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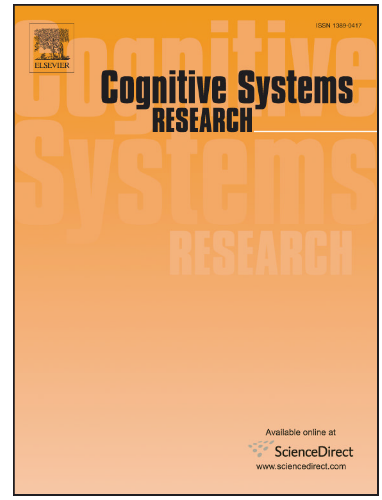

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A Mathematical Model of the Interaction between Bottom-up and Top-down Attention Controllers in Response to a Target and a Distractor in Human Beings

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Short title: The Interaction between Bottom-up and Top-down Attention

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Abstract

Top-down and bottom-up attention are two systems that allocate our neuronal resources for processing different stimuli. To do the tasks efficiently, it is required to suppress irrelevant information. In the presence of both target and distractor, synchronization or desynchronization between the activities of neuronal responses has been observed in different regions of the brain. In the current study, we have proposed a mathematical model to show how the interaction between top-down and bottom-up attention, through synchronization and desynchronization, can lead to the suppression of distractor effects in human beings. The model structure was inspired by the results of neurological studies. The model consists of several oscillating units as a representation of top-down and bottom-up neuronal processing resources. These units communicate with each other through synchronization and desynchronization procedures.

Results of simulations showed that how the mutual interaction between top-down and bottom-up units, which was done using synchronization and desynchronization procedures, led to the selective or divided attention between the target and distractor. It was shown that the activity of responsive units to the distractor could be suppressed by a desynchronous signal transmitted from the top-down attention unit. This model suggests a justification for brain waves synchronization or desynchronization during attentionally demand tasks. The proposed model also provides a tool to investigate the effect of some influencing factors such as the distractor intensity or similarity between the distractor and the target on the function of top-down and bottom-up systems.

Keywords: Attention control; Modelling; Synchronization; Van der Pol oscillator

1. Introduction

Considering the brain processing paths, the attention system can be divided into two types of bottom-up (BU) and top-down (TD) controllers. The BU controller is sensitive to the features of stimuli, is usually activated involuntary, is fast, and contains low-level sensory regions such as occipital and temporal lobes. In contrast, TD controller works based on predefined goals, is usually activated voluntary, has a delay, and includes high-level controlling brain regions such as frontal lobe [1, 2].

In our environment, there is a huge amount of information. To focus on our tasks, we need to eliminate and ignore irrelevant data. The irrelevant stimuli that are not used in an ongoing task are called distractors. Behavioral analyses have shown that distractors can reduce the speed of the individuals' responses. According to the previous studies, it is suggested that slow responses are not due to the reduction of target processing speed. Rather, the reason is the time taken to shift the processing resources from targets to distractors [3-5].

The interactions between TD and BU attention control systems were reported in many neurocognitive studies [2, 6-13]. These interactions and their effects were investigated computationally in visual search, the relationship between attention and consciousness, and neuromarketing [14-16]. The mentioned interactions prevent the entrance of unrelated information to higher-level processing stages. Sometimes, there is a competition between BU and TD processors. If BU units respond to a distractor, and if the response of these units is not suppressed on time, the distractor can affect higher-level processing resources. The TD controller is responsible for suppressing the effect of distractions and enhancing the response to the targets. It has been shown that parietal networks [17] and prefrontal lobe [18] are involved in such enhancement and suppression procedures. Results of neurocognitive studies showed the appearance of desynchronization and synchronization of neuronal activities during attentional experiments [14, 19-28], which may be considered as a mechanism for the mentioned target enhancement and distractor suppression. Synchronization can lead to the increment of neuronal activations, and desynchronization can attenuate them [29].

Despite the large number of available studies, in which synchronization and desynchronization of neuronal activities have been observed in response to various stimuli, the reason behind these observations has not been fully understood. Grossberg in his adaptive resonance theory (ART) proposed some reasons for the neural synchrony phenomenon in memory and learning functions. According to the ART, any neural procedure involved in the stability-plasticity dilemma needs attention, synchrony, resonance, and some other mechanisms. The stability-plasticity dilemma means that an artificial or biological neural system needs flexibility or plasticity to receive and accept new information, but also need stability to preserve old information [30]. A higher level of plasticity can lead to the direction of the attention to new incoming information and may lead to the forgetting of old information. On the other hand, a higher level of stability can suppress the attention towards the new information and can prevent the encoding and retaining the incoming new data. Therefore, a trade-off between the level of plasticity and stability is required to have an optimum learning procedure. ART provides several suggestions for the role of the interaction between BU attention tendencies and TD attention expectations in learning procedure and memory formation. In ART, synchronization has a modulatory effect on stimulus processing and can represent the influence of TD attention on the stability-plasticity dilemma during a learning procedure. According to the ART, when BU data are matched with the TD expectations, attention focus is directed to these data. In other words, the activities of a population of cells are enhanced when it receives TD attention signals. Otherwise, it will be suppressed [31-34]. As mentioned before, in some neurobiological recordings, the activities of TD and BU processors were desynchronized in the presence of the distractor [14, 19-28].

Therefore, the suppression of the activities of cells respond to irrelevant data can be performed through two ways: 1- receiving small or no signal from TD attention as used by the models designed based on ART; 2- receiving a desynchronious signal from TD attention. In the second procedure, a signal with special frequency is produced to suppress the responses to irrelevant information. This phenomenon was observed in a visual attention experiment by measuring steady-state visual evoked potentials [17]. It has been believed that a common mechanism is responsible for both target selection and distractor processing suppression [18]. It is a long lasting debate that how a common mechanism can perform both. Two possible answers have been provided for this debate: 1- TD attention redirect the processing resources to the task-relevant information and distractors are automatically ignored because there is no resource to process them; 2- TD attention proactively suppressed distractors that leads to the target selection [12, 18, 35, 36]. In the current study, we have proposed a mathematical model to show how a processing unit can use synchronization and desynchronization procedures to capture a target and simultaneously suppress the effect of the distractor. In other words, the aim is to find out whether the observed synchronization or desynchronization procedure may have a role in the attention control system (i.e., paying attention to the target and the suppression of the distractor effects). There are, of course, several factors that can affect the interaction between TD and BU processing. One of these factors is the strength of distractor. It has been reported that the stimulus intensity affects the TD attention manipulation [7]. The other factor is the similarity between the distractor and target that affect the processing of TD and BU attention systems [37-41]. Using the proposed model, the influence of these effective factors has also been simulated. Results of simulations showed that how these factors can affect the procedure of synchronization or desynchronization, and consequently, the processing of the target and distractor.

Many brain regions are involved in BU and TD attention and their interactions. In particular, the frontal cortex and basal ganglia are attributed to the TD attention. Occipital and temporal cortices and brainstem are involved in BU attention [42-44]. Parietal lobe has a role in TD and BU interactions [44]. However, these regions were not considered in the proposed model explicitly. The proposed model covers some aspects of behaviors or observations associated with the human TD and BU attention. In other words, the proposed model is a behavioral, functional, or black box model and does not care about the structure of the considered system. However, we have tried to consider the oscillatory nature of the neuronal systems, which has been observed during attentional demanding tasks [45].

The proposed model and the result of simulations can be considered as another confirmation of the power of predictions provided based on the ART. The results also suggest a connection between some characteristics of the external stimuli, the neuronal activities, and behavioral data and provide a computational justification for some behavioral observations.

2. Method

As mentioned in the previous part, some parts of the brain are involved in TD and some of them in the BU attention. Without losing the whole issue, it can be considered that there are two neuronal systems (i.e., TD and BU attention) that respond to incoming stimuli based on their own control policies. The proposed model is a black box model of synchronization and desyncronization behaviors observed during the activities of these two systems and their interactions to suppress the distraction. Therefore, there is no concern about which parts of the brain are exactly involved in either of these two systems. To show synchronization and desynchronization behaviors, oscillatory units are required. According to the definition, synchronization between two systems occurs when they can adjust their time scales through interaction [46]. Regulating and adjusting the time scale can be done through forced or mutual synchronization. In synchronization, frequency/phase locking occurs between the oscillations of two systems and the suppression of natural dynamics of one or both systems may happen. Two systems are desynchronized when the frequency/phase locking cannot be occurred. That is, desynchronization is occurred when two units oscillate with different frequency or they have a phase difference. Therefore, to synchronize two units, the oscillation frequency of both units becomes similar through force or mutual synchronization and gradually the phase is aligned between the oscillating units. This frequency/phase locking can occur by regulating the coupling weight between the oscillating units, which is shown in following sections. In this study, we have modelled the units (TD and BU attention) with Van der Pol oscillators because of the following reasons:

- Van der Pol oscillator is well-known and is popular in modeling the biological system [47, 48] and has been used as a global model of neurons in previous studies [48-51].
- In Van der Pol oscillator, the neuronal details and chemical reactions are not considered. It avoids the complexity of the model.
- By the Van der Pol oscillator, the amplitude and the frequency of the oscillation can be easily regulated, and its relative simplicity makes it analytically tractable.
- Results of the simulation showed that using the Van der Pol oscillator could satisfy the main goal of the model. However, using other more complicated oscillators can increase the capability and of course the complexity of the proposed model.

The Van der Pol oscillator formula can be presented as 1- two first-order differential equations or 2- one second-order differential equation (Eq. (1)). The second-order differential equation is transformed into two first-order equations with the help of an auxiliary variable. The outputs of both formats are the same. In the second format, the variable can be interpreted as the activity of a neuronal unit. However, in the first format, the auxiliary variable has no physical interpretation in our study. Equation (1) shows the mathematical representation of a Van der Pol oscillator.

$$\ddot{Y} - (\lambda - Y^2)\dot{Y} + p^2 Y = 0 \tag{1}$$

where, λ is the bifurcation parameter of the oscillator. When its value is lower than zero ($\lambda \leq 0$), there is no oscillation, and when it is higher than zero, the unit can oscillate at the frequency and the amplitude are respectively determined by the value of p and λ. In Eq. (1), Y is the output of the oscillator. As mentioned before, the proposed model is a behavioral, functional, or black box model. That is, the behavior of its output is different conditions is in agreement with electrophysiological recording and can justify some neurocognitive behaviors in the context of attention. However, the structure, parameters, variables of the Van der Pol oscillator can also be associated with the neuronal systems as follows:

- Van der Pol is an oscillator that its output behavior can simulate the oscillatory nature of the neuronal systems in a simple way.
- The variable of this oscillator, Y, can be associated with the activity of a neuronal unit.
- The parameter, λ, can be associated with the factors involved in determining the intrinsic amplitude of oscillations of a neuronal unit. The effect of changing this parameter on the output behavior of a neuronal unit was shown in [52].
- The parameter, p, can be associated with the intrinsic frequency of a neuronal unit.

Fig. 1 represents a schematic of the proposed model components.

