8 Spatiotemporal characteristics of perceptual decision making in the human brain

Marios G. Philiastides and Hauke R. Heekeren

Neurocognition of Decision Making Group, Max Planck Institute for Human Development, Lentzeallee 94, 14195 Berlin, Germany

Abstract

Perceptual decision making is the process by which information gathered from sensory systems is combined and used to influence our behavior. In recent years, the fields of systems and cognitive neuroscience have aggressively sought to examine the neural correlates of this process. As a result, significant contributions in the area of perceptual decision making have emerged. In this chapter we briefly review the major contributions made to this area by monkey neurophysiology and discuss how these animal experiments have inspired scientists to study the neural correlates of perceptual decision making in humans using non-invasive methods such as fMRI, EEG, and MEG. We present findings primarily from the visual and somatosensory domains, which we use as supporting evidence in proposing a new theoretical model of perceptual decision making. The latter part of the chapter focuses on how to best integrate EEG with fMRI to achieve both high spatial and high temporal resolution to help inform theories of the neurobiology of perceptual decision making. We conclude by providing a motivation on how this framework for perceptual decision making in combination with the techniques presented here can be extended to study the interaction of sensory and reward systems as well as to study value-based decision making in humans.

Key points

1. Perceptual decision making is the process by which information gathered from sensory systems is combined and used to influence our behavior.
2. Findings from monkey physiology experiments parallel those from human neuroimaging experiments.
3. Sensory evidence is represented in sensory processing areas.
4. Accumulation of sensory evidence occurs in decision-making areas that are downstream of the sensory processing areas; these decision-making areas form a decision by comparing outputs from sensory neurons.
5. The functional architecture for human perceptual decision making consists of separate processes that interact in a heterarchical manner in which at least some of the processes happen in parallel.
6. Simultaneous EEG/fMRI measurements and EEG-informed fMRI analysis techniques allow us to characterize the spatiotemporal characteristics of the network processes underlying perceptual decision making in humans.

Handbook of Reward and Decision Making

8.1 Introduction

Perceptual decision making is the process by which incoming sensory information is combined and used to influence how we behave in the world. The neural correlates of perceptual decision making in the human brain are currently under intense investigation by systems and cognitive neuroscience. Fortunately, animal neurophysiology has already laid the foundation upon which critical new hypotheses about human decision making can be based. Specifically, results of single and multi-unit recordings in primates have already proposed that decision making involves three main processing stages: representation of sensory evidence, integration of the available sensory information across time, and a comparison of the accumulated evidence to a decision threshold [1]. Furthermore, some psychological theories suggest that these stages of decision formation are likely to occur in a serial fashion [2,3].

Though the overall simplicity of this hierarchical model is admittedly appealing, perceptual decision making in the human brain is likely to involve a more complex, non-serial cascade of events that includes sensory processing, attention, prior information, reward, evidence accumulation, and motor response networks [4]. An alternative model, as outlined in Fig. 8.1A, involves at least four complementary and partially overlapping systems which interact in a heterarchical manner, with some of the processes occurring in parallel.

In addition to the main processing modules of the simple hierarchical architecture, this four-compartment model includes a system that detects perceptual uncertainty or task difficulty as well as a performance monitoring system. In this chapter we will discuss recent findings from human neuroimaging studies, which use new data analysis techniques to identify the spatiotemporal characteristics of these different systems, to provide support for the extended model proposed here.

The majority of human studies that have addressed this problem use functional magnetic resonance imaging (fMRI) to identify the cortical regions that are participating in decision making [5–8]. The low temporal resolution of fMRI however, imposes limitations on inferring causation as little can be said about the sequence of neural activation in these regions, which is also needed to ultimately infer the true underlying neural network. A different approach to deciphering the temporal characteristics of perceptual decision making is provided by non-invasive measurements of the human electro- and magnetoencephalograms (EEG/MEG). Though the spatial resolution of these imaging modalities is rather low, they possess temporal resolution on the order of milliseconds and in conjunction with advanced single-trial analysis techniques can be used to map out temporally distinct components related to different events during decision formation [9–11].

Though significant progress has already been made using each of these modalities in isolation, the localization restrictions of EEG and MEG and the temporal precision constraints of fMRI, suggest that only a combination of these approaches can ultimately enable the recovery of the spatiotemporal characteristics of the network processes underlying perceptual decision making in humans. This can potentially be achieved by simultaneous EEG/fMRI measurements or by EEG-informed fMRI analysis techniques where EEG-derived regressors are used to model the fMRI data [12–14]. As the across-trial and across-condition variability seen in the identified EEG components may carry important information regarding the underlying neural processes, correlating EEG component activity with the blood-oxygenation-level-dependent (BOLD) fMRI signal could provide images of the source of this variability with high spatial resolution. Figure 8.1B illustrates

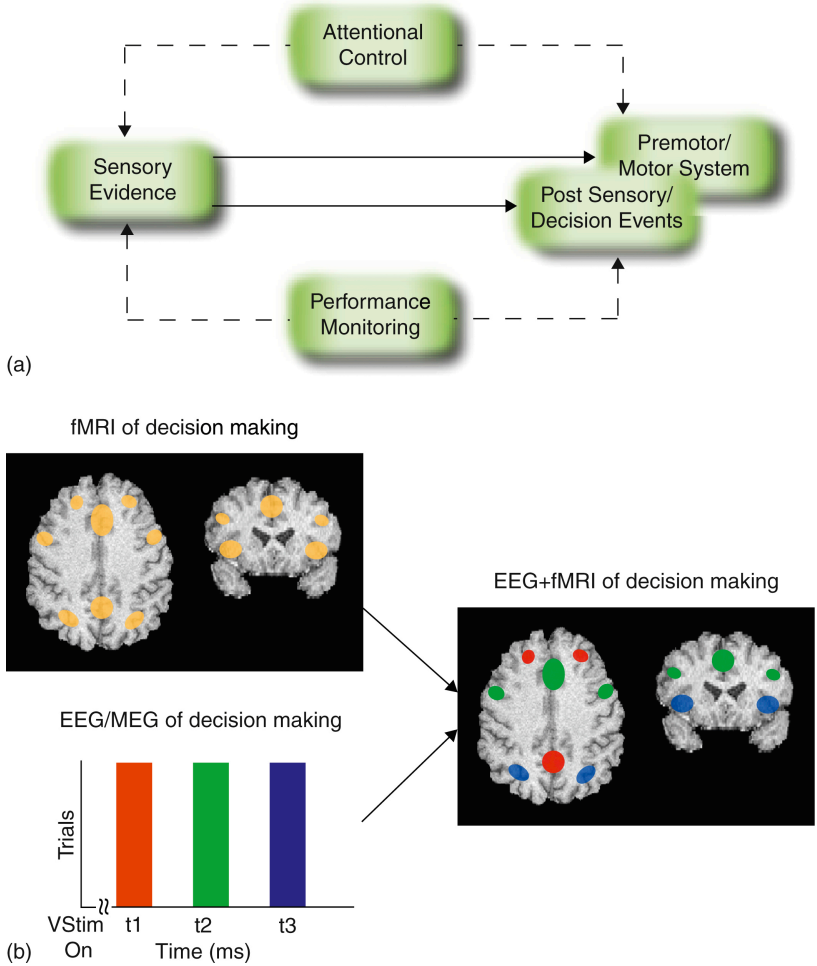

Figure 8.1 A theoretical model for human perceptual decision making. Integrating EEG with fMRI can help reveal the spatiotemporal characteristics of this model. (A) A four-compartment model of perceptual decision making in the human brain. In contrast to traditional hierarchical models of decision making [2,3] the main processes of some of these compartments can happen in parallel. The model includes a system for representing the early sensory evidence, and a system for post-sensory, decision-related processing including comparison and accumulation of sensory evidence and computation of decision variables. As in many tasks, decisions are usually expressed through action; this system includes motor and premotor structures. In addition, it incorporates a system for detecting perceptual uncertainty or difficulty to signal for recruitment of more attentional resources when task demands are increased, and a system for performance monitoring to detect when errors occur and when decision strategies need to be adjusted to improve performance. (B) Identifying the spatiotemporal characteristics of the model presented in (A) requires imaging the brain at both high spatial and high temporal resolution. fMRI can provide the desired spatial resolution while single-trial EEG can identify temporally well-localized features of this model. Developing new techniques to integrate EEG with fMRI can ultimately enable the recovery of the spatiotemporal characteristics of the network processes underlying human perceptual decision making.

the benefits of combining EEG and fMRI in inferring the spatiotemporal characteristics of human decision making.

This chapter is organized as follows. We start out by briefly reviewing the major contributions of monkey neurophysiology to our current knowledge of perceptual decision making. We then discuss how the concepts derived from this animal work also apply to human decision making by providing evidence from a number of recent fMRI, EEG and MEG studies. Where appropriate we use these findings to make references in support of the model outlined in Fig. 8.1A.The latter part of the chapter focuses on how to best integrate EEG and fMRI and provides an example of how the EEG-derived fMRI analysis approach can be a valuable tool in achieving high spatiotemporal characterization of the neural correlates of perceptual decision making in humans. We conclude by providing a motivation on how this framework for perceptual decision making in combination with the techniques presented here can be extended to study reward- and value-based decision making in humans.

8.2 Perceptual decision making in monkeys

8.2.1 Sensory evidence representation

A number of single-unit experiments in primates have already established a clear relationship between neuronal activity in sensory regions and psychophysical judgments. In a discrimination task in which monkeys had to decide the direction of motion from random dot kinetograms consisting of varying amounts of coherent motion, Newsome and colleagues showed that the activity of direction-selective neurons in middle temporal area (MT/V5) can provide a satisfactory account of behavioral performance [15–17]. In addition, trial-to-trial variability in these neuronal signals was correlated with the monkeys' actual choices [18]. That is, when a neuron in area MT fired more vigorously, the monkeys were more likely to make a decision in favor of that neuron's preferred direction of motion. In line with this idea, electrical microstimulation of MT neurons biased the monkeys to commit more and faster choices towards the neurons' preferred direction [19–21]. Taken together, these findings lend support to the notion that neuronal signals in area MT provide the sensory evidence upon which monkeys base their decision regarding the direction of stimulus motion.

Interestingly, this pattern of neural responses appears to extend to even highly complex visual stimuli such as faces. A study, using a rapid serial visual presentation (RSVP) task, identified activity of individual neurons in macaque temporal cortex which predicted whether the monkey responded that it saw a face in the stimulus or not [22]. More recently, and for a similar face versus no-face categorization task, microstimulation of face-selective neurons in inferotemporal (IT) cortex biased the monkeys' choices towards the face category [23]. The magnitude of the effect depended on the degree of face selectivity and the size of the stimulated cluster of face-selective neurons. Moreover, the early time, relative to stimulus onset, at which microstimulation had an effect suggested that neurons in IT can provide the sensory evidence needed for object-based decision making.

