Neurocognitive Approach to Research on the Effects of Workload

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Summary

The concept of workload describes the relationship between a human operator and the momentary task demands. Conventionally workload is defined as a subjective state of the operator that can be reported with use of psychometric scales. The effects of workload on performance and reaction times yield important “objective” sources of information. Signal detection theory provides us with a useful framework within which we can interpret the effects of workload on discriminability (d’) and measures of response bias (β, corresponding to the likelihood ratios of the noise and noise plus signal functions at the criterion). Modern brain imaging techniques can be employed to determine the effects of workload on task-related neural responses in specific regions of the human brain. We describe a neurocognitive approach to research on the effects of workload in simulated (laboratory) and real (field) experiments. The findings suggest that functional brain imaging can provide important new insights into the way operators perform in challenging tasks.

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Introduction

As part of the Festschrift in honour of Alf Zimmer, the present chapter reviews recent results on the effects of uncertainty and workload on human performance and brain activation arising in discrimination tasks between stimuli that only differ from each other. The operator (i.e., the participant in the experiment) has to decide whether a stimulus differs along the one or the other dimension (e.g., colour or shape), whether in a simulated driving scene or in real driving scenarios the car should be steered to the left or the right, or in a memory task whether the second of two sequentially presented gratings had a higher or lower relative spatial frequency compare to the first one. A common factor in all of these tasks is that the discriminations to be made are challenging and there is a correct and incorrect response in each trial. Thus we can combine the methods proposed by SDT to explore subjects' brain activity related to making decisions under uncertainty.

Signal Detection Theory (SDT) is a model of decision making under uncertainty. It has been most widely applied to the study of perceptual detection and discrimination tasks. However, it can usually be applied to any task that can be formulated as decision among two or more possible alternatives. Uncertainty arises because the information presented to the operator on each occasion is perturbed by random fluctuations, characterized in the model as noise. In the model, the operator knows the relative frequencies of the different possibilities and also the likelihood that the information presently at hand originated from each of the possibilities. Because of noise, the likelihood resulting from the occurrence of a given alternative varies from one presentation to another, and that alternative is represented in the decision process by the probability distribution of likelihood values given the alternative. The capacity of the observer to discriminate between two alternatives, called sensitivity in sensory studies, is determined by the degree to which the corresponding distributions are separated. When the distributions are assumed to be equal variance Gaussians, d' is widely used as the measure of separation and capacity to discriminate.

The decision of the operator on each occasion depends both on the likelihood values, on the one hand, and on considerations related to the relative frequencies of the alternatives and on the rewards and costs associated with the possible correct and incorrect decisions, on the other hand. In the model, these latter considerations are represented by a criterion to which the likelihoods are compared. When there are two alternatives, the criterion is often a critical ratio of the two likelihoods and is termed Beta, β.

SDT has multiple uses in the study of workload. It describes a number of performance measures and, given some widely used assumptions, the quantitative relationships among the measure. The latter facilitates comparison and integration of results obtained using different tasks and/or performance measures. The model and the measures distinguish between capacity *per se* and criterion effects, i.e. decision parameters that reflect judgments about the pay-off structure. The model provides a structure and concepts to construct an ideal operator, i.e. a worker that performs at the maximum level possible, given the situation. The ideal not only provides a standard against which the performance of real workers can be compared, but it also identifies various ways in which performance can be degraded, e.g. noise, performance limitations, etc. It also provides a framework for examining the effects of selective attention in optimizing performance under workload.

One application of SDT to the study of workload has been in tasks involving stimulus uncertainty. These are situations in which the decision requires monitoring multiple sources of information, each perturbed by independent noise. An example is the radiologist examining a chest X-ray for signs of a lesion, who must assess multiple locations in the image (Bochud, Abbey, and Eckstein, 2004). Or, in the laboratory, the observer must identify the change in the contrast or in the spatial frequency of a grating without knowing ahead of time which property will change. Performance decreases when uncertainty exists, the drop in performance increasing with the number of independent sources that must be monitored. In the grating example just given, judgments are less accurate when the observer does not know which property will change than when the observer does know, even though the observer can identify simultaneous, uncorrelated changes in both with the same accuracy as judging a change in just one property (Thomas and Olzak, 1996; Olzak and Wickens, 1997). The SDT explanation of these effects is that each additional source that must be monitored adds noise to the decision process. If, as in the stimulus uncertainty case, only one source adds information, the signal-to-noise ratio and, consequently, performance are reduced.

Cuing improves performance in stimulus uncertainty situations (Posner, 1980). Best performance occurs when the cue identifies the target input on every occasion, i.e. 100% validity. Lesser improvement occurs when the cue is less often valid, the degree of improvement increasing with increases in the frequency that the cue is valid. Models based on SDT have identified possible bases for such improvement, making them subject to experimental analysis (Dosher and Lu, 2000; Eckstein, Shimozaki, and Abbey, 2002).

Capacity, resources and the role of attention

Human cognition is thought to have a limited capacity to process incoming sensory signals (Broadbent, 1958; Kahneman, 1973; Wickens & Hollands, 2000). A limited capacity information-processing system implies that the total amount of information provided to the operator exceeds the information that can be processed at any point in time. In other words, the sensory information combined with prior knowledge is greater than the resources available to process this information. Thus human cognition needs to select between the inputs, depending on the task at hand. This selection process is referred to as attention. Several models of attention exist in the cognitive psychology literature, and these models differ based on their underlying assumptions (Broadbent, 1958; Deutsch, 1978; Treisman & Gelade, 1980). Attention can be defined by the process engaged (i.e., selective, focused or divided attention) or by the task at hand (i.e., visual search, inference, dual tasks; see Luck & Vecera, 2002).

