Modelling the Efficiencies and Interactions of Attentional Networks

Fehmida Hussain and Sharon Wood

Representation & Cognition Group, Department of Informatics,
University of Sussex, Falmer, Brighton, BN1 9QJ, UK
f.hussain@sussex.ac.uk and s.wood@sussex.ac.uk

Abstract. Posner and colleagues [38, 40] assert that attention comprises three distinct anatomical areas of the brain responsible for separate aspects of attention, namely alerting, orienting and executive control. Based on this view of attention, the work presented here computationally models the attentional networks task (ANT) which can be used to assess the efficiency and interactions of these disparate networks, collectively responsible for different functions related to attention mechanisms. The present research builds upon the model of ANT to show the modulation effects of one network on the other and suggests how the model can be used to simulate neglect conditions related to attention. The model is evaluated against data sets from experimental studies and the model's fit to data is assessed statistically. Building such models of attention benefits computer vision research, as they are, well informed from both cognitive psychology and neuroscience perspectives.

1 Introduction

1.1 Theories of Attention and Attentional Networks

There are various psychological theories that try to explain how the mechanism of attention takes place. The first systematic theories of attention date back to the 1950s, describing attention as a single phenomenon based on central bottlenecks or limited processing capacity [7]. Later the focus shifted from attention in general to specific theories concerning how people chose among multiple objects, studying specific tasks. A few popular and established theories of attention are Feature Integration Theory [50], Guided Search Theory [57] Bundesen's Theory of Visual Attention [8] and the phenomenon of 'change blindness' and Coherence Theory [45].

Functional neuroimaging has enabled researchers to view many cognitive processes in the window of which brain areas are activated when various attention components are working [12, 39, 21, 15]. There is sufficient evidence to believe that these networks can be distinguished both at cognitive and neuroanatomical levels [44]. This has led to a different kind of theory based on separate but collaborating attentional networks in which attention can be viewed as an organ system or as a system of anatomical areas that consist of more specialized networks. Based on these anatomical findings, Posner proposed his three-component

theory whereby attention is divided into three separate networks: namely, alertness, selectivity and processing capacity [38], later revised and renamed as alerting, orienting and executive control [39–41] (see Figure 1). Similarly, LaBarge's [28] triangular circuit theory of attention requires simultaneous activity of three brain regions that are connected by a triangular circuit.

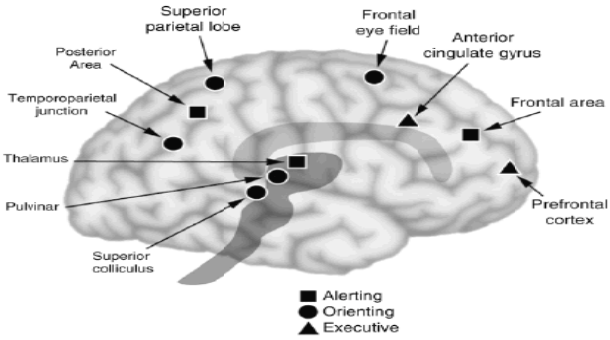

Fig. 1. The neuroanatomy of attentional networks [41] (p6) illustrates the cortical areas involved in the three attention networks. The alerting network (squares) includes thalamic and cortical sites related to the norepinephrine system. The orienting network (circles) is centered on parietal sites and the executive network (triangles) includes the anterior cingulate and frontal areas.

Posner and colleagues state that alerting helps us to prepare for an incoming stimulus so we respond faster and more accurately. Orienting, or selective attention, helps us deal with information overload so that we can select a target among distracters in a cluttered visual scene. Finally, control helps us deal with conflicts in decision making related to attention. Although the attentional networks are anatomically and functionally independent and subtended by separate neural networks in the brain, the three networks operate under the constant influence of one another and orchestrate together to produce efficient and adaptive behavior. At first glance, it may seem that the three-component theory of attention is primarily supported from a neuroscience perspective; however, there is also support for three networks from psychophysical studies: the mechanism of orienting is in line with the classic theories of visual selective attention dealing with tasks like cueing experiments, visual search [50, 57, 8], and so on. The component of executive control relates to the phenomenon of cognitive control and can be supported by theories of cognitive control [47, 12]. Finally, alertness provides a good explanation for theories of enhancement, giving rise to mechanisms like priming and cueing. Hence, the networks theory seems to provide a more complete view of the cognitive phenomenon of attention.

