

Salience Sensitive Control, Temporal Attention and Stimulus-Rich Reactive Interfaces

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1 Introduction

Humans are very good at prioritising competing processing demands. In particular, perception of a salient environmental event can interrupt ongoing processing, causing attention, and accompanying processing resources, to be redirected to the new event. A classic example of this is the well-known *Cocktail Party Effect* (Cherry, 1953). Not only are we easily able to follow just one conversation when several people are speaking, but the occurrence of a salient phrase in a peripheral conversation stream, such as somebody mentioning our name, causes auditory attention to be redirected. It is also clear that emotions, motivation and physiological state in general, play a key role in such prioritisation, e.g. Oatley and Johnson-Laird suggest that:

“... the function of emotion modes are both to enable one priority to be exchanged for another ... and to maintain this priority until it is satisfied or abandoned” (Oatley and Johnson-Laird, 1987).

However, in an agent with multiple goals (such as a human) that is subject to continual environmental input, a compromise needs to be struck between, on the one hand, responding optimally to priority events and, on the other hand, maintaining efficient processing. In the extreme, a system could fail to complete the processing of any attended streams in circumstances where interruption is the norm. The heart of the conflict lies in balancing the need to respond in a timely fashion with the need to respond optimally given the salience of environmental stimuli. The problem is complicated by the fact that salience itself is highly context dependent. Hearing a lion roar may be extremely salient if you are on foot in the African Savanna, but it would be much less salient if you were walking around a zoo. Our capacity to correctly attribute salience to stimuli in a context dependent manner and interrupt or adjust ongoing processing accordingly has obvious adaptive benefits when viewed from an evolutionary perspective.

Current artificial systems clearly do less well. This manifests itself in two ways. Firstly, they are often deficient at adjusting processing in ways that are

appropriate to the situational context and on the basis of the salience of novel events. They may fail to respond appropriately to highly salient events or they may interrupt processing unnecessarily in response to low salience events. Secondly, when interacting with humans, artificial systems can fail to fully utilise salience. In pursuit of a particular goal, interactive systems typically unreel sequences of what amount to ballistic steps, only being receptive at specific breakpoints to a restricted set of anticipated cues. In contrast, a salience sensitive interface would adapt its behaviour according to the attentional and affective state of the user (Picard, 1998).

A major barrier to constructing artificial systems that are appropriately salience sensitive is our relatively poorly developed grasp of how humans adapt their behaviour according to salience. While it is clear that humans do it well, the actual mechanisms are not well understood. Our knowledge of these mechanisms is though improving, aided by the combination of behavioural experimentation and recent advances in brain imaging and EEG (Corbetta and Shulman, 2002, Corbetta et al., 2008). In particular, a number of experimental paradigms, which fall broadly within the study of human attention, have started to reveal how real-time constraints and sensitivity to salient events are resolved in humans. Three such experimental paradigms are the Attentional Blink (AB) task (Raymond et al., 1992), the psychological refractory period (Pashler, 1994) and emotional interference within Stroop experiments (McKenna and Sharma, 2004).

In order to capitalise on the potential of these empirical advances, explicit computational models of salience sensitive control need to be developed. These would provide concrete realisations of the *mechanisms* being revealed and also enable the construction of artificial systems that are appropriately sensitive to salience. The Saliency project, www.cs.kent.ac.uk/~hb5/attention.html, was undertaken at the University of Kent at Canterbury (in collaboration with the Medical Research Council's Cognition and Brain Sciences Unit, www.mrc-cbu.cam.ac.uk) to fulfil this need.

A major theme of the Saliency project was temporal attention, which concerns the capacity of humans to deal with a sequence of attentional episodes. The project explored questions such as how long attention is allocated to one event before it is free to be allocated to a second; how an incoming salient item interrupts processing of an earlier item and causes attention to be redirected; and, most importantly, what actually determines salience in this context, where obvious candidates include relevance to long-term goals and emotional significance. The AB task (Raymond et al., 1992) is one of the key paradigms that has been used to address these questions. Specifically, this paradigm has explored the temporal

constraints and other parameters governing when salient stimuli are missed as a consequence of attention being directed at preceding stimuli. In addition, we now have some hard evidence of how both semantic and emotional salience regulate the allocation of temporal attention (Barnard et al., 2004, Barnard et al., 2005, Anderson and Phelps, 2001).

The Saliency project, summarised in this chapter, concentrated on the development of computational models, validation of these models through behavioural and electrophysiological experimentation and exploration of the implications of these models for the development of computer interfaces. Our modelling of semantic and emotional effects in temporal attention will be discussed in the next section, the implications for construction of reactive human-computer interfaces will be addressed in section 3, followed, in a final section, by some concluding remarks and issues for further investigation.

2 Modelling of Semantic and Emotional Effects in Temporal Attention

2.1 The Attentional Blink and Meaning

We pay attention to information that matters to us and this relevance is a result of the cognitive task we are engaged in, that information's personal salience and our motivational and emotional state. For example, anxious people preferentially pay attention to external threat (MacLeod et al., 1986) and the ways in which humans interact with computers is modulated by the emotional qualities of the interface (Walker et al., 1994). In all these domains, the key questions concern the dynamic redeployment of attention over time, as investigated in the AB (Raymond et al., 1992). A typical AB task is Chun and Potter's letters-in-digits task (Chun and Potter, 1995). In this task, a stream of items is presented one after the other at fixation¹, with each replacing the previous item. Thus, items are presented in Rapid Serial Visual Presentation (RSVP), at around 10 items per second. The majority of items presented are digits, although two letters are placed at different positions within the stream. The participant's task is simply to identify the two targets and then report them when the RSVP stream has ended. The second letter target (T2) is positioned with a number of intervening digits (referred to as the lag) between it and the first target (T1). Report of T2 is impaired dependent upon the position in which T2

¹ A fixation mark probes where the subsequence stimuli will be presented on the screen; and during the experiment, participants fixate on single spatial location.

follows T1. Specifically, if T2 occurs immediately after T1, then its presence is accurately reported (so called, lag 1 sparing). T2 accuracy is lower for slightly longer lags and then recovers back to baseline when T1 and T2 are separated by about half a second or more (generally this is at lags 5-8). This is the basic attentional blink which we abbreviate as AB (c.f. Figure 1). The empirical literature and theoretical accounts of the AB have all assumed that allocating attention to T1 leaves less attentional resources for processing T2.

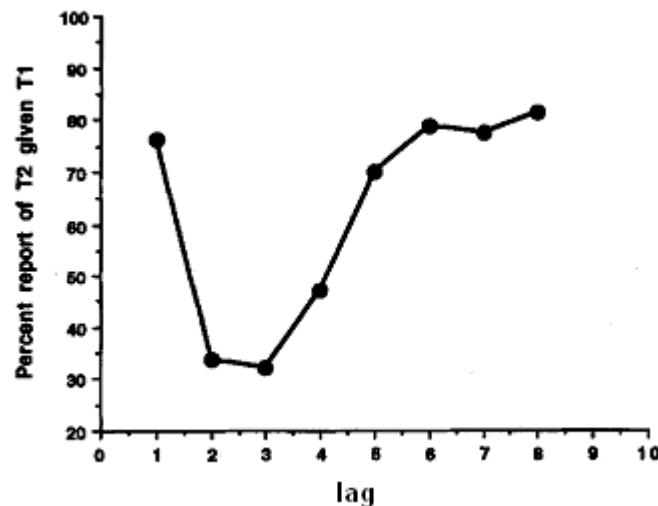


Figure 1 The basic AB effect for letter stimuli. Here, the blink curve is the percentage report of T2 conditional on T1 report, reflecting the effect on T2 report of successfully attending to T1 (Chun and Potter, 1995).

As research on the blink has progressed, not only using letters but also words and pictures, it has become clear that the AB is affected by both the semantic and personal salience of items. Similar blink effects are readily obtained when words are used as list items (and subjects are required to report items from a particular category, e.g. job words). There is also evidence of specific effects of affective variables. Holmes and Richard report differences in target detection in the AB paradigm for high and low anxious people (Holmes and Richard, 1999). More dramatically, Anderson has shown that the blink effect is markedly attenuated when the second target is an aversive word, such as, “rape” or “torture” (Anderson, 2005). This suggests that perception of (high priority) emotionally salient (T2) stimuli can overcome the blink impairment. There is also evidence that patients with damage to specific emotional centres in the brain (viz, unilateral damage to the left Amygdala) show no attenuated blink effect to aversive words (Anderson and Phelps, 2001). The implication is that this region plays a central role in the pathway by which affect-driven salience is assessed. Cumulative evidence from the AB paradigm is revealing how humans

redeploy attentional resources when processing semantically, personally and emotionally salient stimuli and, moreover, it is clarifying the time course at which such mechanisms operate.