In the somatosensory domain, Romo and colleagues used a task in which monkeys had to discriminate the vibration frequency of two sequentially presented tactile stimuli and report which one was the highest. As with the MT experiments, here too, the sensitivity of the average responses in primary somatosensory cortex (S1) was similar to the behavioral sensitivity of the monkeys and the trial-to-trial fluctuations in the neural responses

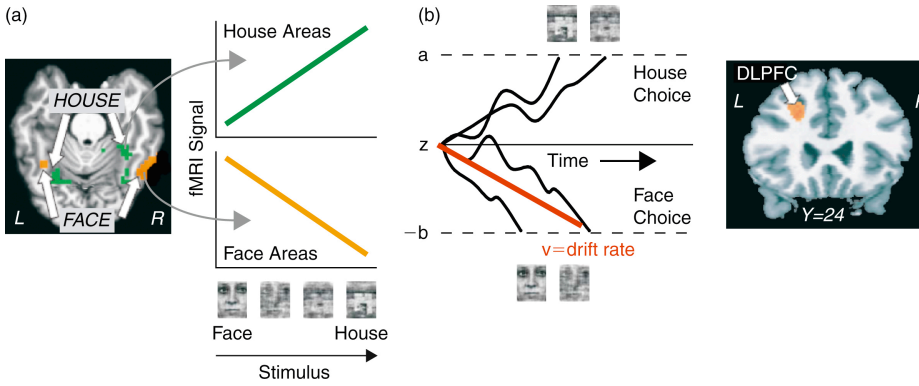

Figure 8.2 Representation and integration of sensory evidence during perceptual decision making in humans. (A) Using fMRI, Heekeren et al. [5] identified face- and house-selective regions (orange and green clusters, respectively) that are thought to represent the sensory evidence required to make a face-house discrimination. Specifically, they found a greater response in face-selective areas to clear images of faces than to noisy images of faces. Conversely, house-selective areas showed a greater response to clear images of houses than to noisy images of house. The orange and green lines illustrate this point in a cartoon-like fashion. (B) Decision making in higher-level brain regions is thought to involve an integration of sensory evidence over time. The diffusion model for simple decision making [27,28] assumes that decisions are made by continuously accumulating sensory information until one of two response criteria (a or b) is reached as illustrated graphically in this panel. Moment-to-moment fluctuations in the sample path reflect noise in the decision process. The accumulation rate, termed drift rate (v) in the model, reflects the quality of the available sensory evidence. For example, clear images of faces/houses contain more sensory evidence than noisy images, and therefore have a higher drift rate. Heekeren et al. [5] showed that such computations are carried out in the DLPFC. See Plate 7 of Color Plate section.

predicted the animals' choices to a small but significant degree [24]. Furthermore, microstimulation of S1 neurons, in the absence of physical stimulation, was sufficient to reproduce the behavioral patterns seen under normal conditions [25,26]. These results demonstrate that signals in S1 represent the evidence used by the monkeys to form the decision.

8.2.2 Accumulation of sensory evidence and decision formation

How can the sensory evidence provided by sensory regions, such as MT and S1, be used to drive the later stages of decision formation? Computational models of decision making, including diffusion and race models, have already proposed that decisions regarding ambiguous sensory evidence can benefit from an accumulation of information over time [27–31] (see Chapter 18). The diffusion model, for two-choice decisions, in particular assumes that in the decision process, evidence is integrated over time to one of two decision thresholds corresponding to the two choices (see Fig. 8.2B for an illustration). The rate of accumulation is called drift rate, and it is determined by the quality of the sensory information. The better the information quality, the larger the drift rate toward the appropriate decision boundary and the faster and more accurate the response. Moreover, trial-to-trial variability in the accumulation of information could result in processes with

the same mean drift rate but terminate at different times (producing different response times) and sometimes at different boundaries (producing errors).

As it turns out there are indeed brain regions in which the neural activity matches predictions made by the model. One such region, which appears to be critically involved in the direction discrimination task, is localized in the lateral wall of the intraparietal sulcus (IPS) and is commonly referred to as lateral intraparietal (LIP) area. LIP was originally shown to be involved in linking sensory and motor processing stages. Furthermore its activity is predictive of the time and direction of a monkey's saccadic eye movements [32–34]. As monkeys are typically trained to indicate their choice by making an eye movement (saccade) towards a target on the side of the perceived direction of motion, this area was studied further for its potential role in decision making.

Single-unit recordings in LIP [34–37] have shown that, for saccades made towards the response field of the neuron under consideration, neural activity increased in a ramp-like fashion, consistent with an accumulator process. The rate at which responses increased was proportional to the amount of coherent motion in the stimulus. This build-up of activity may represent the accumulated difference in firing rates of two opposed pools of direction selective MT neurons. This difference is thought to approximate the logarithm of the likelihood ratio (logLR) in favor of one alternative over another [1,38,39]. More important, by the time the monkey was committed to a particular eye movement response, neural responses in LIP achieved a common value regardless of motion strength, consistent with the idea of a decision boundary that is common to both easy and difficult choices. More recently, these results were extended from a two- to a four-choice direction discrimination task [40]. This pattern of activity was also reported in the frontal eye fields (FEF) and the dorsolateral prefrontal cortex (DLPFC) [41] and is regarded as evidence that all of these areas are involved in the conversion of an analog motion representation into a binary decision variable.

Correspondingly, for the vibrotactile frequency discrimination experiments, regions in the secondary somatosensory (S2), medial premotor cortex (MPC), ventral premotor cortex (VPC), and in the DLPFC were reported as being involved in decision formation [42–45]. As with the motion experiments, responses in these regions are likely to reflect a comparison between the two frequencies under consideration. Similarly to the LIP, responses the MPC and VPC were also shown to form a decision by computing the difference between the activities of neurons in S2 that code for each of the frequencies used for stimulation [44,45]. In addition, neurons in S2 itself responded as a function of both the first (remembered) and second (current) stimulus and their activity was correlated with the monkeys' decisions shortly after both frequencies were presented. This suggested that at least some S2 neurons may combine past and present sensory information to form a decision [43]. Finally, time-dependent persistent activity in the DLPFC during the delay period between the two stimuli, correlated with the monkeys' behavior, suggesting an active role of short-term memory representation in decision making [42,46].

8.3 Perceptual decision making in humans

In this section we review human neuroimaging evidence showing that the principles that have emerged from the neurophysiology work in monkeys also hold for the human brain.

8.3.1 fMRI studies on perceptual decision making

Representation of visual evidence

Heekeren and colleagues used fMRI and a face-house categorization task to investigate perceptual decision making in the visual domain [5]. Previous neuroimaging studies had identified regions in the human ventral temporal cortex that are activated more by faces than by houses, and vice versa: the fusiform face area (FFA) and the parahippocampal place area (PPA), respectively [47–51]. The face-house task can thus be used to identify two brain regions, and to test whether they represent the sensory evidence relevant for the task. There was a greater response in face-selective regions to clearer images of faces ("easy" trials) than to degraded images of faces ("difficult" trials), whereas degraded houses showed a greater response than clearer houses in these face-selective areas. The opposite pattern was found in house-selective regions, namely, a greater response to clearer images of houses ("easy" trials) than to degraded images of houses ("difficult" trials), but a greater response to degraded than to clearer images of faces (Fig. 8.2A).

These results support the concept that face- and house-selective regions represent the sensory evidence for the two respective categories, consistent with the initial processing module of the model in Fig. 8.1A.

Representation of somatosensory evidence

Inspired by the work of Romo and colleagues, recent fMRI studies have used vibrotactile frequency tasks to study somatosensory decision making in the human brain. In this task, individuals had to decide which of two successive vibratory stimuli had a higher frequency. Consistent with neurophysiological data in monkeys, the primary somatosensory cortex exhibited increased activity during the encoding phase (processing of the first stimulus) in tactile decision making [52]. Similarly, using a somatosensory discrimination task, in which participants had to compare the frequency of two successive electrical tactile stimuli, Pleger and associates found that tactile stimuli *per se* evoked activity in, among other regions, somatosensory cortex [7].

The most direct evidence in support of the concept of representation of sensory evidence in the somatosensory domain comes from a transcranial magnetic stimulation (TMS) study which showed that stimulation of primary somatosensory cortex lowered two-point discrimination thresholds of the right index finger and enlarged its neural representation as assessed with fMRI [53]. Notably, this enlargement correlated with the individual TMS-induced perceptual improvement. Taken together, the results of the studies described above provide support for the idea that, similar to the findings in monkeys, primary somatosensory cortex represents the sensory evidence during tactile decision making. Next, we review recent human neuroimaging studies that provide evidence for a comparison of accumulated sensory evidence as a mechanism for perceptual decision making.

Integration of sensory evidence and formation of the decision variable

The single-unit recording studies in monkeys have shown that neuronal activity in areas involved in decision making gradually increases and then remains elevated until a response is made. Importantly, the rate of increase in neural activity is slower during more difficult trials than during easier trials. Furthermore, these studies have shown that downstream cortical regions (i.e., further along the processing chain), such as LIP and the DLPFC, could form a decision by comparing the output of pools of selectively tuned sensory neurons.

A recent fMRI study showed how the BOLD signal can be used to examine the process of accumulation of sensory evidence [8]. Pictures were revealed gradually over the course of 12–20 s and participants signaled the time of recognition with a button press. In several occipital regions, the fMRI signal increased primarily as stimulus information increased, suggesting a role in lower-level sensory processing. There was a gradual build-up in fMRI signal peaking in correspondence with the time of recognition in inferior temporal, frontal, and parietal regions, suggesting that these regions accumulate sensory evidence.

Heekeren and colleagues directly tested whether a comparison operation is also at work in the human brain using the face-house discrimination task described previously [5]. Specifically, based on the neurophysiological data in monkeys, Heekeren proposed that higher-level decision areas should fulfill two criteria. First, they should show the greatest BOLD activity on trials in which the weight of evidence for a given perceptual category is greatest, namely, a higher fMRI signal during decisions about clear images of faces and houses ("easy trials") than during decisions about degraded images of these stimuli ("hard trials"). Second, their BOLD signals should correlate with the difference between the signals in brain areas selectively tuned to the different categories involved; that is, those in face- and house-responsive regions.

Only one brain region fulfilled both criteria [5]: the posterior portion of the left DLPFC uniquely responded more to clear relative to degraded stimuli, and the activity of this region correlated with the difference between the output signals of face- and house-responsive regions (Fig. 8.2B).

Thus, when people make categorical decisions about face and house stimuli, this brain region appears to integrate the outputs from lower-level sensory regions and use a subtraction operation to compute perceptual decisions. Notably, activity in the left DLPFC also predicted behavioral performance in the categorization task [5]. Hence, even for complex object categories, the comparison of the outputs of different pools of selectively tuned neurons appears to be a general mechanism by which the human brain computes perceptual decisions.

Uncertainty, attention, and task difficulty

The human neuroimaging studies reviewed so far have used single-unit recording findings as a constraint to predict decision-related changes in fMRI signals [35]. Specifically, neuronal activity in areas involved in decision making gradually increases with increasing sensory evidence and then remains elevated until a response is made, with a greater rate of increase during easier trials than during more difficult trials. This leads to the prediction of an enhanced fMRI response during easy relative to hard trials in decision-making areas.

Other investigators took a different approach to the identification of regions involved in perceptual decision making: they characterized decision-making regions on the basis of correlations of the BOLD signal with accuracy or response time (RT) [54]. This approach is based on Donders' theory that the time an individual needs to deliberate before responding to a stimulus increases with task difficulty, and thus can be used to differentiate sensory and decision processes. Therefore, in contrast to the neurophysiological work and neuroimaging studies reviewed previously, these investigators have reasoned that BOLD activity in decision-related regions should be correlated with RT; namely, they should show a greater response during difficult trials than during easy trials.