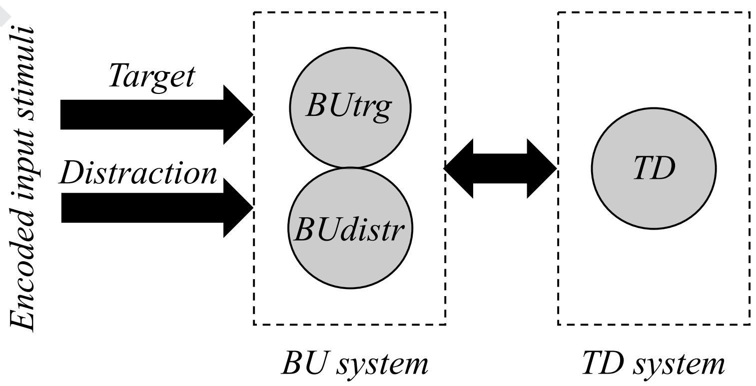

Fig. 1 A schematic of the proposed model components. *TD*: top-down; *BU*: bottom-up; *BUtrg*: the BU neuronal unit respond to the target; *BUdistr*: the BU neuronal unit respond to the distractor.

In our study, we have considered that only two stimuli are presented for the individuals. One of them is a target and the other is a distractor. Bottom-up processors are affected by external stimuli and respond to them. To model the function of BU systems, we have considered two Van der Pol oscillators. These two oscillators are the representation of two groups of neuronal clusters that are sensitive to the features of target and distractor. That is, one of them shows its maximum activity in response to the target and the other to the distractor. Equations (2) and (3) are the models of two neuronal units that are highly sensitive to the target and distractor, respectively.

$$\ddot{Y}_{BUtrg} - (\lambda_{BUtrg} - Y_{BUtrg}^2)\dot{Y}_{BUtrg} + p_{BUtrg}^2 Y_{BUtrg} = A_{trg}\sin(\omega_{trg}) + A_{distr}\sin(\omega_{distr}) \tag{2}$$

$$\ddot{Y}_{BUdistr} - (\lambda_{BUdistr} - Y_{BUdistr}^2)\dot{Y}_{BUdistr} + p_{BUdistr}^2 Y_{BUdistr} = A_{trg}\sin(\omega_{trg}) + A_{distr}\sin(\omega_{distr}) \tag{3}$$

where the subscripts *BUtrg* and *BUdistr* represent the BU neuronal units, which respond to the target and distractor, respectively. Studies on the encoding of sensory information and neural activities reported a relationship between the characteristics of neuronal activities in the frequency domain and the features of an input stimulation [53-55]. It has been believed that the sensory system generates oscillations according to the stimulation features [54, 56]. For instance, two stimuli with different shapes are encoded into different frequency bands by neuronal units. A correlation between the stimulus strength and the amplitude of neuronal activities has been also reported in previous studies [57-59]. Therefore, in this study, the target and distractor were represented by two oscillatory waves with different frequencies, ω_{trg} and ω_{distr}. The amplitudes, A_{trg} and A_{distr}, are respectively the strength of the target and distractor. Each of these Van der Pol oscillators can be forced synchronized by one of the input stimuli that its frequency (ω) is close to the intrinsic frequency of the oscillator (p). Equations (2) and (3) together represent the BU controller, regardless of the influence of TD attention controller.

The interactions between these two controllers (BU and TD) shape our performance in an attentionally demand task. This interaction is not a unidirectional master-slave relation and TD and BU controllers interact bilaterally [60]. That is, in response to one stimulus, TD controller may send commands to suppress the response, while the BU controller directs processing resources toward the stimulus. The mutual interaction between these two neuronal controllers results in the suppression or the enhancement of the stimulus. Therefore, to couple the BU and TD oscillators, we used a mutual coupling mechanism in the mathematical model. Equations (4), (5), and (6) demonstrates the model of TD and BU systems and their interactions with each other.

$$\ddot{Y}_{BUtrg} - (\lambda_{BUtrg} - Y_{BUtrg}^2)\dot{Y}_{BUtrg} + p_{BUtrg}^2 Y_{BUtrg} = A_{trg}\sin(\omega_{trg}) + A_{distr}\sin(\omega_{distr}) + B_{TD\_BUtrg}(Y_{TD} - Y_{BUtrg}) \tag{4}$$

$$\ddot{Y}_{BUdistr} - (\lambda_{BUdistr} - Y_{BUdistr}^2)\dot{Y}_{BUdistr} + p_{BUdistr}^2 Y_{BUdistr} = A_{trg}\sin(\omega_{trg}) + A_{distr}\sin(\omega_{distr}) + B_{TD\_BUdistr}(Y_{TD} - Y_{BUdistr}) \tag{5}$$

$$\ddot{Y}_{TD} - (\lambda_{TD} - Y_{TD}^2)\dot{Y}_{TD} + p_{TD}^2 Y_{TD} = B_{TD\_BUtrg}(Y_{BUtrg} - Y_{TD}) + B_{TD\_BUdistr}(Y_{BUdistr} - Y_{TD}) \tag{6}$$

Equations (4) and (5) are the modified version of Eqs. (2) and (3), in which the role of TD attention has been considered by adding the new term $B\ (Y_i - Y_j)$. This term lets TD and BU oscillators interact mutually. Based on the value of B, which is called coupling weight, TD and BU controllers can synchronize or desynchronize with each other. Equation (6) shows the oscillatory model of TD controller. This Van der Pol oscillator can interact with the BU system through the input terms $B\ (Y_i - Y_j)$. That is, $B_{TD\_BUtrg}(Y_{BUtrg}-Y_{TD})$ shows the influence of TD attention on the activity of the oscillator that responds to the target and $B_{TD\_BUdistr}(Y_{BUdistr}-Y_{TD})$ represents the impact of TD attention on the activity of the oscillator that responds to the distractor. The interaction between BU and TD oscillators depends on the value of coupling weights and the frequency difference between these oscillators. One of the main function of the TD controller is the reduction of the impact of distractors on the processing of a target stimulus. In simulation results, it has been shown that the suggested coupled BU and TD controllers deal with distractor and target stimuli. In other words, considering Eqs (4)-(6), it has been assumed that both target and distractor affect BU processors, however, TD attention unit proactively interacts with BU units to suppress the distractor effects and target selection. This assumption is in agreement with the results of electrophysiological recordings during target distractor experiments [17, 18, 35, 36].

According to the neurophysiological recordings and neuronal modeling, it seems that the response of a population of neurons can be detected by its next layers when the activity of the population reaches a threshold [61-63]. Therefore, in the simulations, such a threshold was defined. It was shown that several factors such as the characteristics of brain pathway or the trade-off between speed, and the accuracy affected the level of this threshold [61]. In the modeling procedure, we did not consider these factors, and the threshold was fix. As shown in the simulation results, changing the level of this threshold had no effect on the goals and expectations of the study and on the provided interpretations. However, in situations that the goal is the speed and accuracy of decision making, the value of this threshold and the dynamic of its changes becomes important. In all simulations, the sampling time (dt) was 0.01s, the initial conditions were $Y_{BUtrg}(0)=Y_{BUdistr}(0)=Y_{TD}(0)=0.5$, and the bifurcation parameters of Van der Pol oscillators were $\lambda_{BUtrg}=\lambda_{BUdistr}=\lambda_{TD}=0.2$. As mentioned in previous paragraphs, the value of λ should be greater than zero to have an oscillator. The value of λ determines the amplitude of oscillations. Since, for simplicity, the stimuli were encoded by different single-frequency waves, the value of λ should also be lower than one. If $\lambda \geq 1$, then the oscillations do not have one frequency, and it leads to the complexity of the model. This parameter is an intrinsic characteristic of a population of neurons. The value of initial condition also depends on the previous state of the population. Changing the value of these parameters (i.e., λ and the initial condition) are not easily controllable by the characteristics of the target or distractor. Therefore, arbitrary fixed values were selected for these parameters in the acceptable range. Target and distractor stimuli were represented by two sine waves with ω_{trg}=6 and ω_{distr}=10. It was supposed that each BU processing unit is predominantly sensitive to one of the target or distractor. As a result, the frequencies of two target- and distractor-sensitive oscillators (i.e., Eqs. (4) and (5)) were adjusted to p_{BUtrg}=6; $p_{BUdistr}$=10. The absolute value of these frequencies (ω_{trg} (p_{BUtrg}) or ω_{distr} ($p_{BUdistr}$)) were selected arbitrary and their changes had no effect on the pattern of results. However, the difference between the value of these two frequencies (ω_{trg} and ω_{distr}) is important. In simulations, it was shown that the ratio of the frequencies affected the results. Another effective factor is the ratio of the target and distractor strengths (A_{distr} and A_{trg}). In simulations, it was demonstrated that how this ratio changed the interaction between TD and BU attention. The coupling weight between TD and BU attention units had a considerable effect on the pattern of responses. The results of simulations that are reported in the next section show that higher values of the coupling weight lead to more influence of TD attention.

3. Results

In this part, the simulation results of the proposed model (i.e., Eqs. (4)-(6)) are presented for different conditions. It worth to be noted that in all figures related to simulation results, the push of the activities of each unit is just presented instead of the whole activity. This is done to make the results clearer and easier to track and interpretation. Fig. 2 shows the oscillations of a unit and the push of its activity as an example.

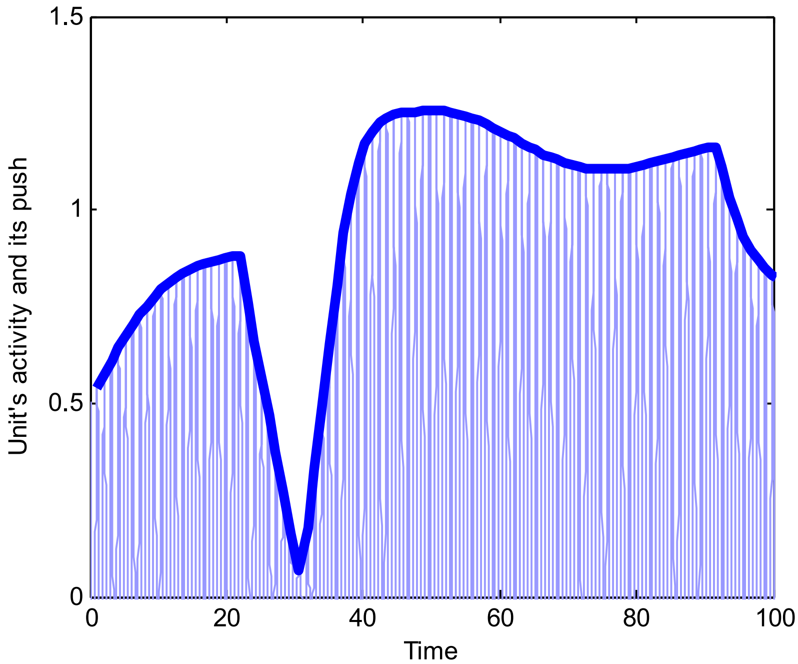

Fig. 2 A representation of an example of a unit's oscillation (thin line) and the push of its activity (thick line)

Fig. 3 shows the push of the activity of BU oscillators (Eqs. (4) and (5)) in response to the simultaneous presentation of a target and a distractor without considering the influence of the TD controller.