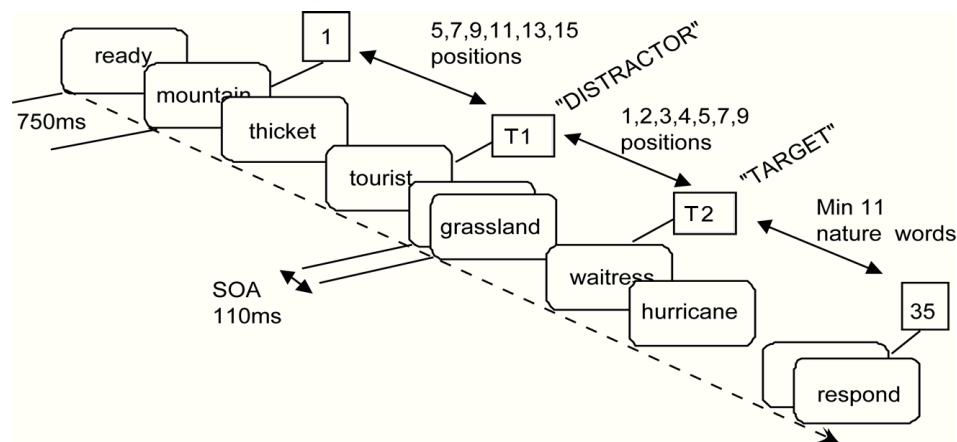


Figure 2 Task schema for the key-distractor blink (Barnard et al., 2004).

In order to examine semantic effects, Barnard et al used a variant of the AB paradigm in which words were presented at fixation in RSVP format, at around 10 items per second (Barnard et al., 2004). Targets were only distinguishable from background items in terms of their meaning. Participants were simply asked to report a word if it refers to a job or profession for which people get paid, such as waitress, and these targets were embedded in a list of background words that all belonged to the same category, e.g. nature words; see Figure 2. However, streams also contained a key-distractor item, which, although not in the target category, was semantically related to that category, e.g. tourist, vegetarian and so on; see Figure 2 (Barnard et al., 2004). The serial-position that the target appeared after the key-distractor was varied. The effect of attentional capture by meaning is encapsulated in the serial position curve (denoted Human-HS) in Figure 3. That is, the key-distractor drew attention away from the target with a clear temporal profile.

Barnard et al used Latent Semantic Analysis (LSA) (Landauer and Dumais, 1997, Landauer et al., 1998, Landauer et al., 2007) to assess similarities between key-distractors and job targets (Barnard et al., 2004). LSA is a statistical learning method, which inductively uses the co-occurrence of words in texts and principle components analysis to build a (compact) multidimensional representation of word meaning. In particular, an “objective” measure of the semantic distance between a pair of words or between a word and a pool of words can be extracted from LSA. The critical finding of Barnard et al was that the depth of the blink induced by a key-distractor was modulated by the semantic salience of that key-distractor, i.e. its proximity in LSA space to the target category.

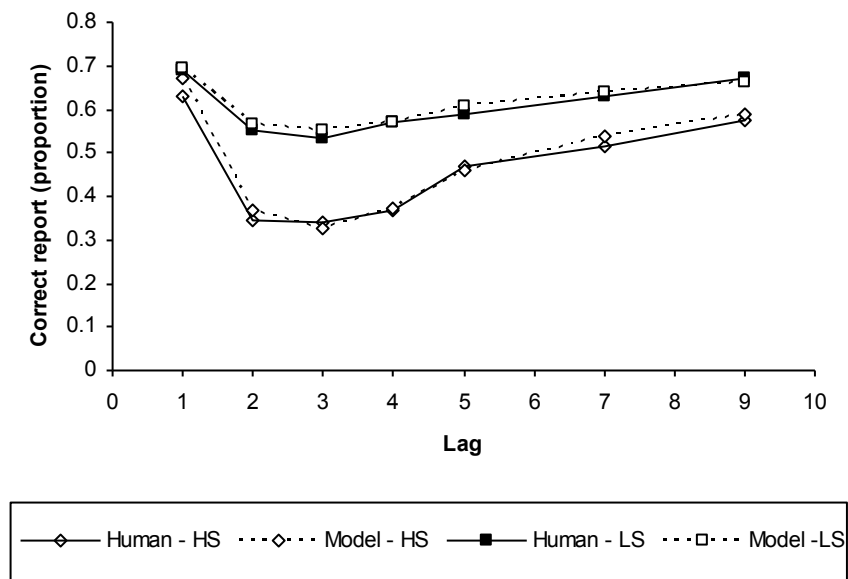


Figure 3 Proportion of correct responses from both humans and model simulations. HS and LS denote high and low salient condition respectively (Su et al., 2007).

When key-distractors were household items, a different category from both background and target words, there was little influence on target report. However, key-distractors that referenced a property of a human agent, but not one for which they were paid, like tourist or husband, gave rise to a classic and deep blink, see Human-HS in Figure 3. We call household items low salient key-distractors and human items high salient key-distractors.

These AB experiments have counterparts in real life. For instance, when an anaesthetist monitors a patient during surgery, they have to consider a range of patient vital signs, as they monitor several physiological metrics, e.g. heart rate, blood pressure, breathing and skin colour. In this environment, events follow one another rapidly as do stimuli in RSVP streams. When a critical event occurs, e.g. a spike in one of the vital signs, the doctor allocates attention to this high-salient stimulus in a manner similar to a participant attending to a target/key-distractor in an RSVP stream. The AB phenomenon suggests that attending to such events could potentially divert the anaesthetist's attention for about 500ms and leave the doctor prone to missing a second critical stimulus. In this respect, the AB paradigm can be taken as generalisable to practical settings. Semantic salience is particularly relevant, because most real world tasks relate to the significance or meaning of events.

2.2 The “Glance-look” Model

Elsewhere, we have presented a detailed account of attentional capture by meaning and the temporal dynamics of that process (Su et al., 2007). Key principles that underlie this account are sequential processing, 2-stages, and serial allocation of attention. We discuss these principles in turn.

2.2.1 Sequential Processing

With any RSVP task, items arrive in sequence and need to be correspondingly processed. We require a basic method for representing this sequential arrival and processing of items. At such cognitive level, our approach can be viewed as implementing a pipeline. (At brain level, how this mechanism is realised remains an interesting as yet open research question.) New items enter the front of the pipeline from the visual system; they are then fed through until they reach the back of the pipeline, where they enter the response system, as shown in Figure 4. The key data structure that implements this pipeline metaphor is a delay-line. This is a simple means for representing time constrained serial order. One can think of a delay-line as an abstraction for items passing (in turn) through a series of processing levels. On every cycle, a new constituent representation enters the pipeline and all constituent representations currently in transit are pushed along one place.

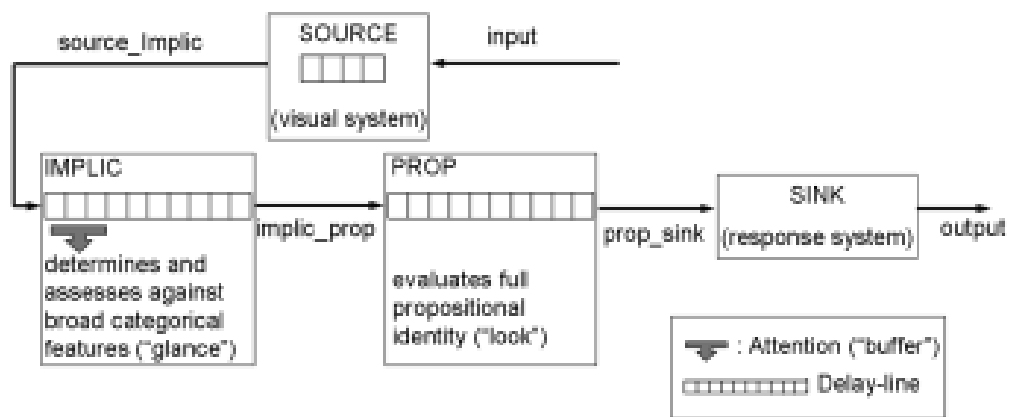


Figure 4 Top-level structure of the “Glance-look” model with implicational subsystem attended.

