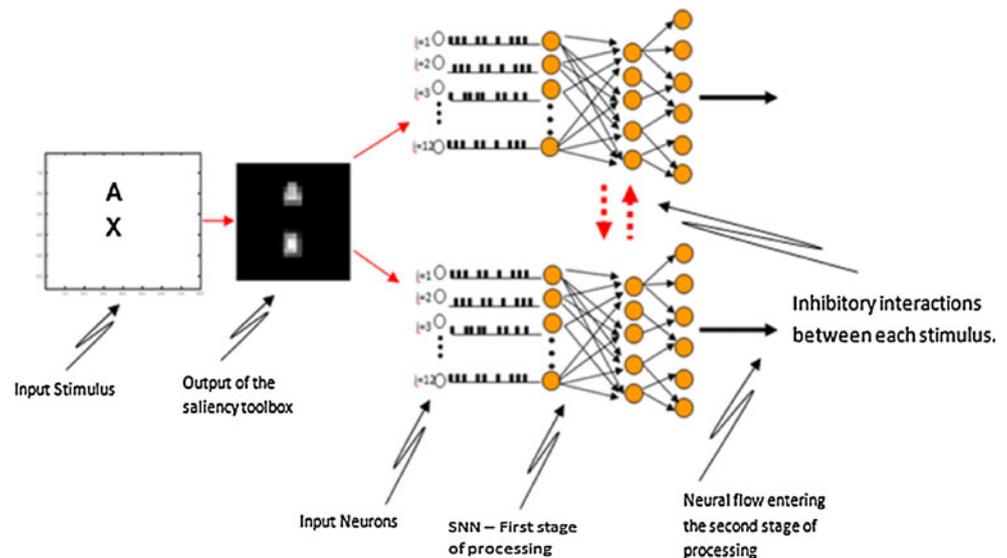


Fig. 5 Competitive interactions between two incoming stimuli



As a result, each stimulus that has been encoded will proceed to the second stage of processing with neural activity which results from these competitive interactions.

Second Stage of Processing

Following the neural interactions in the first stage of processing, the output spike trains will pass through a “temporal filter” that changes the timing of their spikes without affecting their average firing rate. Specifically, based on a pre-defined probability, the temporal appearance of a spike can change in order to become more similar to the pattern of activity of a distinct spike train that maintains the semantic representation of the target. The pre-defined probability reflects the degree of resemblance between the features of an incoming stimulus and those of the target, and thus only the spike train patterns of the stimuli that share features with the target will change significantly. This mechanism in the model is inspired by Crick and Koch [39] who suggested that the selection of stimuli could be made on the basis of synchrony across neurons. Crick and Koch [39] also claimed that visual selective attention could function in a way that it causes changes to the temporal structure of the neural spike trains that represent information to be selected. Indeed, changes in temporal structures seem to be a prerequisite for the presence of neural synchronization.

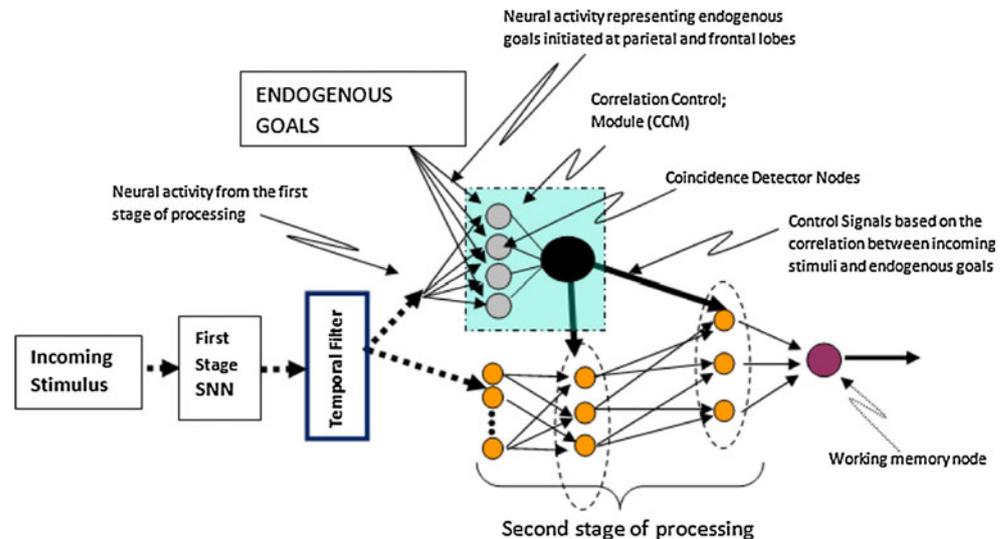
The second stage of processing models the influence of top-down goals to neural activity. The literature suggests that neural activity in area V4, an intermediate stage of visual object-processing pathway in the brain, receives influence from top-down activity [20, 21, 40]. In the present task, the top-down signals that are present in the second stage of processing are assumed to transfer information about the semantics of each stimulus (i.e., if an

incoming stimulus is greater or smaller than 5). Therefore, the second stage of processing is assumed to handle the coupling interactions between the neural activity that represents visual stimuli and the activity that maintains semantic information.