Neurocognitive approaches to workload research

Imaging the effects of uncertainty

Objects in the real world can be defined along numerous physical dimensions. The images these objects generate on the retina can also be defined along an equally large number of dimensions, which are processed more or less separately by the visual system. In the human visual cortex, visual areas are specialized in the processing of specific aspects of visual information, like the colour (e.g., V4; Bartels & Zeki, 2000) or shape (e.g., lateral occipital complex; Malach, et al., 1995; Kourtzi & Kanwisher, 2000; Kourtzi & Kanwisher, 2001) of an object. From these areas, the information is processed to higher-order association cortices, where it is semantically encoded, for example by combination with knowledge about previous experiences. During each fixation period, visual information is encoded by the retina and this information exceeds that which can be processed extensively by the brain. In order to make a selection among these different sources of information, we rely on *attention* to direct our processing resources to behaviourally relevant features of visual scenes.

There is accumulating evidence in the brain-imaging literature that suggests that the exact pattern of cortical activation varies depending on which features subjects selectively attend to during a discrimination task. Where along the visual pathway does this stimulus selection occur? Underlying this question is the issue concerning the *locus* of attention, i.e. the stage of visual information processing modulated by stimulus selection. Two major theories related to this problem have evolved. The so-called *early selection* theory suggests that attentional selection acts at a relatively early stage of visual processing and is based on simple stimulus features (Broadbent, 1958, 1982; Kahneman & Treisman, 1984), whereas the *late selection* theory suggests that selection takes place between the semantic encoding stage and a further stage of visual information processing (Deutsch & Deutsch, 1963; Luck & Vercera, 2002). Behavioural and physiological studies related to this issue have produced conflicting results, some showing attentional modulations of neural activity either exclusively in extrastriate visual cortex (Luck & Girelli, 1998) or also in primary visual cortex (Luck & Vogel, 1997; Motter, 1993; Kanwisher & Wojciulik, 2000).

The simultaneous discrimination of stimuli that can differ along more than one dimension has been used in psychophysics to explore the independence of visual processing. When subjects simultaneously attend to different features of the same object, attention will guide visual processing of these different features.

Following up on the well-cited PET study (Corbetta, Miezin, Dobmeyer, Shulman, & Petersen, et al., 1990; 1991; Corbetta, Miezin, Dobmeyer, Shulman, & Petersen, 1991), in which subject attended to one of three stimulus dimensions, different patterns of brain activation were found depending on which dimension the subjects attended to. (Le, Pardo, & Hu, 1998) measured BOLD responses during sustained or alternately shifted selective attention to the colour or shape of foveally presented stimuli. They found evidence for feature-specific activations in occipital and temporal visual areas and greater activity in the posterior superior parietal lobule, cuneus, precuneus and different parts of the cerebellum during shifts of attention than during sustained attention. The use of large stimulus differences (red vs. green, circle vs. square) makes interpretation of the results difficult, since the stimulus differences alone could evoke different patterns of brain activity.

In the study by (Weerda, Vallines, Thomas, Rutschmann, & Greenlee, 2006), the effects of visual selective and divided attention on the discrimination of subtle differences in the colour and shape of ellipses were studied. In the selective attention or certainty condition, the subject knew which property would change on each trial and could selectively attend to that property. In the divided attention or uncertainty condition, the subject did not know which property would change on a given trial and had to attend to both properties. Resulting differences in performance were compared to the cortical activation patterns evoked by these tasks. By comparing the pattern of BOLD responses evoked during task with uncertainty versus tasks with certainty, we can identify brain regions selectively responsive to the stimulus uncertainty aspect of these tasks. With increasing uncertainty, workload increases and performance drops.