1.2 Attentional Network Test (ANT)

There are numerous tasks that have been used to study the efficiency and interactions of these attentional networks separately. For instance, alerting has been studied using a vigilance task and warning signals. Orienting has been studied using visual search tasks, spatial cueing experiments, and other visual selective attention related tasks. Finally executive control, which involves conflict resolution, is well portrayed by tasks like Stroop, Flanker, Wisconsin card sort, and so on. However, a more holistic approach would be to look at all three networks simultaneously, during execution of a single task. One such paradigm discussed below is the Attentional Network Test (ANT) developed as a behavioral measure of the efficiencies of the three attentional networks within a single task [16, 46].

ANT is a computer based reaction time test which is a combination of cueing experiments [36] and a flanker task [14]. Each trial begins with a cue that informs the participant that a target is coming soon and also where it will occur. In the no-cue condition there is no signal of occurrence in time or location. The target always appears either above or below the fixation point and consists of a central arrow surrounded by flanking arrows that can either point in the same direction (congruent) or in the opposite direction (incongruent). ANT uses differences in reaction time (RT) between each experimental condition to measure the efficiency of each network. The design of ANT is illustrated in Figure 2.

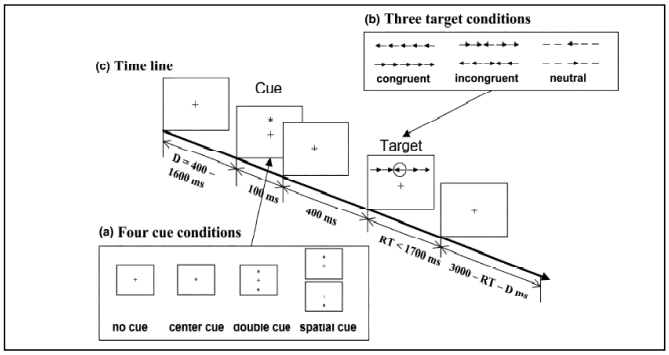

Fig. 2. A sketch depicting the design of the ANT paradigm [53](p121).

The usability of ANT is very diverse and its value can be gauged from its wide application in the study of adults with borderline personality disorder [26], schizophrenia [18, 55], and Alzheimer's disease [17]. Patients with attention deficits/disorders are shown to have specific deficits in the functions specifically of alerting and executive control [43, 41, 6]; autism has been shown to be related to the orienting network, and Alzheimer's, borderline personality disorders and schizophrenia have been shown to be related to executive control [42].

1.3 Computational Modeling of Attention

Computational modeling, a challenging task, is a quickly growing field in not only computer vision, but also in general in cognitive science and neuroscience. With advancements in computational modeling and progress in neuroscience, it would be insufficient to research a cognitive phenomenon from a psychology, neuroscience or computer vision perspective alone; rather, synergizing various disciplines renders tremendous benefits. There are mainly two classes of models relating to attention. There are models that emerge from the point of view of neuroscience and also neuropsychology, built to simulate the neural mechanism of the attentional processes of the brain; the objective is to be able to understand how cognitive functions like perception, memory, thinking, language, decision making, and so on arise from their neural bases. Then there is another class of models that are mainly built to solve computer vision problems. These types of models aim at building computational attention systems which have applications in the field of computer vision and robotics. Typical applications include robot navigation, surveillance tasks, industrial control, and medical imaging.

Based on these needs, there are three broad categories of modeling approaches. A popular and useful approach is that of filter based models [27, 23, 24] used mainly in computer vision applications. Generally this class of computational model responds to the saliency of components of the visual scene such as brightness, contrast and color, essentially corresponding to bottom-up attentional processes. The performance of such models corresponds well with psychophysical data for attention to natural scenes. Further enhancements to this approach reflect learnt associations to regularities in natural scenes, thus contributing a top-down aspect to attention [48, 49, 32, 13]. An alternative approach to modeling uses a connectionist approach which is claimed to be more biologically plausible. A classic example of a connectionist model that simulates the Stroop task is the model of [11] which instead of direct connections uses weight differences which come through practice. Another example, SLAM (SeLective Attention Model) [35] is an extension of McClelland and Rumelhart's [31] model of visual word recognition which adds a response selection and evaluation mechanism. Selective tuning and related work [52], is a connectionist model that achieves selective tuning through a top-down hierarchy of winner-take-all processes. An in depth survey of this approach can be found in [20].