Only data pathways are shown here; c.f. (Bowman et al., 2006, Su et al., in press) for more details.

2.2.2 2-Stages

Like (Chun and Potter, 1995, Bowman and Wyble, 2007), we have argued elsewhere for a 2-stage model (Barnard et al., 2004, Barnard and Bowman, 2004), but this time recast to focus exclusively on semantic analysis and executive processing. In

particular, Barnard and Bowman modelled the key-distractor blink task using a 2-stage model (Barnard and Bowman, 2004). In the context of modelling distributed control, we implemented the 2-stage model as a dialogue between two levels of meaning, see Figure 4. In the first stage, a generic level of semantic representation is monitored and initially used to determine if an incoming item is likely to be salient in the context of the specified task. If it is found to be so, then, in the second stage, the specific referential meaning of the word is subjected to detailed semantic scrutiny. In this stage, a word's meaning is actively evaluated in relation to the required referential properties of the target category. If this reveals a match, then the target is encoded for later report. The first of these stages is akin to first taking a “glance” at generic meaning, with the second rather like taking a closer “look” at the relationship between the meaning of the incoming item and the target category. These two stages are implemented in two distinct semantic subsystems proposed within a multi-level model of cognition and emotion (the Interacting Cognitive Subsystems or ICS architecture). The implicational subsystem supports the first stage and the propositional subsystem supports the second (Barnard, 1999). In this chapter, we refer to this theoretical account as the ‘Glance-look’ model.

These two subsystems process qualitatively distinct types of meaning. One of these, implicational meaning, is holistic, abstract and schematic, and includes the representation and experience of affect (Barnard, 1999). The other is classically “rational”, being based upon propositional representation and captures referentially specific semantic properties and relationships. In the context of the task being considered here, these subsystems can be distinguished as follows:

- Implicational (or Implic). This subsystem performs the broad “categorical” analysis of items, which might be related to Chun and Potter’s first stage of processing, by detecting the likely presence of targets according to their broad categorical features.
- Propositional (or Prop). This subsystem builds upon the implicational representation generated from the glance in order to construct a full (propositional) identification of the item under consideration, which is sufficient to test whether the meaning of the incoming item meets the task specification and should therefore be reported.

The implicational and propositional subsystems perform their corresponding salience assessments as items pass through them in the pipeline.

2.2.3 Serial Allocation of Attention

Our third principle is a mechanism of attentional engagement. It is only when attention is engaged at a subsystem that it can assess the salience of items passing through it. Furthermore, attention can only be engaged at one subsystem at a time. Consequently, semantic processes cannot glance at an incoming item to assess its salience, while looking at and scrutinising another. When attention is engaged at a subsystem, we say that it is buffered (Barnard, 1999), which does not have the usual computer science meaning here. In this respect, salience assignment can only be performed if the subsystem is buffered and only one subsystem can be buffered at a time, as shown in Figure 4.

As previously mentioned, the model presented here can be placed within the context of ICS, both the delay-line and buffering concepts that we use have their roots in ICS. However, most significantly, the implicational-propositional distinction reflects ICS' dual-subsystem central engine, which implements executive functions for controlling attention in a distributed manner (Teasdale and Barnard, 1993).

2.2.4 How the Model Blinks

In many real life situations, stimuli do not arrive as rapidly as in AB experiments, so Implic and Prop will normally interpret the representation of the same item or event over an extended period. However, in demanding situations, such as RSVP, items may fail to be implicationally processed as the buffer moves between subsystems. The buffer movement dynamic, thus, provides the underlying mechanism for the blink, i.e.

- When the key-distractor is found to be implicationally salient, the buffer moves from Implic to Prop, and salience assessment cannot be performed on those words (i.e. a portion of the RSVP stream) entering Implic following the key-distractor. Hence, when these implicationally uninterpreted words are passed to Prop, propositional meaning, which builds upon coherent detection of implicational meaning, cannot be accessed. If a target word falls within this window, it will not be detected as implicationally salient and thus will not be reported.
- When faced with an implicationally uninterpreted item, Prop is no longer able to assign salience and the buffer has to return to Implic to assess implicational meaning. Then, Implic is in a position to assign salience to its constituent representations once again. After this, targets entering the system will be detected as both implicationally and propositionally salient and will be reported. Hence, the blink recovers.

The results of the simulation were compared to human performance in order to verify our theories of temporal attention (Su et al., 2007); see Figure 3.

2.2.5 Semantic Salience

Our model also reflects gradations in semantic salience. We assume that the human cognitive system has a space of semantic similarity available to it similar to that derived from Latent Semantic Analysis (Landauer and Dumais, 1997). The link between principal component analysis (which is at the heart of LSA) and Hebbian learning (O'Reilly and Munakata, 2000), which remains the most biologically plausible learning algorithm, provides support for this hypothesis. Accordingly, we have characterised the assessment of semantic salience in terms of LSA.

To encapsulate the target category in LSA space, we identified five pools of words, for respectively, human relatedness, occupation relatedness, payment relatedness, household relatedness and nature relatedness. Then, we calculated the centre of each pool in LSA space. We reasoned that the target category could be identified relative to these five semantic meanings (i.e. pool centres). This process can be seen as a part of a more general categorisation mechanism that works on all LSA dimensions. In the context of this experiment, it focuses on five strongest related components discussed above.

Next, we needed to determine the significance that the human system placed on proximity to each of these five meanings when making target category judgements. To do this, we trained a two-layer neural network to make what amounts to a “targetness” judgement from LSA distances (i.e. cosines) to each of the five meanings, c.f. Figure 5. Specifically, we trained a single response node using the Delta rule (O'Reilly and Munakata, 2000) to classify words as targets. The words used in the Barnard et al.’s experiment were used as the training patterns (Barnard et al., 2004). During training, for each target word, the five corresponding LSA distances (i.e. cosines) were paired with an output (i.e. response node activation) of one, while the LSA distances for non-target words were paired with an output of zero. This analysis generated five weights: one for each LSA distance. These weights effectively characterise the significance that the target salience check ascribes to each of the five constituent meanings; thereby, skewing LSA space as required by implicational salience assessment.

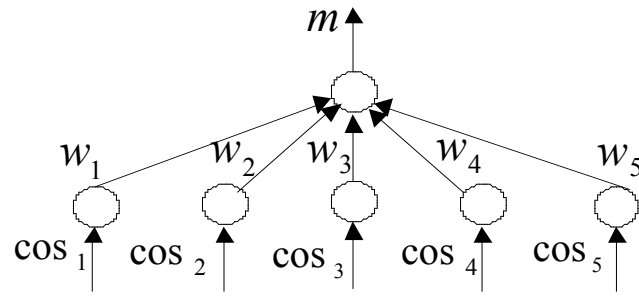


Figure 5 A neural network that integrates five LSA cosines to classify words as targets.

Activation of our neural network response unit (denoted m in Figure 5) became the Implic salience assessment decision axis in our model. Thus, words that generate response unit activation above a prescribed threshold were interpreted as implicationally salient, while words generating an activation below the threshold were interpreted as unsalient.

Importantly, high salience key-distractors were much more likely to generate above-threshold response unit activation than low salience items. This in turn ensured that high salient items were more often judged to be implicationally salient, which ensured that the buffer moved from Implic to Prop more often for high salient items. Since the blink deficit is caused by such buffer movement, targets following high salient items were more likely to be blinked, c.f. Figure 3.

In this way, we demonstrated how key-distractors can capture attention through time, causing semantically prescribed targets to be missed. In addition, our model interfaces with statistical learning theories of meaning (i.e. LSA) to demonstrate how attentional capture over time is modulated by the semantic salience of the eliciting distractor.