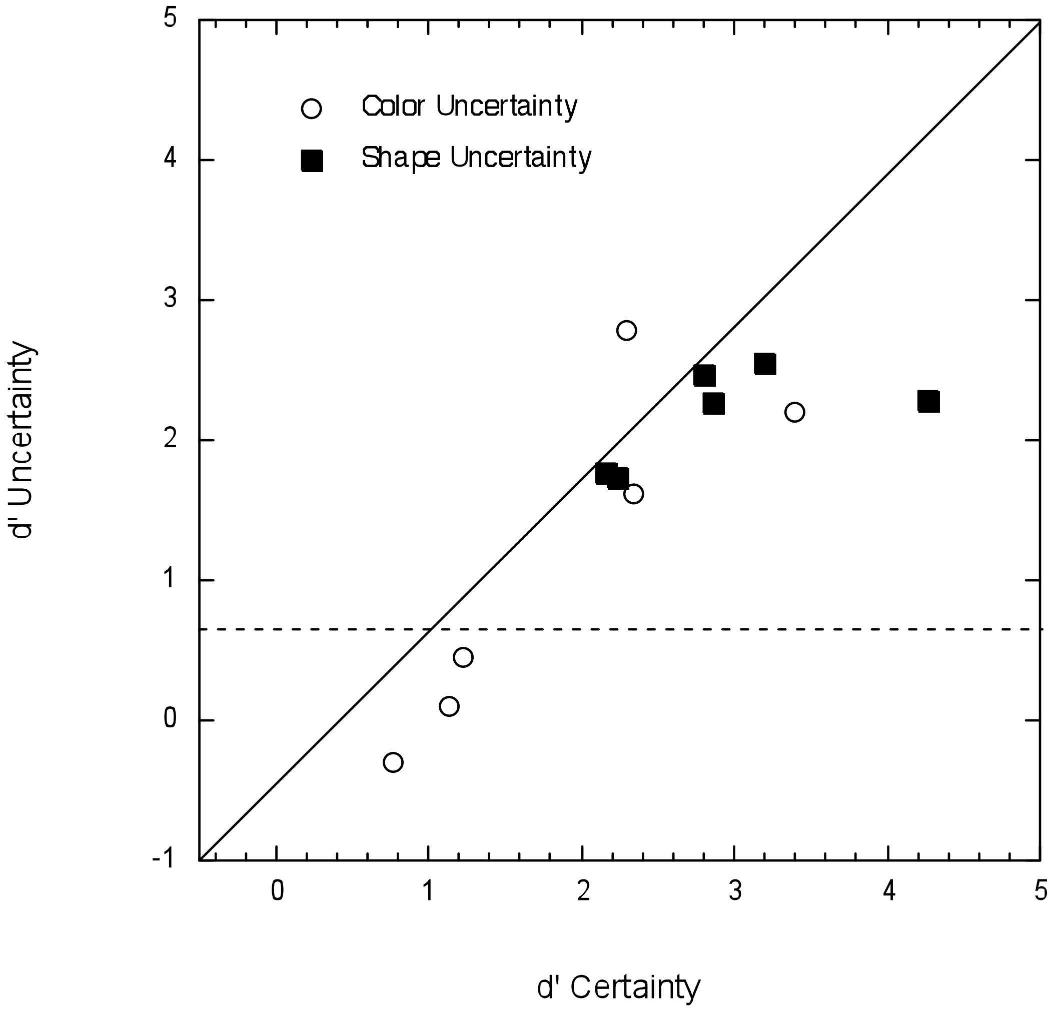


Figure 1: Sensitivity (d') for the different subjects (each data point corresponding to the mean performance level of one of n = 6 subjects) during the uncertainty condition plotted against those during the certainty conditions. The horizontal dashed line indicates the one-tailed confidence limit of chance performance. The diagonal line indicates the level of uniformity between the performance under the certainty and the uncertainty condition. Data points falling below the diagonal indicate that sensitivity declines on trials with uncertainty about the stimulus dimension that would differ. Note that the colour data from 3 subjects fall in the chance level, suggesting the subjects were unable to perform the colour discriminations in the uncertainty condition.

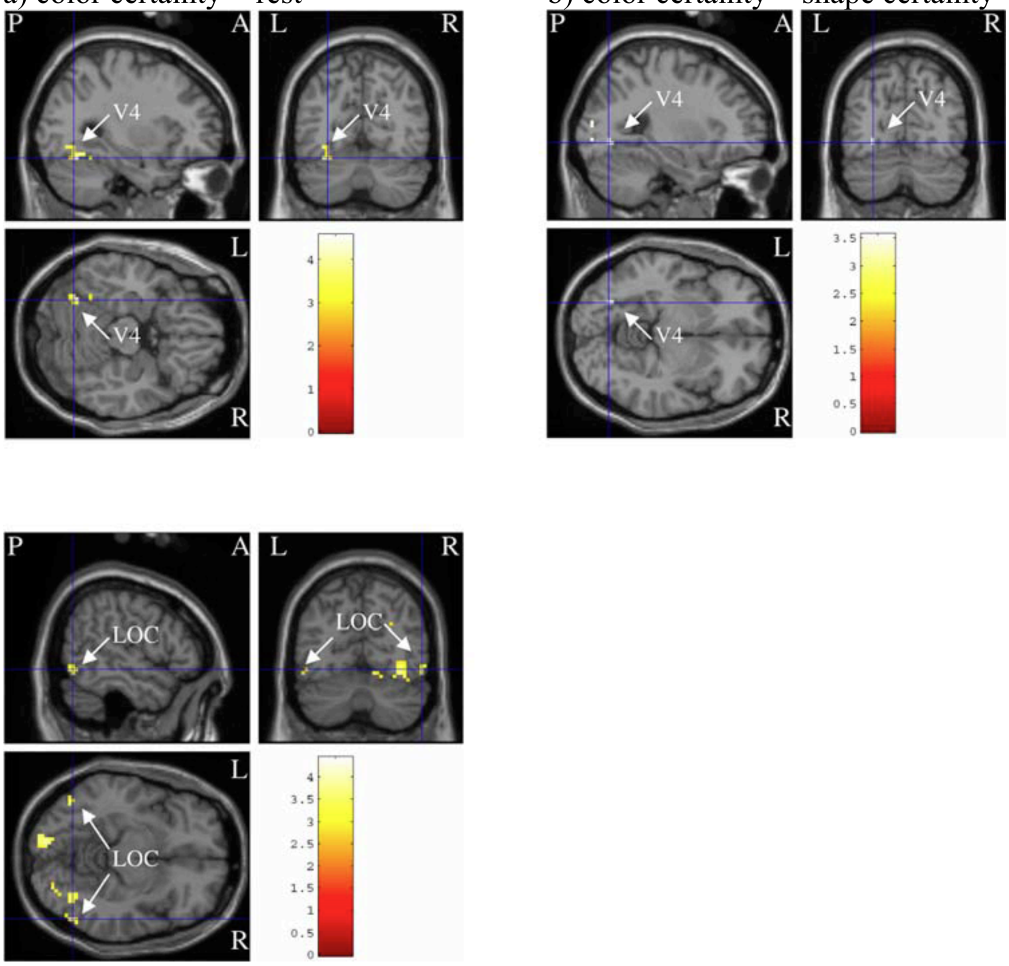
Figure 1 presents the performance on the trials where the subjects were uncertain along with dimension the stimuli would differ plotted against their performance when they knew in advance along which dimension the stimuli would differ. Performance in the uncertainty condition is reduced compared to that for the certainty condition in the same subjects. An analysis of variance (ANOVA) revealed a main effect of certainty-uncertainty ($p < 0.01$). Consistent with the accuracy results, reaction times were longer in the uncertainty than in the certainty conditions ($p = 0.03$). Although the stimulus differences to be discriminated were individually adjusted to make colour and shape discriminations equally accurate, the scores of three of the subjects are markedly lower on the colour task than their scores on the shape task. The lower performance occurs in both certainty and uncertainty conditions and, in the latter case, none of the proportion correct scores exceeds the 95% confidence limit for chance performance.