Studies using single-cell recordings have shown that attention enhances the firing rates of neurons that correspond to attended stimuli and suppresses the firing rates of neurons encoding unattended stimuli [21, 41]. Furthermore, other studies have shown that a different neural mechanism for attentional selection could exist on the basis of neural synchronization and thus emphasized the theoretical predictions originally made by Crick and Koch [39]. Indeed, the hypothesis that neural synchronization is a mechanism of selection has been supported by many experiments showing that neurons corresponding to stimuli selected by attention exhibit enhanced gamma-frequency synchronization [42, 43]. More specifically, many recent studies have linked neural synchronization with top-down attention in visual area V4 [44–46]. For example, Gregoriou et al. [47] have provided evidence for enhanced oscillatory coupling between area V4 and an area in the prefrontal cortex known as the frontal eye field (FEF) when attending a stimulus. Thus, one can infer that neurons in the prefrontal cortex which presumably transfer information about the endogenous goals can generate neural synchronization in visual areas, especially when there is correlation or resonance between bottom-up sensory information and top-down signals.

The experimental studies that document the synchronization between cortical areas involved in top-down processing and early areas of the visual cortex are compatible with several predictions and theories. For instance, the resonance theory proposed by Grossberg [48] claims that temporal patterning of neural activity could be ideally

Fig. 6 The correlation control module and the second stage of processing in the computational model



suiting to achieve the matching of top-down predictions with bottom-up inputs. Furthermore, in their Global Workspace Model, Dehaene et al. [49] suggested that global neural activity that represents the attended stimulus can be achieved more easily when there is “resonance” between bottom-up sensory information and top-down signals. A similar prediction was made in the review by Engel et al. [50] who stated that top-down effects which induce particular patterns of subthreshold fluctuations in dendrites of a target population could be “compared” to temporal patterns arising from peripheral inputs. Along the same lines, Womelsdorf et al. [51] suggested that synchronization of neural activity could be generalized as the “handshaking” between cognitive top-down control and the matching sensory bottom-up information.

In line with the above scientific suggestions, a correlation control module (CCM) composed primarily of coincidence detection neurons is included in the model. This module is responsible for evaluating the correlation between the neural activity of encoded stimuli and the activity that represents the top-down signals which maintain the properties of the target in a given behavioural context (i.e., endogenous goals possibly held in prefrontal cortical areas, see Fig 6). Based on the degree of correlation, a control signal will be generated for the amplification of its neural activity. Specifically, the strength of the control signal may have many variations, mainly based on the total firing of the CD neurons of the CCM. That is, if two signals are correlated then the CD neurons will fire more frequently and will consequently elicit a stronger control signal (Fig 6). Furthermore, an increase in the degree of correlation will generate synchronization of neural activity in the SNN of the second stage of processing. In fact, the strong correlation between an incoming stimulus and the endogenous signals will result in a gradual increase of

synchronous firing by the CD neurons. This “wave” of synchronous firing will pass through multiple connections to the SNN of the second stage and convey it in its general behaviour.

The implementation of the CCM in the current model was inspired by what is currently known about the functional role of pyramidal cells, the main neurons found in the visual cortex. The pyramidal neurons have one large dendrite that branches upward into the higher layers of the cortex, as well as an axon which may be long enough to reach distant areas of the brain. Pyramidal neurons have been observed to respond best to the coincident activation of multiple dendritic compartments [25]. Therefore, a network of CD neurons may function as a mechanism that controls the correlation between two streams of information that originate from different cortical areas. Thus, the CCM may be cited in anatomical locations where interaction between top-down signals and bottom-up sensory information has been observed. As already mentioned, Corbetta et al. [37] reviewed experimental findings that document the distinction between two distinct networks that may be responsible for stimulus-driven and goal-directed processing. Spontaneous activity that is correlated with both networks has been observed in regions of the prefrontal cortex [52] which poses as a possible site for the CCM in the brain. In addition, several studies have provided evidence for an interaction between signals containing sensory information in visual area V4 with signals of behavioural context [53–55].