The third approach uses cognitive architectures which are mainly symbolic in nature but which may incorporate subsymbolic constructs. According to Howes and Young [22] (quoted by [19] p302), "a cognitive architecture embodies a scientific hypothesis about those aspects of human cognition that are relatively constant over time and relatively independent of task." Cognitive architectures are widely used to model human behavior, offering a broad theory of human cognition based on a wide selection of human experimental data, and implemented as a running computer simulation program [2, 4, 33]. Various popular architectures today are ACT-R [2] Soar [29] and EPIC [25]. There are a number of examples of cognitive models found in the literature which try to model certain aspects of attention. For example, Lovett's [30] implementation of Stroop is a

good example of an ACT-R implementation of a model of cognitive control. The ACT-R theory has also been extended to include a theory of visual attention and pattern recognition whereby production rules direct attention to primitive visual features in the visual array [5]. The ACT-R theory itself embeds Posner's spotlight metaphor [36], Trieisman and Sato's feature synthesis model [51] and Wolfe's guided search model [57]. The advantage of having such a theory is two-fold: one is to model information processing limitations in obtaining information from the screen; the second is to "remove the magical degrees of freedom in going from a description of an experiment to a cognitive model." [5] (p65).

1.4 Computational Modeling of Attentional Networks

There are various models found in the literature, such as those cited above, that are built to study a specific component of attention. However, simulating the performance of the three together has been sparse. We have come across two such models that implement the attentional networks, both simulating their performance on ANT). The first [56] is a connectionist model based on the Leabra (local error-driven and associative, biologically realistic algorithm) [34]. The second model [53] is a symbolic model based on the cognitive architecture of ACT-R 5.0. Wang and colleagues have also attempted to primitively link and compare the two approaches [54] .

2 Model of Attentional Networks

The work reported in this paper is based on a reimplementation of Wang and Fan's [53] model, extending it to study the modulation effects of the attentional networks and proposing how this modeling effort can be applied in various attention related neglect conditions. It is implemented in ACT-R 6.0 [3, 1] which, as described earlier, provides support for theory of visual attention [5] and incorporates both symbolic and sub-symbolic components.

2.1 Design

The model has six distinct modules which are involved in performing the generic ANT trial: fixation and cue expectation, 'cue or stimulus' processing, cue processing, stimulus expectation, stimulus processing and response. These functional components are mapped into a number of production rules within the symbolic part of the architecture that cover all the possible ANT conditions; however not all rules are fired in any one particular trial, firing depending upon the cue or stimulus.

The ACT-R model interacts with the outside world using perceptual motor modules for finding and extracting information from its *Visicon* (Visual Icon). It mimics the spotlight metaphor in which a variable size spotlight moves across a visual field, fixating on an object so that its features can be recognized. Once recognized, the object features become available for higher level processing. The implemented model uses two main buffers in the vision module: the visual-location

buffer which can see the basic features but cannot recognize the semantics (as in a pre-attentive stage), and a visual buffer to which attention needs to be moved in order to do higher level processing (as in the attentive stage). The way the model deals with the visual input is a good example of the case where both pre-attentive and attentive processes work together. Capacity limits can be related to the number of items attended. In the context of ACT-R, *finsts* maintain a record of the objects that have been attended to and thus provide a mechanism which allows one to explicitly specify how many items can be attended to and for how long. *Finsts* are limited in number and how long they persist, both controlled by ACT-R parameters: the default number of *finsts* is set to four, and the default decay time is three seconds [1]. The model decides whether a stimulus is a cue or target on the basis of pre-attention, but requires full attention to process the target and respond regarding the direction of the arrow. This is in line with ACT-R's theory of attention, whereby, in order for it to know what is in the environment; it must move its attentional focus over the visual scene. It is interesting to note here that ACT-R has the ability to prevent the system from returning to previously attended objects, thus implementing the phenomenon of 'inhibition of return'. The model achieves this by allowing only items tagged as 'attended new' to be 'stuffed' into the visual-location buffer. Buffer stuffing is a mechanism in the ACT-R architecture that corresponds to the concept of bottom-up processing in visual attention. However, based on the goals of the model, the buffer is 'stuffed' using certain predefined criteria and hence reflects top-down control.