Functional Imaging Results

Weerda, et al. (2006) analyzed their fMRI data by contrasting the activation during the color and shape discrimination to baseline and to each other. Using a regions-of-interest approach, the authors compared activations when subjects had certainty that the stimuli would differ in color (compared to baseline resting levels; Fig. 2a). The ROI analysis revealed more pronounced activations in the ventral visual area V4 when the subjects attended to the color of the stimuli, whereas activation was more pronounced in the lateral occipital area (LOC) when subjects attended to the shape of the stimuli (Fig. 2c). The differential contrast between activations evoked by the color compared to the shape discriminations (Fig. 2b) indicated somewhat more activation in left V4 during the color task with stimulus certainty.

a) color certainty > rest

b) color certainty > shape certainty



c) shape certainty > rest

Fig. 2. Regions of interest (ROI) analysis of extrastriate visual areas. a) Area V4 in the contrast color-certainty > rest; b) Area V4 in the contrast color-certainty > shape-certainty; c) Area LOC in the contrast shape-certainty > rest. Sagittal, coronal and axial overlays of pooled functional data of all subjects and a normalized mean anatomical image. Colors code t-statistic. (After Weerda et al., 2006, with permission).

Effects of stimulus uncertainty

Analysis of the results with respect to the effects of uncertainty revealed robust activation in the posterior parietal cortex when the subjects were uncertain about the dimension along which the stimuli could differ (color or shape; Fig. 3). Increase brain activations were found bilaterally in the posterior parietal cortex (Fig. 3a) and in the left dorsolateral prefrontal cortex (Fig. 3b). This form of stimulus uncertainty challenges the subjects more by demanding that they attend simultaneously to both dimensions. Thus, the subjective workload of the subjects increased when stimulus uncertainty was increased. These results are based on observations made in 6 subjects and thus need to be confirmed in large subject samples. A recent study by (Serences, et al., 2009) suggest that similar differences are evident for orientation and colour judgments with sinewave gratings.

a) posterior parietal cortex b) prefrontal cortex

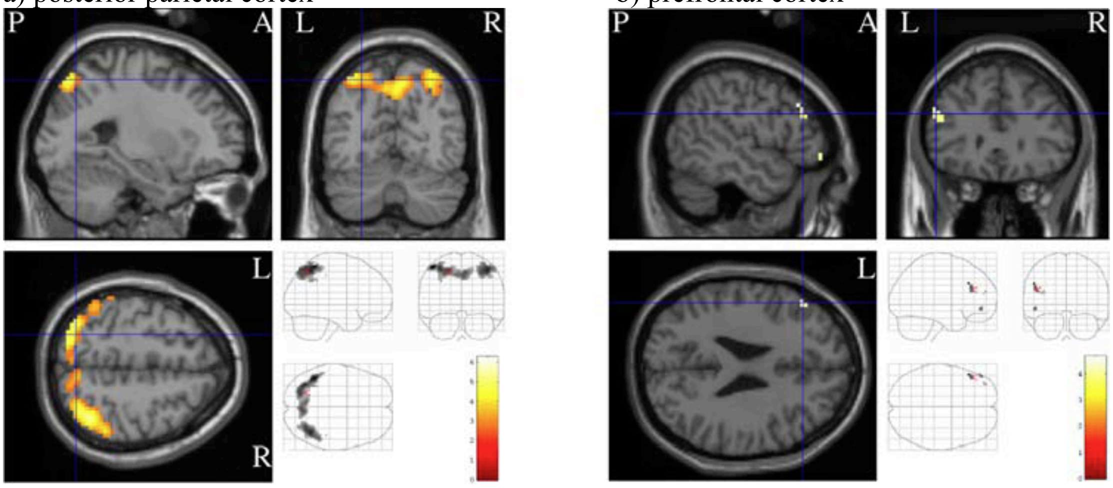


Fig. 3. ROI analysis of the contrast uncertainty > certainty: a) Posterior parietal BAs 7 and 40; b) Lateral prefrontal BA 46. In the lower right corner, respectively, ‘‘glass brains’’ are displayed with the Talairach grid overlay and greyscale-coded T-values. Each glass brain presents 2D projections of the activations onto the standard brain. (After Weerda et al., 2006, with permission).

Simulated Driving Experiments

Dual tasks have been developed to test for limited capacity in divided attention paradigms. Compared with single tasks, dual tasks can give us insights into task-switching and limited capacity mechanisms (Wickens, 2000). Event-related potentials can be used to map changes in brain activation related to dual tasks (Andreassi, 2001). A prominent component of the ERP in cognitive tasks is the P3, which is expressed in a positive wave with a maximum around 300 msec poststimulus. The amplitude of this positive ERP component is dependent on the stimulus and task: rare stimuli (oddballs) evoke a prominent P3 (Andreassi, 2001), the amplitude of which varies with workload (Fowler, 1994; Kramer, et al., 1995). Differences for easy and hard dual task have been recently reported by Brisson & Jolicoeur (2007) for combined tone and shape discriminations.

In experiments described by Raabe et al. (2006) volunteers perform a primary task (simulated driving under high and low workload demands), while an additional secondary task is performed (listening to intermittent sinusoidal tones of constant frequency). The introduction of seldom, unpredictable oddballs in the form of single tones (one octave above that of the “standards”) is expected to evoke a robust positivity in the EEG approximately 300 ms poststimulus. The amplitude of this evoked response is reduced under high, compared to low, workload (Kramer, Trejo, & Humphrey, 1995). This neural activity should be associated with hemodynamic responses that can be detected in fMRI (Soltani, 2000). A further aim of this study is to locate this cortical activity in human cortex and see how workload effects the extent and distribution of the fMRI response.

A commercially available computer game (DTM-Racedriver, Codemasters, U.K.) was adapted for the fMRI environment. The test driver could control the simulated speed and steering of the racecar through appropriate manipulation of the keyboard (response box in fMRI), which was practiced prior to the recording session. During the experiments, volunteers were instructed to “drive” a racecar in separate runs under low (self-paced) and high (pace determined by lead car) workloads. While driving the volunteers were instructed to attend to frequent and low (80%, 1000 Hz) or seldom and high tones (20%, 2000 Hz), which were presented via headphones in both experiments. In a control condition, subjects had to manually respond after each oddball tone. The EEG recordings were based on 40 trials per condition. To keep the relative occurrences of the frequent and seldom tones constant, the position of the seldom tone within a given trial was variable, with the restriction that the seldom tones were not allowed to appear consecutively.