2.2.6 Emotional Blink

As previously discussed, emotions have a major influence on salience sensitive control and the interaction between emotional salience and temporal attention is being actively investigated in the AB literature. Consequently, we have incorporated emotional salience into the “Glance-look” model. We have particularly focussed on modelling the effect of threatening stimuli in Barnard’s key-distractor AB tasks (Barnard et al., 2005). In this task, participants search an RSVP stream of words for a word in a target category, e.g. jobs. Again, performance on the target identification task is investigated as a function of the lag that the target item appears relative to a key-distractor. However, rather than being semantically salient, in this task, the key-distractor is a threatening word. The main finding in this study was that

the threatening key-distractor only captured attention with participants that were both high state and high trait anxious and the attentional capture was late and short, c.f. Figure 6 solid lines (where only at Lag 4, human high state and high trait anxious differs significantly from human low state anxious). State anxiety is transitory anxiety experience at a particular time (often in the recent past or during the experiment). On the other hand, trait anxiety refers to a more general and long-term experience of anxiety; and it often reflects individual differences in reaction to threat (Spielberger, 1972, Spielberger, 1983).

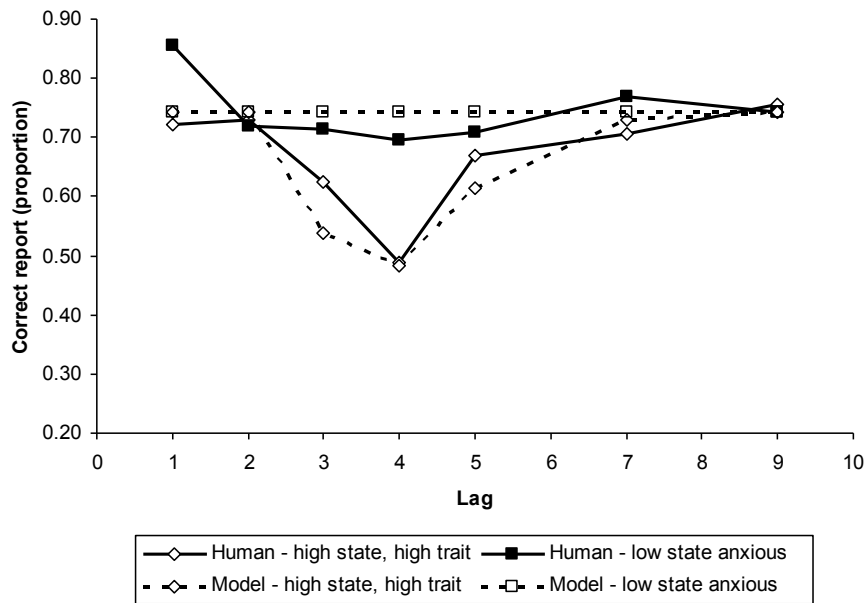


Figure 6 Target report accuracy by serial position comparing human data (Barnard et al., 2005) and model simulations for high state and high trait anxious and low state.

Consistent with the ICS framework, this attentional capture by threat was modelled through the addition of a body-state subsystem, c.f. Figure 7. It is assumed that the body-state subsystem responds to the glance at meaning, i.e., to implicational meaning. A bodily evaluation of salience is then fed-back to Implic; thereby, enriching the representation. In effect, the body state feeds back information in the form of a “somatic marker” (Damasio, 1994, Bechara et al., 2000), which, in the context of the task being considered here, would be a threat marker. Furthermore, it is assumed that high anxiety levels (both state and trait) are required before this body-state feedback has sufficient strength to have a major effect on implicational salience. Thus, for high state and high trait anxious individuals, threatening key-distractors are implicationally interpreted as highly salient when body state feedback enhances their implicational representation. This enhanced representation precipitates a detailed “look” at the meaning of these items by initiating a buffer move to Prop. Any new

items, in particular targets, that arrive at Implic while the buffer is at Prop will be missed. However, since threatening key-distractors are not semantically salient, the buffer will move swiftly back to Implic and the blink is restricted in its length and depth, c.f. Figure 6 dotted lines.

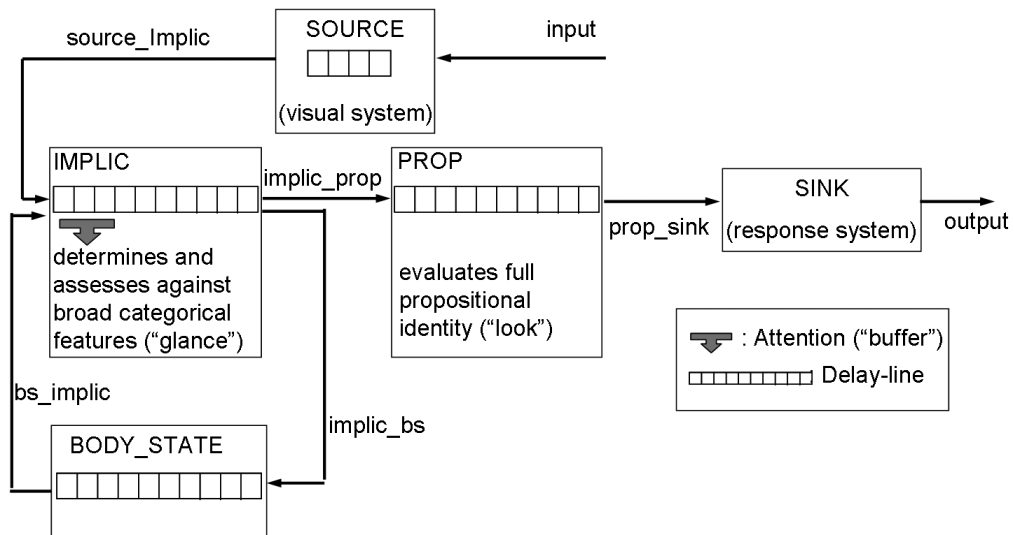


Figure 7 The “Glance-look” model extended with body-state subsystem

3 Implications for Construction of Reactive Human Computer Interfaces

Our theoretical findings are relevant to a number of different application areas, e.g. robotics and HCI. However, we have focused on a specific class of human computer interfaces, which we call *Stimulus Rich Reactive Interfaces*. This class of system has the following characteristics: 1) Stimuli arrive rapidly; 2) there is typically a central task, from which the rapidly arriving peripheral stimuli can capture attention; 3) safety is critical, e.g. a high degree of certainty is required that the user/operator perceives certain stimuli; and 4) physiological feedback of the cognitive state of the user is available, enabling the system to adapt its behaviour in order to optimise operator performance. Examples of Stimulus Rich Reactive Interfaces include, flying a plane, driving a car, monitoring a patient, or even viewing web pages. To take the first of these as a case in point, flying, or particularly landing, a plane would be the central task; incoming sensory data (e.g. the presence of other planes or turbulence) would yield streams of rapidly arriving peripheral stimuli; safety is clearly critical; and a spectrum of physiological

feedback, e.g. eye trackers, EEG electrodes in helmets, heart and skin conductance monitors, could be built into the cockpit.

We have investigated Stimulus Rich Reactive Interfaces in a number of ways, as elaborated in the following sections. First, we have developed a prototype test system, which we have used to evaluate attentional capture from a central task (Wyble et al., 2006). Second, we have explored the feasibility of extracting online EEG measures of attentional engagement and perception (Wyble et al., 2006); and third, we have applied the “Glance-look” model of the human salience detection system to evaluating the feasibility of Stimulus Rich Reactive Interfaces (Su et al., 2008).

3.1 Attentional Capture in HCIs

Theoretical work has identified a set of attentional mechanisms (Bowman and Wyble, 2007). We have also explored the practical implications of these mechanisms. Two findings that have particularly inspired our practical explorations are the existence of a very rapid (first phase) of attention, called transient attentional enhancement, which acts within 150ms of stimulus presentation; and a finding that even such rapid attentional deployment is modulated by task set, e.g. it could be initiated by detection of an item in a target category (Bowman and Wyble, 2007). Such mechanisms have great relevance for the development of stimulus rich human computer interfaces. In particular, in interfaces with rapidly arriving streams of information, it is important to understand how stimuli capture attention, both in order to prevent distraction from a central task and to ensure critical stimuli are not missed.

To explore this issue, we developed a prototype test interface that contains a central task involving driving through a virtual maze and the presentation of an intermittent stream of competing stimuli of varying levels of salience. Centrally presented arrows are followed in the driving task and, as a reflection of the presentation methods typically used in this setting, the stream of competing stimuli is presented via a head mounted display. The colour relationship between the central arrows and stimuli in the competing stream is varied. How this “task prescribed” colour relationship impinges upon attentional capture by stimuli in the competing stream is investigated.

