# Chapter 4

# Attentional Resources and Control

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How we select, modulate, and keep focused on information that is relevant to behaviour is critical to understanding human performance. Such diverse processes as memory storage and retrieval, action selection, and decision making cannot be fully described without consideration the role that attention plays in them. On the one hand, attention is involved in the selection and modulation of incoming sensory information or information from memory. In this sense, attention determines the fate of selected items. Items that receive attention are processed more quickly and remembered better than items that do not receive attention's "boost" (Levin & Simons, 1997). On the other hand, because competition for attentional resources is an integral part of most activities, attention is needed to maintain goal-directed behaviour. The role of attention in modulating sensory processes to select locations or objects in space was discussed in Chapter 3. In this chapter, we consider the investment of attentional resources across time and how internally generated information–such as information retrieved from memory–is operated on by attention in order to guide task performance. Whether driving a car in the city or playing a game of Ultimate Frisbee ®, multiple stimuli and options for action compete for selection, and attention is needed to bias behaviour to fit action goals. Tasks differ in the extent to which they call on the ability to suppress irrelevant information, maintain focus, or divide attentional resources. Understanding and aiding task performance thus depends on a characterization of which of these abilities is employed at any point in time. An understanding of the neural basis of attention sheds further light on how attention supports performance by maintaining focus, keeping task goals active, and coordinating information processing. A topic in attention particularly relevant to neuroergonomics is how attention can be measured on-line so that the operator can be aided or the task environment adapted to augment human performance.

## 4.1 Quantifying and Describing Attention

If we are to monitor human behaviour and adapt the task environment to improve task performance, it is necessary to be able to measure and characterize the different aspects of attention. The measurement of attention is made complicated by the fact that attention shifts are not always overt (i.e., not always accompanied by eye movements) and by the fact that the task environments of real interest–such as the cockpit or the control room–require that a range of attentional abilities be deployed dynamically. Chapter 1 provided an overview of the techniques most often used in basic research on human performance. In this section, we cover how these techniques have been applied to characterizing attention and, in particular, how they might be used in realistic task environments.

### 4.1.1 Eye Movements and Pupil Diameter

The eyes may not be the mirror of the soul, but they tell us much about how attention is allocated. As discussed in Chapter 1, eye movements and attention are tightly coupled (Findlay, 2009). For example, the attention-capturing, abrupt onset of an object drives a saccade toward it (Ludwig & Gilchrist, 2002). These stimulus-driven saccades are triggered by sensorial events and are automatic in the sense that they occur even when they hurt task performance. In fact, Theeuwes (2004, 2010) has argued that items in the visual field capture attention according to their salience irrespective of the task at hand, and that goal-driven control comes into play only after capture has taken place. This view is based on the finding that when a display contains a salient singleton, attention seems to be captured by that singleton, thus increasing reaction times to the target (e.g., Theeuwes, 1992).

Voluntary, goal-driven saccades, such as those made in response to a cue which indicates the possible location of a forthcoming target, serve the purpose of moving the eye to search for relevant information or to bring that information into focus. In any environment where eye movements are needed to bring information into focus, the patterns of saccades, or scan paths, can tell us much about how attention is allocated. In addition to providing information about what is looked at, and where, scan paths can be analysed to uncover attentional strategies. According to one theory (Noton & Stark , 1971a, 1971b) observers scan new stimuli during a first exposure and store the sequence of fixations in memory as a spatial model. This spatial model is the scanpath. During subsequent viewings of the same stimulus, the scanpath is followed, at least in part, thus facilitating stimulus recognition (Noton & Stark, 1971a, 1971b) or search efficiency (Myers & Gray, 2010). The availability of new software for computing and comparing scanpaths (Christino, Mathot, Theeuwes, & Gilchrist, 2010) will likely lead to new insights into how scanpaths can be used to predict performance.

Whereas eye movements allow us to infer where attention has been allocated, the diameter of the pupil allows us to infer the degree to which resources are invested in a task. The degree of engagement of a person with a task (or with another person) is reflected directly in the diameter of the pupil (Kahneman, 1973). The relationship between pupil diameter and mental effort was first reported in depth by Hess and Polt (1964), who measured pupil dilation during the mental multiplication of two numbers. When the task was relatively difficult (e.g., 16 x 23) pupil diameter was greater than when the multiplication was relatively easy (e.g., 7 x 8). The so-called task-evoked pupillary response (change in pupil diameter as a function of task requirements; Beatty, 1982) is computed from the raw pupillary record in much the same way as an event-related potential (ERP) is computed from electroencephalographic (EEG) activity (see Chapter 1). The averaging process reveals short-latency (onset 100-200 ms), phasic, task-evoked dilations that terminate rapidly when processing is completed.

Beatty (1982) reviewed several decades of work based on using the task-evoked pupillary response to reveal the degree of difficulty of perceptual, short-term memory, language, reasoning, and attention tasks. For example, the amplitude of the task-evoked pupillary response is found to be reduced across a session in a vigilance task, and the reduction in amplitude is similar to the reduction in performance. More recently, Kristjansson, Stern, Brown, and Rohrbaugh (2009) applied a polynomial curve-fitting method for quantifying parameters from single task-evoked pupillary responses (TEPRs). They used a multilevel-modeling framework to identify TEPR parameters associated with long latency responses (responses for which alertness was presumed to be low) and normal latency responses (presumably reflecting an alert state). Pupil diameter, linear pupil dilation rate, and curvilinear pupil dilation rate were found to differ significantly between the long latency and normal latency responses, leading Kristjansson et al. to suggest that these parameters might be useful neurocognitive markers of operator state in an alertness monitoring system.

### 4.1.2 Electroencephalography (EEG)

Whereas overt attentional shifts can be studied with eye movements, covert shifts of attention (i.e., shifts in attention made without moving the eyes, head, or body; Posner, 1978) cannot. In combination with behavioural measures such as reaction time and accuracy in detection or identification tasks, EEG has been used extensively to study the covert allocation of attention.