Binder and associates manipulated difficulty so as to affect both accuracy and RT in a phonetic discrimination task [54]. As task difficulty decreased, accuracy increased

sigmoidally from chance performance to nearly perfect with easy trials. In contrast, RT was biphasic, with shorter RTs for very easy items and very hard items, and longer RTs for items of intermediate difficulty. These authors found that BOLD activity in regions just adjacent to primary auditory cortex correlated with accuracy, whereas BOLD activity in the anterior insula and the inferior frontal gyrus positively correlated with RT. These data were interpreted to support a sensory processing role (auditory identification) for the areas where BOLD signal correlated with accuracy and a decision-related role for areas where BOLD signal correlated with RT.

A related goal of some investigators has been to eliminate differences between trials in terms of stimulus evidence and thereby reduce the overall influence of either attention or task difficulty on the fluctuations in BOLD signal, which characterize decision-making regions. For instance, Thielscher and Pessoa [55] asked study participants to decide whether a given face expressed fear or disgust. They focused their analysis on trials where there was no facial expression visible in the stimuli (i.e., neutral faces) and therefore no trial-to-trial difference in the amount of sensory evidence [55]. Similar to Binder and colleagues [54], they postulated that decision-related regions should show a positive correlation between RT and fMRI signal amplitude. They too found that BOLD activity was positively correlated with RT in the inferior frontal gyrus/anterior insula, as well as in the anterior cingulate cortex (ACC).

A related strategy was adopted by Grinband and associates [56] who manipulated perceptual uncertainty independently of stimulus evidence. They asked individuals to classify a line segment as being either long or short, based on a learned, abstract categorical boundary. They reported regions in a fronto-striatal-thalamic network, including a large region of the medial frontal gyrus, whose activity increased with perceptual uncertainty independent of stimulus evidence, and suggested that these regions may be involved in comparing a stimulus to a categorical boundary.

All of the studies cited here [54–56] as well as [8] have associated the medial frontal gyrus and the inferior frontal gyrus/anterior insula with perceptual decision-making, based on the finding of a greater response during difficult than easy trials. Heekeren et al. have found a similar response pattern in these regions [5,6]. However, they have suggested that their role in perceptual decision making is to bring to bear additional attentional resources to maintain accuracy in decision making when the task becomes more difficult. Their interpretation is congruent with the attentional control module illustrated in Fig. 8.1A. Recent studies by Philiastides and colleagues [10,14] may provide a resolution for these different conceptualizations (see following).

The role of the motor system

Neurophysiological studies in monkeys as well as modeling studies suggest that the brain regions involved in selecting and planning a certain action play an important role in forming decisions that lead to that action. To test whether this result also holds for the human brain, Heekeren et al. [57] asked human observers to make direction-of-motion judgments about dynamic random-dot motion stimuli and to indicate their judgment with an eye movement to one of two visual targets. In each individual, the authors localized regions that are part of the oculomotor network, namely, the FEF and an eye-movement related region in the IPS, presumably corresponding to area LIP of monkeys [58]. Importantly, during the period of decision formation, between the onset of visual motion and the cue to respond, the percent BOLD change in both the FEF and IPS was highly correlated with the strength of the motion signal in the stimuli [57]. These data

are thus consistent with the single-unit studies in monkeys reporting that FEF and LIP participate in the process of forming a perceptual decision.

The results are also similar to a study of oculomotor decision making by Heinen and colleagues [59] who had participants play "ocular baseball" while undergoing fMRI. In this game, the subjects had to indicate whether they thought a dot moving across a computer screen would cross into a visible strike zone or not. Subjects scored a point when they correctly predicted a "strike," so that their eye movements pursued a dot that eventually crossed into the strike zone. Subjects also scored a point on trials when they correctly predicted a "ball" and withheld an eye movement (e.g., remained fixated) when the dot missed the strike zone. When the results of a task with identical motor behavior were compared to the "baseball" trials, decision-related signals were found in the superior parietal lobule, FEF, and ventrolateral prefrontal cortex. In line with the monkey data, these results suggest that, when a decision is associated with a specific movement, formation of the decision and preparation of the behavioral response share a common neural substrate. Put more generally, the findings support the view that the human motor system also plays an important role in perceptual decision making (cf. Green and Heekeren, forthcoming).

More recently, Heekeren et al. have investigated whether decisions may be transformed into motor actions in the human brain independent of motor planning and execution – that is, at an abstract level [6]. Individuals performed the direction-of-motion discrimination task and responded either with button presses or saccadic eye movements. Areas that represent decision variables at a more abstract level should show a greater response to high coherence (easy) relative to low coherence (difficult) trials, independent of the motor system that is used to express the decision. Heekeren and associates found four such areas: left posterior DLPFC, left posterior cingulate cortex, left IPS, and left fusiform/parahippocampal gyrus. Most important, the increase in BOLD activity in these regions was independent of the motor system the participants used to express their decision. The results from this fMRI study are in line with the finding by Kim and Shadlen in monkeys that neural activity increases proportionally to the strength of the motion signal in the stimulus [41]. However, the findings in humans suggest that the posterior DLPFC is an important component of a network that not only accumulates sensory evidence to compute a decision but also translates this evidence into an action independent of response modality.

Notably to date, neurophysiological studies in monkeys have not found neurons whose activity reflects decisions independently of response modality. In fact, one could conclude from the neurophysiological studies in monkeys that "to see and decide is, in effect, to plan a motor-response" [60]. In contrast, in humans, Heekeren et al. found regions of the cortex that responded independently of the motor effectors used [6]. Based on these findings, one could speculate that humans may have evolved a more abstract decision-making network, thereby allowing a more flexible link between decision and action.

Performance and error monitoring

Neuroimaging studies have corroborated neurophysiological findings in monkeys in showing that the posterior medial prefrontal cortex (also referred to as ACC), plays an important role in performance monitoring, error monitoring, and signaling the need for adjustments of behavior [12,61] (see also [62]). An intriguing possibility is that these monitoring systems may selectively adjust the sensitivity in sensory brain regions rather than changing decision criteria. Evidence for this comes from a recent fMRI study, which showed that monitoring mechanisms enhance performance by transiently amplifying cortical responses to task-relevant information. In that study, Egner and Hirsch monitored fMRI activity in the FFA while participants performed a task in which face information

was sometimes relevant and sometimes irrelevant [63]. Brain activity during trials that followed incongruent trials (where the face information was a possible confound with the non-face information) was compared with activity during trials that followed congruent trials. Egner and Hirsch found that the BOLD-response in the FFA was significantly increased by task relevance. This study also showed that amplification of FFA activity was mediated by the DLPFC, as the level of interaction between DLPFC and FFA was greater during the high FFA activity trials immediately following incongruent trials. Thus, this study shows how the performance-monitoring system and the system that represents sensory evidence interact during perceptual decision making as highlighted in Fig. 8.1A.

8.3.2 EEG/MEG studies on perceptual decision making

Even though fMRI provides millimeter spatial resolution, due to slow scanning rates and the low-pass nature of the BOLD response, its temporal resolution is rather limited. To overcome this limitation advanced methods that use EEG and MEG measurements have been developed to study the temporal characteristics of perceptual decision making in humans.

Single-trial EEG reveals temporal characteristics of decision making

Traditionally, the analysis of EEG has relied on averaging event-locked data across hundreds of trials as well as across subjects, to uncover the neural signatures of the neurocognitive process under investigation. The underlying assumption of this approach is that trial averaging increases signal-to-noise ratio (SNR) by minimizing the background EEG activity relative to the neural activity correlated with experimental events. While this assumption is generally valid, it also carries a major detriment; it conceals inter-trial and inter-subject response variability which may carry important information regarding the underlying neural processes. In contrast, single-trial methods usually exploit the large number of sensor arrays by spatially integrating information across the scalp to identify EEG components that optimally discriminate between experimental conditions. Spatial integration enhances the signal quality without loss of temporal precision common to trial averaging. The resulting discriminating components describe the spatial extent but, more important, the temporal evolution of the underlying cortical activity.

Methods that have been used for such analysis include independent component analysis (ICA) [64–66], common spatial patterns (CSP) [67,68], support vector machines (SVM) [69,70], and linear discrimination (LD) based on logistic regression [71,72]. LD in particular can be used to compute a set of spatial weights, which maximally discriminate between experimental conditions over several different temporal windows, thus allowing the monitoring of the temporal evolution of discriminating activity. Unlike CSP, which tries to identify orientations in sensor space that maximize power, LD tries to maximize discrimination between two classes. Also unlike ICA, which is designed to minimize the correlation between spatial components (i.e., make spatial components as independent as possible [73]), LD is used to identify components that maximize the correlation with relevant experimental events. All of these techniques linearly transform the original EEG signal via the following transformation:

$$\mathbf{Y} = \mathbf{W}\mathbf{X}, \tag{8.1}$$

where $\mathbf{X}$ is the original data matrix, $\mathbf{W}$ is the transformation matrix (or vector) calculated using the different techniques, and $\mathbf{Y}$ is the resulting source matrix (or vector). Figure 8.3 illustrates how the technique can be used for a binary discrimination.