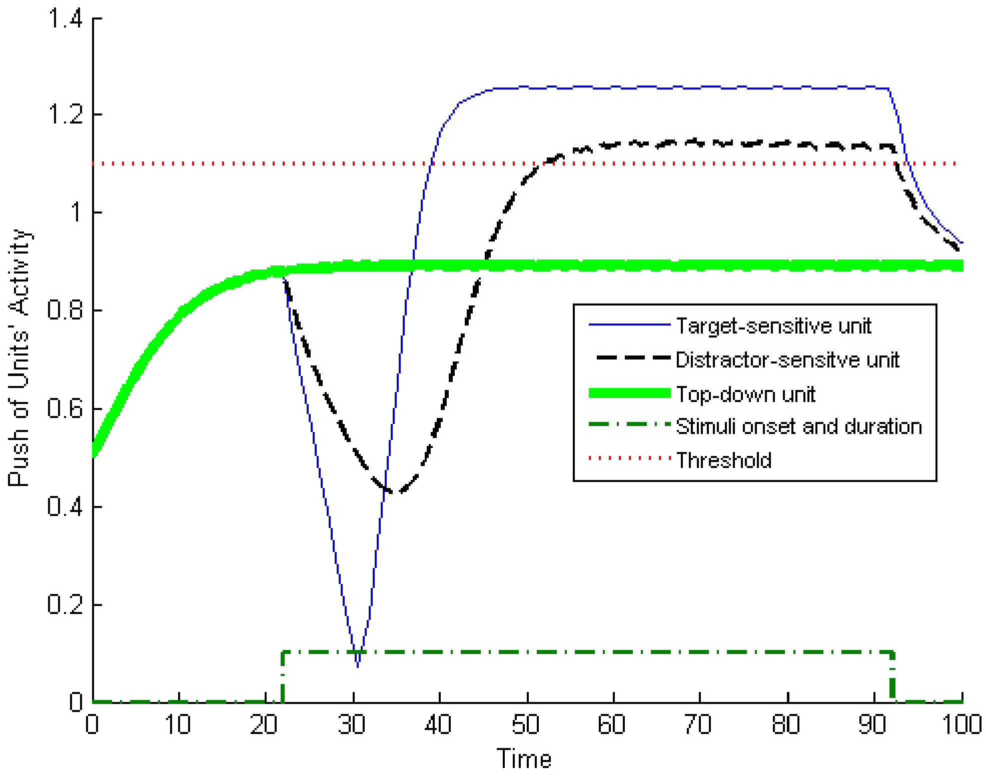

Fig. 3 The push of the activity of BU units in response to a target and a distractor without considering the effect of the TD controller (B_{TD_BUtrg}=$B_{TD\_BUdistr}$ =0). Blue solid line represents the push of the activity of the oscillator that is more sensitive to the target (Eq. (4)). Black dashed line shows the push of the activity of the oscillator that is more sensitive to the distractor (Eq. (5)). Thick solid green line shows the push of the activity of TD controller unit (Eq. (6)). Dark green dot-dashed line demonstrates the onset and duration of stimuli. Red dotted line indicates a threshold of the effectiveness of responses (sampling time (dt)=0.01s; A_{distr}=A_{trg}=1; B_{TD_BUtrg}=$B_{TD\_BUdistr}$=0; λ_{BUtrg}=$\lambda_{BUdistr}$=0.2; $Y_{BUtrg}(0)$=$Y_{BUdistr}(0)$=0.5; p_{BUtrg}=6; $p_{BUdistr}$=10; ω_{trg}=6; ω_{distr}=10).

Fig. 3 shows that after a desynchronization period, the activities of both the target- and distractor-sensitive BU units increase and pass the threshold. In all simulations, the stimuli (target and distractor) were presented for a short duration shown by a dark green dot-dashed line in figures. After stopping the presentation of stimuli, the responses of target and distractor sensitive units gradually decrease and return to a baseline level. Because there is no stimulus to excite them. In Fig. 4, the effect of the TD controller was added by increasing the coupling weights from zero to 0.5.

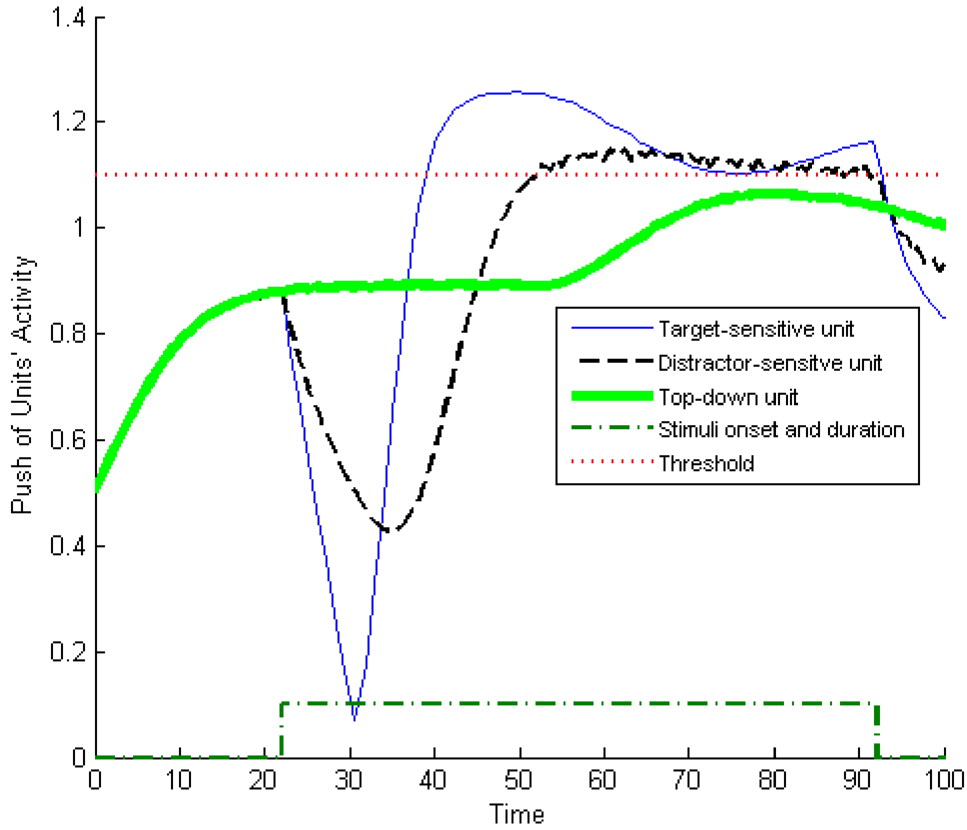

Fig. 4 The push of the activity of BU units in response to a target and a distractor with considering the effect of the TD controller (B_{TD_BUtrg}=$B_{TD\_BUdistr}$ =0.5). Blue solid line represents the push of the activity of the oscillator that is more sensitive to the target (Eq. (4)). Black dashed line shows the push of the activity of the oscillator that is more sensitive to the distractor (Eq. (5)). Thick solid green line shows the push of the activity of TD controller unit (Eq. (6)). Dark green dot-dashed line demonstrates the onset and duration of stimuli. Red dotted line indicates a threshold of the effectiveness of responses (sampling time (dt)=0.01; A_{distr}=A_{trg}=1; B_{TD_BUtrg}=$B_{TD\_BUdistr}$=0.5; λ_{BUtrg}=$\lambda_{BUdistr}$=0.2; $Y_{BUtrg}(0)$=$Y_{BUdistr}(0)$=0.5; p_{TD}=6; p_{BUtrg}=6 ;$p_{BUdistr}$=10 ;ω_{trg}=6 ; ω_{distr}=10).

According to Fig. 4, adding the effect of the TD controller causes a graduate reduction of the distractor-sensitive unit's activity. It can be seen that the activity of the target-sensitive unit has decreased for a short period of time, and then has increased after the reduction of the distractor effect. According to the previous evidence [64-66], the TD controller enhances the activity of target-sensitive neuronal units and weakens the activity of distractor-sensitive processing resources. Therefore, the frequency of TD unit's oscillations (p_{TD}) was equal to the frequency of the BU target-sensitive unit's oscillations. This selection leads to a synchronization between the TD and target-sensitive BU units' activities, and consequently, the enhancement of the response to the target. On the other hand, the selected frequency for the TD processing unit causes a desynchronization between the TD and distractor-sensitive BU units' activities, and the attenuation of the response to the distractor.

To reduce the delay of decreasing the effect of distractor, increasing the coupling weights between TD and BU units is one of the selectable options. Fig. 5 shows that how increasing the coupling weights from 0.5 to one leads to a faster reduction of the activity of the distractor-sensitive BU unit. However, the temporary reduction of the target-sensitive unit's activities is higher than the previous state.

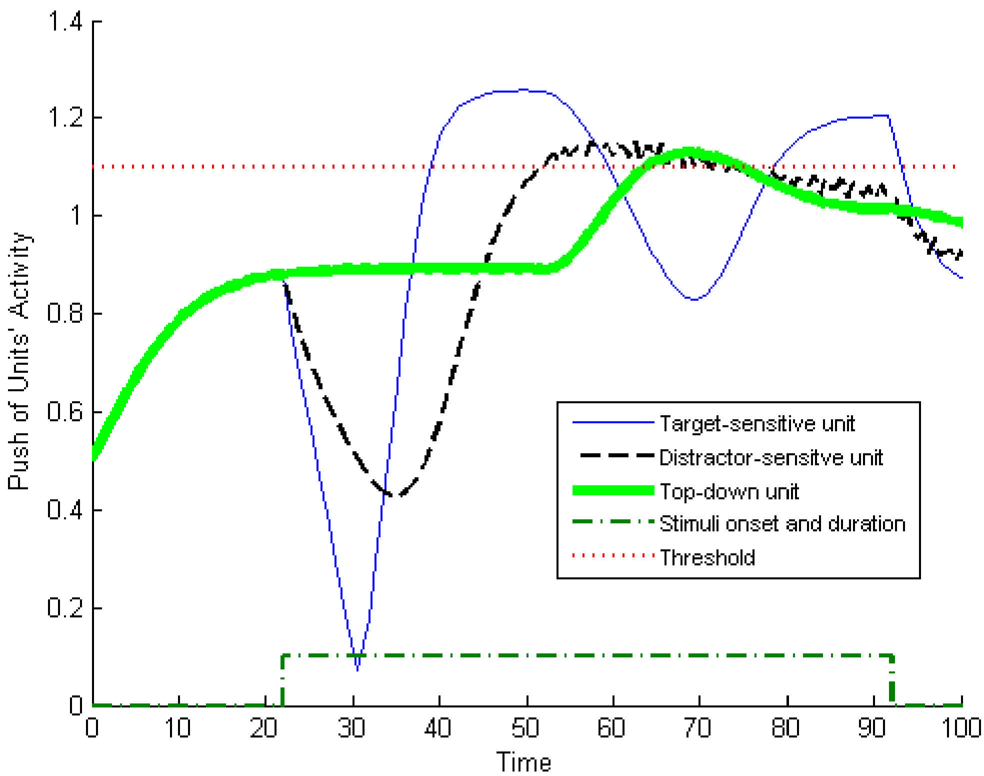

Fig. 5 The push of the activity of BU units in response to a target and a distractor with increasing the effect of the TD controller (B_{TD_BUtrg}=$B_{TD\_BUdistr}$ =1). Blue solid line represents the push of the activity of the oscillator that is more sensitive to the target (Eq. (4)). Black dashed line shows the push of the activity of the oscillator that is more sensitive to the distractor (Eq. (5)). Thick solid green line shows the push of the activity of TD controller unit (Eq. (6)). Dark green dot-dashed line demonstrates the onset and duration of stimuli. Red dotted line indicates a threshold of the effectiveness of responses (sampling time (dt)=0.01; A_{distr}=A_{trg}=1; B_{TD_BUtrg}=$B_{TD\_BUdistr}$=1; λ_{BUtrg}=$\lambda_{BUdistr}$=0.2; $Y_{BUtrg}(0)$=$Y_{BUdistr}(0)$=0.5; p_{TD}=6; p_{BUtrg}=6 ;$p_{BUdistr}$=10 ;ω_{trg}=6 ; ω_{distr}=10).