Event related potentials. The ERP and its components were introduced in Chapter 1 (see Table 1-1). In general, the components that occur early in the ERP, in particular the P100 and the N100, are modulated in amplitude or latency depending on the degree of attention given to the event used as the reference for computing the ERP (Eimer, 1994). Later ERP components, such as the P300 (which reflects the identification of a target object), are modulated by attention in an all-or-none fashion. In the case of the P300, it is absent for objects that must be ignored (Kok, 1999, Toffanin, Johnson, & de Jong, 2011), and is delayed as a function of increasing attentional demands (Dell'Acqua, Jolicoeur, Vespignani, & Toffanin, 2005; Vogel & Luck, 2002). Some ERP components are directly related to specific mechanisms of attention rather than being modulated by attention. Four examples of such components are the N2 posterior-contralateral (N2pc), the reorienting negativity (RON), the ipsilateral-invalid negativity (IIN), and the P4 posterior-contralateral (P4pc). The N2pc is a negative peak observed about 200 ms after target onset which reflects spatial shifts of visual attention towards the target (Woodman & Luck, 1999) or attentional capture (Kiss, Van Velzen, & Eimer, 2008). The RON (Schroger & Wolff, 1998) is a negative deflection observed at fronto-central sites between 400 and 600 ms after onset of a distracting event and reflects the reorienting of attention towards task-relevant stimuli. The INN (Hopfinger, 2005) is a negative-going waveform appearing over ipsilateral-posterior scalp sites between 200 to 300 ms after the appearance of a target at an uncued location. Hopfinger suggested that INN reflects disengagement from an erroneously cued location and reorienting towards the target location after the onset of the target. Because the INN is exogenously triggered, it seems to reflect exogenous disengagement, or disengagement evoked by the capture of attention by another object. Toffanin et al. (2011) proposed that endogenous attentional disengagement might be reflected by a positivity observed 400 ms after target onset at posterior-contralateral sites (the P4pc). The P4pc can be interpreted as reflecting the undoing of attentional capture as required to prepare for the onset of a forthcoming target.

An important paradigm for measuring the spatial allocation and control of visual attention is the Posner cuing paradigm (Posner et al., 1980). In this paradigm, observers are cued to direct attention (while keeping the eyes at a central fixation point) toward the left or right by the appearance of a cue in the left or right hemifield, respectively. When the interval between the cue and target is short (about 100 ms) and the cue is valid, such that the cue and target appear on the same side, reaction time to the target is faster than when the cue is invalid (i.e., when cue and target appear on different sides). Posner and Petersen (1990) explained this cuing effect in terms of a sequential model according to which attention must be disengaged from the cued location on invalid trials before being moved to the target location. A common finding using the Posner cuing paradigm is that the P1 component of the ERP is enhanced for targets in the cued versus uncued location (e.g., Hopfinger & Mangun, 1998). Additionally, three ERP components (the early directing attention negativity (EDAN); the anterior directing attention negativity (ADAN); and the late directing attention positivity (LDAP); Eimer, Forster, & Van Velzen, 2003; Praamstra, Boutsen, & Humphreys, 2005) have been identified as occurring in the time interval between the onset of the cue and the onset of the target, and therefore are thought to reflect the orienting of covert attention in anticipation of an expected event. The EDAN is a negative deflection measured at occipital electrodes contralateral to the direction indicated by the cue and is thought to reflect the decoding of the direction indicated by the cue. The ADAN is a negativity observed at frontal sites contralateral to the direction indicated by the cue and is thought to reflect the initiation of an attentional shift. Finally, the LDAP is a posterior positivity contralateral to the direction indicated by the cue and seems to reflect preparatory activation of the visual cortex in anticipation of the onset of the target.

Components such as the EDAN, ADAP, and LDAP may provide information about where attention will be allocated or how information will be processed (Eimer et al., 2003). However, these components are not always found when expected. It has been suggested that the LDAP will only appear when attention-directing cues accurately indicate when a target will appear, which limits the usefulness of the component as a predictor of readiness to process visual information (Green & MacDonald, 2010). In this respect, lateralized changes in alpha-band EEG oscillations (see Chapter 1), which have also been linked to biasing of visual cortex in anticipation of an impending target (e.g., Worden, Foxe, Wang, & Simpson, 2000), may provide a more reliable index of upcoming performance.

EEG rhythmicity. Although ERPs have proven to be useful in the study of the temporal dynamics of attention, they are limited in that they fail to capture brain activity related to stimulus processing that is not time-locked to event onset (i.e., induced activity, Tallon-Baudry & Bertrand, 1999), nor is it possible to draw conclusions about how different brain networks (or regions of interest) interact on the basis of ERPs alone. Both induced activity and interactions between brain networks can be visualized using time-frequency analysis of the EEG (Donner & Siegel, 2011, Fries, 2005). Time-frequency analysis involves quantifying the amplitude (or power) of a certain frequency band across time. The frequency band is determined by the experimenter, and typically includes frequencies ranging from 0.1 to 100 Hz. One way of using the resulting time-frequency spectrograms is to compare them for different experimental conditions much as one might compare fMRI images. Another approach is to compute coherence values, that is, “correlations” across time (i.e., autocorrelations) between regions of interest covered by the electrodes used. These coherence values reflect whether two or more regions of interest are in communication with each other.

Time-frequency analysis has led to new insights about attention, including how it is allocated. For example, Lakatos et al. (2009) performed a time-frequency analysis of data recorded from primary visual and auditory cortices in macaques performing a cross-modal selective attention task. They observed that the amplitude of the EEG response increased only in the modality-specific area corresponding to the attribute of the stimulus to be attended. However, supramodal modulation of the EEG by attention was also observed: The phases of the oscillations in both cortices were synchronized to the onset of the attended stimuli, regardless of the modality to be attended.