The subsymbolic part of ACT-R is used in the model to implement various parameters like rule firing time, noise, to induce randomness, utility values set to deal with conflicting productions in case of incongruency, and so on. In the case of multiple choices of matching productions, the internal conflict resolution mechanism of ACT-R is applied. In ACT-R, the utility module provides support for the productions' subsymbolic utility value which is used in conflict. This value is a numeric quantity associated with each production that can be learned while the model runs or specified in advance for each production. If there are a number of productions competing with expected utility value *Uj* then the probability of choosing production i is described by formula (1).

$$Probability(i) = \frac{eU_i\sqrt{2s}}{\sum_j eU_j\sqrt{2s}} \tag{1}$$

In this default ACT-R formula [1], the summation is over all productions which are currently able to fire; s is the expected gain noise, that is the noise added to the utility values, and e is the exponential function.

2.2 Results

The model is treated as a simulated human subject in an ANT experiment, using the same dataset as used in the human studies [16], and interacting with the same experimental software [5] . The time from the stimulus presentation

to the key press is recorded as the reaction time (RT). The efficiency of each network is measured using formulae (2)–(4).

$$\textit{Alerting efficiency} = \textit{RT(no-cue) - RT(double-cue)} \quad (2)$$

$$\textit{Orienting efficiency} = \textit{RT(center-cue) - RT(spatial-cue)} \quad (3)$$

$$\textit{Executive Control efficiency} = \textit{RT(incongruent) - RT(congruent)} \quad (4)$$

Table 1 reports the results produced by the new implementation, comparing these results with the human data and with Wang et al's earlier implementation [16, 53] indicating a faithful reimplementation of the original ACT-R 5.0 model, as well as reproducing a close approximation to the original human data set.

Table 1. Comparison of Results of Fan et al's [16] Study, Wang et al's ACT-R 5.0 model [53] and the ACT-R 6.0 model presented here.

	Human data			Wang's Model			ACT-R 6 new model		
	neutral	congruent	incongruent	Neutral	congruent	incongruent	neutral	congruent	incong
Nocue	529	530	605	527	526	621	520	521	592
Center	483	490	585	487	486	580	482	483	557
Double	472	479	574	467	466	562	464	459	531
spatial	442	446	515	441	441	522	441	441	527
Correlation Coefficients with human data				**0.99**			**0.97**		

3 Modelling Attention Related Disorders

As mentioned earlier, ANT has been widely used to assess which attentional networks are affected by various attention related deficits [26, 55, 17, 43, 41, 6]. ANT is considered a relatively sensitive tool for assessing attention related disorders because it can closely determine the efficiency of individual attentional networks corresponding to distinct areas in the brain and can be used to assess which particular network is affected by a particular condition.

3.1 Design

The model described in Section 2 has been modified to simulate one such study which uses a modified version of ANT to assess the role of the various attentional networks in Alzheimer's disease. The study models the findings of Fernandez-Duque & Black [17] which assesses attention processes in Alzheimer's disease and in aging subjects. Their study uses a modified version of ANT which is varied to take into account the cost of disengaging from an invalid location. The modified version of ANT, in addition to a no-cue, cued and double (neutral) cue condition, also uses an invalid cue condition in which the cue appears in a location opposite to the target location.

The model was modified to incorporate the new invalid cue condition. To reflect the changes in attention network functionality demonstrated in these studies, the following changes were made to the model. Orienting effect was altered by tuning the buffer stuffing mechanism of ACT-R by increasing the *screen-x* values that determine what will be placed in the visual buffers using the command *(set-visloc-default :screen-x (within 20 180) :attended new)*. This corresponds to a slower orienting effect because the *screen-x* values range wider compared to where the target is placed on the screen and there is a higher probability of choosing a location other than the center arrow. The effect of lesioning the cognitive control network, which increases the congruency effect, is modelled by using productions that make the model refocus every time a distractor is picked up by mistake using production: *refocus-again-if-incongruent*. This results in an extra *move-attention* and thus the reaction time slows down. Similarly, in the case of an invalid cue, the model calls an extra production which shifts the focus of attention from the invalid location to the actual location of the target which takes more milliseconds compared to valid priming. The overall rule firing time (that is the ACT-R parameter *:dat*, the default activation time) is reset to 50 ms rather than 40 ms as used in the Wang et al model [53] and its reimplementation.

3.2 Results

The overall reaction times recorded by the model and compared with human data are given in Table 2. The model seems to fit the human data well with a correlation of 0.95.

Table 2. The reaction times for Alzheimer's disease(AD) subjects and model.