Fig. 6 demonstrates the effect of increasing the strength of distractor with respect to the target. In our proposed model, the strengths of the target and distractor are determined by the value of A_{trg} and A_{distr}. These strengths were equal in previous simulations. In Fig. 6, the distractor intensity is twice the target strength.

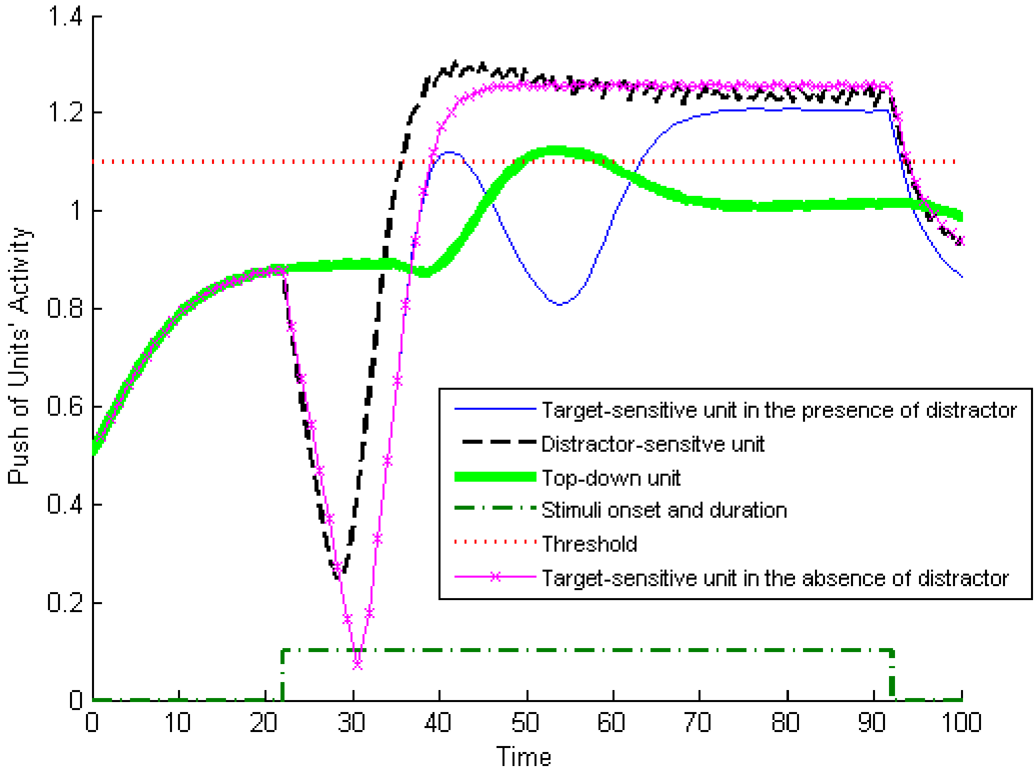

Fig. 6 The push of the activity of BU units in response to a target and a distractor with increasing the strength of distractor with respect to the target (A_{distr}=2; A_{trg}=1). Blue solid line and pink line with star represent the push of the activity of the oscillator that is more sensitive to the target (Eq. (4)) respectively in the presence and absence of the distractor. Black dashed line shows the push of the activity of the oscillator that is more sensitive to the distractor (Eq. (5)). Thick solid green line shows the push of the activity of TD controller unit (Eq. (6)). Dark green dot-dashed line demonstrates the onset and duration of stimuli. Red dotted line indicates a threshold of the effectiveness of responses (sampling time (dt)=0.01; A_{distr}=2; A_{trg}=1; B_{TD_BUtrg}=$B_{TD\_BUdistr}$=1; λ_{BUtrg}=$\lambda_{BUdistr}$=0.2; $Y_{BUtrg}(0)$=$Y_{BUdistr}(0)$=0.5; p_{TD}=6; p_{BUtrg}=6 ;$p_{BUdistr}$=10 ;ω_{trg}=6 ; ω_{distr}=10).

According to Fig. 6, after a delay, a little reduction is observed in the distractor-sensitive unit's activity, but it is not satisfactory. Therefore, increasing the strength of distractor with respect to the target led to the disability of the TD controller to reduce the distractor effect considering the previous coupling weights.

Another observation is that in the presence of the distractor, the activity of the target-sensitive unit (solid blue line) is lower than the state with no distractor (pink line with stars in Fig. 6). Fig. 7 shows how increasing the similarity between the target and distractor may affect the function of the TD controller and processing activities of BU units. In our model, the mentioned similarity is represented by decreasing the frequency difference (i.e., $|\omega_{trg}\text{-}\omega_{distr}|$) between the sine waves that have been considered as a representation of stimuli. In previous simulation results, this difference was four (i.e., $|\omega_{trg}\text{-}\omega_{distr}|=4$). In Fig. 7, this difference has been reduced to 0.5 (i.e., $|\omega_{trg}\text{-}\omega_{distr}|=0.5$).

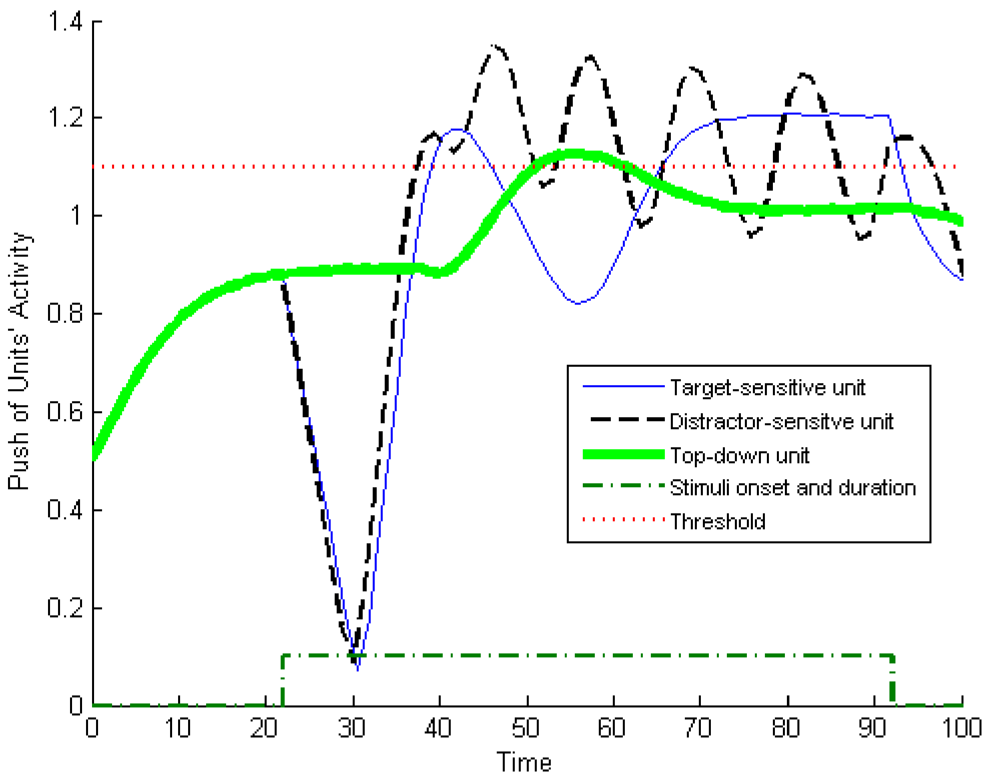

Fig. 7 The push of the activity of BU units in response to a target and a distractor with increasing the similarity between the distractor and target ($p_{BUtrg}=6$;$p_{BUdistr}=5.5$;$\omega_{trg}=6$; $\omega_{distr}=5.5$). Blue solid line represents the push of the activity of the oscillator that is more sensitive to the target (Eq. (4)). Black dashed line shows the push of the activity of the oscillator that is more sensitive to the distractor (Eq. (5)). Thick solid green line shows the push of the activity of TD controller unit (Eq. (6)). Dark green dot-dashed line demonstrates the onset and duration of stimuli. Red dotted line indicates a threshold of the effectiveness of responses (sampling time (dt)=0.01; $A_{distr}=A_{trg}=1$; $B_{TD\_BUtrg}=B_{TD\_BUdistr}=1$; $\lambda_{BUtrg}=\lambda_{BUdistr}=0.2$; $Y_{BUtrg}(0)=Y_{BUdistr}(0)=0.5$; $p_{TD}=6$; $p_{BUtrg}=6$;$p_{BUdistr}=5.5$;$\omega_{trg}=6$; $\omega_{distr}=5.5$).

Comparing the results shown in Fig. 7 and Fig. 5, it is observed that increasing the similarity between the target and distractor led to the inability of the TD controller to reduce the activity of the distractor-sensitive unit.

All the above results were for a single trial. However, in real experiments, the stimuli are usually presented several times. In each repetitive presentation of the stimuli, the brain state (i.e., the phase of the units activity) is different. That is, the brain has a baseline activity, by the presentation of a stimulus (event), parts of the brain produce a potential related to that event, which adds to the base activity. The base activity of the brain can affect the produced event-related potential [67]. Therefore, the timing and amplitude of the brain response to the incoming stimulus may vary trials by trials, which has been shown in studies of the brain signals [68, 69]. To extend the results, Fig. 8 shows the outcome of 50 repetitions of the stimulus presentation, which simulated by considering random initial states in each repetition.