The EEG rhythm most commonly coupled to attention mechanisms is the gamma rhythm (30-100 Hz; Fries et al., 2001). Gradual increases in the level of gamma synchronization have been found to depend on the degree of attention directed toward a stimulus (Khalbrock, Butz, May, & Schnitzler, 2012), suggesting that gamma rhythm could be used as a reliable measure of attentional allocation. The relation between gamma-band synchronization and attention is, however, likely to be more complex than a simple increase in synchronization as a function of the amount of attention allocated. In fact, gamma oscillations have been linked to oscillations at lower frequencies, and the role of gamma oscillation in selecting information may depend on interactions between gamma rhythms and lower ones, such as the alpha and theta rhythm. For example, Fries (2009) described the process of viewing natural scenes as one of segmenting the scene and selecting the relevant segment. In this context segmentation is served by a lower rhythm (theta or alpha) and selection by the faster gamma rhythm. Attention to, or enhancement of, specific objects results from iterative loops in which the visual scene is segmented at lower rhythms and the relevant segment is selected with the faster rhythm until the object of interest is selected and "in focus".

Brain rhythms of other frequencies than the gamma band have been related to the investment of resources. For example, high-amplitude alpha rhythm is associated with a state of cortical "idling" (i.e., a resting state) and lower alpha amplitude (desynchronization) is associated with task engagement (Klimesch, 1999). Frontal theta synchronization (which produces high amplitude theta rhythm), on the other hand, is higher when engaged in a task (Gevins et al., 1998). Beta has also been related to resources invested in a task, with increased amplitude in the beta rhythm being related to increasing task difficulty (Brookings et al., 1996) . Because alpha, theta, and beta activity all are related to task engagement, Pope, Bogart, and Bartolome (1995) proposed the engagement index, an index of the workload associated with a task that combines information about the alpha, beta, and theta rhythms according to the formula (beta power / (alpha power + theta power) ). This index has been used experimentally in real-time to determine whether an operator is overloaded or under-loaded while performing a task (Freeman, Mikulka, Prinzel, Scerbo, 1999).

Steady State Evoked Potentials (SSEPs). An alternative way of measuring attentional allocation can be seen as a compromise between the use of ERPs and time-frequency analysis of the EEG. This method involves measuring the steady-state potentials evoked by rapidly changing, repetitive stimulation (Regan, 1989). Regan (1966) introduced the steady-state evoked potential (SSEP) as a means of overcoming some of the disadvantages of ERP analysis, such as the sensitivity of the ERP signal to muscle or movement artifacts and the difficulty of determining the spectral composition of the ERP. In this method, repetitive stimulation (such as a flashing background of a certain frequency) evokes an ERP-like waveform in the EEG which is repeated for the duration of the repeated stimulus, and these repetitions increase the frequency resolution of the SSEP. The power of the SSEP is thus concentrated within the frequency band of the stimulation and can be easily extracted from noise.

An aspect of the SSEP that may make it especially useful in neuroergonomic applications is that it is modulated by visuospatial attention (e.g., Morgan et al., 1996). Use of the SSEP to track attentional allocation is sometimes referred to as "frequency tagging" (Tononi et al., 1998). For example, when two steams of visual information are presented on backgrounds of two different frequencies, and the observer is instructed to attend to either one stream or the other, the amplitude of the SSEP is greater for the frequency at the location to be attended. Moreover, the amplitude of the SSEP reflects the amount of attention received by the object evoking the SSEP, being greater when attention is selectively devoted to one stream of information rather than divided across two streams of information (Toffanin, Johnson, de Jong, & Martens, 2009). Although the relationship between attentional allocation and the visual SSEP is robust, the link between the auditory SSEP and attentional allocation is not as transparent: Some studies report modulation of auditory steady-state responses by attention (e.g., Saupe, Widmann, Bendixen, Muller, & Schroger, 2009), but others do not (e.g., de Jong, Toffanin, & Harbers, 2010; Linden, Picton, Hamel, & Campbell, 1987). Attending to the frequency of the oscillation (and not just to the target stimulus) might be a necessary condition for modulation of the auditory SSEP by attention (Saupe et al., 2009). Alternatively, many of the studies that have reported null effects of attention on auditory SSEPs may have been confounded because attention has an effect on the power of gamma band oscillations in the visual areas but not in the auditory areas (Khalbrock et al., 2012), and many auditory SSEP studies have used a 40-Hz (gamma band) oscillation. More work on the efficacy of the SSEP as an index of auditory attention is needed before conclusions as to the efficacy of the measure can be reached.

### 4.1.3 Brain Networks and Functional Magnetic Resonance Imaging

Many fMRI studies have been conducted in an attempt to pinpoint which brain areas and networks are responsible for attentional selection and attention orienting. As discussed in Chapter 1, two processing pathways are involved in visual processing, and each of these may be modulated by attention. The occipito-temporal, or ventral path, carries information regarding object identity from V1 and V2 in the occipital lobes to the inferotemporal cortex (IT) and V4 where the object is “recognized”, and on to ventral area 46 in the prefrontal cortex (PFC) if the recognized object is to be maintained in working memory (Deco & Zihl, 2006; Desimone & Duncan 1995). The occipito-parietal, or dorsal, path is involved in processing the spatial location of the object. Information is carried from V1 and V2 to the posterior parietal cortex (PPC), where object location and the spatial relationship of an object with other objects are processed. The dorsal part of area 46 in the PFC is involved in maintaining the spatial location of the object.

The structures of the dorsal and ventral pathways illustrate the dependency between working memory and attention (Knudsen, 2007; Miller & Cohen, 2001). Information about the current target is assumed to be stored in a template in area 46 of the PFC. The template influences the competition between stimuli in V1 and V2 by means of recurrent loops in PPC and IT. Endogenous or top-down attention results from interaction between PFC, PPC, and IT: Feedback biases the primary visual areas to process information about identity and location present in the template (for an extensive reviews see Kastner & Ungerleider, 2002; Corbetta & Shulman, 2002; Corbetta, Patel, & Shulman, 2008).