EEG correlates of (simulated) driving

Figure 4 shows the grand averages for the Pz (left) and Cz (right) electrodes and a topographic map of their scalp distribution. The black and red curves illustrate the mean ERP responses to the seldom tones during the high and the low workload condition, while the green curve shows the response to the seldom tones in a control condition, in which the subjects were instructed to manually respond after each oddball. The largest P3 amplitude was found at Pz in the control task that demanded a stimulus-dependent response to the oddballs on the part of the subject (green curve). For the experimental conditions (passive listening during simulated driving), P3 amplitudes at Pz decreased from the low (red curve) to the high (black curve) workload condition. The difference between both conditions was significant ($p<0.05$; $t=2.46$).

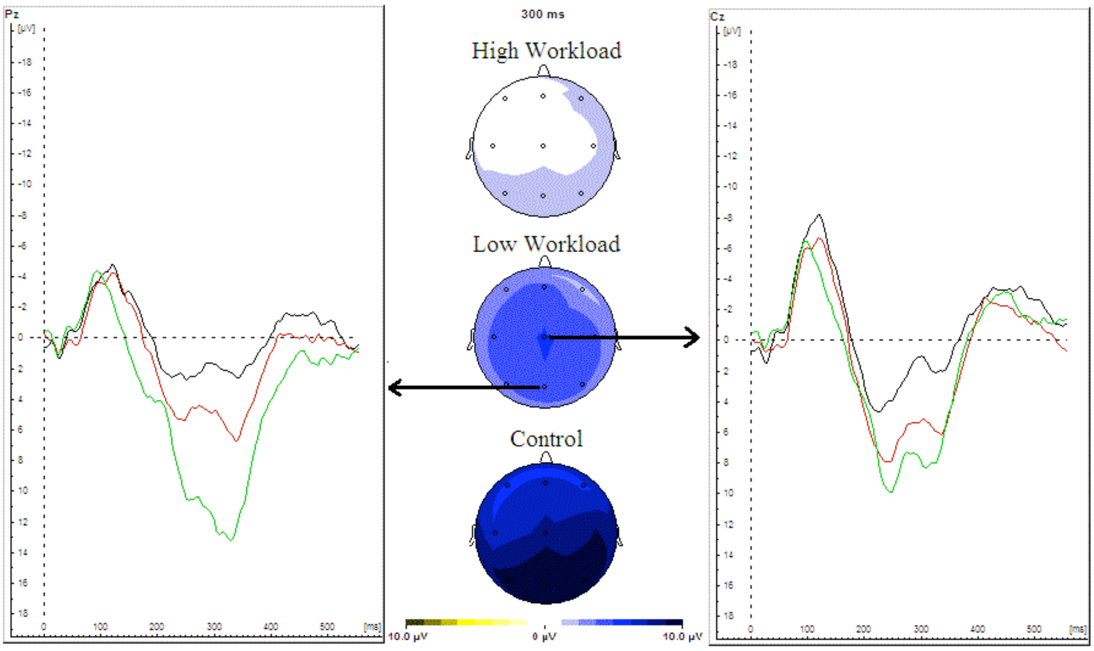


Figure 4: Grand averages and topographic map (300 ms poststimulus) of the event-related potential recorded in three conditions: high workload (black), low workload (red), control condition (green). (After Raabe et al., 2006)

fMRI correlates of (simulated) driving

The brain activation levels shown in Figure 5 depict an overview of the hemodynamic response to cortical activation under the conditions of low (upper graphs) or high (lower graphs) workloads. In the fMRI experiment one trial consisted of 7 tones. The third position within one trial could either be a frequent or a seldom tone. A total of 96 frequent and 24 seldom trials were conducted in a randomized order. Brain activations evoked by seldom auditory stimuli compared with frequent tones are more widely distributed during low workload and this activation is strongly reduced during high workload. Low workload is associated with activation in the right anterior operculum, as well as in the right perisylvian region (Fig. 5), whereas during high workloads subjects exhibited a more focused activation in the right auditory and associated cortex (Fig. 6).

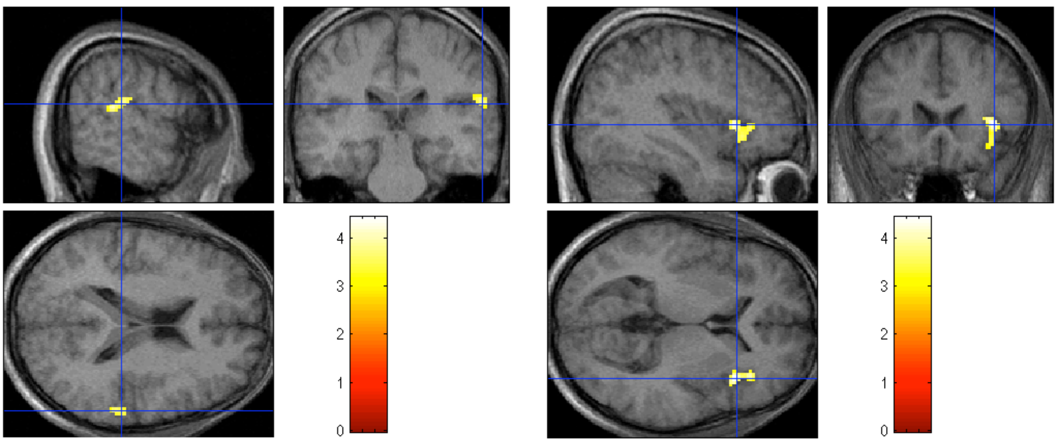


Figure 5: Brain regions activated in the low workload condition contrasting the deviant sounds against the standards: a) right perisylvian area and b) right frontal operculum.