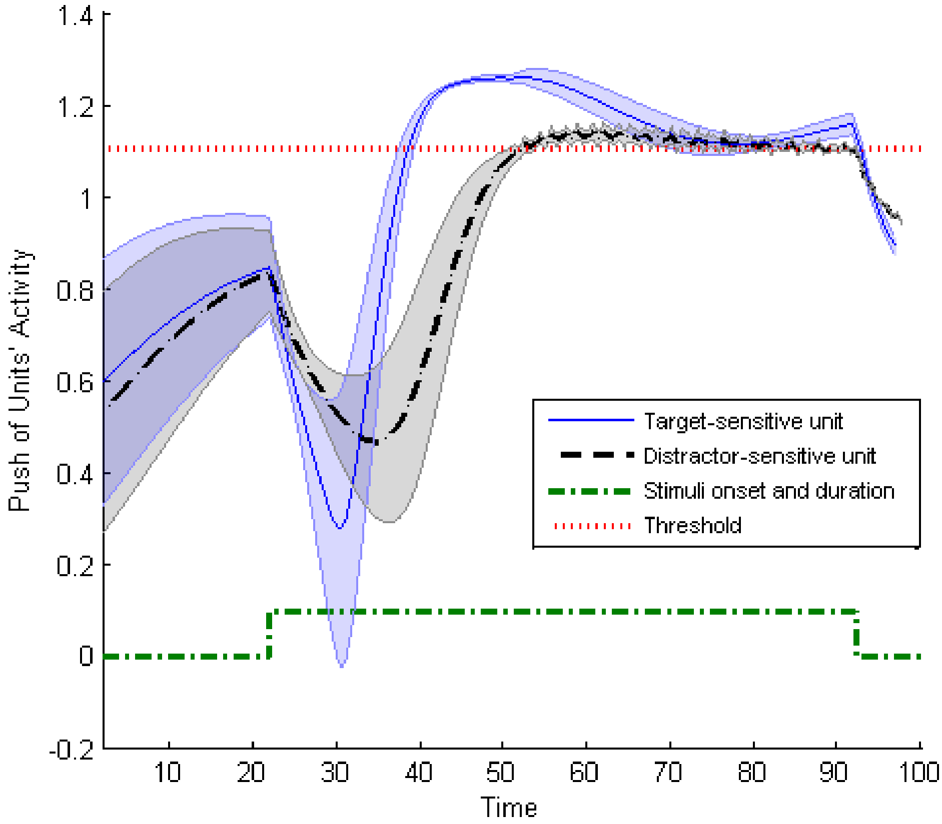

Fig. 8 The push of the activity of BU units in response to a target and a distractor, which were presented 50 times, with considering the effect of the TD controller (B_{TD_BUtrg}=$B_{TD\_BUdistr}$ =0.5). Blue solid line represents the push of the activity of the oscillator that is more sensitive to the target (Eq. (4)). Black dashed line shows the push of the activity of the oscillator that is more sensitive to the distractor (Eq. (5)). The shaded areas shows the variation of responses in each repetition of the simulation with a random initial condition. Thick solid green line shows the push of the activity of TD controller unit (Eq. (6)). Dark green dot-dashed line demonstrates the onset and duration of stimuli. Red dotted line indicates a threshold of the effectiveness of responses (sampling time (dt)=0.01; A_{distr}=A_{trg}=1; B_{TD_BUtrg}=$B_{TD\_BUdistr}$=0.5; λ_{BUtrg}=$\lambda_{BUdistr}$=0.2; p_{TD}=6; p_{BUtrg}=6 ;$p_{BUdistr}$=10 ;ω_{trg}=6 ; ω_{distr}=10).

According to Fig. 8, the differences between the responses of each repetition are in the amplitudes and latencies of crossing the threshold. This figure is for the condition reported in Fig. 4. However, for other mentioned conditions, the changes are the same.

In the above simulations (i.e., Fig. 8), the model parameters were fixed and only the initial conditions (baseline activities) were changed for each repetition of the stimulus presentation. This simulation is approximately equivalent to giving 50 stimuli to a person and recording his/her brain activities. To statistically analyze the difference of responses in two conditions (with and without distractor), it is required to simulate the interpersonal differences by the proposed model. According to previous studies, individual differences can be attributed to the strength of oscillation and amplitude of brain activities [70-72]. In the proposed model, the strength and amplitude of oscillations are determined by the value of λ. In the next simulations, we considered 30 blocks of 50 trials. In each block, we ran the model with a random value of λ. Over the 50 trials of each block, the value of λ was fixed and the initial conditions were changed randomly. Such an arrangement, shown in Fig. 9, was intended to simulate the presentation of 50 stimuli to 30 different individuals.

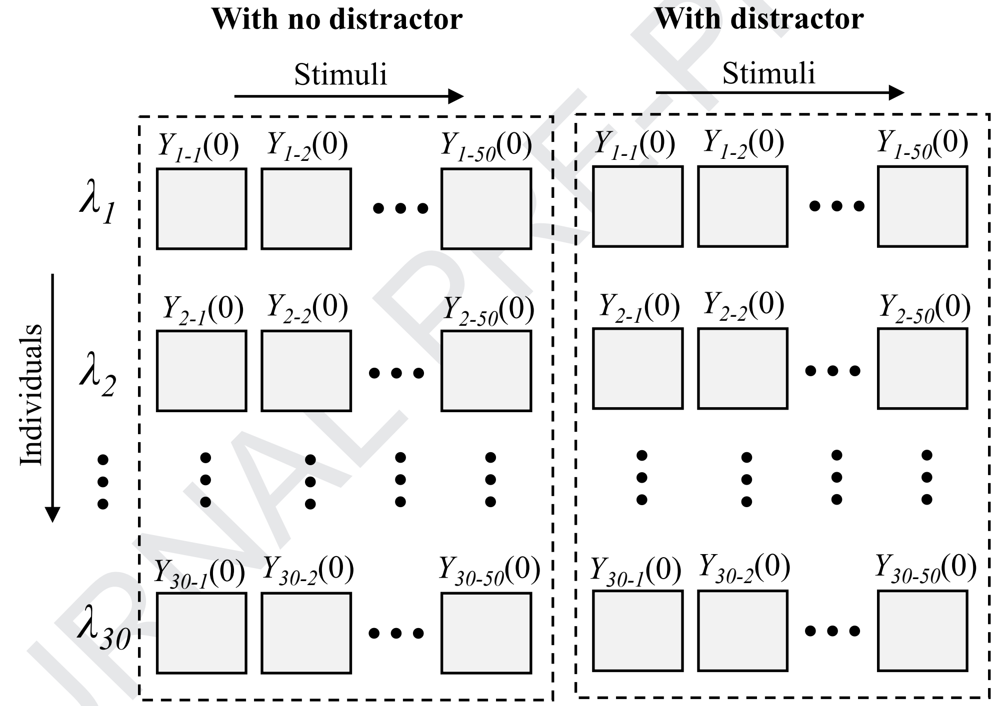

Fig. 9 Model simulation arrangement to simulate the presentation of 50 stimuli to 30 different individuals. Each row (block) has a different random value of λ. Each gray square shows a trial, which is simulated with a random value of the initial condition $Y_{i\text{-}j}(0)$ (the sub-index i represent the number of subjects (i.e., running the model with a different λ) and the sub-index j indicates the number of trials or repetition of the stimuli).

Mean and variability of the amplitudes and latencies of the brain responses, which affect the reaction time [73, 74], are some measures that are usually used to investigate and compare the response of the brain to events or stimuli. The results of simulations and measurements were averaged over 50 trial for each block. The responses of the proposed model to the target stimulus were compared in two conditions: 1) with no distractor; 2) with the distractor. Fig. 10 demonstrates the results of this comparison. The results of statistical analyses (paired t-test) were summarized in Table 1. The null hypothesis of the statistical test was “there is no significant difference between the response of the model in trials with and without distractor” (The significant level was set at 0.05).

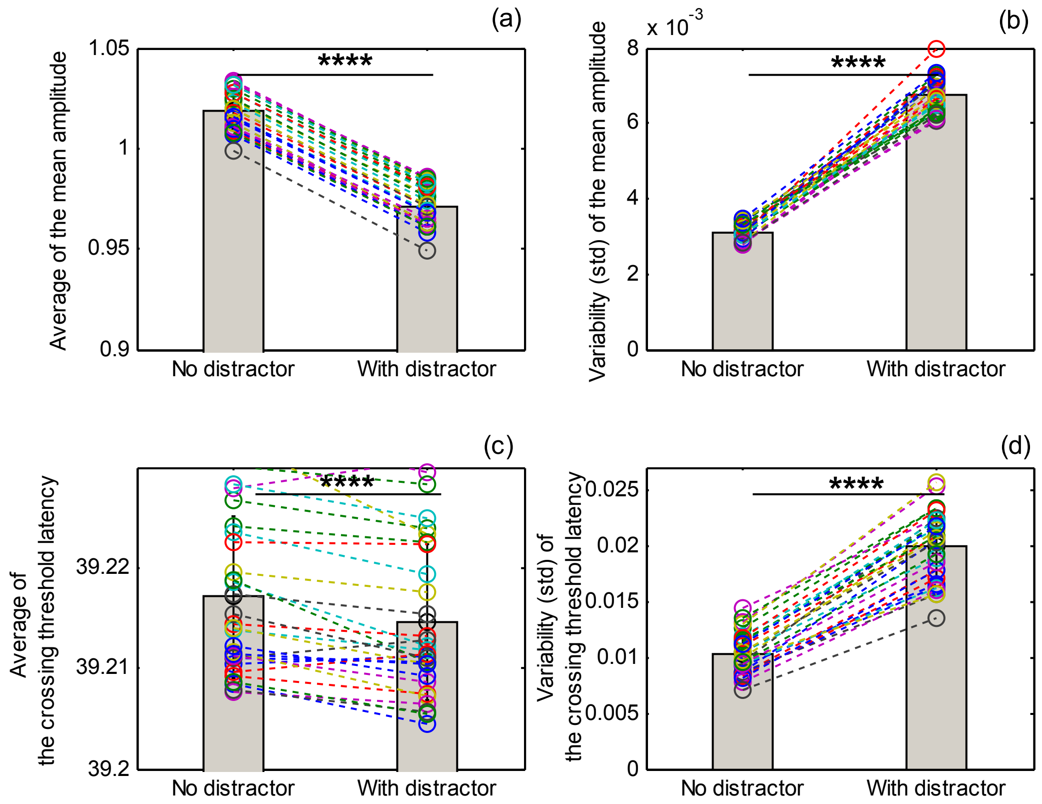

Fig. 10 A comparison between the responses of the model in two conditions, with and without distractor based on four measures: (a) average of the mean amplitude; (b) variability (standard deviation (std)) of the mean amplitude; (c) average of the crossing threshold latency (i.e., the time sample in which the response crosses the predefined threshold); (d) variability (std) of the crossing threshold latency, over 50 repetitions (trials). Each dashed line represent the simulation of the model with a random λ (the average results obtained from one row in Fig. 9) The stars above the bars show the statistical significant difference between two conditions with *p-value* < 0.0001) (sampling time (dt)=0.01; A_{distr}=A_{trg}=1; B_{TD_BUtrg}=$B_{TD\_BUdistr}$=0.5; p_{TD}=6; p_{BUtrg}=6 ;$p_{BUdistr}$=10 ;ω_{trg}=6 ; ω_{distr}=10).

Table 1. Results of statistical comparisons between the responses of the model in two conditions, with and without distractor based on four measures. Paired t-test with the null hypothesis of "there is no significant difference between the response of the model in trials with and without distractor" was used (The significant level was set at 0.05).

Measures \ Condition	No distractor	With distractor	Paired t-test results
Average of the mean amplitude	1.0191±0.0095	0.9712±0.0096	t(29) = 243.8430 $p < 0.0001$
Variability (std) of the mean amplitude	0.0031±0.2085e-03	0.0067±0.4517e-03	t(29) = 39.6721 $p < 0.0001$
Average of the crossing threshold latency	39.2171±0.0081	39.2146±0.0077	t(29) = 5.0579 $p < 0.0001$
Variability (std) of the crossing threshold latency	0.0103±0.0018	0.0199±0.0031	t(29) = 28.4959 $p < 0.0001$

According to Fig. 10 and Table 1, it can be observed that in trials with distractor the amplitude and the crossing threshold latency is lower than those of in trails with no distractor. However, the variability of these two measures increases by the presence of distractors.

4. Discussion on relevance of simulation results with observations in attentional experiments

In this section, the results of some studies and experiments conducted in the field of attention are presented along with the results of the proposed mathematical model to validate the simulation results and to show the relevance of them with neurobehavioral observations.