	Congruent – AD Subject	Incongruent-AD Subject	Congurent-Model	Incongurent-model
Nocue	851	947	545	680
Uncued	817	982	545	680
Cued	729	889	488	599
Alert	761	958	520	614

The efficiency of each network is measured using formula (4) from the original experiment and formulae (5)–(6). Figure 3 compares the model generated results with the human study results. As reported in the human study [17], the alerting cue increased the congruency effect but the presence of a spatially valid cue was ineffective in reducing the cost of incongruency.

$$Alerting\ \ efficiency\ = RT(no\text{-}cue)\ \text{-}\ RT\ (neutral) \tag{5}$$

$$Orienting\ efficiency\ = RT(uncued)\ \text{-}\ RT(cued) \tag{6}$$

The results reproduced by the model are in line with the findings of experiments studying attention related deficits in Alzheimer's patients. The model may po-

tentially be used to see how the networks modulate each other and whether enhancing one network could make up for deficit in the other [9]. These results can be compared with the simulated results of the un-lesioned model, to demonstrate the inhibitory efffect of the attentional networks.

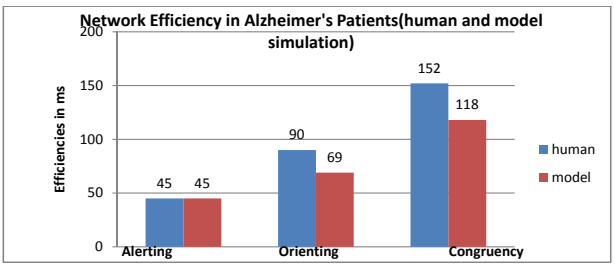

Fig. 3. The efficiencies of all three attentional networks are plotted for human data [17] vs the model simulation in ACT-R 6.0. The correlation of the efficiencies is 0.99.

4 Modulation Effects of Alerting, Orienting and Executive Control

In the original ANT it is difficult to study the interactions of networks since the alerting and orienting effects have been measured using the same variable; that is, spatial cueing is used for orienting whereas temporal cueing is used for alerting. In order to clearly identify the modulating effect of one network on the other, Callejas and colleagues [9, 10] modified the ANT using a separate tone for alerting whilst retaining cueing for orienting, as illustrated in Figure 4. An alerting sound was added to the original design of Fan et al [16], and the new cueing variables used were: no-cue, where the stimulus is not preceded by a cue; cued, where a spatial cue is presented in the location where the stimulus is expected; and un-cued, where a cue appears in a location opposite to the location of the stimulus (invalid priming).

Callejas et al found that both auditory signal and visual cue exert an influence on congruency; alerting having an inhibitory effect whereas orienting has an enhancing effect.

4.1 Design

The experimental design used to model this study involves 2 (auditory signal) x 3 (visual cue) x 2 (congruency) conditions. The symbolic component of the

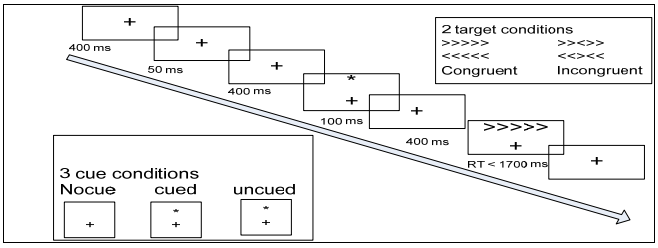

Fig. 4. A sketch of the design of the adapted version of ANT [10].

architecture implements each condition using rules such as *detect-sound*, *notice-stimulus-at-cued-top-location*, and so on. The model determines whether there is a high frequency tone produced by the auditory module of ACT-R and a flag is set indicating whether alerting is present or absent. Also, depending on the cue type, the model presents it on the screen; if its nocue, then the target appears without being preceded by a cue. In the case of the cued condition, the arrows are presented in the expected correct target location and, in the case of un-cued, the model presents the arrows in the incorrect location opposite to that of the expected target location. In the nocue condition, the model has an extra production which handles the 'surprise' condition where the target appears without any priming effect.

In the case of no alerting sound, the model implements an extra production which makes the system do an additional state change which increases the overall reaction time. In the case of an alerting signal, no such state switching is required. Similarly, in the uncued condition, an extra move-attention is required to move focus to the actual target location, whereas in the cued condition, the focus is already at the target location which saves milliseconds. The sub-symbolic component of ACT-R implements the attentional networks by using utility values and noise to help the model resolve conflicts and also make human-like errors. Incongruency is handled by two identical productions namely *refocus-again-if-incongruent* and *harvest-target-directly-if-incongruent* with different utility values (utility values are described in section 2.1).