Functional MRI studies have revealed that the presence or absence of activity in PFC provides a measure of attention in terms of cognitive control (Miller & Cohen, 2001). When performing a repetitive task, with the passing of time the execution of the task becomes increasingly automatic, as reflected by the withdrawal of attention from the task. In other words, a consequence of practice is the reduction of the need for active control in coordinating the actions required to achieve a goal. This is reflected by a shift of cerebral activity: Whereas performance of a novel task is characterized by interplay between frontal and parietal areas, automated tasks can be performed relying on parietal areas only (Petersen, Mier, Fiez, & Raichle, 1998). Miller and Cohen proposed that this shift stems from withdrawing cognitive control from the areas necessary for the task. PFC involvement is thus necessary for the coordination of the different brain areas involved in performing a task when the task is novel, but with practice new connections between task-relevant areas are made, circumventing the need for cognitive control.

### 4.1.4 Functional Near Infrared Spectroscopy (fNIRS)

Following its introduction in 1993 by Villringer, Planck, Hock, Schleinkofer, and Dirnagi, fNIRS (see Chapter 1) has become an increasingly popular measure of attention (Huppert, Hoge, Diamond, Franceschini, & Boas, 2006). The portability and user-friendliness of fNIRS are promoting its popularity among neuroergonomists.

That fNIRS is a reliable index of the investment of resources in a task was shown in a study by Ayaz et al. (2012). As mentioned in Chapter 1, fNIRS measures changes in concentration of oxygenated and deoxygenated haemoglobin. Therefore, increases in resource investment should be reflected by a relative increase in oxygenation when comparing high versus low task load conditions. To establish the reliability of fNIRS as an indicator of mental workload (defined as the difference between the resources available to the operator and the resource demand of the task), Ayaz et al. monitored fNIRS responses during an n-back task, a standard memory task in which participants monitor a stream of individually presented stimuli and indicate whenever the current stimulus matches the one before (i.e., the one on trial n-1; "1-back" task) or the one on trial n-2 (the 2-back task), and so forth (Smith & Jonides, 1997), as well as during a complex real-life task, air traffic control. Moreover, in order to investigate whether it was possible to capture changes in brain activity as a function of practice or developing expertise, fNRIS was measured across nine consecutive days during 2-3 hour sessions during which participants learned to manoeuvre a simulated unmanned air vehicle.

Because the left PFC, located in the inferior frontal gyrus, reflects working-memory related activity, Ayaz et al. (2012) measured differences in fNIRS between high- and low-memory load conditions from a sensor located above the left PFC, at the inferior frontal gyrus. Higher oxygenation was observed for a 3-back task than for a 0- or 1-back task, but not for a 2-back task. Differences in task demands in the air traffic control task were measured from a different site, within the medial PFC, or frontopolar cortex, and showed a difference in oxygenation when the easy version of the task was compared to the hard one. Levels of oxygenations changed with increments in task practice in line with the general reduction in brain activity following practice that has also been observed in imaging studies (Kelly & Garavan, 2005; Petersen et al., 1998): Average total haemoglobin measured from the left PFC was higher during the beginning than during the advanced phase of the training. In summary, although subtle changes in task load may not always be reflected in blood oxygenation differences as measured by fNIRS, there is promise that fNIRS could be an effective tool for characterizing task demands.

## 4.2 Augmented Interaction

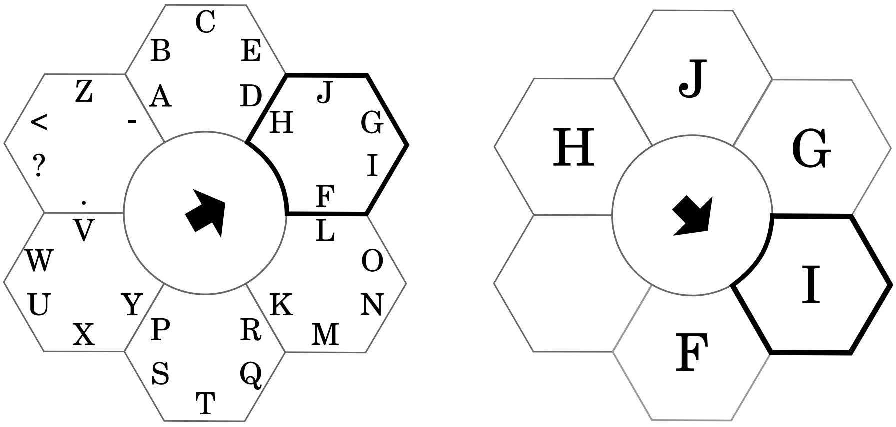
As discussed in Chapter 1, identifying neural markers of operator state that can be used to predict performance in the short-term is one of the most important goals in neuroergonomics. With regards to attention, much evidence for the existence of such markers comes from fMRI and EEG studies. However, embedding EEG and fMRI in real-world settings is beset by practical problems. In addition to cost considerations, these problems include that fMRI, in particular, is not portable, that both EEG and fMRI require trained personnel for measurement and analysis, and that most research has relied on averaging across many trials. Moreover, many of the attentional measures that can be made with fMRI and EEG require nearly total immobilization of the participant. The susceptibility of the techniques to motion artefacts have until now precluded the use of EEG and fMRI in many applied settings, but issues of portability and embedding of EEG, in particular, are gradually being resolved (Parasuraman, 2011b).