4.1. Event related desynchronization and event related synchronization

Event-related desynchronization (ERD) and event-related synchronization (ERS) are two phenomena that are usually observed in brain signals after the presentation of an event. The decrease and increase of the amplitude of brain oscillations in response to a stimulus are respectively called ERD and ERS. Fig. 11 (a)-(c) show the results of previous studies and the appearance of ERD and ERS in response and paying attention to sensory input. Fig. 11 (d) shows the behavior of the proposed model in response to a stimulus, which is similar to the pattern of brain electrical recordings. More discussion about the possible mathematical reasons for the appearance of ERD and ERS and the relationship between the characteristics of ERD and ERS and an oscillatory model has been provided in our previous study [52].

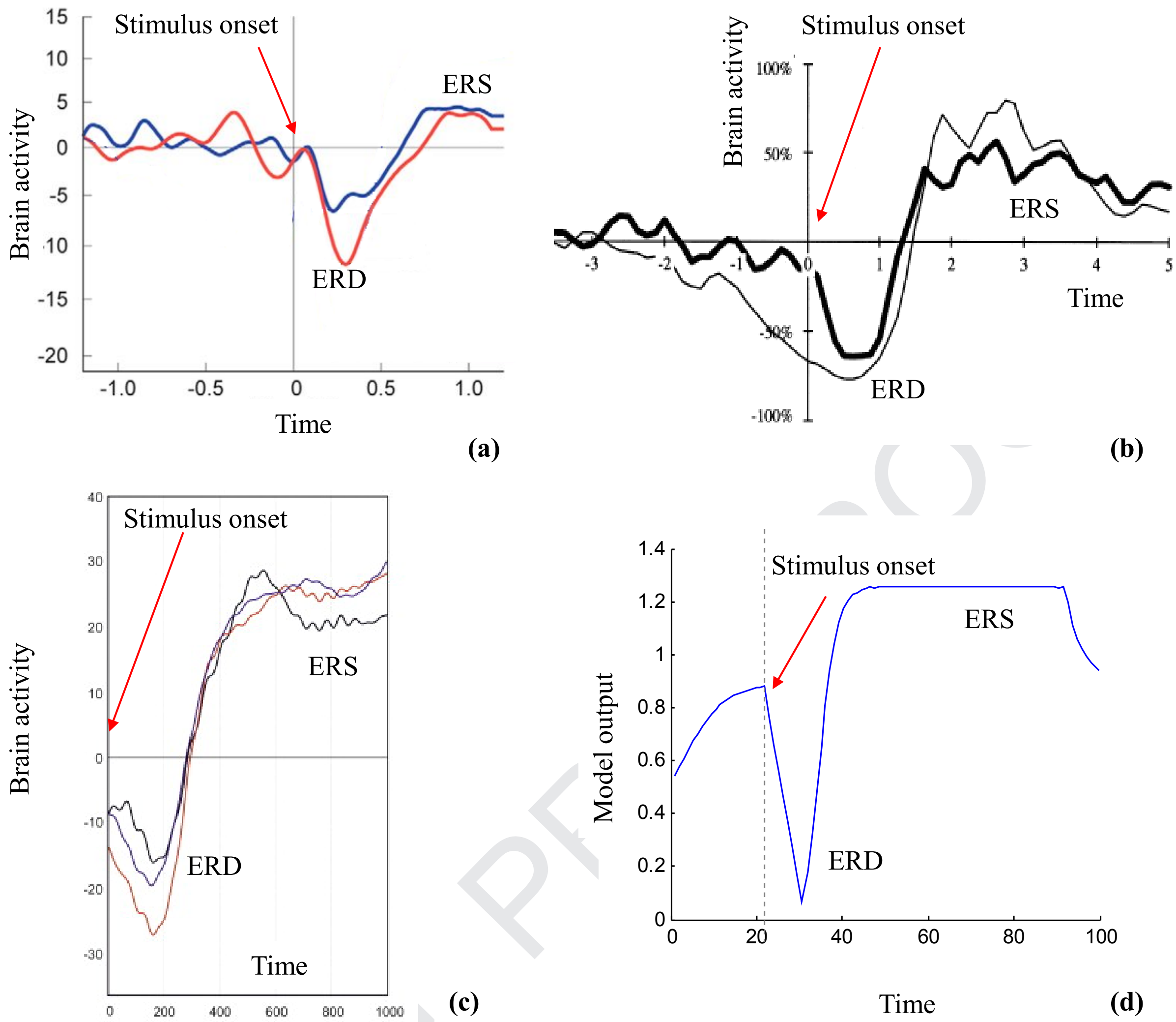

Fig. 11 The appearance of ERD and ERS (a) in an auditory task in two different conditions (adapted from [75]); (b) in a motor related task in two different conditions (adapted from [76]); (c) in a visual task in three different conditions (adapted from [77]); (d) in the proposed model output.

4.2. Two-peak fluctuation of brain activity in target processing

In a target distractor experiment, the frontal EEG activity revealed the effect of the distractor on target processing [78]. Fig. 12 (a) shows the activity of frontal electrode sites in that experiment. A two-peak fluctuation is seen during synchronization procedure in all frontal channel, which is nearly similar to what obtained in the model simulation results (Fig. 12 (b)). No justification has been provided for such fluctuation. According to the mathematical simulation of the proposed model, it can be suggested that the fluctuation may be due to the share of attentional resources between target and distraction, which with more description is presented in the discussion section. Results are also in agreement with this claim that higher-level cognitive processes such as TD attention affect the characteristics and shape of synchronization and desychronization of neuronal activity in response to a stimulus [14, 19-28, 79].

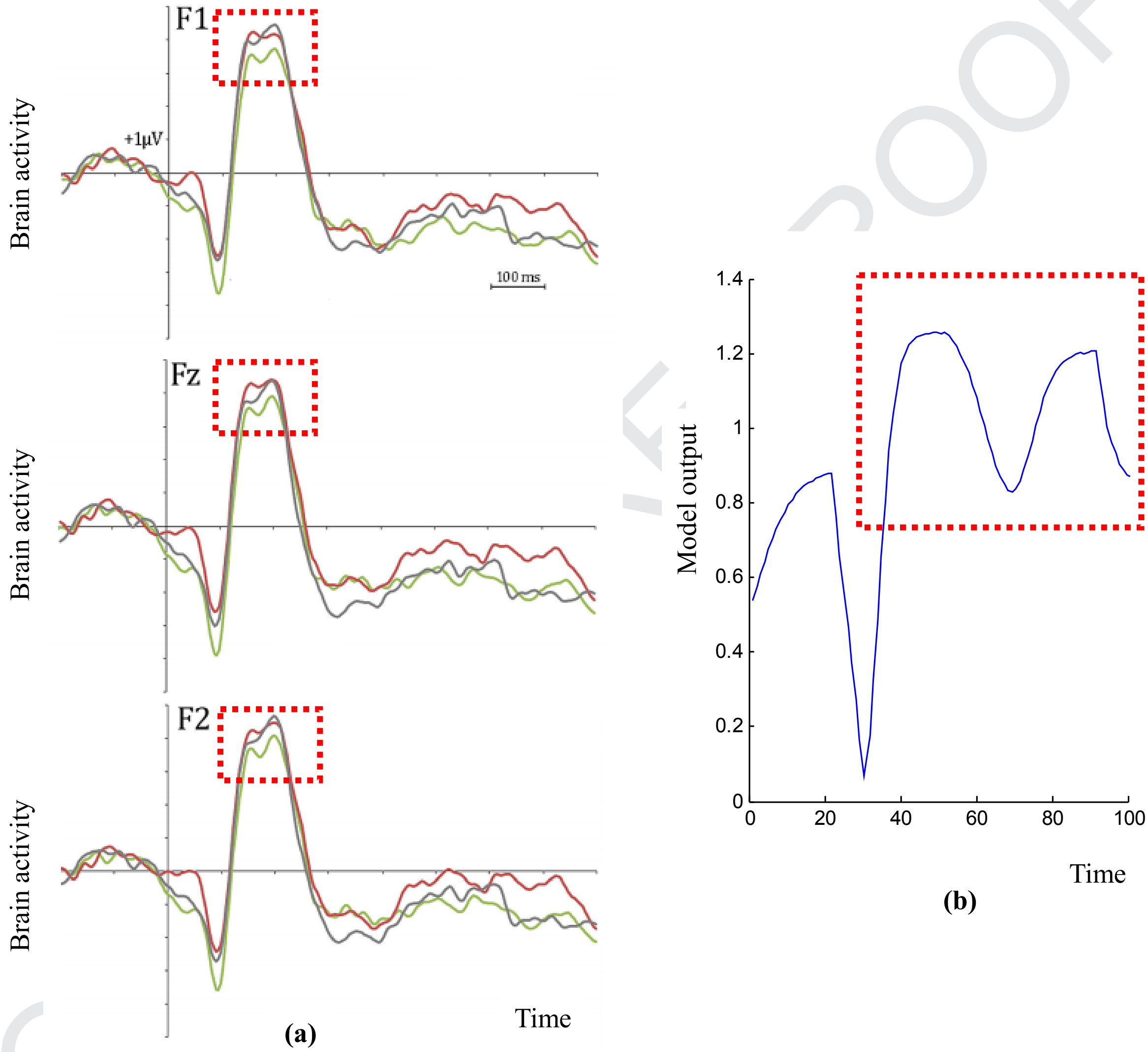

Fig. 12 (a) the activity of frontal electrode sites in a target distractor experiment (adapted from [78]); (b) the output of the proposed model. The dotted squares are shown to bold the appearance of the two-peak fluctuation.

4.3. A common mechanism for modulation of both target and distractor processing

Results of mathematical simulations showed that TD attention modulates the processing of both target and distractors. This result is in agreement with previous brain imaging studies in target distractor paradigms [18, 35, 36, 80].

Neural recordings demonstrated a common prefrontal mechanism is responsible for both of these modulations (i.e., target selection and distractor processing suppression) [18]. Our proposed model shows how this common mechanism can be mathematically represented. In Fig. 4-Fig. 7, the thick green line represents the activity of the TD unit (Eq. (6)). It can be observed how the influence of the activity of this single unit affect the processing of both target and distractor. This unit interacts with target and distractor processing units by an especial frequency that can lead to the target selection and simultaneously distractor processing suppression.

4.4. Effect of the distractor on the amplitude of neuronal response to the target

Previous studies also reported the smaller amplitude of brain event-related responses in trials with distractor in comparison with conditions with no distractor [81-83]. This result is consistent with the output behavior of the proposed model. Fig. 13 demonstrates the amplitude reduction in the presence of distractor in brain signals and the model output. More information about these effects is provided in general discussion section.