4.2 Results

The overall reaction times recorded by the model compared with human data are given in Table 3. Pearson correlation coefficient was used to measure the degree of linear correlation between the two results. The coefficients came out to be 0.89 giving a good fit to the data. The efficiency of each network is measured using formulae (4), (6) and (7).

$$\textit{Alerting efficiency} = \textit{RT(no-alert)} - \textit{RT (alerted)} \tag{7}$$

Table 3. Results generated by the ACT-R model along with human data from Callejas et al [9] in brackets.

Mean Reaction Times for each condition for the experiment and (the model simulation)						
	No alerting tone			Alerting tone		
	No cue	Cued	Uncued	No cue	Cued	uncued
Congruent	573 (577)	533 (527)	561(595)	530 (545)	519 (475)	547 (545)
Incongruent	644 (690)	617 (597)	648 (710)	625 (680)	603 (543)	659 (680)

The model showed similar interactions between the networks as in the original experiment in which the alerting network has an inhibitory influence on the congruency effect (cf. "clearing of consciousness" [37] p7401). Also, the orienting network had an influence on the control network; that is, when the location of the target was cued correctly, the congruency effect was smaller compared to the condition in which the location of the target was cued in the opposite location. Interestingly, alerting speeded up the orienting of attention. The modulation effects of the attentional networks are illustrated in Figure 5.

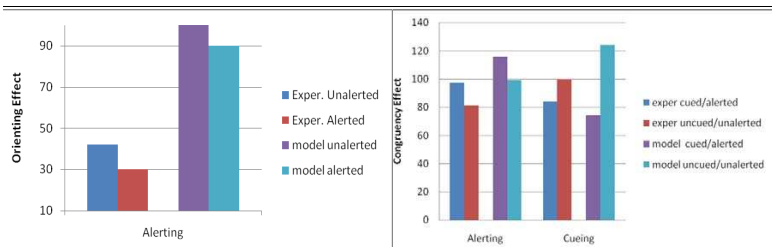

Fig. 5. Interactions between the variables. Congruency effect as a function of cueing and alerting; Orienting effect as a function of alerting.

These results can help us to understand not only how our attentional systems work but also explain how they function in a coordinated way to produce effective behavior. We are able to see how the control network can benefit from the work done by the orienting network in order to resolve conflict better and faster; the alerting system helps us prepare for a task and hence prevents the control network from doing processing work. Also, the orienting network can take advantage of this preparatory state of the system to speed up the orienting process. This clearly shows that, although these networks may be anatomically and functionally independent, they function under the influence of each other to produce effective behavior.

5 Conclusion and Future Work

The work described in this paper is based on the assertion that the whole attentional process comprises operations that help us to select a target found among distracters, to prepare ahead for an incoming stimulus so response is fast and correct, and to be able to resolve conflict and exert control whenever required. In the paper, through modeling the three components of attention, namely alerting, orienting and executive control, to jointly explain the cognitive phenomenon of attention, it seems we are approaching a more holistic view of the mechanisms of selective attention. The purpose of ACT-R models described in this paper is three-fold: (1) to facilitate simulating the behavioral study so that further predictions can be made; (2) to determine which networks may be affected or be functioning abnormally in attentional disorders in clinical patients, by simulating the effect of Alzheimer's on attention related conditions; and (3) to assess the behavior and efficiency of attentional networks and to study their modulation effects.

This work is still in progress and there are several areas that we would like to look into in further depth. For example we have plans to model other attentional related disorders, such as schizophrenia, in a similar fashion which may enable us to make further predictions about the behavior and efficiencies of the network and potentially also suggest non-clinical methods of attention training.