Previous studies, in particular by Most et al, suggest that task set from a central (driving) task interacts with speed of response to infrequent obstacles (Most et al., 2007). Our findings suggest though that, as long as the competing stimuli task

is independent of the central task, the human cognitive system can isolate the two, allocating separate task sets to each, with little inter-task interference (Wyble et al., 2006).

3.2 EEG and Reactive Interfaces

We have also explored the feasibility of using EEG in reactive/adaptive computer interfaces as a source of feedback on the cognitive state of the user. This has involved running experiments to evaluate the utility of two potential EEG measures. We have investigated whether modulations in EEG power in the alpha band (around 10 Hz) at posterior areas (particularly, occipital cortex) can be used as a measure of attentional readiness in the visual modality. We have also considered whether a positive deflection in the P3 region (around 350ms post-stimulus presentation) could be used as a measure of whether a stimulus was perceived.

Both these measures are of potential value, but they are somewhat different in their character and utility. Alpha band information is proactive, in the sense that it predicts whether the subject *will* perceive a later stimulus. In contrast, P3 information is reactive, in the sense that it predicts whether a stimulus *has been* perceived. These measures open up the possibility of withholding presentation of a critical stimulus until the user is ready, and potentially enable re-presentation of a critical stimulus that has been missed. P3 information would have particular value if it were combined with eye-tracking to determine which stimuli are being fixated when a perceptual event is detected.

In the context of Stimulus Rich Reactive Interfaces, the key question to answer is whether these measures can be reliably extracted online, i.e. in real-time. Thus, we have investigated the extent to which online extraction of these measures predicts target report. Our research suggests that, with current methods, the approach based on alpha band power is not feasible. However, an approach based on P3 detection is feasible; it forms a relatively reliable online measure of whether an item has been perceived and can be extracted (Wyble et al., 2006).

3.2.1 P3 Detection

When one records EEG from the human scalp, the signal measured is deflected by ongoing cognitive operations. In the EEG literature, these deflections are referred to as components, which are observed in the Event Related Potential (ERP) that emerges from averaging together a large number of trials time locked to the onset of a salient stimulus.

ERP components occur at specific temporal intervals following a stimulus and

can be manipulated experimentally; hence, they have been associated with particular cognitive processes. Whereas the early components in an ERP waveform are particularly associated with sensory processing of target stimuli, the later components are associated with high-level processing of a stimulus. A key late component is the P3 (i.e., the third positive peak of the ERP, also referred to as the P300 due to its typical latency of 300ms post-stimulus). Although some researchers have identified a frontally located P3a component, which is elicited by infrequent but task-irrelevant stimuli, we focus on the P3b, which has its maximum over parietal electrode sites. The P3b (called P3 from here on) is present for stimuli that are both infrequent and relevant to the task (Squires et al., 1975). As the P3 is only observed for target stimuli that are detected by the subject (Vogel et al., 1998), it can be assumed to be an indication of an item being encoded into working memory (Donchin, 1981).

Depending on the amount of noise in the signal, one normally has to average across a considerable number of trials to obtain a clean ERP waveform. However, the P3 component is often large enough to be detected even in the raw EEG. Of course, one cannot draw conclusions about P3 latency and shape from raw P3s; however, they are often clear enough to be detected on a trial-by-trial basis. The algorithm used in our approach focuses on these raw P3s.

Two examples of raw P3s recorded from human participants are shown in Figure 8. In this experiment, participants viewed an RSVP stream containing digits as background items and a single letter target. The task was to report the identity of the single letter included in the stream. Items were presented at fixation, with each replacing the previous item at a rate of 20 items per second. EEG was recorded from multiple electrodes while subjects performed this task. The following P3 analyses were restricted to the three parietal electrodes, *P3*, *Pz* and *P4*. The diagram on the left hand side shows a clear P3, while the P3 in the diagram on the right hand side is less obvious. The shape and time course of the P3s can be influenced by many factors, and (as is evident here) there are often substantial individual differences. Some P3s are more readily detectable than others.

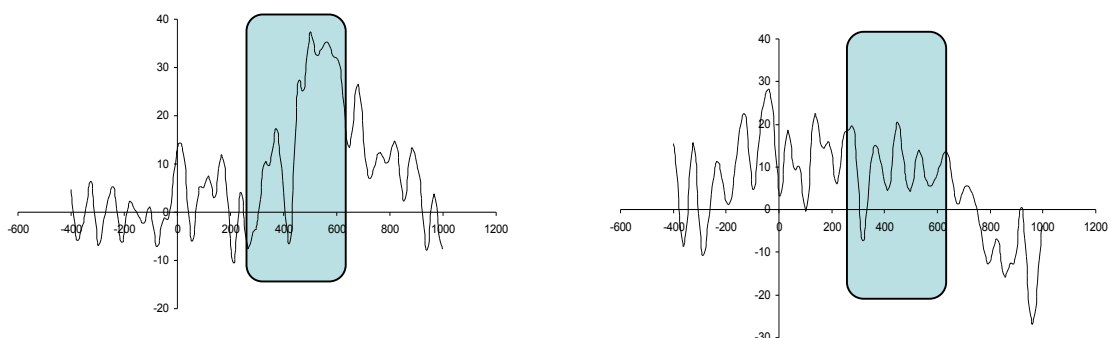


Figure 8 Examples of raw P3s recorded from human participants (targets were presented at time 0, the y-axis units are mV (relative to a reference electrode), and the x-axis denotes time in milliseconds) (Su et al., in press). Note that EEG is often plotted with the y-axis reversed, e.g. negative up and positive down, we have avoided this convention for reasons of presentational clarity. The shaded areas represent the P3 regions. These raw EEG signals are very noisy, so P3 is the only visible deflection and other earlier components such as P1 and P2 can only be seen when average across a large number of runs as in ERP data.

For each trial, an algorithm determined whether subjects did or did not see a target based on the EEG data after the time of the target presentation. A measure of total area under the curve was computed for each participant (Figure 8), centered around the time of maximal P3 amplitude. This time window was selected within the 300-700 ms after the target, but varied for each individual subject. This measure was taken for both target seen and target missed trials. A threshold value for each participant was set at 50% of the area under the curve from the average of all target-seen trials. Then, for each trial, we determined if the P3 exceeded this value. If a target-seen trial had a P3 of larger area than the threshold, the value was counted as a hit; otherwise the trial was scored as a miss. On target-missed trials, if the P3 area was larger than the threshold, the trial was scored as a false alarm, otherwise it was a correct rejection. With these measurements of percent hits and percent false-alarms, we were able to compute a d' score of algorithm sensitivity individually for each subject (McNichol, 1972). d' is the difference between the z-transforms of hit rate and false alarm rate.

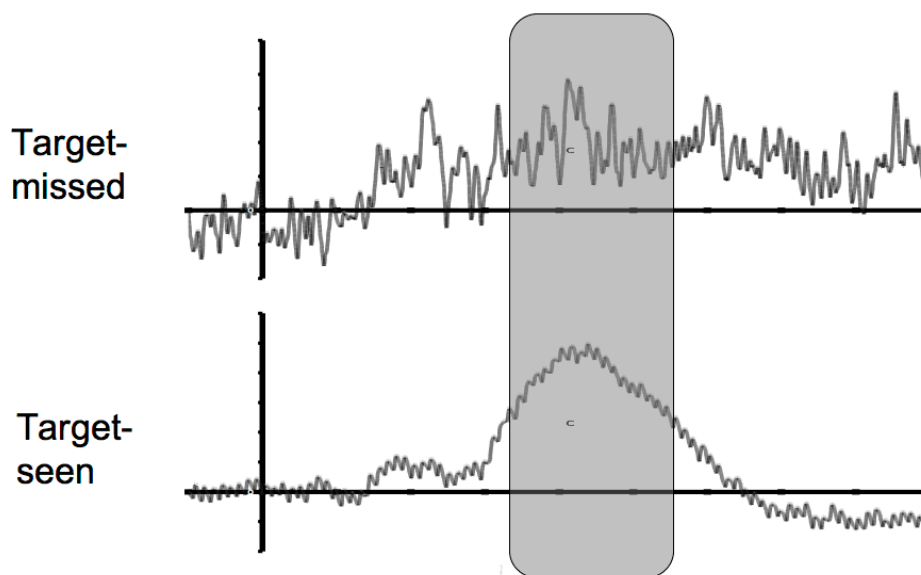


Figure 9 ERPs of a participant for target-seen and target-missed trials. The shaded region represents the time points chosen to detect a P3 for this subject.