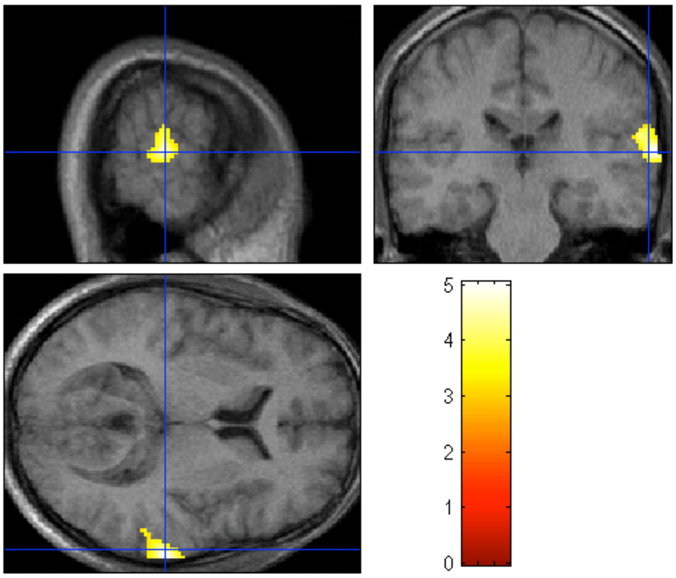


Figure 6: Brain region activated in the high workload condition contrasting the responses to the deviant sounds against those evoked by the standards: right auditory cortex.

The results of these experiments (Raabe et al., 2006) indicate that varying levels of workload during simulated driving have a direct and significant effect on the neural correlates of selective attention**:** Using an auditory oddball paradigm with seldom target tones, we could derive a P3 component in the ERP, the amplitude of which was reduced by a high workload. These findings are in good agreement with those of Brisson and Jolicoeur (2007). Our findings further suggest that workload demands placed on the subjects in a dual-task situation has a significant effect on the fMRI-BOLD response to auditory stimuli. As the P3 component in the time-resolved EEG was the only ERP-component that differed significantly over experimental conditions, we speculate that this response is related to the fMRI findings. The differences between responses to the seldom tones in the fMRI represent the hemodynamic correlate of the measured differences in P3 amplitude in response to auditory oddballs.

The results indicate that low workload is associated with a more widespread activation of sensory and associative cortical areas. These areas are particularly sensitive to changes in sensory stimulation (Downar et al., 2000). The brain activation in the high workload condition appear to be more restricted to the primary sensory processing of the deviant stimulus (Müller, et al., 2003). With increasing workload a more focal fMRI response and a lower amplitude in the ERP response to the oddball stimulus were observed. Related findings have been reported for a simulated passenger situation in an earlier fMRI study (Walter et al. 2001).

These results support a limited capacity model of attention, where an increase in the demands of the primary task leads to a reduced performance in secondary tasks. Changes in performance in dual tasks could be related to interference between the different sensory modalities (e.g., visual and auditory) or could be related to increased noise owing to more stimulus uncertainty. The combination of behavioural, EEG and fMRI measures could provide new insights into a driver's mental workload. The high temporal resolution of the EEG can be coupled to the high spatial resolution of the fMRI to provide a more precise description of the neural correlates of sensory processing under different workloads.

Effects of workload on drivers in real driving scenarios

Event related potentials

The evaluation of driver psychophysiological state by analysis of dynamics in ERP correlates of sensory and cognitive brain functions and its coupling with driver assistance systems (DAS) is of great interest within the automotive section.
The aim of these studies is to develop a tool capable of evaluating the driver's workload by analysis of continuously monitored physiological parameters like scalp recorded event-related electrical brain activity (ERP). The implementation of the system is based on signal analysis of single-stimulus evoked ERP variability. This variability is analyzed in driving tasks with different levels of complexity and used as an individual template for a given driver's cognitive state. Various states serve as indicators for the operator's cognitive performance capacity limits and will also serve as templates for future real-time cognitive state detection algorithms. The ability to detect such threshold states may have implications for drive safety and driving ergonomics.
Event-related potentials (Fig. 6 left) data were analyzed for topographical differences of amplitude or latency in an oddball paradigm while switching the advanced cruise control system ACC (Fig. 6 right) on or off (block design, duration: 30 min).

Fig. 6. a) Method of ERP-recording; b) Functionality of ACC (Distronic).

When ACC is used clear differences appear both for latencies and amplitudes during mid-latency information-processing stages (i.e. P3 latencies decreased while amplitudes increased; Fig. 7).

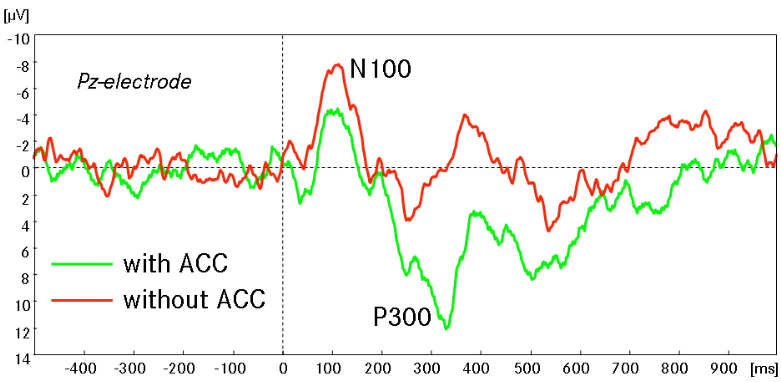


Figure 7: Example of P3 potentials evoked by an auditory stimulus during driving in two conditions: with and without active ACC.