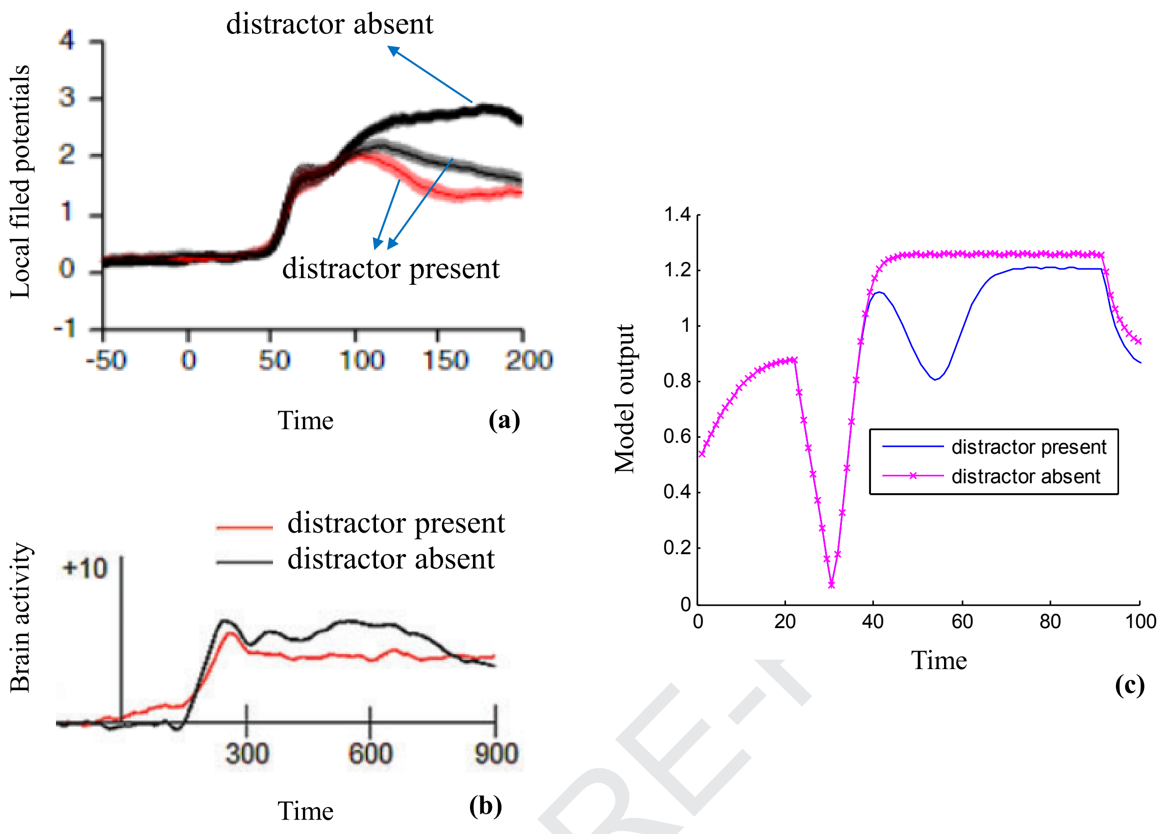

Fig. 13 The effect of the presence of distractors on (a) local field potentials recorded from a monkey's frontal brain (adapted from [18]); (b) event-related potentials recorded from a fronto-central human brain channel (adapted from [83]); (c) the proposed model output.

4.5. The effects of distractor's characteristics

The presence of distractors is an issue that can engage and challenge the attention control system and affects the pattern of neural responses to targets. The effects of distractors on attention system cannot easily be represented by a linear equation. The non-linear nature of attention control system has been shown using behavioral and electrophysiological recordings [84-90]. The proposed model is non-linear and can represent some reported non-linear features of the attention system as follows:

- Environmental noise is a common problem that affects our efficiency to process task-relevant information. Our attention system deals with environmental noise to suppress its negative effect and selects the targets. The strength of the distractor can affect the procedure of target selection and distractor suppression [2, 11, 91]. The effect of noise or distractor level on our target processing performance (e.g. speed and accuracy of responses) has been presented by nonlinear semi-exponential (red dashed line Fig. 14) [84, 85] or bell-shaped functions (blue solid line in Fig. 14) [86, 87].

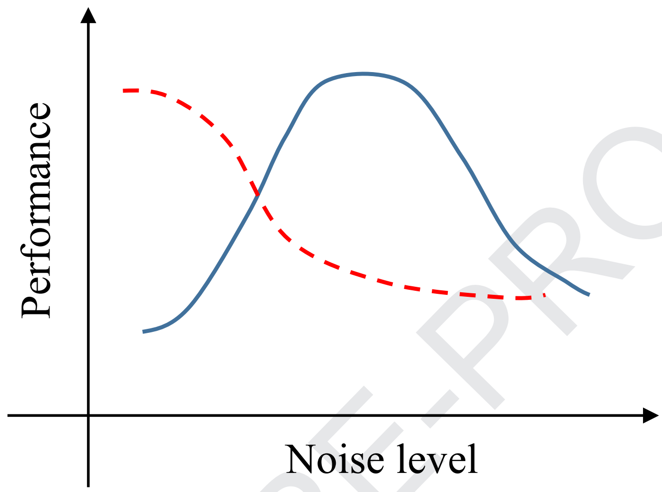

Fig. 14 Two reported non-linear relationships between the noise level and the performance (e.g. speed and accuracy of responses); red dashed line represents a semi-exponential relationship and blue solid line represents a bell-shaped relationship.

The bell-shaped relationship was reported in studies that their participants were inattentive or sub-attentive [86, 87]. It means that when we are in a sub-attentive condition, a low-level of noise can help us and improve our performance. In other words, the presence of a low level distractor demands cognitive control in comparison with the condition of no distractor. The presence of this cognitive control may improve performance [92]. Increasing the level of noise upper than a certain threshold can lead to a performance drop. However, when we are in a normal or super-attentive condition, even a low level of noise can weaken our performance (red dashed line in Fig. 14). These nonlinear behaviors can be justified by the proposed model. In mathematical simulations, increasing the strength of distractor needs the increment of the influence of TD attention to avoid the interfering effect of the distractor. Increasing the influence of TD attention has two effects: 1- the increment of synchronization between TD and target processing BU units and 2- the increment of desynchronization between TD and distractor processing BU units. In the sub-attentive mode, it can be interpreted as a non-optimal level of synchronization between processing units. Therefore, the first effects can increase the attention to the target and improves performance. However, the strength of both effects is limited and cannot suppress the negative effects of all kinds of noise and distractors. When the strength of distractor is high not the first effect nor the second one cannot lead to the optimum target processing and distractor suppression. Therefore, the performance will drop. On the other hand, when we are in a super-attentive mode, mathematically it means that the synchronization between units is in a near maximum state. Therefore, even a little increase is not possible to suppress incoming low-level noise or distractors. For example, considering Fig. 4 to Fig. 6 shows that incoming a distractor leads to the increment of the TD unit influence (i.e., increasing the parameter *B*). This increment affects the synchronization and desynchronization procedures and suppresses the distractor effect to improve behavioral performance. However, as shown in Fig. 6, at a certain level of TD unit influence, increasing the strength of distractor cannot be compensated through the mentioned synchronization and desynchronization procedures. Therefore, noise or distractor cannot be suppressed and behavioral performance (i.e., speed and accuracy of responses) will drop.

As shown in simulation results, the TD unit shows a nonlinear behavior in response to different distractors. Its activity increases in the presence of distractor (comparing condition (1) and (2) in Fig. 15). Its amplitude increases to suppress the effect of distractor and then decreases to avoid higher consumption of limited resources. The changes in its activity have nonlinear behavior. It has been claimed that such changes in controlling strategy of TD unit to select the target and suppress the distraction can be presented by an implicit (or automatic) form of control [93]. The level of changes also depends on the characteristics of the distractor, which is shown in Fig. 15 (b). According to this figure, the similarity between the distractor and the target and distractor with high strength can lead to the increment of the TD unit's activity. Such behaviors can be associated with goal maintenance. It has been believed that the presence of distractor can lead to a goal switch. In order to maintain the main goal, the effort of TD attention system is required, which leads to the increment of its activity. Some characteristics of the distractor make it harder to keep the main goal, suggesting higher effort of TD unit [5].

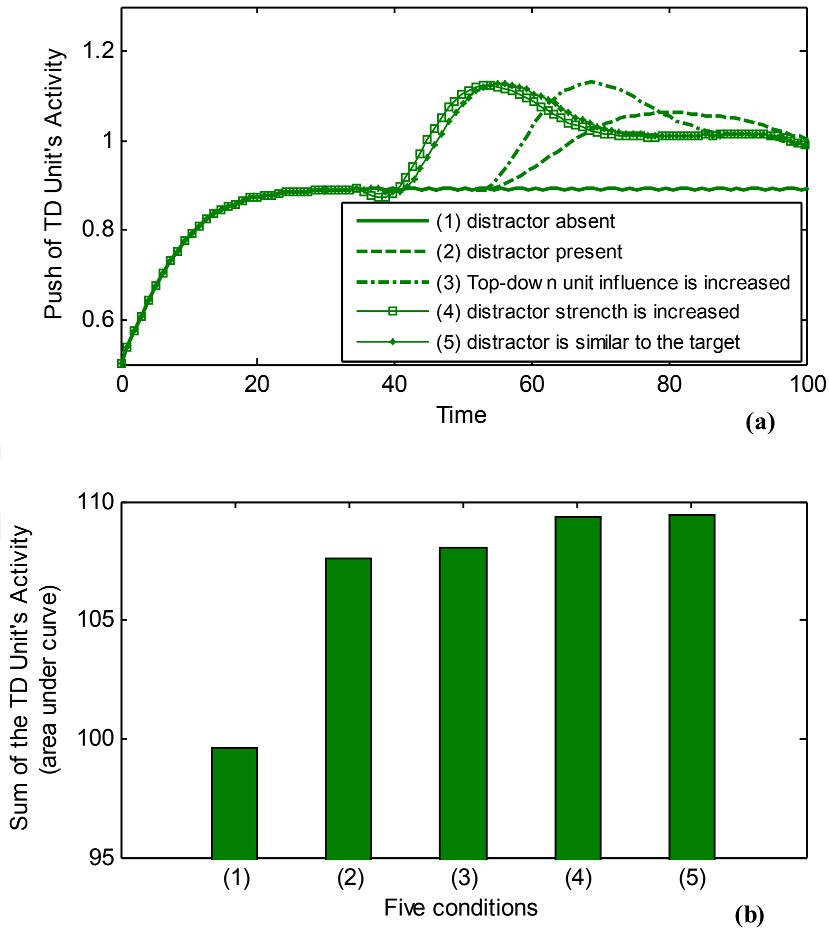

Fig. 15 (a) Push of TD unit activity in five conditions; (b) the sum (area under the curve) of the TD unit's activity in five conditions: (1) distractor absent, (2) distractor present, (3) TD unit influence is increased, (4) distractor strength is increased, and (5) distractor is similar to the target.

5. General discussion

As mentioned, one of the main functions of TD attention is reducing the effect of unwanted stimulus or distractor. In our proposed model, this function is done by a mutual interaction between BU and TD controllers. That is, TD controller causes a desynchronization between the coded distractor stimulus and the activity of BU processors. Such interaction between the oscillatory activities of TD and BU units acts as a gate to permit the processing of target-related information and avoid the entrance and further processing of distractors. It has been believed that thalamus has an important role in regulating the gating mechanism [13].