### 4.2.1 Brain-computer Interfaces

Much of the excitement about the use of EEG and other methods to trace correlates of attention in real-time comes from research on brain-computer interfaces (BCIs; also referred to as brain-machine interfaces, or BMIs). Brain-computer interfaces rely on measurement of brain activity to interact with a computer. A BCI aims to support, enhance, or substitute human function to “elevate the computer to a genuine prosthetic extension of the brain” (Vidal, 1973, p. 158). In general, a BCI translates brain activity into computer commands (Cecotti, 2011). Most BCI applications have been clinical in nature. For example, Donchin and colleagues (Donchin, Spencer, Wijesinghe, 2000; Farwell & Donchin, 1988) describe how locked-in patients (patients who are essentially immobilized and unable to speak) could learn to use a “P300 speller”. The P300 speller works on the principle that the appearance of an infrequent target evokes a P300. In the original P300 speller, a 6 x 6 matrix of characters is presented. The patient is to focus attention on just one of the 36 characters (the one they wish to “spell”) while the intensity of the individual rows and columns of the matrix are intensified one at a time in a rapid (e.g., 100 ms with 75 ms between intensifications), random sequence. The probability that a row or column containing the target is intensified is one in six. Because targets are rarely highlighted, they can be considered "oddballs" and should elicit a P300 (Donchin, 1981). The relatively rare highlighting of the target stimulus in the random sequence of stimuli constitutes an oddball paradigm (ref), and the target will thus elicit a P300 response to the target stimulus. The EEG of the patient is measured while the task is performed, and the P300 is computed on-line and linked to the symbol that evoked it. The interface then displays the selected letter. Research on the P300 speller illustrates many characteristics of BCI research.

Since the introduction of the P300 speller, much work has been done to improve the on-line calculation and classification of the P300 and to improve the speed of spelling (e.g., Allison & Pineda, 2006; Cecotti, 2011; McFarland, Sarnacki, Townsend, Vaughan & Wolpaw. 2011; Pires, Nunes & Castelo-Branco, 2012). Spelling devices have also been based on the visual SSEP (Gao, Xu, Cheng, Gao, 2003). SSEP-based spelling devices use the changes in amplitude of the SSEP evoked by an object presented on an oscillating background to determine what object or command is receiving attention. Stimulus selection requires simply that attention be focussed on the oscillating background of the desired command. The major advantage of SSEP-based BCI in comparison with other systems is that a lengthy calibration period (during which the user learns to make the appropriate responses and the classifier is taught' to recognize them) is not required: The system is ready to spell as soon as the participant has been prepared for EEG acquisition.

SSEP-based BCIs have also been used for tasks such as map-based navigation (Bakardjian, Tanaka, & Cichocki, 2010), control of neuroprosthetic devices (Muller-Putz & Pfurtscheller, 2008), and video games (Lalor et al., 2006). Importantly, whereas in the P300 speller attention can be directed toward only one command at a time, in a SSEP-based BCI attention can be directed toward multiple commands simultaneously. However, simultaneous execution of different commands has not yet been introduced to SSEP-based BCIs. Moreover, it appears that part of the activity driving the SSEP in these applications is related to eye movements (Cecotti, 2011). Given that eye tracking also has the potential of establishing which object the operator is focusing on–and enjoys the advantage of being simpler to use and analyse than EEG–it still needs to be proven that the SSEP gives more information than eye movements



alone.

Still other types of spellers are based on imagined movement as, for example, moving the right hand or the left foot (Ramoser, Muller-Gerking, & Pfurtscheller, 1999). Motor-imagery BCI uses spatial information in the EEG that is available because activity related to lateralized movements is also lateralized in the brain, and hand and foot movements are represented in different brain locations. Motor-imagery BCI is based on identifying the brain state correlated with thinking of a lateralized movement and using this information to send commands to the computer. For example, in the Hex-o-spell graphical user interface (Muller et al., 2008) the participant attempts to control a cursor displayed on the centre of the screen which rotates when, for example, the participant imagines moving the right hand and stops when the user imagines moving the left hand. The goal is to point the cursor to one of six hexagons arranged around a circle to select a command within that hexagon. Once a hexagon is selected, the commands within that hexagon are distributed around the circle such that just one command is in each of the hexagons around the circle (see Figure 4.2.1).

BCIs based on motor imagery are active BCIs, because the brain activity used by the BCI system is generated by the user independently of external events (Zander & Kothe, 2011). SSEP- and P300-based BCIs are instead reactive BCIs, in the sense that a brain response is evoked by an external stimulus (an oscillation or an oddball stimulus, respectively). In some senses active BCIs can be considered a more “pure” form of brain-machine communication because the user evokes a brain state and the machine interprets the user’s state. Active BCIs are, however, susceptible to BCI illiteracy (Kluber & Muller, 2007), the phenomenon that only some users can learn how to interface with the machine.

To solve the problem of BCI illiteracy recent approaches have combined different types of BCI in one, hybrid BCI (Pfurtscheller et al., 2010). Brunner et al. (2010), for example, created a model hybrid BCI based on SSEP and motor imagery. The model was based on EEG data of participants who had been shown arrows and instructed either to imagine moving the corresponding hand (e.g., left-pointing arrow = imagine left hand movement) or to pay attention to a set of spatially corresponding, flickering light emitting diodes (LEDs; e.g., left-pointing arrow = attend LEDs on the left side of the computer screen), or to do both. The performance of the model was better when both the motor imagery and SSEP signals were used than when only one of the signals was used. Moreover, the authors showed that this was not an artefact due to the fact that more data was supplied to the classification algorithm. However, in a follow-up study in which the hybrid BCI was actually implemented on-line, the performance of the hybrid BCI was less promising than in the simulation study (Brunner, Allison, Altstatter, & Neuper, 2011). In fact, the performance of the hybrid BCI was not significantly better than the performance of an SSEP-based BCI. Moreover, participants reported that using the hybrid BCI was more difficult than using the SSEP-based BCI, which is likely a result of dual-task interference due to having to imagine hand movements while focusing attention on the LEDs.