Results show that driver assistance supports the driver by decreasing driver's workload as measured by P3 variability. As an immediate application, P3 based workload measures can be used as indicators for assessing the impact of DAS on driver's workload. To further improve the temporal resolution of workload assessment, we used the P3 time series to obtain context dependent measures. For this purpose we calculated the moving average of three successive P3 amplitudes and plotted the results in a roadmap (Fig. 8). Low P3 values (lowest quintile, red circles) were allocated to a high workload, medium values (mean high quintile, yellow circles) denote medium workload, and the larger values (upper quintile, green circles) denote the low workload category. The results show that this analysis allows us to relate different workload-levels to driving situations with different levels of difficulty.

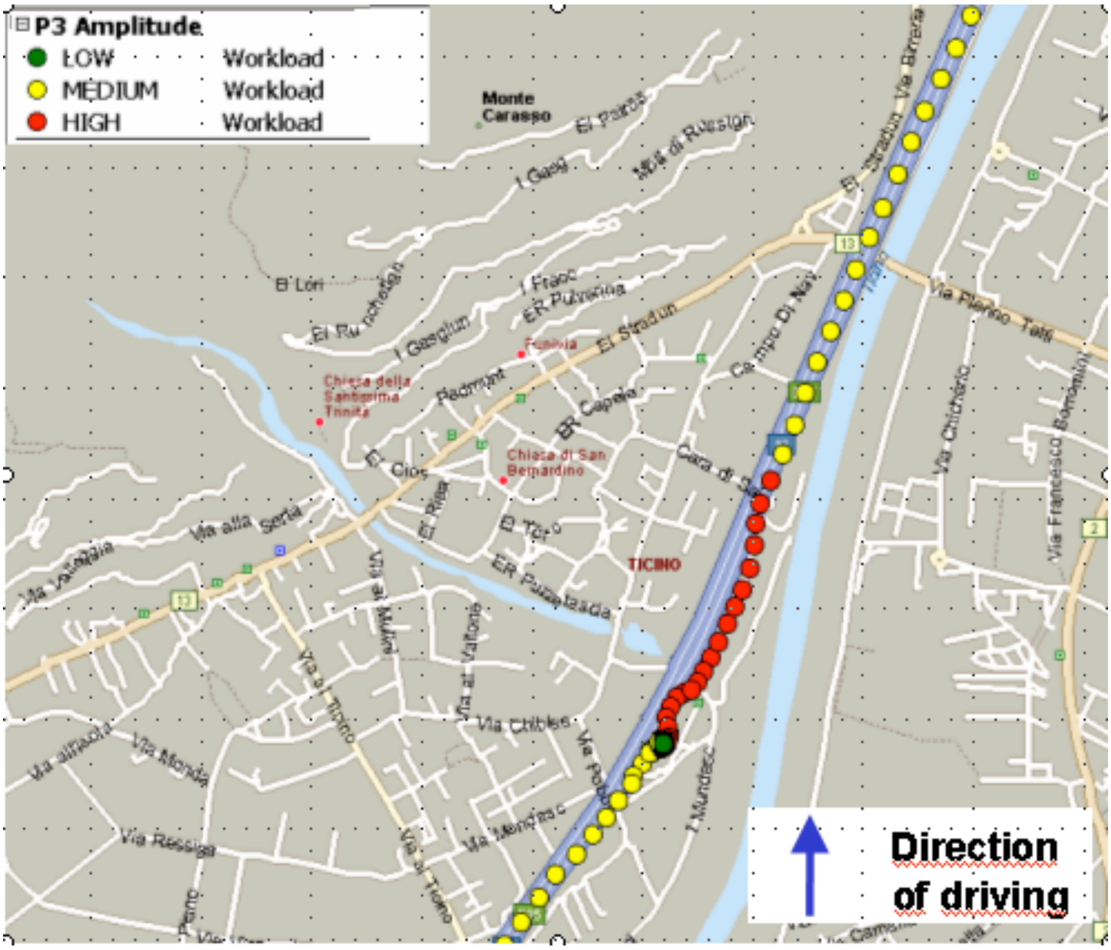


Fig. 8: Workload estimation during normal driving (yellow), during a break (green), and while reentering the highway (red circles).

Continuous Measures of Driver Mental Load based on spontaneous EEG

Unlike ERPs, which offer only an indirect measure of the driver's mental load elicited by external probe stimuli, correlates of mental workload can be extracted from the spontaneous EEG activity, thus offering a continuous measure. This promises to be a more sound and substantial approach, but also far more challenging. Numerous studies have demonstrated that with increased mental processing effort alpha waves

(8–13 Hz) decrease and theta (4–8 Hz) activity is enhanced, e.g. (Murata, 2006). However, research using EEG alpha band power to study neurophysiological correlates of mental workload during driving is rare. Mental workload measurements in real operational environments have so far been reported by Sterman and Mann (1995) and by Hankins and Wilson (1998). In a study presented by we took a first step towards developing a continuous measure of driver mental load based on spontaneous EEG recordings. The study was designed such that two secondary tasks were presented in a controlled manner as subjects drove a predetermined course. The presentation of experimental stimuli and route were consistent from subject to subject, while the complexity introduced by traffic situations varied in an uncontrolled manner across experimental conditions and subjects. One secondary task was a mental arithmetic task (cognitive load: MAT: n-back in steps of 27), the second one an auditory workload task (sensory load: AWT: superimposed voices). Both tasks induced mental load according to a block design in which high mental workload phases (task on) were followed by low mental workload phases (task off).

Fig. 9: Mitigation by scheduling; schematic representation. Left: In the Reference Session, tertiary stimuli (Auditory Commands, magenta dots) are continuously presented during the Mental Arithmetic (top) or Auditory Workload (bottom) tasks. Right: In the AugCog Session, mitigation consists in suppressing tertiary stimuli during the high-workload blocks (red and blue bars) and instead presenting them during the baseline periods (black bars).

The mental workload detector consisted of two parts: feature extraction and classification. Feature extraction involved artifact removal, channel selection, spatial filtering, and power computation of an individualized alpha band.