For the 12 participants, the d' ranged from 0.39 to 1.69 per participant. For the participant with the highest d' score, hits were 62% with only 8% false alarms. The average d' across all subjects was 0.82. This represents a substantial extraction of information (note, chance performance would correspond to a d' of zero). Figure 9 illustrates the ERP for participant 5 for both target-seen and target-missed trials, with the temporal window used to discriminate between them marked in grey.

3.2.2 Building an Interface Device

As mentioned above, a common method of ensuring that a critical piece of information is perceived by the user is to use a salient visual or auditory cue to capture attention. However, if an environment is particularly rich in such critical signals, the user can be faced with an overwhelming number of such alerts, forcing some alerts to be ignored. Information overload thus renders all of the inputs at the same level of salience relatively less informative.

The Brainwave Based Receipt Acknowledgement device would attempt to use brainwaves generated by a user to provide the computer controlling the interface with feedback about whether the user did or did not see a particular piece of information. This sort of device should allow the computer to avoid the use of frequent alarm signals in information rich environments, by simply re-presenting stimuli until they have been successfully noticed, much as packets are retransmitted over a noisy communications network.

The Brainwave Based Receipt Acknowledgement signal must operate quickly to be useful in a time-critical environment, such as a pilot cockpit. Therefore, the acknowledgement must be present almost immediately after the occurrence of a cognitive event in the mind of the user. The algorithm described is ideal for this sort of application. It is simple enough to be executable on minimal hardware platforms in real-time, using off the shelf IC components with minimal power requirements.

The system we describe (Figure 10) is intended to fit within a head-mounted system. It requires 3 electrodes held against the scalp with an elastic headband, a small circuit-board (perhaps 6 by 6 centimeters in size) with components powered by a battery pack. The system communicates with the outside world by infrared, thus isolating the user from any electric currents or ground loops, and allowing for free movement.

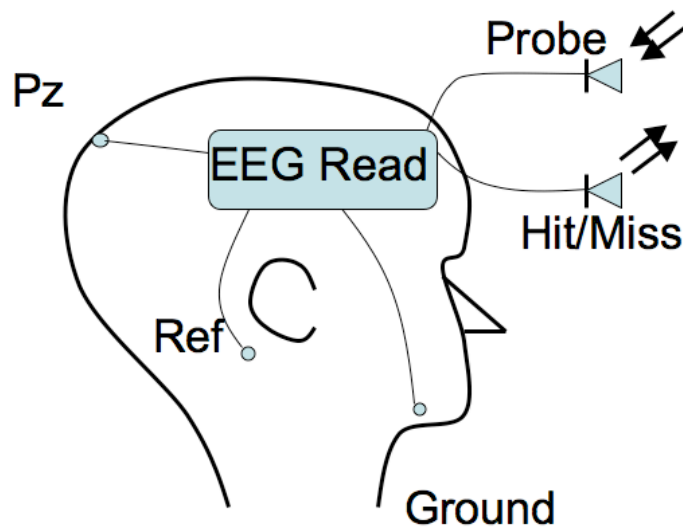


Figure 10 Diagram of Brainwave Based Receipt Acknowledgement device. The Probe input is a light sensor, which will trigger a detection event.

When presenting a target to the user, the computer interface device sends a stimulus time-locked probe (e.g. an infrared input) to the input port of the Brainwave Based Receipt Acknowledgement system, triggering the detection of P3 correlates of receipt acknowledgement. The system replies to the interface with a single flash of its LED if it has determined that the target was seen. The detection algorithm described above would be used, as depicted in Figure 10.

3.3 Performance Analysis of Reactive Computer Interfaces

A major benefit of computational modelling is that it provides a concrete “executable” realisation of a theory. As a result, hypothetical explorations can be run, e.g. the consequences of degrading or even removing a component can be investigated or the implications for a variety of design and parameter choices can be examined in simulation. The latter of these options is our particular focus here.

We have applied our simulations of the human salience detection system to evaluating the feasibility of a variety of Stimulus Rich Reactive Interfaces. As previously discussed, we have developed a (cognitive-level) model of the ICS central engine, the “Glance-look” model, with which we have simulated attentional capture in the context of Barnard’s key-distractor AB task. The same core system would be at work when human operators interact with Stimulus Rich Reactive Interfaces. Thus, we have used this model to evaluate the performance trade-offs that would arise from varying key parameters in such systems.

Examples of the types of questions we have investigated include the following. How effective does prediction of the operator's attentional and perceptual state have to be for performance to benefit from the use of an Stimulus Rich Reactive Interfaces? How these performance benefits are affected by the temporal profile of stimulus arrival, e.g. whether it is fast or slow, regular or bursty?

3.3.1 Modelling P3s

In order to explore the effectiveness of the Brainwave Based Receipt Acknowledgement system, it is important to consider how the "Glance-look" model could be extended to generate P3s. The full details of our P3 modelling can be found in (Su et al., in press). Here, we simply summarize that work.

There is good evidence (Donchin, 1981, Vogel et al., 1998) that the P3 indexes working memory update. Accordingly, we view update of referential working memory as the main generator of the P3 in our model. Although the model does not explicitly simulate such an update process, we can assume that it would be engaged while an item is processed propositionally. Specifically, the length of the P3 is determined by the length of time the buffer stays at Prop, while the amplitude of the P3 at any moment is proportional to the number of propositionally salient elements in transit through Prop.

Perhaps the major difficulty with EEG research is the presence of what, in the context of a particular experiment, can be viewed as extraneous noise. In order to reflect this particular complexity, we extracted segments of noise from our EEG experiments that were not contaminated by target processing. This noise was then added on top of the pure P3 signal generated from the model. However, in order to reflect individual differences in P3 size, we included a multiplicative constant, called the scale factor, which modulated the size of the pure model generated P3. Thus, a scale factor of zero yields a noise only trace, while P3 component size increases with the scale factor. Figure 11 shows two model generated P3s, one with a large scale factor and the other with a small scale factor.

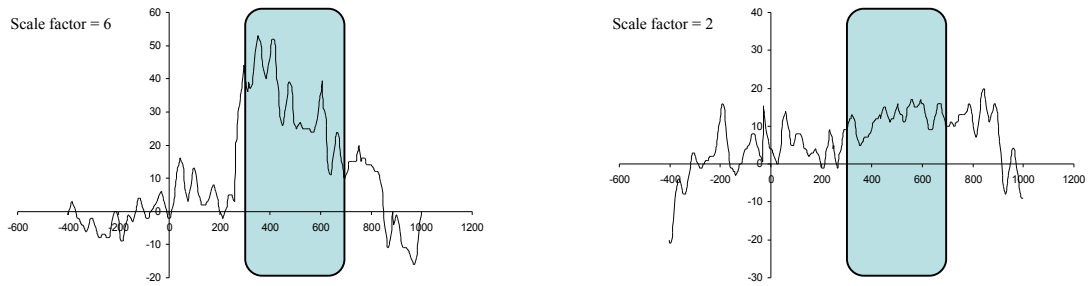


Figure 11 Examples of virtual P3s generated from model simulations (targets were presented at time 0, the unit for the y-axis is mV and the x-axis is ms). Note that the simulation only models the P3, and so other components of a typical EEG, such as the N1 and the N2, are absent. As a result, the virtual EEGs generated here do not necessarily look like real EEGs other than in respect of the presence of a large positive deflection at around 300-700ms, i.e. the shaded regions (Su et al., in press).

3.3.2 Event Traffic

Our objective was to explore in simulation the performance of the salience assessment system during interaction with a variety of interface presentation methods. Specifically, we explored the effectiveness of an AB-aware presentation system that attempts to avoid presenting salient stimuli during the blink window. In addition, we consider how effective a Brainwave Based Receipt Acknowledgement system would be at improving performance.

In order to investigate these issues, we needed a method for simulating event traffic from a computer interface. We explored event sequences with three varieties of event, corresponding to the presentation of high salience items, low salience items and background items. We simulated the uncoordinated occurrence of such items at an interface using the *b*-model (Wang et al., 2002). This approach enabled us to vary three key parameters: burstiness, number of events and aggregation level. The first two concepts are familiar, while the last controls the density of stimuli across the entire simulation window. In this way, our simulations explored how accurate detection of high salient events varies as a function of burstiness and aggregation across presentation methods.