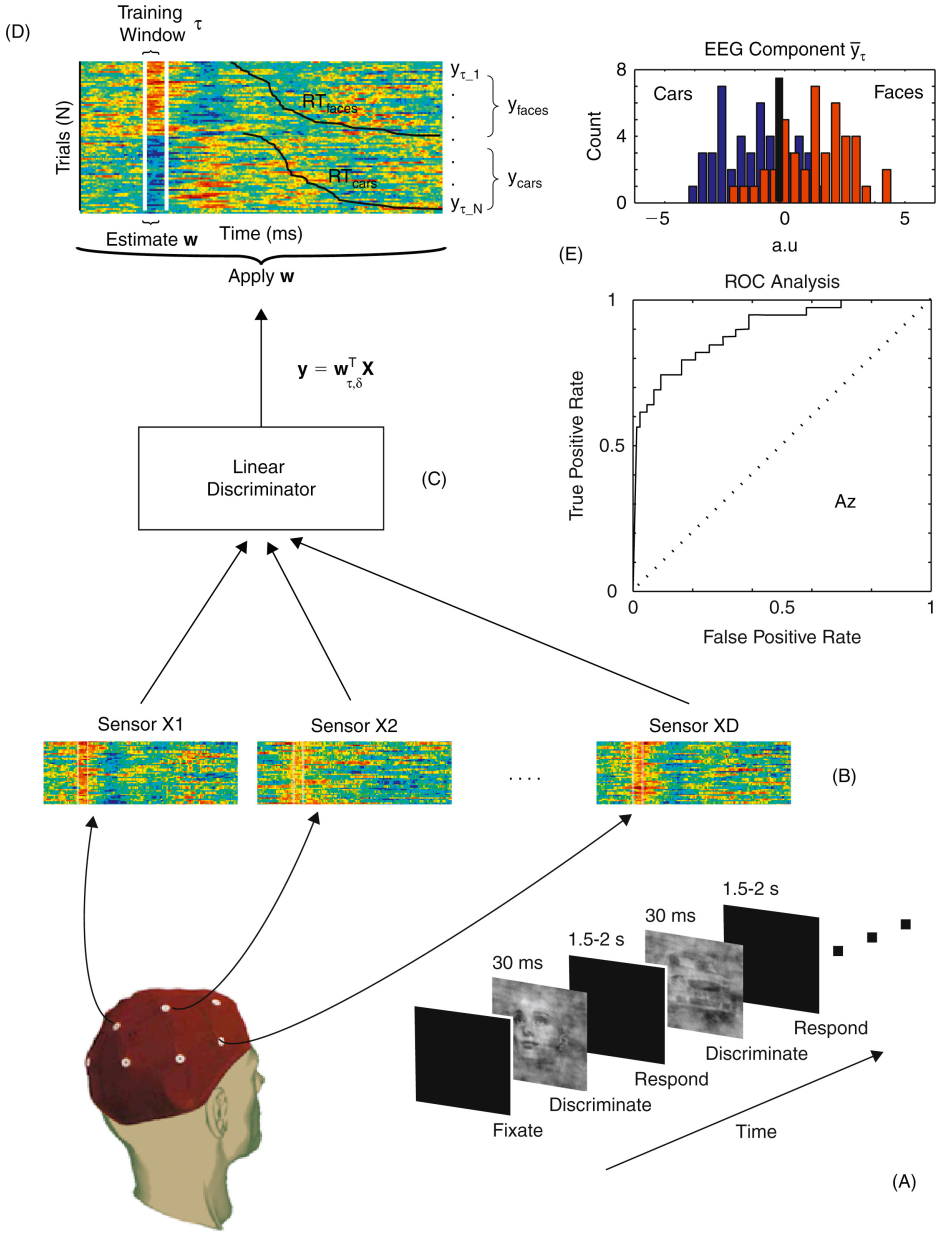

Figure 8.3 Summary of the single-trial EEG linear discrimination approach. (A) Subjects are discriminating between two classes of images while EEG is simultaneously recorded from D sensors. (B) EEG trials are locked to stimulus onset and a time window is defined with a latency, τ, relative to the stimulus and a width, δ (typically 50 ms wide). (C) EEG data from each sensor ($\mathbf{X}_1 \rightarrow_D$) and each window are used to train a linear classifier (i.e., estimate spatial filters $\mathbf{w}_{\tau,\delta}$), to discriminate labeled trials (here, faces versus cars). (D) The linear classifier, through application of $\mathbf{w}_{\tau,\delta}$ on the

One of the first studies to use single-trial analysis of the EEG to explore the temporal characteristics of perceptual decision making in humans and to precisely quantify the relationship between neural activity and behavioral output was that of Philiastides et al. [9]. Motivated from the early work of Newsome and colleagues in primates [15,18], these authors reported the first non-invasive neural measurements of perceptual decision making in humans, which lead to neurometric functions predictive of psychophysical performance on a face versus car categorization task (Fig. 8.3A).

Similar to Heekeren and colleagues [5], Philiastides et al. manipulated the difficulty of the task by changing the spatial phase coherence of the stimuli in a range that spanned psychophysical threshold. Carrying out the LD approach (as outlined in Fig. 8.3) at different time windows and coherence levels revealed two EEG components that discriminated maximally between faces and cars as seen in Fig. 8.4A for one subject.

The early component was consistent with the well-known face-selective N170 [74–78] and its temporal onset appeared to be unaffected by task difficulty. The late component, appeared on average around 300 ms post-stimulus at the easiest condition, and it systematically shifted later in time and became more persistent as a function of task difficulty. Both of these components were sensitive to decision accuracy in that a high positive and a high negative discriminator output value ($\bar{\mathbf{y}}_{\tau\_i}$, see Fig. 8.3B–D for details) indicated an easy face and car trial, respectively, whereas values near zero indicated more difficult decisions.

To directly compare the neuronal performance at these two times to the psychophysical sensitivity as captured by each subject's psychometric function, the authors constructed neurometric functions for each of the two components. Analogous to Britten et al. [15], receiver operating characteristic (ROC) analysis was used to quantify the discriminator's performance at each coherence level. The neurometric functions were then obtained by plotting the area under each of the ROC curves (i.e. A_z values, see Fig. 8.3E) against the corresponding coherence level. Neurometric functions from the late component were a better match to the psychophysical data than those from the early component (Fig. 8.4B). A third neurometric function, which was obtained by training a linear discriminator while integrating data across both time windows, was found to be an excellent predictor of overall behavioral performance. Finally, choice probability analysis [18] revealed that the late component also predicted the subjects' actual choices more reliably than the early one, indicating that this component reflects the content of the final decision.

Figure 8.3 (*Continued*)

D sensors, collapses the *D*–dimensional EEG space into a 1–dimensional discriminating component space **y**. Compared to individual sensors this 1–dimensional projection is considered a better estimator of the underlying neural activity, as it usually carries a higher SNR and reduces interference from other sources. To visualize the profile of the discriminating component across trials (indexed by $i = 1 \rightarrow N$), the classifier, trained only on EEG within each of the selected windows, is applied across all time points to construct the component map seen here. Trials of class 1 (i.e., faces) are mapped to positive **y**–values (red), whereas those of class 2 (i.e., cars) to negative ones (blue). In this example the sigmoidal curves represent the subject's reaction time profile for each of the two image classes. (E) The discriminating components are validated using a ROC analysis based on a leave-one-out procedure. Specifically, left-out single-trial discriminating components, averaged within the training window (i.e., $\bar{\mathbf{y}}_{\tau\_i}$), are used to generate discriminator output distributions for each of the two classes. The area under the ROC curve, also known as an A_z value, is used to quantify the degree of separation between the two distributions and can be used to establish a relationship between behavioral and neuronal responses as in [15,144]. See Plate 8 of Color Plate section.

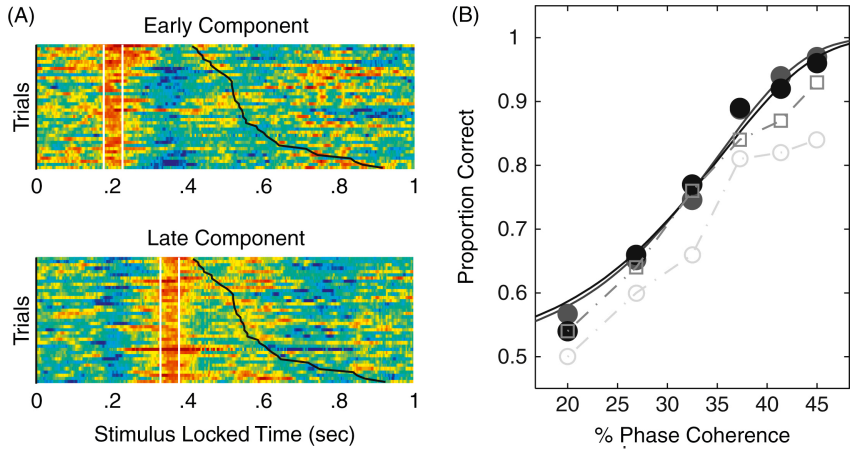

Figure 8.4 Single-trial EEG components correlate with decision accuracy on a face versus car discrimination task. (A) Discriminant component maps for the early (≈170 ms) and late (≈300 ms) decision accuracy components identified by [9]. All trials are aligned to the onset of visual stimulation (time 0 ms) and sorted by RT (black sigmoidal curves). Unlike the discriminant component maps in Fig. 8.3 only half the trials are represented here. Specifically, each row of these maps represents the output of the linear discriminator for a single face trial with the mean of all car trials subtracted (i.e., $\mathbf{y}_{\text{face}\_i} - \overline{\mathbf{y}}_{\text{cars}}$). (B) Comparison of one subject's psychometric function (gray solid line) with neurometric functions obtained from the early component (light-gray dotted line), the late component (dark-gray dotted line), and a combination of the two (black solid line). Note that integrating data across both time windows helped produce a neurometric function that was statistically indistinguishable from its corresponding psychometric curve. In addition, the neurometric function from the late component alone was a better match to the psychophysical data than that of the early one. See Plate 9 of Color Plate section.

Situated somewhere between the early and late components, around 220 ms post-stimulus, there was yet a third component the strength of which systematically increased with increasing task demands. This decision difficulty component was a good predictor of the onset time of the late decision accuracy component. Philiastides and colleagues speculated that this component reflects a top-down influence of attention on decision making rather than a mere bottom-up processing of the stimulus evidence. To substantiate this claim they used a variant of the original behavioral paradigm where the same stimuli were colored red or green, and the subjects were either cued to perform a color discrimination or the original face categorization task [10]. While leaving the stimulus evidence unchanged, they compared the amplitude of the difficulty component during a challenging face discrimination with that of a trivial color discrimination. They found that the difficulty component was significantly reduced when the subjects were merely discriminating the color of the stimulus. As the images were identical in the two tasks, these results ruled out the possibility that this component simply reflects the early processing of the stimulus.

Additionally, this new version of the experiment has produced further evidence on the role of the early and late components. The authors found that the early component remained unaffected by task demands, in that for the color discrimination the response of this component to face versus car stimuli was unchanged. In contrast, the response of the

late component was largely eliminated when subjects were making a color decision. Finally, the response of the late component was correlated with mean drift rate in a diffusion model simulation [10, 144]. This was the first study to link human brain signals with parameters of the diffusion model, suggesting that the late EEG component reflects the post-sensory evidence that is fed into the diffusion process, which ultimately determines the decision.

These results taken together suggest that the different EEG components can be thought of as representing distinct cognitive events during perceptual decision making. Specifically, the early component appears to reflect the stimulus quality independent of the task (face/car or color discrimination) and is likely to provide the early sensory evidence, consistent with the first processing stage in the four-compartment model of perceptual decision making presented in Fig. 8.1.A. In contrast, the late component better represents information in the actual face/car decision process as it was shown to be a good predictor of overall behavioral performance during face categorization (Fig. 8.4B) while its responses to the color discrimination were virtually diminished. Consistent with a top-down attentional control system (Fig. 8.1.A, the difficulty component appears to be implicated in the recruitment of the relevant attentional and other neuronal resources required to make a difficult decision. It further predicts the onset time of the late component, which is consistent with the idea that as the brain is engaging additional resources a delay in the next processing module (e.g., late component) is observed.

The role of synchronized activity in perceptual decision making

EEG and MEG signals are thought to arise primarily from oscillatory components in the brain [79]. This oscillatory activity often exhibits power changes in response to different experimental events. Moreover, these changes are not necessarily phase-locked to the events that caused them and they would therefore tend to cancel out in the average evoked potentials [80]. Time-frequency decomposition of EEG/MEG data has recently gained much popularity as it can ultimately capture these changes when applied on single-trial data prior to averaging.

A time-frequency representation (TFR) describes the variation of the spectral energy of the signal over time and is a valuable tool for interpreting non-stationary signals. There are many approaches to obtain a TFR, however for the analysis of neural data the two most commonly used methods are wavelets [81] and multitapers [82,83]. Wavelet decomposition involves convolving the data with a basis function (usually a Morlet wavelet). Wavelets have a length that scales inversely with frequency such that the time-frequency product remains unchanged. This means that for higher frequencies the temporal resolution increases in the expense of frequency resolution (i.e., time-frequency resolution trade-off). In contrast, multitapers are based on a windowed Fourier transform where a set of Slepian windows or discrete prolate spheroidal sequences (DPSS) are chosen so that power bleeding into neighboring frequencies is minimized. Unlike wavelets the temporal and frequency specificity of multitapers does not scale with frequency. Wavelets can be quite sensitive to low-amplitude signals, whereas multitapers have a high degree of frequency specificity and are better suited for detecting high-amplitude transients [84].