Other researchers have proposed applications of BCI based on the fMRI signal (Weiskopf,et al., 2004a). The fMRI allows a very fine-tuned analysis of the spatial distribution of brain activity (Haynes & Rees, 2006; Spiers & Maguire, 2007), and therefore could potentially be used to implement more BCI commands than an interface using EEG. Moreover, recent developments in fMRI research suggest that the time constraints associated with acquiring and processing an MRI image (approximately 1 second) do not pose a significant limitation for the analysis of the signal in real-time. Weiskopf et al. (2007), for example, showed that fMRI can be used for self-regulation of brain activity, or neurofeedback (Weiskopf et al., 2004b). Factors which have prevented fMRI-based BCI from becoming more popular than EEG are that fMRI is more expensive, less portable, requires more training, and relies more heavily on skilled personnel than EEG.

### 4.2.2 Adaptive Interfaces

Whereas BCI research, as such, has focussed mostly on clinical applications or on active and reactive BCIs, research on adaptive interfaces focuses on using information about operator state to allocate tasks to the operator versus the machine in work environments (Sheridan, 2011). Adaptive interfaces can be viewed as an extension of the person, or a machine interacting with the person, rather than a human and a machine trying to control each other. Adaptive interfaces are intended for use in any environment in which tasks or processes are partly or fully automated. Such a system requires that information about operator state can be measured and classified in real-time and that some tasks can be allocated to either the human operator or to the machine itself. Adaptive systems have the potential to solve problems of operator underload and overload (Parasuraman, 2011b; Young & Stanton, 2002a, b). When an operator is underloaded, arousal levels may decrease below a desired level or an operator may become complacent and fall "out of the loop", losing situation awareness as a result (Wiener & Curry, 1980). Effects of overload include excessive mental workload (defined as the difference between the processing demands imposed by a task and the resources available to the operator at a given point in time), stress or other costs of compensating for the need to maintain primary task performance (Halpern et al., 2009; Lim, Wu, Wang, Detre, Dinges et al., 2010; Matthews et al., 2000; Sperandio, 1978), or performance decrement. Accurate, on-line assessment of mental workload has the potential to reduce human error by signalling overload (or underload) and may provide data that can be used to modify the task environment to match the available resources of the operator to task demands.

Most work on adaptive interfaces takes the approach of measuring mental workload on-line, and classifying load as either too low or too high (e.g, Byrne & Parasuraman, 1996). In order to create an adaptive system, one must therefore have a reliable indicator of load and a means of calculating load on-line. In the past several decades, most research has focussed on cardiovascular and EEG measures. For example, the amplitude of the P300 component of the ERP, which reflects the classification of a target object (Donchin, 1981), has been shown to be sensitive to workload. The P300 is an attractive option in adaptive automation because it is sensitive to the momentary demands of the task. The added value of the P300 as an indicator of workload was demonstrated by Prinzel, Freeman, Scerbo, Mikulka, and Pope (2003). They had participants perform a compensatory tracking task together with an auditory oddball task. EEG was measured, and the tracking task was switched from a manual to an automated mode based on the engagement index (Pope et al., 1995). Performance of those for whom the adaptive automation was based on the engagement index was better than for yoked control participants (i.e., participants who received the same automation schedule as that of a participant in the EEG group). ERPs were computed offline, and the P300 evoked by the auditory oddball stimulus was found to parallel the sensitivity to task demands of the performance and subjective measures across conditions.

The measurement of EEG may also provide insight into dual-task demands. In one study of changes in workload due to dual-task demands, Lei and Rottingen (2011) measured the EEG of people who were driving in a driving simulator while performing an n-back task. The difficulty of the driving and n-back task were manipulated, and modulations of the EEG spectrum evoked by the changes in task difficulty were measured. Lei and Rottingen found that alpha power was attenuated and theta power was increased when workload was high as compared to when it was low. Most importantly, the changes in power depended on which task was manipulated, with changes in alpha power being more sensitive to workload changes during the driving task and changes in theta power being more sensitive to workload changes in the n-back task. These results suggest that it may be possible to use combinations of different frequency bands to determine which tasks should be supported. The results also suggest that the use of a combination of different frequencies, as in the engagement index (Pope et al., 1995), may provide a more general and reliable estimate of mental workload than reliance on any one frequency band.

Basing adaptive support on cardiovascular measures such as heart-rate variability (which decreases as workload increases; Tattersall & Hockey, 1995) is less intrusive and therefore potentially more widely applicable than EEG-based adaptive support. For example, cardiovascular measures might be used to make the task of the ambulance dispatcher easier. Ambulance dispatching requires that emergency situations be understood and that ambulances be dispatched to accident sites as promptly as possible while keeping coverage of the region of which the operator is in charge. Mulder, Dijksterhuis, Stuiver, and de Waard (2009) showed that it was possible to track workload in an ambulance-dispatching task simulator with measures such as heart-rate variability. However, the task support they provided in high-workload conditions (shading the area on a map of the region being monitored that an ambulance could cover within 15 minutes) did not result in performance improvements. These results point to a challenge in adaptive automation: Knowing that the operator is overloaded is not enough–there must also be a means available of supporting the operator in a meaningful way.

A marker of resource investment discussed earlier in this chapter is pupil dilation. Pupil dilation has been used together with eye-movement activity to measure workload in applied settings. When people observe a screen or display, scan paths are characterized by a certain amount of randomness, or, entropy. One important finding is that scan-path randomness is inversely related to workload (Harris, Glover, & Spady, 1986): As workload increases, scanning patterns become more stereotyped. Whether or not performance suffers will depend on whether the relevant information is still viewed as scan paths become more stereotyped. Hilburn, Jorna, Byrne, and Parasuraman (1995) used scan-path randomness–together with pupil dilation and heart-rate variability–in an adaptive decision aiding system for air-traffic control. When high workload was detected support was provided by reallocating part of the human task to the machine (for similar applications based on the relationship between eye-movements and workload see, e.g., Alhstrom & Friedman-Berg, 2006; Stasi, Marchitto, Antoli, Baccino, & Canas, 2010).