3.3.3 Performance of Constructive Interface

The existence of the attentional blink deficit can be responded to by spacing out the presentation of salient stimuli through time. We call such an approach constructive. The key parameter that can be varied is window size, i.e. the fixed

interval that is placed between consecutive high salient items. Su et al explores how performance, in this case report of high salient items, varies according to burstiness, aggregation level and number of high salient items presented (Su et al., in press). These simulations demonstrated the generally improved performance offered by the AB-aware system (with 600ms window size) when compared with the AB-unaware system.

With this constructive approach, there is a clear trade-off between the probability of correct report and urgency. That is, as the window size is increased, at least when increased up to around 720ms, performance improves, while the average delay enforced on each item increases. This is shown in Figure 12, where the probability of an item being seen increases as window size increases until a size of 2400ms, where performance drops again. The reason for this decline at the biggest window size is because the simulation has a fixed time period in which to complete the presentation, and with a window size of 2.4 seconds, a proportion of items fail to be presented in the allotted time.

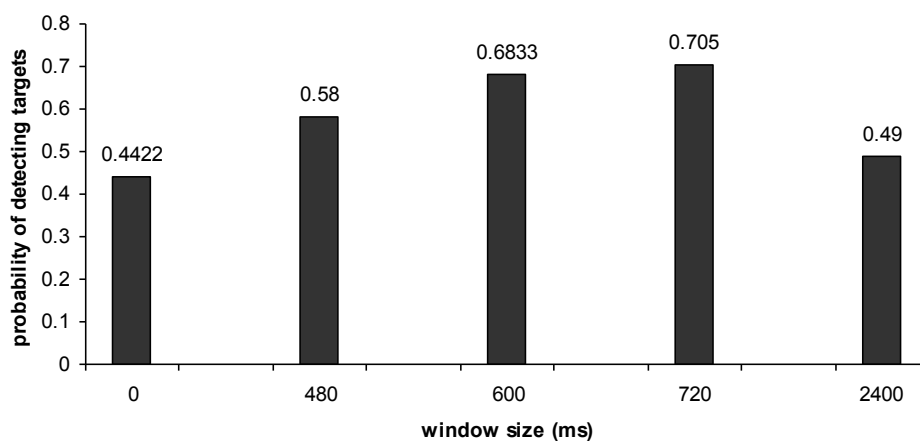


Figure 12 Performance (measured as probability of detecting targets) of AB-unaware and AB-aware systems by varying the window sizes of the stimuli. The AB-unaware system is a special case of the AB-aware system with a window size of 0 (Su et al., in press).

One simple observation that emerges from these simulations is that this constructive approach never does much better than a 70% chance of reporting the high salience item, while it never does worse than a 40% chance of correct report. (Here, we use slightly different parameters for event traffic than in (Su et al., in press).) This is easily explained though, since the highest performance on the blink experiment (c.f. Figure 3) is never much greater than 70%, while the worst performance does not fall much below 40%. Thus, the model's performance limits

on these constructive interfaces is inherited from the blink experiments that the model was originally devised to simulate. Clearly then, no constructive approach could exceed such a maximum performance. Any desire to improve performance beyond this limit requires us to consider reactive approaches.

3.3.4 Reactive Approach

The main reactive approach is the Brainwave Based Receipt Acknowledgement system; so called since it reacts to the user's cognitive state. Thus, here we consider the effectiveness of such an approach in simulation. Accordingly, we have extended the "Glance-look" model of salience sensitive control with EEG feedback, as discussed in subsection 3.3.1. This system is depicted in Figure 13, where the component labeled device compares the Prop-generated P3 with a criterion/threshold and re-presents the stimulus if the threshold is not met. There is an analogy here with *stop-and-wait* protocols from computer communication networks (Tanenbaum, 2002), since, for each stimulus presented, the device waits for a successful acknowledgement (i.e. P3 detection) until it presents the next stimulus. Furthermore, this waiting period may involve multiple negative acknowledgements (i.e. below criterion P3s) and re-representation cycles.

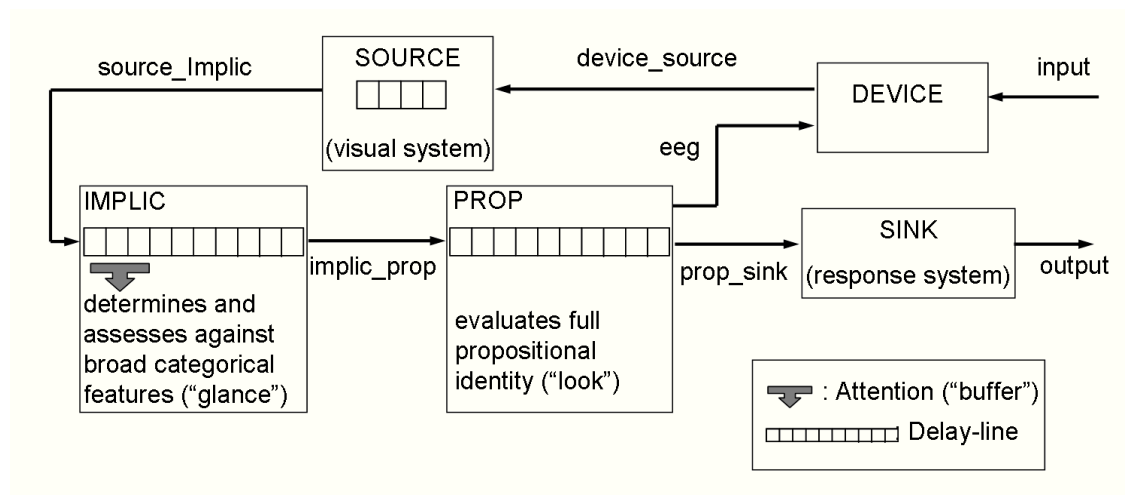


Figure 13 Top-level structure of the "Glance-look" model with computer interaction (through device) and implicational subsystem attended (Su et al., in press).

We first explored how P3 detection sensitivity varies with the scale factor. We work within a signal detection framework (Snodgrass and Corwin, 1988) and measure sensitivity in terms of d' . This reflects the difference in hit and false alarm rates. Hits correspond to simulation runs in which the Brainwave Based Receipt Acknowledgement system detects the presence of a P3 (i.e. above criterion

activation) when the target was indeed detected by the model, while false alarms correspond to situations in which the Brainwave Based Receipt Acknowledgement registers the presence of a P3 erroneously, i.e. when no target was detected by the model. Unsurprisingly, d' sensitivity increases as the scale factor increases. This can be easily observed in Table 1, where we explore the match between natural number scale factors and participant d' s. (Note that allowing scale factors to range over the real numbers and employing a simple search algorithm would enable us to match the d' of all participants to any level of accuracy.)

Table 1 Comparison of experimental results across 12 human participants with model simulations. The table is ordered by human d' scores. Participants 2, 6, 7 & 8 can only be matched by model simulation using real number scale factors (Su et al., in press).

Participants	Human d'	Model d'	Scale factor
11	0.39	0.44	3
1	0.48	0.44	3
7	0.53		
6	0.56		
2	0.59		
3	0.61	0.65	4
12	0.73	0.85	5
10	0.93	0.85	5
9	1.07	1.02	6
4	1.09	1.02	6
8	1.21		
5	1.69	1.7	10

The overall effectiveness though of the reactive approach needs to be assessed in terms of the model's report accuracy when configured with a Brainwave Based Receipt Acknowledgement system. That is, we need to consider the probability of correctly detecting high salient items in the presence of P3 detection and re-presentation. We also wish to compare this reactive approach with the earlier constructive approach with different window sizes. Such a comparison is made in Figure 14, where proportion correct report is presented for the Brainwave Based Receipt Acknowledgement system with different scale factors and different P3 threshold criteria. The parameters of these simulations are that repeated items are only counted once, the aggregation level is set fixed to 6, the number of high salient items is set to 20, the b value, which controls burstiness, was chosen randomly between 0 and 0.5 and correct report is the proportion of high salience items reported within a bounded time period.