References

1. The ACT-R Website, http://act-r.psy.cmu.edu/actr6/
2. Anderson, J.R.: Rules of the mind. Lawrence Erlbaum Associates, Hillsdale, NJ(1993)
3. Anderson, J.R., Bothell, D., Byrne, M.D., Douglass, S., Lebiere, C., Qin, Y.: An integrated theory of the mind. Psych. Rev., 111(4), 1036–1060 (2004)
4. Anderson, J.R., Lebeire, C.: The atomic components of thought. Mahwah, NJ: Lawrence Erlbaum (1998)
5. Anderson, J.R., Matessa, M., Douglass, S.: The ACT-R theory and visual attention. Proc. Seventeenth Ann. Conf. Cog. Sci. Soc., Nashville, Tennesse, 61–65 (1995)
6. Booth, J., Carlson, C.L., Tucker, D.: Cognitive inattention in the ADHD subtypes. Proc. Tenth Mtg Int. Soc. Res. Child and Adolescent Psychopathology (ISRCAP), Vancouver (2001)
7. Broadbent, D.E.: Perception and Communication. London: Pergamon Press (1958)
8. Bundesen, C.: A Theory of Visual Attention. Psych Rev, 97, 523–547 (1990)
9. Callejas, A., Lupianez, J., Tudela, P.: The three attentional networks: on their independence and interactions. Brain Cognition, 54, 225–227 (2004)
10. Callejas, A., Lupianez, J., Funes, M.J., Tudela, P.: Modulations among the alerting, orienting and executive control networks. Exp. Brain Res., 167, 27–37 (2005)
11. Cohen, J., McClelland, J.L., Dunbar, K.: Automatic processes in the Stroop effect: A parallel distributed processing account. Bull. Pscyhonomic Soc., 25, 239 (1987)
12. Corbetta, M., Shulman, G.L.: Control of goal-oriented and stimulus-driven attention in the brain. Nature Reviews, 3(3), 201–215 (2002)
13. Droll, J.A., Gigone, K, Hayhoe, M.M.: Learning where to direct gaze during change detection. J. Vision, 7(14), 1–12 (2007)

14. Eriksen, B.A., Eriksen, C.W.: Effects of noise letters upon the identification of a target letter in a non search task. Perception and Psychophysics, 16, 143–149 (1974)
15. Fan J., McCandliss B.D., Fossella J., Flombaum J.I., Posner M.I.: The activation of attentional networks. Neuroimaging, 26, 471–79 (2005)
16. Fan J., McCandliss B.D., Sommer T., Raz M., Posner M.I.: Testing the efficiency and independence of attentional networks. J. Cogn. Neurosci. 3(14), 340–47 (2002)
17. Fernandez-Duque, D., Black, S.E.: Attentional networks in normal aging and Alzheimer's disease. Neuropsychology, 20(2), 133–143 (2006)
18. Gooding, D., Braun, J., Studer, J.: Attentional network task performance in patients with schizophrenia–spectrum disorders: Evidence of a specific deficit. Schizophrenia Res., 88(1-3), 169–178 (2006)
19. Gray, W.D., Young, R.M., Kirschenbaum, S.S.: Introduction to this special issue on cognitive architectures and human-computer interaction. Human-Computer Interaction, 12, 301–309 (1997)
20. Heinke, D., Humphreys, G.W.: Computational Models of Visual Selective Attention: A Review. In Houghton, G., Ed., Connectionist Models in Psych., 273–312, Psychology Press (2005)
21. Hopfinger, J.B., Buonocore, M.H., Mangun, G.R.: The neural mechanisms of top-down attentional control. Nat. Neurosc. 3, 284–291 (2000)
22. Howes, A., Young, R. M.: The role of cognitive architecture in modeling the user: Soar's learning mechanism. Human-Computer Interaction, 12(4), 311–343 (1997)
23. Itti, L., Koch, C., Niebur, E.: A model of saliency-based visual attention for rapid scene analysis. IEEE Trans. Patt. Anal. Mach. Intell. 20, 1254–1259 (1998)
24. Itti, L., and Koch, C.: Computational modeling of visual attention. Nature Reviews Neuroscience, 2(3):194-203 (2001)
25. Keiras, D.E. Meyer, D.E.: An overview of the EPIC architecture for cognition and performance with application to human-computer interaction. Human-computer Interaction, 12, 391–438 (1997)
26. Klein, M.R.: Chronometric explorations of disordered minds. Trends Cog. Sci., 7(5), 190–191 (2003)
27. Koch, C., Ullman, S.: Shifts in selective visual attention: towards the underlying neural circuitry. Hum. Neurobiol., 4, 219–227 (1985)
28. Labarge, D.: Attention, awareness, and the triangular circuit. Consc. and Cog., 6, 140–181 (1997)
29. Laird, J.E., Newell, A., Rosenbloom, P.S.: Soar: An architecture for general intelligence. Art. Intell., 33(3), 1–64 (1987)
30. Lovett, M.C.: A Strategy-Based Interpretation of Stroop. Cog. Sci. 29(3), 493–524 (2005)
31. McClelland, J. and Rumelhart, D.: An interactive activation model of context effects in letter perception: Part 1. An account of basic findings. Psych. Rev., 88, 375–107 (1981)
32. Navalpakkam, V., Arbib, M.A., Itti, L.: Attention and Scene Understanding, In: Neurobiology of Attention, Eds. L. Itti, G. Rees, J.K. Tsotsos, 197–203, San Diego, CA: Elsevier (2005)
33. Newell, A.: Unified Theories of Cognition. Cambridge, MA: Harvard University Press (1990)
34. O'Reilly R.C., Munakata Y.: Computational Explorations of Cognitive Neuroscience. Cambridge, MA: MIT Press (2000)
35. Phaf, R.H., Van der Heidgen, A.H.C., Hudson, P.T.W.: SLAM: A connectionist model for attention in visual selection tasks. Cog. Psych., 22, 273–341 (1990)