Results

The computational model for visual selective attention was implemented in the MATLAB—Simulink platform. We

have run the model under four conditions to provide simulation data for each combination of cueing and compatibility. The simulations were run 50 times for each of the four conditions and reaction time was recorded. Reaction time in the simulations was operationalized as the interval between the encoding of the probe (i.e., firing of the first spike in the first stage of the model) and the firing of the working memory node to denote that a decision was made.

Median reaction times (RT's) from the simulations are presented in Fig 7. Comparing these findings with those from the experiment of Naccache et al. [19; Figure 2] one can verify that, although the model is overall slower in responding, it does replicate the pattern of behavioural findings.

This pattern of latencies produced by the model is a consequence of the competitive interactions of neural activity in the first stage of the model and the modulation of activity by top-down signals in the second stage of the model. Specifically, in the uncued conditions, the input neurons that correspond to the prime generate spike trains for 29 ms (i.e., the duration of the prime) with a mean firing rate that is based on its saliency. This neural activity combined with inhibitory interactions from backward and forward masking is not adequate to advance strongly in the neural pathway of the computational model. In fact, in most of the cases, it is completely suppressed before it even reaches the second stage of processing. Therefore, even though the prime contains semantic information, its interference is diminished, and as a consequence the processing of the target is not influenced.

In the cued conditions, top-down signals initiated by the presence of cue interfere with the processing of prime and target. Specifically, these top-down signals that are represented in the model by a series of spike trains begin to excite the input neurons very shortly after the appearance of the cue. This interaction results into an increase of the initial firing rate of any stimuli that appear within this temporal window. In the present experiment, both the prime and the target are presented in this interval. It should be pointed out that the firing rate of the prime is still not

strong enough to enter working memory and thus to be consciously perceived. Nevertheless, it is critically sufficient to “push” the neural activity of the prime in the second stage of processing and therefore to exert semantic interference to the processing of the target.

Discussion

The previous sections have presented a computational model that successfully simulates the findings of Naccache et al. [19] from a task that has sparked a debate regarding the relation between selective attention and consciousness.

The combination of backward and forward masking in this task makes the prime non-accessible for conscious report but it can nevertheless affect performance in the task. Koch and Tsuchiya [13] suggested that the visual masking technique in this task allows for an independent manipulation of attention and consciousness. They claimed that in order to obtain the priming effect it is necessary to allocate top-down attention to a perceptually invisible stimulus; this suggests, in their opinion, that two distinct processes are involved. On the other hand, Mole [56] posits that it is possible to visually process some of the attributes of an item and manipulate them with attentional mechanisms, even if the item has not been consciously experienced. Therefore, the proposition that attention and consciousness are two distinct processes is according to Mole not sufficient to explain the behavioural results.

The interpretation put forward by Dehaene and colleagues [57] is based on the assumption that every stimulus causes a different level of processing depending on its strength. They argued that every stimulus can trigger subliminal, preconscious or conscious processing. Subliminal processing is defined as a condition in which the information is inaccessible due to insufficient bottom-up activation. Preconscious processing causes enough activation to achieve conscious access, but the stimulus remains in a non-conscious state because of a lack of top-down attentional amplification. Conscious processing involves the interaction of top-down attention with the neural activity of a stimulus, in such a way that the activity exceeds the “threshold” of conscious access. Based on the logic of Dehaene et al. [57], the strength of the prime in the cued condition is sufficient to reach the level of pre-conscious processing and therefore to semantically interfere with the processing of the target, but it is not adequate to reach the level of conscious processing.

This threefold distinction of stimulus processing is based on the global workspace hypothesis implemented in the model of Dehaene et al. [49] as well as on neuroscience findings regarding the relation between attention and consciousness. For example, many studies have shown that