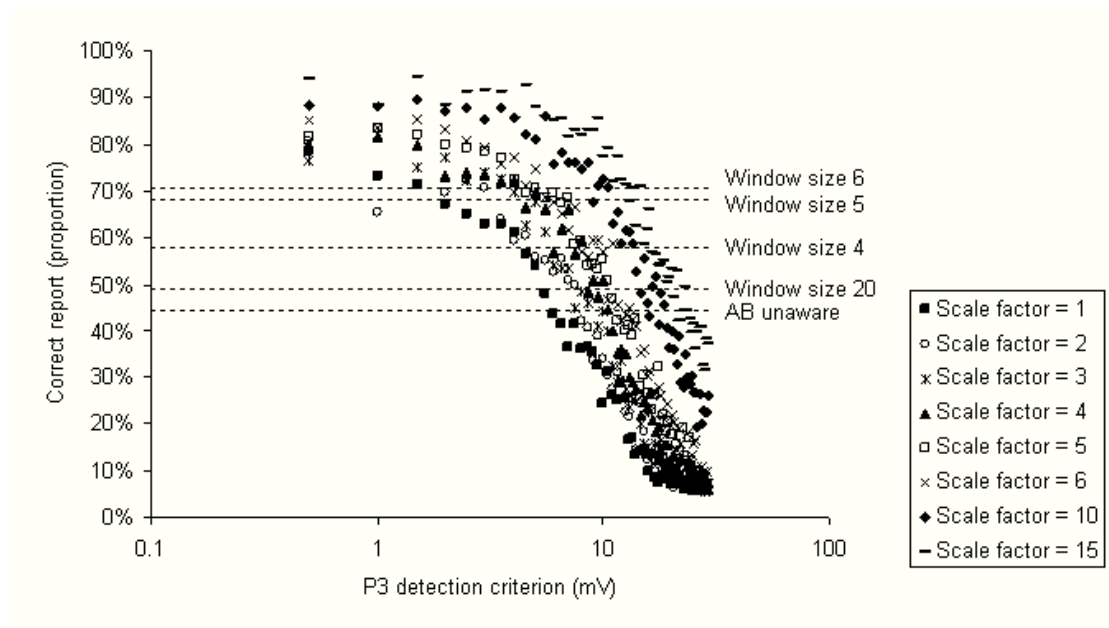


Figure 14 Performance (measured as probability of detecting the targets) of the reactive approach using EEG feedback with variability in the P3 detection criterion. Each set of data has a different scale factor, which captures differences in discrimination. For comparison, absolute performance of constructive approach is shown for different window sizes (Su et al., in press).

This figure demonstrates that the reactive interface can outperform the hard performance upper limit for the constructive approach. To show this, we include horizontal lines indicating performance of the constructive approach for various window sizes. Furthermore, as anticipated, the reactive approach performance improves as the scale factor increases. This is because sensitivity (i.e. d') increases with an increasing scale factor. In addition, the diagram also reflects the interaction between accuracy and urgency. The latter of these shows up in generally reduced performance with large P3 detection criterion values. This is because with large P3 criteria, the miss rate becomes very large, since the criterion for responding hit becomes extremely strict. Consequently, the system enters a cycle of repeatedly failing to obtain an acknowledgement and re-presenting the target. Continuing the analogy with computer communication protocols, this situation is similar to a stop-and-wait protocol with an extremely lossy acknowledgment channel. In our simulation, this continued re-presentation manifests as a decline in accuracy, since the full quota of high salient items fails to be presented within the allotted time period.

One potential benefit of the type of analysis discussed here is that it could serve as a feasibility check; that is, the clarity of an individual's P3 could be used to

derive a scale factor for that individual. Then, in simulation, a feasibility analysis could be performed to determine the effectiveness of implementing a Brainwave Based Receipt Acknowledgement system for that individual.

4 Discussion

There are a number of ways in which our work can inform the construction of human-computer interfaces that adapt their behaviour according to the attentional/emotional state of the user. One area is affective computing (Picard, 1998), which has a great potential to create “human-centred” systems; having been made possible by a number of emotion recognition technologies, e.g. recognition of facial expressions, voice intonation, EEG and galvanic skin response. Many applications of these technologies have been proposed, e.g. systems which learn user preferences or help humans (such as autistic children) to recognize emotions. A typical example of affective computing would be an intelligent tutoring system that modulates its tuition according to the student’s emotional state, e.g. curious, fascinated, puzzled, frustrated or anxious. For example, the system might regulate demands on the student according to their level of anxiety; it might make subtle (affect-related) changes to the interface in response to user frustration; or it might present emotionally sympathetic responses, e.g. via an avatar, (c.f. Morel & Ach in this volume).

However, in order to reap the full benefits of affective computing, not only is it important to understand emotions, it is also critical to understand the executive processes (in particular attention) within which emotions function. For example, knowing how an (affective) tutoring system should respond to the anxiety level of the student is dependent upon how anxiety modulates human attention. In addition, knowing when to present emotionally sympathetic responses requires an understanding of how emotional stimuli (e.g. emotional expressions) modulate attention and the time frames over which this modulation functions. These are exactly the kinds of questions that are being answered by empirical phenomena such as the AB (Raymond et al., 1992) and affective variants of the task (Barnard et al., 2005). The salience project has attempted to act as a bridge between these studies and HCI.

The issue of context is also an area that invites further investigation, and is particularly important in HCI domains where situational awareness is critical. For example, pilots or anaesthetists need to rapidly create an accurate representation of

their current situation, by detecting, integrating and interpreting data gathered from a noisy environment. However, for reasons such as task overload, fatigue etc, human operators often miss salient events and thus build an incorrect picture of the situational context in which they are operating. A major goal of HCI research is to build devices that help humans to attend to salient events, to correctly prioritise environmental stimuli and thus to operate with situational awareness. Once again, in order to construct such systems, we need to understand how attentional resources are deployed, the time-course of this deployment and how priority levels are assigned to competing stimuli. This is a central objective of our research programme.

In order to make such a link between theory and practice, the Saliency Project has made a number of contributions. First, we have developed computational models crossing abstraction levels. For example, we have developed neural models of the basic attentional blink (which is not semantic in nature) (Bowman and Wyble, 2007) and we have developed “cognitive-level” symbolic models of semantic and emotional attentional blink effects, as discussed earlier. Secondly, we have verified predictions arising from these models, both behaviourally (Bowman and Wyble, 2007, Wyble et al., in press) and electrophysiologically (Craston et al., in press). Thirdly, we have explored the implications of our modelling and experimental work for the development of computer interfaces. This has involved behavioural experiments focused on how peripheral distractors can or cannot capture attention away from a central driving task; considering how effective the EEG P3 component could be as an HCI acknowledgement signal; and using the “Glance-look” model of saliency sensitive control to assess the efficacy of a variety of computer interfaces, including a P3 acknowledgement system.

Our research also suggests a number of avenues for future work. For example, it would be revealing to undertake further behavioural experiments focussed on attentional capture in more realistic HCI interfaces. These might particularly consider the distracting effects of semantically and emotionally salient stimuli. In addition, there is much room for research exploring the practicality of the Brainwave Based Receipt Acknowledgement system proposed here. For example, it would be interesting to integrate such a P3 detection system with eye-tracking. This would enable a spatial measure of attentional focus to be integrated with a measure of the presence or absence of conscious perception. Thus, one could determine both whether a stimulus is perceived and what that stimulus might be in a display. Indeed, spatial aspects of attention have been largely ignored in our research to date. Thus, there is considerable room to explore rapidly arising stimuli across a number of spatial locations.

More widely, we have argued that many of the goals of HCI research require us to understand human executive processes. Such an understanding will greatly inform interface construction. However, it also prompts the question of mechanisms that should be used to construct such systems. Techniques such as user modelling and task analysis have made important contributions to interface construction (Schraagen et al., 2000, Diaper and Stanton, 2004). However, it is unlikely that they will be sufficient in a domain in which dynamic sensitivity to salience and timing is critical. We believe our computational modelling activities can also help here by providing an abstract specification of user behaviour, which can be placed at the centre of interface usability analysis.

5 Acknowledgments

The UK Engineering and Physical Sciences Research Council supported this research (grant number GR/S15075/01). The participation of Philip Barnard in this project was supported by the Medical Research Council (project code U.1055.02.003.00001.01). We thank Patrick Craston, Srivas Chennu and Dell Green for their contribution to the collection and analysis of the EEG data.

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