Fig. 3 showed a situation that two simultaneous target and distractor stimuli were presented and the influence of the TD controller was eliminated. Therefore, both stimuli were processed by BU units, passed the threshold, and consequently, affected higher-level processing systems. To avoid energy consumption for the processing of the distractor, its effect should be reduced by the TD attention. Fig. 4 demonstrated how increasing the coupling weights between TD and BU units from zero to 0.5 affected the processing of the distractor by the BU unit. It was observed that after a delay, the influence of the TD controller started and BU units desynchronized with the distractor stimulus. Accordingly, the activities of the distractor-sensitive unit decreased below the threshold. However, a temporary reduction of target-sensitive unit's activities was also observed, which is consistent with previous EEG observations [78]. While TD controller consumed energy to remove the effect of distractor, the processing of the target stimulus also dealt with some alternation. That is, the processing of a target in the presence of a distractor is not the same as when there is no distractor. This result was also observed in the repetition of simulation for several trials (Fig. 8). As shown in Fig. 10 (a), in trials with the distractor, the amplitude of the target-sensitive unit's activity is lower than that of in trails with no distractor. Previous studies also reported the smaller amplitude of brain event-related responses in trials with the distractor in comparison with conditions with no distractor [81-83]. The reduction of the response amplitude has been attributed to the increment of the cognitive load [81]. According to the results, it can be claimed that the proposed model provides a mathematical justification and lends further evidence to the accuracy of the results of previous studies that show the effect of distractors on the amplitude of brain responses. This outcome (i.e., amplitude reduction) is also consistent with previous studies that have shown when attention is divided between different stimuli (e.g., the target and distractor), the activities of neuronal processing units decrease in comparison with the situation with no division of attention [94, 95]. These results can be interpreted based on the late selection [96] or capacity [97, 98] models of attention. According to the late selection models of attention, two or more actions can be performed simultaneously in lower neural processing stages [96]. However, attentional resources have a limited capacity [97, 98]. In some studies, this limitation was associated with the blood glucose level restriction [99]. When two BU units run simultaneously, both want to use the attentional resources. Therefore, when there is no distractor, a higher amount of resources are available for processing the target, which has been shown by the pink line with stars in Fig. 6. Ignoring the distractor engages the inhibitory and self-control system. It is believed that self-control and attention control systems use the same resource, which is the blood glucose level. Therefore, in the presence of distractors, the processing units of the target and the inhibitory system need to share the common resource that can lead to the reduction of response to the target. In summary, the following statements can be mentioned about the activities of BU units in the presence of the distractors:

- According to the late selection models of attention, two BU units can be active at the same time, specifically when the modalities of the target and distractor are different. That is, both target and distractor can be perceived simultaneously.

- According to the capacity models of attention, the mentioned perception may not be as complete and accurate as there is no distractor. Because the capacity of attentional resources is limited and needs to be shared between the target and distractor. This also is in agreement with the “load theory of attention” [100]. This theory suggests that processing the distractors can interfere with the processing the target. The interference can lead to information overload and the alternation of brain response pattern. In the load theory of attention, the mentioned capacity is associated with the capacity of working memory, which is involved in dealing with irrelevant stimuli [81].
- According to the late selection models of attention, the higher level processing stages of targets and distractors cannot be done simultaneously. Therefore, the TD controller tries to damp the negative effect of the distractor. Consequently, as shown in Fig. 4 and the subsequent figures, until the start of the influence of the TD controller, the activities of both BU units are stable. As far as the capacity of the BU processing resources is allowed, the mentioned bistability can exist. This bistability was also observed in human or animal neural recordings [101, 102].

Based on the results shown in Fig. 10 (b), in trials with a distractor, moreover than the decrement of the amplitude of neuronal responses, the variability of this amplitude increases. These demonstrations may be related to the various mechanisms that our neural systems use to reduce the impact of distractors and enhance the targets processing. Regulation of the amplitude (sensory gain) and the variability (noise modulation) of neural responses are two mechanisms that the neural systems use to facilitate the perception and processing of relevant information [103]. In the simulation results shown in Fig. 10 (b), the alternation of the variability of the response amplitude are because of the distractor effect on the synchronization procedures. That is, in the presence of a distractor, the activity of the distractor-sensitive unit and the signals transmitted by the TD controller to attenuate the effect of the distractor can interfere with the synchronization procedure of processing the target. The effect of these interferences depends on several factors such as the phase difference between the activities of the distractor-sensitive and target-sensitive units, which affect the synchronization procedure, or the time of the start of the influence of the TD controller. Therefore, the effect of the distractor is not exactly the same in all trials, which may lead to the variability of the amplitude of the neural responses. Therefore, it can be suggested that some of the observed alternations of the neural response variability may not be because of a mechanism that the brain uses to suppress the distraction. They may be due to the interference effects of the distractor-sensitive unit's activity on the neural responses to the target.

In addition to the alternation of the amplitude of neural responses, in the presence of distractors, the mean and variability of the crossing threshold latency were changed. Fig. 10 (c) showed that the average of the crossing threshold latency decreases in trials with a distractor in comparison with trials without distractors. However, it can be observed that there is a high variation between the results obtained in each run (between-subjects variability). In some cases, the latency has increased, in some of them, decreases and in some, no change has been observed. This inconsistency has also been observed in previous studies. In some researches, the decrement of the event-related response latency was observed by the presence of distractors [104]. Some studies reported the increment of the brain event-related response latency in trials with distractors [105]. Some others showed that distractors had no considerable effects on the latency of brain responses to the target [81, 83]. However, the variability of this measure (i.e., crossing threshold latency) increases by the presence of distractors. The increment of the variability of the latency of brain event-related responses has also been reported in previous studies [82]. It has been shown that mean and variability of neuronal response latencies have positive correlation with the recorded behavioral reaction times [106, 107]. In summary, results of simulations shown in Fig. 10 (c, d) suggested that the presence of distractors may lead to the responses with higher variability, which are usually observed in the performance of individuals especially ones with attention deficit/ hyperactivity disorder (the impulsive subtype) that are more sensitive to the distractors [108, 109].

Fig. 5 showed that increasing the effect of the TD unit led to a stronger and faster reduction of the distractor effect. However, the negative effect on target processing increased. This observation is congruent with the outcomes of studies that have shown the alternation of brain activity when different levels of attention are allocated to the distractor [110, 111]. That is, more attention to the distractor, or consuming more energy to remove its negative effect leads to the less attention to the target and consequently, the decrement of the activities of brain areas that are involved in the target processing.

The other factor that can affect the interaction between TD and BU units is the strength or the saliency of the distractor stimulus with respect to the target. The proposed model allows investigating the effect of these factors mathematically. Simulation results shown in Fig. 6 demonstrated that TD controller could not reduce the effect of the distractor effectively when the strength of distractor was higher than the target. In other words, in the competition between the TD controller and the BU distractor-sensitive unit, the BU won up and the distractor affected the BU resources. In neurological studies, it has also been reported that salient stimuli can attract the focus of attention and be processed by BU neuronal processing resources regardless of whether these stimuli are targets or distractors [91]. That is, BU processing resources are very sensitive to high intensity or salient stimuli [2] and the TD controller cannot easily reduce this high sensitivity [11].

It has been claimed that increasing the similarity between the distractor and the target increases the TD controller efforts to eliminate the effect of the distractor [37-41]. The results presented in Fig. 7 confirm this claim. Our mathematical model suggests that the increment of the similarity between the distractor and the target increases the probability of synchronization between the target-sensitive BU unit's activity and the coded distractor stimulus and also between distractor-sensitive BU unit and the TD oscillator. In other words, due to the similarity between the target and the distractor ($\omega_{trg} \approx \omega_{distr}$), the TD controller efforts cannot lead to the desynchronization between the coded distractor and the activities of its sensitive units. As a result, the impact of distractor is not reduced, and may be further processed mistakenly.

Simulations showed a delay between the onset of the distractor and the influence of the TD controller to reduce the effect of this distractor. Such a delay has also been observed in neural and behavioral recordings [4, 112]. However, in situations where the arrival time of the distractor is predictable, TD controller can start the required action before the entrance of distractor to reduce the mentioned delay [21].

As shown in Fig. 8, the general pattern of brain responses to the presented repetitive stimuli are nearly the same, but there are some differences in the amplitudes and latencies of responses in each trial, which is known as "trial-to-trial variability [68, 69]." This variability may be due to the alternation of the initial conditions in each repetition, which affect the synchronization procedure [52]. In addition to the inter-trial variability, there is a between-subjects variability that has been shown in Fig. 10. It has been believed that the amplitude and strength of the brain oscillations and activities have a correlation with the individual differences [70-72]. In the proposed model, this variability was represented through the random selection of λ, which determined the intrinsic oscillation amplitude of the model's units. As shown in Fig. 10, the between-subject variability (the variability of the dashed lines) in the "average of the crossing threshold latency" is higher than that of in other measures. Therefore, considering the strength of brain activities as a basis of individual differences led to the variation of response latencies. This result can be considered as a confirmation on both groups of studies that associated the individual differences with 1) the strength of neural responses [70-72], and 2) the latency of neural responses [113].

As shown in Fig. 11, ERD or ERS may be observed in response to any sensory input. It has previously been believed that ERD and ERS can be seen in motor-related tasks [114]. Therefore, the results of this study mathematically show the possible appearance of ERD and ERS is also possible in response to any sensory input, which is consistent with recent EEG studies on sensory processing [75, 77, 114].

In summary, the proposed model, which was designed based on the synchronization and desynchronization procedures, showed the possible role of these procedures in target selection and suppression of distraction effects. The proposed model mathematically provides a possible answer to the long-standing debate concerns how the target selection and suppression of task-irrelevant information processing are processed within the same attention control system.

This model showed the effect of the stimuli intensity and the similarity between the target and distractor on the mentioned procedures and the performance of the attention control system. In studies developed based on the ART, desynchronization between the incoming stimulus and whatever that is in the memory can attract the attention and trigger the learning procedure. However, in the proposed model, desynchronization was used as a tool to attenuate the effect of the distractor and synchronization was used to enhance the target processing. The results of the current study are consistent with the prediction of the ART that most of the cognitive functions shape through synchronization or desynchronization between different brain regions.

6. Conclusion

In this study, using a mathematical model, it has been shown that TD and BU attention systems may interact to suppress the effect of the distractor. A suggestion about the possible role of synchronization and desynchronization between neuronal activities in response to target and distractor stimuli was provided. The model showed how changing the distractor intensity or the similarity between the target and distractor may affect the synchronization procedures and finally the function of the attention control system. In the proposed model, the similarity between the target and distractor was simulated by the proximity and similarity in frequency. As mentioned in the method part, this assumption in simulation is based on the coding of stimuli features into frequencies of neural oscillations [53-55]. Therefore, this model can be used to predict the effect of some characteristics of incoming external stimuli on the performance of the selective or divided attention. In other words, using the proposed model, it is possible to estimate how to reduce or increase the delay of the attenuation of the effect of the distractor by varying some of the target or distractor characteristics. When the presence of distractor is predictable, the influence of the TD attention can be started before the presentation of the distractor. This reduces the delay of the TD attention effect. The prediction procedure has not been considered in the current version of the model. Therefore, the proposed model can mimic the interaction of the TD and BU attention for situations that the distractor is not predictable. The possibility of predicting the distractor affects the dynamic of the mentioned interaction. For future works, a block of prediction can be added to the model to develop it for situations that the onset of distractors is predictable.

The value of initial condition and the bifurcation parameter (λ) were fixed in all simulations, however, some drugs or electrical stimulation can change the value of these parameters. Therefore, investigating the effect of electrical stimulation on the procedure of distraction attenuation is suggested as a future work. A modification of the model to investigate the role of the appearance of different brainwave frequencies during the interaction between BU and TD attention would also be suggested.

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Declaration of Interest

There is no declaration of interest.

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Highlights

- A model was proposed to show the interaction between bottom-up and top-down attention.
- Synchronization and desynchronization can lead to the selective or divided attention.
- Top-down attention can suppress the effect of distractor through desynchronization.
- The effect of some factors on the distractor impact can be investigated by the model.