36. Posner M.I.: Orienting of Attention. Quart. J. Exp. Psych., 32, 3–25 (1980)
37. Posner, M.I.: Attention: the mechanism of consciousness. Proc. Nat. Acad. Sci., 91(16), 7398–7402 (1994)
38. Posner, M.I., Boies, S.J.: Components of attention. Psych. Rev., 78, 391–408 (1971)
39. Posner M.I., Fan J.: Attention as an organ system. In Neurobiology of Perception and Communication: From Synapse to Society. De Lange Conference IV, Ed. J. Pomerantz. London: Camb. Univ. Press (2007)
40. Posner, M.I. and Petersen, S.E.: The attention system of the human brain. Ann. Rev. Neurosc., 13, 25–42 (1990)
41. Posner M.I., Rothbart M.K.: Research on attention networks as a model for the integration of psychological science. Ann. Rev. Psych. 58, 1–23 (2007)
42. Posner, M.I., Rothbart, M.K., Vizueta, N., Levy, K.N., Evans, D.E., Thomas, K.M., Clarkin, J.F.: Attentional mechanisms of borderline personality disorder. Proc. Nat. Acad. Sci., 99(25), 16366–16370 (2002)
43. Posner, M.I., Sheese, B.E., Odludas, Y., Tang, Y.: Analyzing and shaping human attentional networks. Neur. Networks, 19, 1422–1429 (2006)
44. Raz, A.: Anatomy of Attentional Networks. Anatom. Rec., Part B, New Anatomist, 281(1), 21– 36 (2004)
45. Rensink, R.A.: The dynamic representation of scenes. Visual Cognition, 7, 17–42 (2000)
46. The Sackler Institute for Developmental Psychobiology, http://www.sacklerinstitute.org/users/jin.fan/
47. Schneider, W., Shiffrin, R.M.: Controlled and automatic human information processing: I. Detection, search and attention. Psych. Rev., 84, 1–66 (1977)
48. Torralba, A.: Modeling global scene factors in attention, J. Opt. Soc. Am., Special Issue on Bayesian and Statistical Approaches to Vision, 20(7), 1407–418 (2003)
49. Torralba, A., Oliva, A., Castelhano, M., Henderson, J.M.: Contextual Guidance of Attention in Natural scenes: The role of Global features on object search. Psych. Rev. 113(4) 766–786, (2006)
50. Treisman, A.M., Gelade, G.: A feature-integration theory of attention. Cog. Psych., 12, 97–136(1980)
51. Treisman, A.M., Sato, S.: Conjunction search revisited. J. Exp. Psych.: Hum. Percept. and Perf., 16, 459–478. (1990)
52. Tsotsos, J.K., Culhane, S., Wai, W., Lai, Y., Davis, N., Nuflo, F.: Modeling visual attention via selective tuning, Art. Intell., 78(1-2), 507–547 (1995)
53. Wang H., Fan J., Johnson T.R.: A symbolic model of human attentional networks. Cog. Sys. Res. 5, 119–34 (2004)
54. Wang, H., Fan, J., Yang, Y.: Toward a Multilevel Analysis of Human Attentional Networks. In K. Forbus, D. Genter and T. Regier (Eds), Proc. 26th Ann. Conf. Cog. Sci. Soc., Chicago, Illinois, 1428–1433 (2004)
55. Wang, K., Fan, J., Dong, Y., Wang, C., Lee, T.M.C., Posner, M.I.: Selective Impairment of attentional networks of orienting and executive control in Schizophrenia, Schizophrenia Res., 78, 235–241 (2005)
56. Wang, H., and Fan, J.: Human attentional networks: A connectionist model. J. Cog. Neurosc., 16(10), 1678–1689 (2007)
57. Wolfe, J.M.: Guided Search 2.0: A revised model of visual search. Psychonomic Bull. and Rev., 1(2), 202–238 (1994)