Multiple workload indices were also used in a study by Hwang et al. (2008) in which the workload of operators performing the shutdown procedure for a nuclear power plant was measured. Hwang et al. estimated workload from a combination of measures which included parasympathetic/sympathetic ratio, heart rate, and diastolic and systolic blood pressure (all of which tend to increase as workload increases), and heart-rate variability and eye-blink frequency and duration (all of which tend to decrease as a function of increasing workload). The different indices were used as input to a neural network model, and the model was run to determine the contribution of each parameter to workload in the task (the procedure by which the weights were assigned can be likened to the estimation of coefficients in a multiple regression model). All seven of the predictors used by Hwang et al. were found to contribute significantly to the capacity of the neural network model to discriminate between workload states.

## 4.3 Augmenting Attention, and Cognition

New technologies (e.g., medical scanning technology and unmanned military drones) are producing an unprecedented number of complex images. Humans outperform machines in processing these images, but are limited in the number of images that they can process in a given amount of time. An important issue is thus how target detection (whether of a tumour or a weapons installation) can be enhanced. It is beginning to be evident that neuroergonomics can take up this problem where image processing leaves off. For example, Gerson, Parra, and Sajda (2006) describe an EEG-based BCI that can be used to make a selection of images presented to observers in rapid serial visual presentation to be re-presented to the observers for additional analysis. The BCI can classify in real-time a stereotypical spatiotemporal response associated with targets (in this case, natural scenes containing people as opposed to unpopulated scenes). Images identified as potentially containing targets can then be examined in detail. Such a technique has the advantage of allowing large numbers of images to be scanned quickly (the typical presentation rate is 100 ms per item), leaving time to devote to the further processing of potential targets. The accuracy of classification of targets embedded in scenes presented in rapid serial visual presentation may be able to be increased by using pupil diameter measures in addition to the EEG response (Qian et al., 2009). Using classifiers to triage images has the potential to help image analysts who must classify many images and promises reductions in detection time and improvements in detection accuracy.

Another ambitious project for enhancing cognition is the attempt to implement binoculars with image processing functionality. The United States defense department is currently working to develop image-enhancing binoculars under the name "Cognitive technology threat warning system" (CT2WS). The aim of the CT2WS project is to support soldiers in identifying possible threats. Real-time EEG signals, measured via an in-helmet EEG system are subjected to algorithms to classify the visual inputs gathered through the binoculars. The program uses saliency maps (Kock & Ullman, 1985), first developed as a computational model of bottom-up attentional selection, as the basis for threat-detection. The saliency map algorithm analyses the visual information the soldier is seeing and determines which information is the most salient by decomposing the visual information into saliency maps. A saliency map combines elementary features such as color, orientation, direction of movement, and disparity to determine which objects in a visual scene are salient.

In the CT2WS context, the saliency map selects potential targets from the visual scene. When the soldier views a scene, the saliency map algorithm marks potential threats, and the EEG of the soldier is monitored to determine whether or not a threat is perceived. For example, the saliency map presented to a soldier looking into a forest may identify a deer or a tank, both of which have features which distinguish them from the surrounding trees. Because the saliency map itself cannot distinguish between objects–the EEG signal evoked by the soldier in response to the two "threats" is used to classify objects as friend or foe. The process of threat identification is monitored by a learning algorithm to optimize the identification process. The algorithm is adaptive in the sense that it learns the combination of the EEG response and the stimulus which evoked it, thereby optimizing the classification capacity of the threat-detection algorithm.

### 4.3.1 Enhancing Attention Through Training

Improving attentional state through "brain training" has a long and venerable history. Neurofeedback, a form of biofeedback in which some feature of an individual's brain activity (e.g., alpha rhythm) is made visible to the participant (e.g., via a ball that bounces higher as alpha synchronizes), has been used to treat children with attention deficit/hyperactivity disorder (ADHD) since the 1970s (e.g., Lubar & Shouse, 1977). In neurofeedback some aspect of the EEG, such as the amplitude of the alpha rhythm, is used to change the state of the displayed activity, such as the bounce of the ball. As the person learns to make the ball bounce faster or higher, alpha amplitude is either increased or decreased, depending on the goal of the neurofeedback (e.g., Hardt & Kamiya, 1976; see Weiskopf et al., 2004, for an example using fMRI).

In the case of ADHD, neurofeedback has been used to increase or decrease the amplitude of alpha, beta, and theta oscillations. Children with ADHD show spectral abnormalities in the EEG, such as increased frontal theta amplitude and decreased alpha and beta oscillations, in comparison to non-ADHD children (Clarke, Barry, McCarthy & Selikowitz, 1998). Lubar, Swartwood, Swartwood, and O'Donnel (1995) showed that training children to increase the amplitude of the upper alpha rhythm (12-15 Hz; also referred to as the sensorimotor rhythm) and the lower beta rhythm (15-18 Hz) can enhance sustained attention and alleviate the symptoms of ADHD. In fact, neurofeedback training of the sensorimotor and lower beta rhythm may improve the functioning of ADHD sufferers to the same extent as does medication by methylphenidate (a commonly used psychostimulant; Fuchs, Birbaumer, Lutzenberg, Gruzelier, & Kaiser, 2003). Importantly, the effects of neurofeedback training are persistent and more long-lasting than the administration of medication, suggesting that brain training can have powerful effects on attention and behaviour (Tang & Posner, 2009).