A recent MEG study using time-frequency analysis techniques based on multitapers [85] has shown that during the same motion discrimination task used in monkey experiments neural activity in the high gamma range, namely 60–100 Hz, was monotonically increasing with respect to the strength (i.e., coherence) of the visual motion. The analysis was restricted to the early stages of visual presentation to ensure that only those regions

involved in encoding the intensity of the physical stimulus were represented. Using "beam forming" source reconstruction techniques [86,87], the authors were able to attribute the strongest gamma-band modulation to several motion-responsive regions in occipitoparietal and occipitotemporal cortex. Of particular interest was the prevalence of such modulation in area V5/MT + , which is thought to represent the human-homologue of monkey MT. These findings are seminal in that they begin to bridge the gap between monkey electrophysiology and human neuroimaging. They also provide support that motion-selective regions, such as MT + , represent the sensory evidence (Fig. 8.1A) upon which human observers base their decisions regarding direction discrimination.

In a separate study, Donner et al. [11] have also used multitaper-based TFR of MEG data to explore the neural correlates of perceptual decision making in humans. They used a visual motion detection task where subjects reported whether a small amount of coherent motion was present or not (yes/no paradigm) in a conventional random-dot kinetogram. The TFR approach revealed an induced steady-state response, reflective of non-phase locked fluctuations of ongoing oscillatory activity, in response to the stimulus. This activity was sustained for the entire period that the dynamic random dot patterns remained on the screen.

The authors then tested whether this activity covaried with behavioral performance. They found MEG activity in the beta band (12–24 Hz) to be larger before correct than error trials. Similar to [9,18] they used signal detection theory, namely ROC analysis (on correct versus error choices), to quantify the association between neural data and behavioral choices. They showed that data from the 12–24 Hz range could predict behavioral choices on a single-trial basis. A closer look at the time course of this beta band activity revealed a gradual build-up in the difference signal between correct and error choices consistent with accumulator models [29,38]. Finally, activity in this frequency band was also shown to reflect the accuracy of the decision, rather than the content (i.e., yes or no), by virtue of the fact that it was higher before "correct rejects" than before "false alarms" in the physical absence of the motion target. Taken together, these results clearly implicate the source of this oscillatory activity in the actual decision-making process (Fig. 1A). A source reconstruction based on "beam formers" [86,87] identified the posterior IPS (pIPS) and DLPFC as potential sources.

The findings from the fMRI, EEG, and MEG studies presented in this section provide converging insights into the neural basis of perceptual decision making in humans as outlined in the model of Fig. 8.1A. At the same time they emphasize the importance of combining these imaging modalities to infer the spatiotemporal profile of the interactions between the different processing modules of this model. In the next section we present a new approach on how to best integrate single-trial EEG with fMRI to decipher the spatiotemporal characteristics of perceptual decision making.

8.4 Spatiotemporal characterization of decision making by integrating EEG with fMRI

Simultaneous EEG/fMRI measurements can potentially enable the fusion of EEG and fMRI in a manner that circumvents the disparate space and time scales on which the two datasets are acquired. Animal experiments have already demonstrated that hemodynamic signals are more closely coupled to synaptic than spiking activity and that changes in the fMRI BOLD signal can correlate tightly with synchronized oscillatory activity recorded from local field potentials (LFPs) [88–91]. Under these premises, it is reasonable to

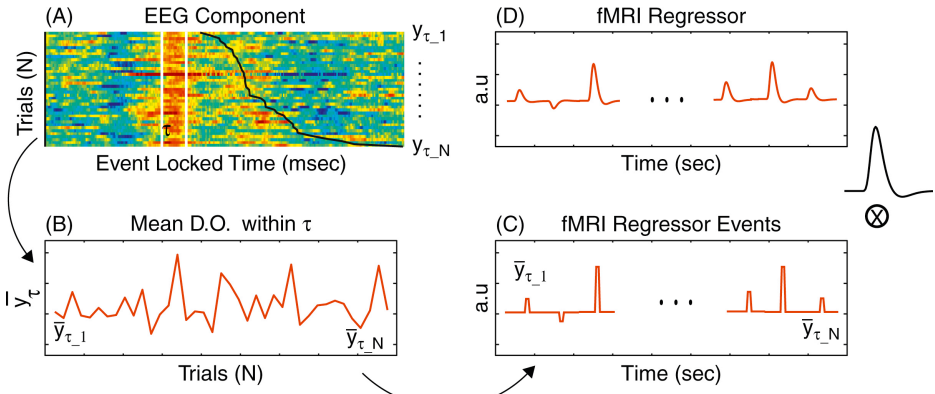

Figure 8.5 Graphical representation of how single-trial EEG can be used to construct fMRI regressors. The discriminator output (DO) can be used to derive as many fMRI regressors as there are temporally distinct EEG components. The onset time and duration of each of the regressor events are determined by the onset time (τ) and duration (δ) of the EEG components as identified by the single-trial EEG analysis (as in Fig. 8.3). More important, the amplitude of each regressor event will be based on the output of the linear discriminator $\mathbf{y}_\tau$ as defined in Eq. 8.2. See Plate 10 of Color Plate section.

assume that neural activity reflected in the EEG could also correlate well with the underlying BOLD hemodynamic response. In that case, constructing EEG-derived fMRI regressors based on pre-defined, highly discriminating EEG components could yield the desired high spatiotemporal information needed to describe the neural correlates of perceptual decision making, as well as other neurocognitive processes, non-invasively in humans.

One way to construct EEG-derived fMRI activation maps that will depend on task and subject specific electrophysiological source variability is to take advantage of the single-trial discrimination approach described earlier. Specifically, the discriminator output for each trial can be used as the basis for parametrically modulating the amplitude of the different fMRI regressor events. Figure 8.5 outlines the main steps involved in this process.

Single-trial discrimination of the EEG is initially performed to identify components of interest (Fig. 8.5A). Assuming the discriminator is trained with T samples within each window (τ) of interest, the output $\mathbf{y}_\tau$ has dimensions $T \times N$, where N is the total number of trials. To achieve more robust single-trial estimates for $\mathbf{y}_\tau$, averaging across all training samples is performed:

$$\bar{\mathbf{y}}_{\tau\_i} = \frac{1}{T}\sum_{j=1}^{T}\mathbf{y}_{\tau\_ij}, \tag{8.2}$$

where i is used to index trials and j training samples. This is shown graphically in Fig. 8.5B. $\bar{\mathbf{y}}_\tau$ is then used to modulate the amplitude of the different fMRI regressor events (Fig. 8.5C). Finally, the parametric regressor is convolved with a prototypical hemodynamic response function (Fig. 8.5D), which is used to model the fMRI data in the context of a general linear model (GLM). This process can be repeated for multiple windows/components (τ's), each resulting in a separate regressor. Identifying the brain regions that

correlate with each of these regressors will enable a comprehensive characterization of the cortical network involved in the neurocognitive process under investigation.

In the absence of simultaneous EEG/fMRI measurements, however, one could still combine knowledge acquired from the single-trial EEG analysis with fMRI to achieve both high temporal and high spatial resolution information on decision making. Assuming multiple EEG components are identified *a priori* as part of a continuum of cognitive stages involved in decision making, an EEG-informed fMRI study can potentially reveal the cortical regions involved in each stage. In this case, an important requirement is that the different EEG components respond uniquely to different experimental manipulations/conditions so that the EEG-derived regressors are independent. After all this is a requirement that every sensible fMRI experimental design should satisfy. Then averaging the discriminator output associated with each component and each experimental condition across trials can be used to modulate the amplitude of the different regressor events:

$$\bar{y}_{\tau}^{c} = \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{j=1}^{T}\mathbf{y}_{\tau\_ij}^{c}, \tag{8.3}$$

where c is used to index the different experimental conditions. Also note that $\bar{y}_{\tau}^{c}$ is now a scalar – that is, all similar trials are modeled in the same way. Though the inter-trial variability will ultimately be concealed in this formulation, important information regarding the localization of each of the EEG components that would otherwise be unattainable using EEG or fMRI alone can now be achieved.

The experimental observations from the cued version of the behavioral task used in [10] were well suited for this approach. The strength of the early component was proportional to stimulus evidence and it remained unchanged between the face/car and color discriminations. The late component also responded as a function of stimulus evidence during face categorization but it was stronger across all difficulty levels relative to the early one. It was, however, virtually eliminated during the color discrimination. Unlike the early and late components, the strength of the difficulty component was proportional to the difficulty of the task. The authors repeated the same paradigm during fMRI and used their earlier EEG results to inform the analysis of the functional data. Specifically, they introduced three parametric regressors (one for each of their early, difficulty, and late components) and they used Eq. 8.3 to estimate the relative strengths of each of their components with respect to the difficulty (i.e., low [L] versus high [H] coherence) and the type of task (i.e., face versus car [FC] or red versus green [RG]) to modulate the heights of the corresponding regressor events (i.e., $\bar{y}_{\tau}^{\mathrm{FC,L}}$, $\bar{y}_{\tau}^{\mathrm{FC,H}}$, $\bar{y}_{\tau}^{\mathrm{RG,L}}$, $\bar{y}_{\tau}^{\mathrm{RG,H}}$,$\tau = \{\text{early, difficulty, late}\}$).

For the early component, they reported significant activations in areas implicated in early visual processing of objects/faces. In particular, they found bilateral activations in an area around the fusiform gyrus (FG), activations in superior temporal gyrus/sulcus (STG/STS) as well as significant activations in the cuneus (CU). In addition, an independent localizer scan was used to identify the FFA. A region of interest (ROI) analysis revealed that the signal change in this area was predominantly explained by the early component. Both the FFA and STS have previously been implicated in early visual processing of faces using neuroimaging [48,92–94] and field potentials recorded directly from the cortical surface [95–97]. The CU was also shown to be critical in early visual processing [98,99], including evidence from studies on visual extinction and spatial neglect of faces [100]. These results verify the hypothesized role of the early component

in processing the incoming sensory evidence, consistent with the initial processing module of the four-compartment model introduced in this chapter.

For the difficulty component, a number of brain regions that are typically associated with the human attentional network were activated, providing support for the attentional control system shown in Fig. 8.1A. These included the supplementary and frontal eye fields (SEF/FEF), the ACC, the DLPFC, as well as the anterior insula (INS). Attention-related fluctuations were previously found in oculomotor structures such as the SEF and FEF [101–103] while microstimulation experiments in primates have revealed causal links between these areas and regions involved in early visual processing [104,105]. Though these findings have yet to be demonstrated in humans, they suggest that there might exist reciprocal interactions between the attention-related system and the early sensory evidence module, as shown in Fig. 8.1A.

The ACC has previously been shown to participate in conflict monitoring and error detection and to signal the need for greater cognitive adjustments [106–109], suggesting an active role of a performance monitoring system in decision making as highlighted in Fig. 8.1A. The DLPFC was also shown to exert attentional control by representing and maintaining the attentional demands of a task [107,110]. DLPFC was also implicated in directing efficient [111,112] and successful [113,114] working memory encoding and maintenance. The anterior INS on the other hand, is likely to participate in the integration of multimodal information as evident by its widespread projections to and from both the frontal and parietal cortices [115–117]. Taken together, these observations substantiate the authors' earlier claim regarding the presence of an attentional control system that exerts top-down influence on decision making.