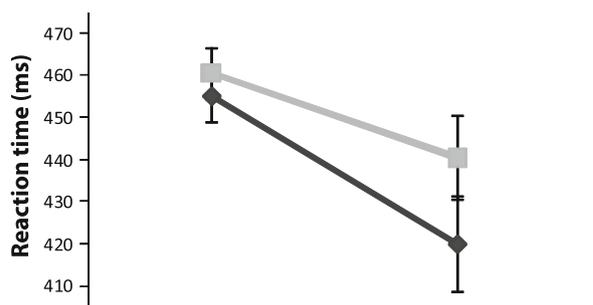


Fig. 7 Median RT's from the simulations. *Error bars* represent standard errors

neural activity is observed in extrastriate visual areas even if the participants deny seeing any stimulus [58–60]. Moreover, in a study by Sergent et al. [61], similar occipito-temporal event-related potentials were evoked by a visible word and by a word that was rendered invisible through masking. This finding is consistent with the hypothesis of different levels of processing proposed by Dehaene et al. [57] as it documents that intense occipito-temporal activation is present in the cortex along with lack of conscious awareness of the stimulus that initiated it. However, these findings can also support the claim that attention and consciousness are two distinct, albeit interacting, processes. Perhaps then the crucial difference between the claims of Dehaene et al. [50] and Koch and Tsuchiya [13] is that according to the former top-down attention is regarded as necessary for conscious awareness of a stimulus while for the latter consciousness can occur without top-down attention.

Our take on the relation between attention and consciousness is shaped by the findings of the presented study. Our proposed explanation for the experimental findings by Naccache et al. [19] is formulated at the detail of the low-level neural interactions in the brain and it therefore provides a concrete basis for the development of a theoretical framework around the relation between attention and consciousness. Importantly, the model was designed according to what is currently known about the neural mechanisms underlying attention and visual processing. Therefore, it relies on a number of biologically plausible mechanisms (e.g., saliency map in the visual cortex, low-level competitive interactions, a CCM simulating the functioning of pyramidal cells, cortical synchronization of neural activity for attended stimuli) whose involvement in the functioning of attention has been documented by previous studies.

In the implementation of the described computational model, we adopted the hypothesis that the primary processing of visual information is performed in a feed-forward manner within the visual cortex. This is based on evidence from the literature suggesting that complex visual processing can be reflected in the human cortex within 130–150 ms, [62]. For visual information to become conscious, however, we embrace the theory of Lamme [63] who argued that sustained neural activity is required, possibly through global feedback from frontal regions of the cortex to visual areas and back. This reverberatory activity can gradually build up until it is sufficient to propagate in parietal and prefrontal regions that are believed to support short-term memory and other processes that relate to consciousness. This neural process has also been adopted by other scientists as a possible explanation for the creation of consciousness. For instance, Dehaene et al. [57] suggested that if a stimulus is strong enough, then it can access a global network with long range axons

that communicate with different cortical areas, and therefore, it can initiate loops of neural activity. As a consequence, a self-amplifying system will gradually push the corresponding stimulus into conscious awareness. Furthermore, in a slightly different interpretation, Taylor [64] suggested that these loops of neural activity are possible candidates for the signals that generate the experience of ownership, that is, the experience one has of being aware of an external or internal stimulus. In a recent report on the CODAM model, Taylor [65] regards this activity as a copy of the attention control signal denoted as the corollary discharge of the attention movement control signal. The copy of the attention signal was originally proposed in the CODAM model as a component used to make attention more effective. At the same time, however, it can account for the creation of the “inner self”.

In our computational model, we incorporate this reverberatory activity through forward and feedback interactions between the first and second stage of processing as explained in previous sections. These loops of neural activity may interact with the processing of stimuli that appear in the visual field within different temporal windows, providing thus an account for forward and backward masking interference. Finally, we assume in the model that conscious report of a certain stimulus requires activation of the corresponding working memory nodes which are connected to the output layer of the second stage of processing. Therefore, the experience of being perceptually aware of a stimulus can only be achieved if a stimulus sufficiently activates working memory.

Based on the implementation of our model, we argue that the relation between attention and consciousness can become more obvious if we consider top-down and bottom-up attention to be distinct processes. The neural path following the two stages of processing in our model can be seen as an independent attentional system that relies first on bottom-up information but subsequently on top-down signals as well. As a result, each stimulus that enters the visual field initiates neural activity that will progress in the visual cortex according to the “constructive rules” that underlie bottom-up attention combined with any interaction that might arise from a separate system that maintains endogenous goals. Furthermore, all stimuli that appear within the same temporal window compete with each other to win a place in working memory. Depending on the “strength” of each stimulus, which is reflected in the firing rate of its neurons, inhibition takes place and influences the neural progression of any other competitive stimuli. This inhibitory interaction can be negligible or significant and more importantly, it can influence the neural progression through the corresponding areas of the visual cortex of a certain stimulus, regardless of whether the stimulus that initiated the inhibition eventually accesses working

memory or not. Therefore, although at the very initial stages of visual processing the route to consciousness coincides with processes involved in bottom-up attention, top-down attention may play a key role on whether a stimulus reaches conscious awareness.

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