Neurofeedback training has also been shown to improve cognitive performance in non-clinical populations. Using a mental rotation task, for example, Hanslmayr, Sauseng, Doppelmayr, Schabus, and Klimesch (2005) found that neurofeedback training of the alpha rhythm improved task performance. Hanslmayr et al. used neurofeedback to train their participants to maximally synchronize upper alpha rhythm (12-15 Hz)–indicating a relaxed state– in the interval between the task trials. This neurofeedback training led to improvements in task performance, but only for the participants who were successful in learning to increase their alpha response. Enhancement with neurofeedback has also been found for memory task performance (Lantz & Sterman, 1988), attention tasks (Egner & Gruzelier, 2004), and memory capacity (Vernon et al., 2003).

It may also be possible to train attention using basic cognitive tasks. Rueda, Rothbart, McCandliss, Saccomanno, and Posner (2005) devised a training module to augment executive attention in children (4 and 6 years old). The training program involved a series of exercises such as object tracking, Stroop-like exercises, discrimination of stimuli, anticipations of events, and resolution of conflict. ERPs were measured before and after the five-session training program during the performance of the attention network task (ANT; Rueda et al., 2004). The ANT is a modified flanker task (i.e., a task in which a target must be attended and distractors assigned to a competing response must be ignored) which measures attention orienting, alerting, and the capacity to resolve conflict. Rueda et al. found a general benefit of the training when comparing the performance of the group receiving training against the group not receiving training. However, the effect of training was largely limited to the four-year old children, which suggests that such training is beneficial only in early stages of development.

Although the benefits of the type of training given by Rueda et al. (2005) may be restricted to young children, training of attentional skill has been shown, in some studies, to transfer across tasks in adults, as well. For example, several studies have shown that playing “first-person shooter” action video games may improve performance in basic attentional tasks such as the flanker task, attentional blink task (detecting two targets presented in rapid serial visual presentation), and an enumeration task (e.g., Green & Bavalier, 2003). Green and Bavalier reported that people who habitually played action video games spread attention more widely in time and space than non-gamers. However, many attempts to replicate findings such as these have failed (e.g., Murphy & Spencer, 2009; see Boot, Blakely, & Simons, 2011, for a critical meta-analysis of improved cognition after video-gaming).

There is promising work showing that attention can be enhanced. It may also be possible to identify when one is most likely to be able to learn new material and to capitalize on these "optimum learning" moments. A person's ability to remember new information changes from moment to moment (Corkin, 2002). Yoo et al. (2012) used this fact to select optimal learning intervals by monitoring the activity of brain areas associated with the formation of memories. The parahippocampal cortex (PHC), located in the medial temporal lobe, is responsible for the successful formation of memories of scenes, as reflected by greater PHC activation for remembered than forgotten scenes (Brewer, Zhao, Desmond, Glover, & Gabrieli, 1998). Moreover, prestimulus activity in a particular area of the PHC, the parahippocampal place area (PPA), is correlated with successful memory for scenes. Yoo and collaborators measured PPA activity in real time to determine when good or poor time intervals in which to present information occurred. They found that memory for scenes was significantly better for scenes presented during good time intervals (indicated by low PPA activity) as compared to scenes presented during poor time intervals (indicated by high PPA activation).

### 4.3.2 Using Drugs to Enhance Attention

Using drugs to enhance cognitive ability may be becoming as prevalent as doping in sports. The question is whether some cognition enhancing drugs have a place in healthy human performance. One drug, caffeine, has a long and proven history of use as a performance enhancer. One recent study using the ANT (Fan et al., 2002), for example, demonstrated that caffeine improves the attentional functions of alerting and executive control, although a too-high dose of caffeine (400 mg) hurts orienting of attention (Bruny, Mahoney, Lieberman, & Taylor, 2010). Despite the fact that caffeine is widely accepted in Western societies, a new trend toward the use of drugs originally designed to alleviate symptoms associated with neuropsychological impairments by individuals hoping to boost cognitive capacities gives cause for concern (see Sahakian & Morein-Zamir, 2007). Drugs used to treat ADHD, in particular, are increasingly being used by students to improve concentration when cramming for exams (Babcock & Byrne, 2000), and other stimulants are used by long-haul truckers (da Silva, de Pinho, de Mello, de Bruin, & de Bruin, 2009). or by aircrew members on military missions (e.g., Ramsey, Werchan, Isdahl, Fischer, & Gibbons, 2008). Another commonly used drug, Modafinil, promotes wakefulness and is used by people with disturbed sleeping patterns (e.g., due to jet lag, shiftwork, or sleep apnea; see Chapter 6), but also by people hoping to improve their ability to concentrate (Sahakian & Morein-Zamir).

Individuals vary in how they react to different drugs. For example, bromocriptine, a dopamine agonist, enhances various executive functions for low-working memory capacity individuals, but has a detrimental effect on the performance of high-working memory capacity individuals (Kimberg, D'Esposito, & Farah). The fact that different people react differently to the same drugs makes it difficult to specify a general protocol for the use of drugs to enhance cognitive function, and uncertainty about the long-term effects various drugs might have, as well as ethical considerations (see Chapter 1), put into question the desirability of recommending performance enhancement for healthy human operators.

## 4.4 Conclusion

In nearly all tasks, adequate performance depends on the availability of attentional resources and the appropriate allocation of attention. Many techniques to measure attention have been developed. Some of these measures (such as pupil dilation and the EEG-based engagement index) are non-specific in that they reflect the degree of arousal of a person or the overall effort being exerted whereas others (such as the P300) are specific to the processing of a particular stimulus. Much work has focussed on using these measures to improve basic attentional skills or task performance. Physiological measures of mental workload, in particular, have been applied in adaptive automation. Neurofeedback and BCIs have, to date, primarily seen clinical applications, but the techniques being developed show promise for augmentation of attentional abilities and improvements in perception and cognition. The extent to which attention can be augmented by training, drugs, or neurofeedback remains controversial. Exciting lines of research do, however, suggest that basic abilities can be improved upon. Even if this should turn out not to be the case, neural and other physiological measures of attention are already proving to enhance performance in many tasks by using data obtained from the operator to modify how stimuli are presented and processed.

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