Finally, activations correlating with the late component were found in the lateral occipital complex (LOC) and in the right ventrolateral prefrontal cortex (rVLPFC). Aside from its involvement in object categorization [118–122], the LOC has been implicated in "perceptual persistence" [123,124], a process in which a percept assembled by lower visual areas is allowed to remain in the visual system as a form of iconic memory [125,126]. A possible mechanism of this "persistence" involves feedback pathways in the ventral stream, which allow a visual representation to reverberate via "local" loops [125–127]. The brief stimulus durations used in these experiments suggest that perceptual persistence is a likely mechanism by which rapid object decision making is instigated. That is, for brief presentations the accumulation of evidence is not based on the decaying stimulus traces themselves but rather on a durable representation of the stimulus retained in short-term memory. This interpretation explains why the late component was a better predictor of overall behavioral performance than the early one, why it correlated with mean drift rate in a diffusion model simulation, and why it disappeared when a demanding face versus car discrimination was no longer required (e.g., during color discrimination).

The other activation that correlated with the late component was in the rVLPFC. Current evidence implicates VLPFC in decision-making tasks that involve uncertainty or risk [128]. Moreover, activity in VLPFC appears to subserve the active maintenance and retrieval of information held in short-term memory to facilitate executive processes such as active selection, comparison, and judgment of stimuli [129–131]. Hence, the pattern of activity in VLPFC appears to be in line with the perceptual persistence interpretation, also seen in LOC, as a means of driving the final decision-making stages. Figure 8.6 summarizes these findings in a form of a spatiotemporal diagram.

Note the striking similarities between this diagram and the theoretical model for perceptual decision making introduced in Fig. 8.1A, which suggest that the EEG-informed

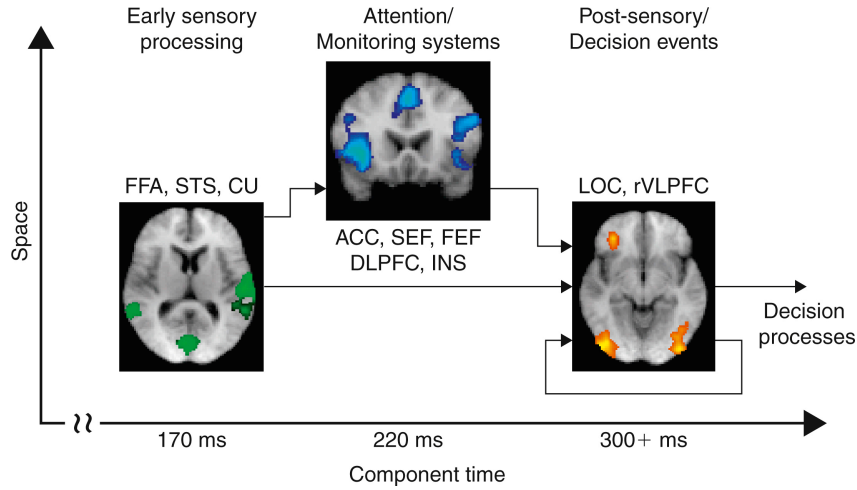

Figure 8.6 Spatiotemporal diagram of perceptual decision making during a face versus car discrimination task [14]. Using an EEG-informed fMRI analysis, Philiastides and associates identified the cortical regions correlating with each of their EEG temporally specific components, and in doing so, they demonstrated that a cascade of events associated with perceptual decision making, which included early sensory processing (early component), task difficulty and attention (difficulty component), and post-sensory/decision-related events (late component), takes place in a highly distributed neural network. The interactions between the different compartments are in part based on their experimental observations and in part based on anatomical and functional connectivity evidence from the literature. The similarities between this spatiotemporal diagram and the model introduced in Fig. 8.1.A suggest that the EEG-informed fMRI approach can enable the recovery of the spatiotemporal characteristics of different neurocognitive processes in the human brain.

fMRI approach is a promising new tool in mapping out the spatiotemporal characteristics of different neurocognitive processes in the human brain.

8.5 From perceptual to reward-based decision making

In this chapter we presented recent findings from fMRI, EEG, and MEG studies on perceptual decision making in humans. We also presented a method for integrating EEG with fMRI and we demonstrated its efficacy in achieving high spatiotemporal characterization of perceptual decision making. We now briefly present new research directions that look at other factors thought to influence perceptual decision making, such as neuromodulation, reward, and prior probability that can benefit from this new technique.

8.5.1 Neuromodulation of perceptual decision making

Although diffusion models of perceptual decision making postulate noise as a fundamental aspect of signal processing the neurobiological sources of noise and their contribution to cortical dynamics remain elusive. Patient studies, neurocognitive aging research,

and genomic imaging studies indicate that the neurotransmitter dopamine (DA) modulates noise in information processing [132–136]. It will thus be important to investigate how dopaminergic neuromodulation affects perceptual decision making. The *COMT* gene for example regulates DA levels in the prefrontal cortex by affecting DA catabolism, which in turn might have an effect on the neuronal SNR in the different decision-making processing modules. Investigating how individual differences in DA-related genes modulate neural information processing will further our understanding of the neural correlates of perceptual decision making in humans.

8.5.2 Modulation of perceptual decision making by reward information

Reward-based decision making in humans, especially in the context of reinforcement learning and reward-related activity in dopaminergic systems [62,137–140], has already been studied, mostly using fMRI. Surprisingly, however, little research has been done to explore the potential effects of reward on perceptual decision making, whether on sensory function or motor planning and action selection. One hypothesis is that in situations where rewarding outcomes depend on decisions associated with different perceptual tasks, reward signals are propagated back to sensory systems, in the form of a "teaching signal," where they can shape early sensory representations to optimize reward outcome.

To date the only study that addressed this issue is by Pleger et al. [141]. They used a tactile discrimination task, in which subjects had to discriminate the relative frequency of two successive somatosensory stimuli applied to the same finger, while manipulating the reward rate received at the end of each trial. Not only did higher rewards improve behavioral performance but they also led to increased BOLD responses in the ventral striatum, a key component of the human reward system. More important, however, these authors demonstrated that during reward delivery and in the absence of somatosensory stimulation, the S1 controlateral to the judged finger was re-activated and this re-activation was proportional to the amount of reward. Finally, they showed that reward magnitude on a particular trial influenced responses on the subsequent trial, with better behavioral performance and greater controlateral S1 BOLD responses for higher rewards.

These results clearly demonstrate that the systems involved in valuation interact with early sensory systems; however, it still remains elusive how these interactions are mediated. It also remains unclear whether reward signals also interact with other modules of the four compartment model presented in Fig. 8.1A. Designing new paradigms that can benefit from the EEG-informed fMRI approach presented in this review can help provide answers to these questions.

8.5.3 Valuation-based/reward-based decision making

Often when we make decisions, the benefit of an option needs to be weighed against accompanying costs. So far, little is known about how the brain does this [142]. Notably, the only available theoretical models to date come from the literature on perceptual decision making, which has modeled binary perceptual choices as a race-to-barrier diffusion process (as reviewed in this chapter). It is, however, unclear whether this class of model also applies to value-based decision making.

References

[1] J. Gold, M. Shadlen, The neural basis of decision making, Annu. Rev. Neurosci. 30 (2007) 535–574.
[2] A. Tversky, D. Kahneman, The framing of decisions and the psychology of choice, Science 211 (1981) 453–458.
[3] I. Opris, C. Bruce, Neural circuitry of judgment and decision mechanisms, Brain Res. Rev. 48 (2005) 509–526.
[4] H. Heekeren, S. Marrett, L. Ungerleider, The neural systems that mediate human perceptual decision making, Nat. Rev. Neurosci. 9 (2008) 467–479.
[5] H. Heekeren, S. Marrett, P. Bandettini, L. Ungerleider, A general mechanism for perceptual decision-making in the human brain, Nature 431 (2004) 859–862.
[6] H. Heekeren, S. Marrett, D. Ruff, P. Bandettini, L. Ungerleider, Involvement of human left dorsolateral prefrontal cortex in perceptual decision making is independent of response modality, Proc. Natl. Acad. Sci. USA 103 (2006) 10023–10028.
[7] B. Pleger, C. Ruff, F. Blankenburg, S. Bestmann, K. Wiech, K. Stephan, A. Capilla, K. Friston, R. Dolan, Neural coding of tactile decisions in the human prefrontal cortex, J. Neurosci. 26 (2006) 12596–12601.
[8] E. Ploran, S. Nelson, K. Velanova, D. Donaldson, S. Petersen, M. Wheeler, Evidence accumulation and the moment of recognition: dissociating perceptual recognition processes using fMRI, J. Neurosci. 27 (2007) 11912–11924.
[9] M. Philiastides, P. Sajda, Temporal characterization of the neural correlates of perceptual decision making in the human brain, Cereb. Cortex 16 (2006) 509–518.
[10] M. Philiastides, R. Ratcliff, P. Sajda, Neural representation of task difficulty and decision-making during perceptual categorization: a timing diagram, J. Neurosci. 26 (2006) 8965–8975.
[11] T. Donner, M. Siegel, R. Oostenveld, P. Fries, M. Bauer, A. Engel, Population activity in the human dorsal pathway predicts the accuracy of visual motion detection, J. Neurophysiol. 98 (2007) 345–359.
[12] S. Debener, M. Ullsperger, M. Siegel, K. Fiehler, D. von Cramon, A. Engel, Trial-by-trial coupling of concurrent electroencephalogram and functional magnetic resonance imaging identifies the dynamics of performance monitoring, J. Neurosci. 25 (2005) 11730–11737.
[13] S. Debener, M. Ullsperger, M. Siegel, A. Engel, Single-trial EEG-fMRI reveals the dynamics of cognitive function, Trends Cogn. Sci. 10 (2006) 558–563.
[14] M. Philiastides, P. Sajda, EEG-informed fMRI reveals spatiotemporal characteristics of perceptual decision making, J. Neurosci. 27 (2007) 13082–13091.
[15] K. Britten, M. Shadlen, W. Newsome, J. Movshon, The analysis of visual motion: a comparison of neuronal and psychophysical performance, J. Neurosci. 12 (1992) 4745–4765.
[16] K. Britten, M. Shadlen, W. Newsome, J. Movshon, Responses of neurons in macaque MT to stochastic motion signals, Vis. Neurosci. 10 (1993) 4745–4765.
[17] M. Shadlen, W. Newsome, Motion perception: seeing and deciding, Proc. Natl. Acad. Sci. USA 93 (1996) 628–633.
[18] K. Britten, W. Newsome, M. Shadlen, S. Celebrini, J. Movshon, A relationship between behavioral choice and visual responses of neurons in macaque MT, Vis. Neurosci. 14 (1996) 87–100.
[19] C. Salzman, K. Britten, W. Newsome, Cortical microstimulation influences perceptual judgements of motion direction, Nature 346 (1990) 174–177.
[20] C. Salzman, C. Murasugi, K. Britten, W. Newsome, Microstimulation in visual area mt: effects on direction discrimination performance, J. Neurosci. 12 (1992) 2331–2355.

[21] J. Ditterich, M. Mazurek, M. Shadlen, Microstimulation of visual cortex affects the speed of perceptual decisions, Nat. Neurosci. 6 (2003) 891–898.
[22] C. Keysers, D.-K. Xiao, P. Foldiak, D. Perrett, The speed of sight, J. Cogn. Neurosci. 13 (2001) 90–101.
[23] S. Afraz, R. Kiani, H. Esteky, Microstimulation of inferotemporal cortex influences face categorization, Nature 442 (2006) 692–695.
[24] E. Salinas, A. Hernandez, A. Zainos, R. Romo, Periodicity and firing rate as candidate neural codes for the frequency of vibrotactile stimuli., J. Neurosci. 20 (2000) 5503–5515.
[25] R. Romo, A. Hernandez, A. Zainos, E. Salinas, Somatosensory discrimination based on cortical microstimulation, Nature 392 (1998) 387–390.
[26] R. Romo, A. Hernandez, A. Zainos, C. Brody, L. Lemus, Sensing without touching: psychophysical perfrormance based on cortical microstimulation, Neuron 26 (2000) 273–278.
[27] R. Ratcliff, A theory of memory retrieval, Psychol. Rev. 85 (1978) 59–108.
[28] R. Ratcliff, F. Tuerlinckx, Estimating parameters of the diffusion model: approaches to dealing with contaminant reaction times and parameters variability, Psychon. Bull. Rev. 9 (2002) 438–481.
[29] M. Mazurek, J. Roitman, J. Ditterich, M. Shadlen, A role for neural integrators in perceptual decision making, Cereb. Cortex 13 (2003) 1257–1269.
[30] R. Bogacz, Optimal decision making theories: linking neurobiology with behaviour, Trends Cogn. Sci. 11 (2007) 118–125.
[31] S. Grossberg, P. Pilly, Temporal dynamics of decision-making during motion perception in the visual cortex, Vision Res. 48 (2008) 1345–1373.
[32] J. Schall, Neural basis of saccade target selection, Rev. Neurosci. 6 (1995) 63–85.
[33] C. Colby, J. Duhamel, M. Goldberg, Visual, presaccadic, and cognitive activation of single neurons in monkey lateral intraparietal area, J. Neurophysiol. 76 (1996) 2841–2852.
[34] M. Shadlen, W. Newsome, Neural basis of perceptual decision making in the parietal cortex (area LIP) of the rhesus monkey, J. Neurophysiol. 86 (2001) 1916–1936.
[35] J. Roitman, M. Shadlen, Response of neurons in the lateral intraparietal area during a combined visual discrimination reaction time task, J. Neurosci. 22 (2002) 9475–9489.
[36] A. Huk, M. Shadlen, Neural activity in the macaque parietal cortex reflects temporal integration of visual motion signals during perceptual decision making, J. Neurosci. 25 (2005) 10420–10436.
[37] T. Hanks, J. Ditterich, M. Shadlen, Microstimulation of macaque area lip affects decision-making in a motion discrimination task, Nat. Neurosci. 9 (2006) 682–689.
[38] J. Gold, M. Shadlen, Neural computations that underlie decisions about sensory stimuli, Trends Cogn. Sci. 5 (2001) 10–16.
[39] T. Yang, M. Shadlen, Probabilistic reasoning by neurons, Nature 447 (2007) 1075–1080.
[40] A. Churchland, R. Kiani, M. Shadlen, Decision-making with multiple alternatives, Nat. Neurosci. 11 (2008) 693–702.
[41] J. Kim, M. Shadlen, Neural correlates of decision making in the dorsolateral prefrontal cortex of the macaque, Nat. Neurosci. 2 (1999) 176–185.
[42] R. Romo, C. Brody, A. Hernandez, L. Lemus, Neuronal correlates of parametric working memory in prefrontal cortex, Nature 399 (1999) 470–473.
[43] R. Romo, A. Hernandez, A. Zainos, L. Lemus, C. Brody, Neuronal correlates of decision-making in secondary somatosensory cortex, Nat. Neurosci. 5 (2002) 1217–1224.
[44] R. Romo, A. Hernandez, A. Zainos, Neuronal correlates of decisionmaking in ventral premotor cortex, Neuron 41 (2004) 165–173.
[45] A. Hernandez, A. Zainos, R. Romo, Temporal evolution of a decision-making process in medial premotor cortex, Neuron 33 (2002) 959–972.

[46] C. Brody, A. Hernandez, A. Zainos, R. Romo, Timing and neural encoding of somatosensory parametric working memory in macaque prefrontal cortex, Cereb. Cortex 13 (2003) 1196–1207.
[47] J. Haxby, The functional organization of human extrastriate cortex: a PET-rCBF study of selective attention to faces and locations, J. Neurosci. 14 (1994) 6336–6353.
[48] N. Kanwisher, J. McDermott, M. Chun, The fusiform face area: a module in human extrastriate cortex specialized for face perception, J. Neurosci. 17 (1997) 4302–4311.
[49] G. McCarthy, A. Puce, J. Gore, T. Allison, Face-specific processing in the human fusiform gyrus, J. Cogn. Neurosci. 9 (1997) 605–611.
[50] R. Epstein, N. Kanwisher, A cortical representation of the local visual environment, Nature 392 (1998) 598–601.
[51] A. Ishai, L. Ungerleider, A. Martin, J. Schouten, J. Haxby, Distributed representation of objects in the human ventral visual pathway, Proc. Natl. Acad. Sci. USA 96 (1999) 9379–9384.
[52] C. Preuschhof, H. Heekeren, B. Taskin, T. Schubert, A. Villringer, Neural correlates of vibrotactile working memory in the human brain, J. Neurosci. 26 (2006) 13231–13239.
[53] M. Tegenthoff, P. Ragert, B. Pleger, P. Schwenkreis, A. Forster, V. Nicolas, H. Dinse, Improvement of tactile discrimination performance and enlargement of cortical somatosensory maps after 5 Hz rTMS, PLoS Biol. 3 (2005) 2031–2040.
[54] J. Binder, E. Liebenthal, E. Possing, D. Medler, B. Ward, Neural correlates of sensory and decision processes in auditory object identification, Nat. Neurosci. 7 (2004) 295–301.
[55] A. Thielscher, L. Pessoa, Neural correlates of perceptual choice and decision making during fear-disgust discrimination, J. Neurosci. 27 (2007) 2908–2917.
[56] J. Grinband, J. Hirsch, V.P. Ferrera, A neural representation of categorization uncertainty in the human brain, Neuron 49 (2006) 757–763.
[57] H. Heekeren, S. Marrett, P. Bandettini, L. Ungerleider, Human fMRI evidence for representation of a perceptual decision in oculomotor areas, in: Society for Neuroscience, 35th Annual Meeting Abst. 228.8, 2005.
[58] M. Sereno, S. Pitzalis, A. Martinez, Mapping of controlateral space in retinotopic coordinates by a parietal cortical area in humans, Science 294 (2001) 1350–1354.
[59] S. Heinen, J. Rowland, B. Lee, A. Wade, An oculomotor decision process revealed by functional magnetic resonance imaging, J. Neurosci. 26 (2006) 13515–13522.
[60] A. Rorie, W. Newsome, A general mechanism for perceptual decision-making in the human brain?, Trends Cogn. Sci. 9 (2005) 41–43.
[61] K. Ridderinkhof, M. Ullsperger, E. Crone, S. Nieuwenhuis, The role of the medial frontal cortex in cognitive control, Science 306 (2004) 443–447.
[62] M. Rushworth, T. Behrens, Choice, uncertainty and value in prefrontal and cingulate cortex, Nat. Neurosci. 11 (2008) 389–397.
[63] T. Egner, J. Hirsch, Cognitive control mechanisms resolve conflict through cortical amplification of task-relevant information, Nat. Neurosci. 8 (2005) 1784–1790.
[64] S. Makeig, M. Westrfield, T. Jung, S. Enghoff, J. Townsend, E. Courchesne, T. Sejnowski, Dynamic brain sources of visual evoked responses, Science 295 (2002) 690–694.
[65] T. Jung, S. Makeig, M. McKeown, A. Bell, T. Lee, T. Sejnowski, Imaging brain dynamics using independent component analysis, Proc. IEEE. 89 (2001) 1107–1122.
[66] J. Onton, M. Westerfield, J. Townsend, S. Makeig, Imaging human EEG dynamics using independent component analysis, Neurosci. Biobehav. Rev. 30 (2006) 802–822.
[67] C. Guger, H. Ramoser, G. Pfurtscheller, Real-time EEG analysis with subject-specific spatial patterns for a brain computer interface BCI, IEEE. Trans. Rehabil. Eng. 8 (2000) 441–446.
[68] H. Ramoser, J.M.-G.G. Pfurtscheller, Optimal spatial filtering of single trial EEG during imagined hand movement, IEEE. Trans. Rehabil. Eng. 8 (2000) 441–446.

[69] T. Lal, M. Schroder, T. Hinterberger, J. Weston, M. Bogdan, N. Birbaumer, B. Scholkopf, Support vector channel selection in BCI, IEEE. Trans. Biomed. Eng. 51 (2004) 1003–1010.
[70] M. Thulasidas, C. Guan, J. Wu, Robust classification of EEG signals for brain-computer interface, IEEE. Trans. Neural Syst. Rehabil. Eng. 14 (2006) 24–29.
[71] L. Parra, C. Alvino, A. Tang, B. Pearlmutter, N. Young, A. Osman, P. Sajda, Linear spatial integration for single-trial detection in encephalography, Neuroimage 17 (2002) 223–230.
[72] L. Parra, C. Spence, A. Gerson, P. Sajda, Recipes for the linear analysis of EEG, Neuroimage 28 (2005) 326–341.
[73] A. Hyvarinen, J. Karhunen, E. Oja, Independent Component Analysis, John Wiley and Sons, New York, 2001.
[74] D. Jeffreys, Evoked studies of face and object processing, Vis. Cogn. 3 (1996) 1–38.
[75] S. Bentin, T. Allison, A. Puce, A. Perez, G. McCarthy, Electrophysiological studies of face perception in humans, J. Cogn. Neurosci. 8 (1996) 551–565.
[76] E. Halgren, T. Raij, K. Marinkovic, V. Jousmaki, R. Hari, Cognitive response profile of the human fusiform face area as determined by MEG, Cereb. Cortex 10 (2000) 69–81.
[77] J. Liu, M. Higuchi, A. Marantz, N. Kanwisher, The selectivity of the occipitotemporal M170 for faces, Neuroreport 11 (2000) 337–341.
[78] B. Rossion, C. Joyce, G. Cottrell, M. Tarr, Early laterization and orientation tuning for face, word, and object processing in the visual cortex, Neuroimage 20 (2003) 1609–1624.
[79] P. Nunez, R. Srinivasan, Electric Fields of the Brain: The Neurophysics of EEG, Oxford University Press, New York, 2005.
[80] C. Tallon-Baudry, O. Bertrand, Oscillatory gamma activity in humans and its role in object representation, Trends Cogn. Sci. 3 (1999) 151–162.
[81] S. Schiff, A. Aldroubi, M. Unser, S. Sato, Fast wavelet transformation of eeg, Electroencephalogr. Clin. Neurophysiol. 91 (1994) 442–455.
[82] D. Thomson, Spectrum estimation and harmonic analysis, Proc. IEEE. 70 (1982) 1055–1096.
[83] P. Mitra, B. Pesaran, Analysis of dynamic brain imaging data, Biophys. J. 76 (1999) 691–708.
[84] M. van Vugt, P. Sederberg, M. Kahana, Comparison of spectral analysis methods for characterizing brain oscillations, J. Neurosci. Methods 162 (2007) 49–63.
[85] M. Siegel, T. Donner, R. Oostenveld, P. Fries, A. Engel, High-frequency activity in human visual cortex is modulated by visual motion strength, Cereb. Cortex 17 (2007) 732–741.
[86] B. Van Veen, W. van Drongelen, M. Yuchtman, A. Suzuki, Localization of brain electrical activity via linearly constrained minimum variance spatial filtering, IEEE. Trans. Biomed. Eng. 44 (1997) 867–880.
[87] J. Gross, J. Kujala, M. Hamalainen, L. Timmermann, A. Schnitzler, R. Salmelin, Dynamic imaging of coherent sources: studying neural interactions in the human brain, Proc. Natl. Acad. Sci. USA 98 (2001) 694–699.
[88] N. Logothetis, J. Pauls, M.A. Augath, T. Trinath and A. Oeltermann, Neurophysiological investigation of the basis of the fMRI signal, Nature 412 (2001) 150–157.
[89] N. Logothetis, What we can do and what we cannot do with fMRI, Nature 453 (2008) 869–878.
[90] J. Niessing, B. Ebisch, K. Schmidt, M. Niessing, W. Singer, R. Galuske, Hemodynamic signals correlate tightly with synchronized gamma oscillations, Science 309 (2005) 948–951.
[91] A. Viswanathan, R. Freeman, Neurometabolic coupling in cerebral cortex reflects synaptic more than spiking activity. neurometabolic coupling in cerebral cortex reflects synaptic more than spiking activity, Nat. Neurosci. 10 (2007) 1308–1312.
[92] A. Puce, T. Allison, S. Bentin, J. Gore, G. McCarthy, Temporal cortex activation in humans viewing eye and mouth movements, J. Neurosci. 18 (1998) 2188–2199.

[93] J. Haxby, E. Hoffman, M. Gobbini, The distributed human neural system for face perception, Trends Cogn. Sci. 4 (2000) 223–233.
[94] E. Hoffman, J. Haxby, Distinct representation of eye gaze and identity in the distributed human neural system for face perception, Nat. Neurosci. 3 (2000) 80–84.
[95] T. Allison, A. Puce, D. Spencer, G. McCarthy, Electrophysiological studies of human face perception: potentials generated in occipitotemporal cortex by face and nonface stimuli, Cereb. Cortex 9 (1999) 415–430.
[96] A. Puce, T. Allison, G. McCarthy, Electrophysiological studies of human face perception. III. effects of top-down processing on face-specific potentials, Cereb. Cortex 9 (1999) 445–458.
[97] A. Puce, T. Allison, G. McCarthy, Electrophysiological studies of human face perception. II. response properties of face specific potentials generated in occipitotemporal cortex, Cereb. Cortex 9 (1999) 431–444.
[98] J. Cohen, W. Peristein, T. Braver, L. Nystrom, D. Noll, J. Jonides, E. Smith, Temporal dynamics of brain activation during working memory task, Nature 386 (1997) 604–608.
[99] G. Ganis, W. Thompson, S. Kosslyn, Brain areas underlying visual mental imagery and visual perception: an fMRI study, Brain Res. Cogn. Brain Res. 20 (2004) 226–241.
[100] P. Vuilleumier, N. Sagiv, E. Hazeltine, R. Poldrack, D. Swick, R.D. Rafal, J. Gabrieli, Neural fate of seen and unseen faces in visuospatial neglect: a combined event-related functional MRI and event-related potential study, Proc. Natl. Acad. Sci. USA 98 (2001) 3495–3500.
[101] M. Corbetta, E. Akbudak, T. Conturo, A. Snyder, J. Ollinger, H. Drury, M. Linenweber, S. Petersen, M. Raichle, S. Petersen, M. Raichle, D. Essen, G. Shulman, A common network of functional areas for attention and eye movements, Neuron 21 (1998) 761–773.
[102] J. Schall, V. Stuphorn, J. Brown, Monitoring and control of action by the frontal lobes, Neuron 36 (2002) 309–322.
[103] T. Kelley, J. Serences, B. Giesbrecht, S. Yantis, Cortical mechanisms for shifting and holding visuospatial attention, Cereb. Cortex 18 (2008) 114–125.
[104] T. Moore, K. Armstrong, M. Fallah, Visuomotor origins of covert spatial attention, Neuron 40 (2003) 671–683.
[105] T. Moore, K. Armstrong, Selective gating of visual signals by microstimulation of frontal cortex, Nature 421 (2003) 370–373.
[106] C. Carter, T. Braver, D. Barch, M. Botvinick, D. Noll, J. Cohen, Anterior cingulate cortex, error detection, and the online monitoring of performance, Science 280 (1998) 747–749.
[107] A. MacDonald III, J. Cohen, V. Stenger, C. Carter, Dissociating the role of the dorsolateral prefrontal and anterior cingulate cortex in cognitive control, Science 288 (2000) 1835–1838.
[108] J. Kerns, J. Cohen, A. MacDonald, R. Cho, V. Stenger, C. Carter, Anterior cingulate conflict monitoring and adjustments in control, Science 303 (2004) 1023–1026.
[109] J. Brown, T. Braver, Learned predictions of error likelihood in the anterior cingulate cortex, Science 307 (2005) 1118–1121.
[110] M. Milham, M. Banich, A. Webb, V. Barad, N. Cohen, T. Wszalek, A. Kramer, The relative involvement of anterior cingulate and prefrontal cortex in attentional control depends on nature conflict, Cogn. Brain Res. 12 (2001) 467–473.
[111] D. Bor, J. Duncan, R. Wiseman, A. Owen, Encoding strategies dissociate prefrontal activity from working memory demand, Neuron 37 (2003) 361–367.
[112] P. Olesen, H. Westerberg, T. Klingberg, Increased prefrontal and parietal activity after training of working memory, Nat. Neurosci. 7 (2004) 75–79.
[113] L. Pessoa, E. Gutierrez, P. Bandettini, L. Ungerleider, Neural correlates of visual working memory: fMRI amplitude predicts task performance, Neuron 35 (2002) 975–987.
[114] K. Sakai, J. Rowe, R. Passingham, Active maintenance in prefrontal area 46 creates distractor-resistant memory, Nat. Neurosci. 5 (2002) 479–484.

[115] M. Mesulam, E. Mufson, Insula of the old world monkey. II: afferent cortical output and comments on function, J. Comp. Neurol. 212 (1982) 23–37.
[116] M. Mesulam, E. Mufson, Insula of the old world monkey. II: efferent cortical output and comments on function, J. Comp. Neurol. 212 (1982) 38–52.
[117] L. Selemon, P. Goldman-Rakic, Common cortical and subcortical targets of the dorsolateral prefrontal and posterior parietal cortices in the rhesus monkey: evidence for a distributed neural network subserving spatially guided behavior, J. Neurosci. 8 (1988) 4049–4068.
[118] T. James, G. Humphrey, J. Gati, R. Menon, M. Goodale, The effects of visual object priming on brain activation before and after recognition, Curr. Biol. 10 (2000) 1017–1024.
[119] T. James, G. Humphrey, J. Gati, R. Menon, M. Goodale, Differential effects of viewpoint on object-driven activation in dorsal and ventral streams, Neuron 35 (2002) 793–801.
[120] K. Grill-Spector, T. Kushnir, T. Hendler, R. Malach, The dynamics of object-selective activation correlate with recognition performance in humans, Nat. Neurosci. 3 (2000) 837–843.
[121] K. Grill-Spector, Z. Kourtzi, N. Kanwisher, The lateral occipital complex and its role in object recognition, Vision Res. 41 (2001) 1409–1422.
[122] K. Grill-Spector, N. Knouf, N. Kanwisher, The fusiform face area subserves face perception, not generic within-category identification, Nat. Neurosci. 7 (2004) 555–562.
[123] S. Ferber, G. Humphrey, T. Vilis, The lateral occipital complex subserves the perceptual persistence of motion-defined groupings, Cereb. Cortex 35 (2002) 793–801.
[124] M. Large, A. Aldcroft, T. Vilis, Perceptual continuity and the emergence of perceptual persistence in the ventral visual pathway, J. Neurophysiol. 93 (2005) 3453–3462.
[125] V.D. Lollo, Temporal characteristics of iconic memory, Nature 267 (1977) 241–243.
[126] M. Coltheart, The persistences of vision, Philos. Trans. R. Soc. Lond. B Biol. Sci. 290 (1980) 57–69.
[127] R. VanRullen, C. Koch, Visual selective behavior can be triggered by a feed-forward process, J. Cogn. Neurosci. 15 (2003) 209–217.
[128] S. McClure, D. Laibson, G. Loewenstein, J. Cohen, Separate neural systems value immediate and delayed monetary rewards, Science 306 (2004) 503–507.
[129] M. Petrides, The mid-ventrolateral prefrontal cortex and active mnemonic retrieval, Neurobiol. Learn. Mem. 78 (2002) 528–538.
[130] S. Prince, S. Daselaar, R. Cabeza, Neural correlates of relational memory: successful encoding and retrieval of semantic and perceptual associations, J. Neurosci. 25 (2005) 1203–1210.
[131] T. Hanakawa, M. Honda, G. Zito, M. Dimyan, M. Hallett, Brain activity during visuomotor behavior triggered by arbitrary and spatial constrained cues: an fMRI study in humans, Exp. Brain Res. 172 (2006) 275–282.
[132] G. Winterer, D. Weinberger, Genes, dopamine and cortical signal-to-noise ratio in schizophrenia, Trend Neurosci. 27 (2004) 683–690.
[133] G. Winterer, F. Musso, G. Vucurevic, P. Stoeter, A. Konrad, B. Seker, J. Gallinat, Dahmen, D. Weinberger, COMT genotype predicts BOLD signal and noise characteristics in prefrontal circuits, Neuroimage 32 (2006) 1722–1732.
[134] A. Meyer-Lindenberg, D. Weinberger, Intermediate phenotypes and genetic mechanisms of psychiatric disorders, Nat. Rev. Neurosci. 7 (2006) 818–827.
[135] T. Lotta, J. Vidgren, C. Tilgmann, I. Ulmanen, K. Melen, I. Julkunen, J. Taskinen, Kinetics of human soluble and membrane-bound catechol omethyltransferase: a revised mechanism and description of the thermolabile variant of the enzyme, Biochemistry 34 (1995) 4202–4210.
[136] S. MacDonald, L. Nyberg, L. Backman, Intra-individual variability in behavior: links to brain structure, neurotransmission and neuronal activity, Trend Neurosci. 29 (2006) 474–480.
[137] J. O'Doherty, Reward representations and reward-related learning in the human brain: insights from human neuroimaging, Curr. Opin. Neurobiol. 14 (2004) 769–776.

[138] J. O'Doherty, A. Hampton, H. Kim, Model-based fMRI and its application to reward learning and decision making, Ann. NY Acad. Sci. 1104 (2007) 35–53.
[139] N. Daw, J. O'Doherty, P. Dayan, B. Seymour, R. Dolan, Cortical substrates for exploratory decisions in humans, Nature 441 (2006) 876–879.
[140] P. Montague, B. King-Casas, J. Cohen, Imaging valuation models in human choice, Annu. Rev. Neurosci. 29 (2006) 417–448.
[141] B. Pleger, F. Blankenburg, C. Ruff, J. Driver, R. Dolan, Reward facilitates tactile judgments and modulates hemodynamic responses in human primary somatosensory cortex, J. Neurosci. 28 (2008) 8161–8168.
[142] A. Rangel, C. Camerer, P. Montague, A framework for studying the neurobiology of value-based decision making, Nat. Rev. Neurosci. (2008) 545–556.
[143] D. Green, J. Swets, Signal Detection Theory and Psychophysics, John Wiley & Sons, New York, 1966.
[144] R. Ratcliff, M.G. Philiastides and P. Sajda, Quality of evidence for perceptual decision making is indexed by trial-to-trial variability of the EEG, Proceedings of National Academy of Science (PNAS), 2009, doi:10.1073/pnas.0812580106.