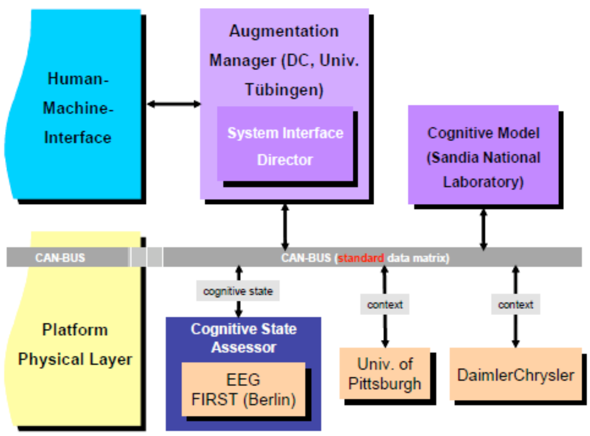


Fig. 10: Schematic representation of the vehicle’s technical architecture. Bottom: Vehicle-sensor data (“DaimlerChrysler”) and information about the driver’s body movements (“Univ. of Pittsburgh”) were directly fed onto the CAN bus. By contrast, EEG signals (“FIRST, Berlin”) were evaluated by the

EEG-based classifiers ("Cognitive State Assessor") before being fed onto the CAN bus. Top: The context-based classifiers ("Cognitive model, Sandia") got their inputs (vehicle-sensor and body-movement data) from the CAN bus and wrote their outputs back onto the bus. Finally, the augmentation manager read all classifier outputs from the CAN bus and combined them in order to obtain a criterion for deciding whether mitigation measures should be triggered (After: Bruns et al. HCI 2005).

A linear model was used for classification wherein parameters were computed by standard linear discriminant analysis (LDA) of the feature vectors obtained from the high and low workload conditions of the training session. Using the cross-validation technique on a training set, the parameter set best discriminating and generalizing between high and low mental load conditions was assessed separately for each subject. The quality of the workload detector, which had a temporal resolution of 200 ms was assessed by analyzing the match between calculated detector workload and the default workload structure of the high/low block experiment design.

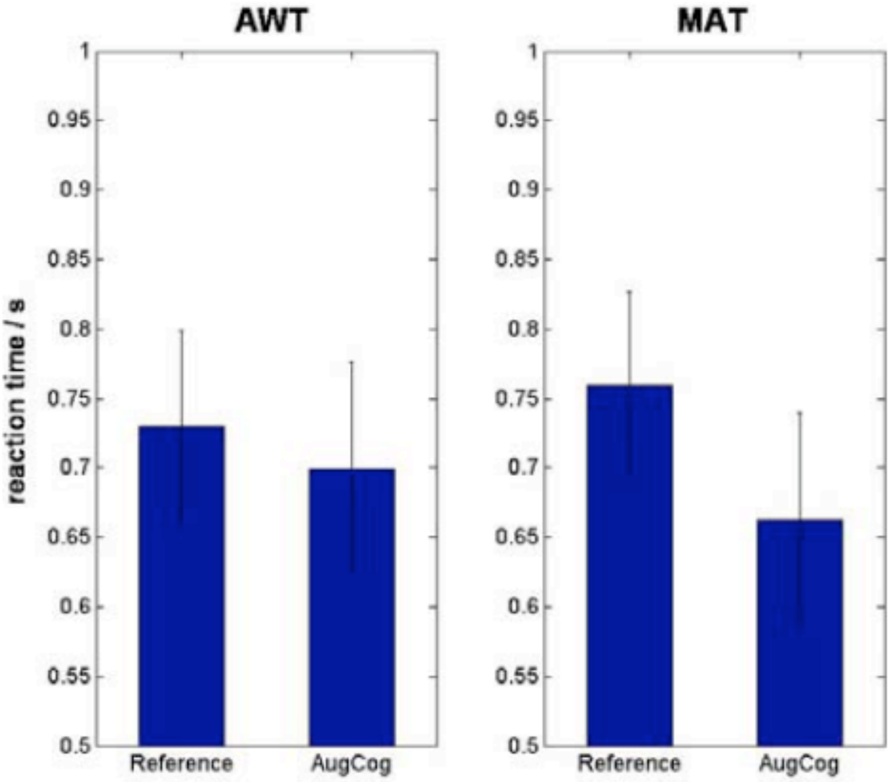


Fig. 11: Reduction of reaction times as a consequence of activating the AugCog system. Error bars represent averaging across the 5 subjects and reflect the large inter-individual variability of performance values, which makes it imperative to use a paired design.

The results showed an average detection accuracy of 70 %. However, the inter-subject variability of the detector performance was very large, ranging between 55 % and 90 %. Especially in an open environment like real traffic driving, the consideration of individual differences and careful artifact rejection are essential to obtaining a good signal-to-noise ratio. Wilson and Fisher (REF?) used topographical information about the EEG to classify fourteen different mental tasks and thus showed that the use of individual subject EEG patterns had a great advantage over the use of group derived bands. Especially the EEG alpha band has been shown to hold an individually unique signature that may vary with age, memory performance and attentional demands

[REF ? 30]. Our current research demonstrated that mental workload detection based on spontaneous EEG recordings is possible with a high temporal resolution; furthermore, it allows a differentiation between different types of mental load, i.e. mental calculation and auditory attention. These results represent a first step towards developing robust, generally applicable and reliable mental workload detectors with high temporal resolution. Further research in the domain of neurophysiology, signal analysis and machine learning is necessary. Ultimately, the effort will culminate in a commonly applicable approach that will enable us to detect traffic situations that cause high driver workload, thus improving the development of specific driver assistance systems to support the driver. Additionally, it will be possible to quantify the benefit of driver assistance systems in early development stages.

fMRI correlates of visual working memory

The findings discussed above indicate that varying workload levels affects the ability of an operator to adequately respond to sensory stimuli. In addition to the cognitive process of attention, the concept of working memory has been introduced to help us understand how much information can be held "on-line" to assist us to solve tasks. Visual working memory refers to the neural and cognitive processes related to the ability of individuals to hold information in memory after the sensory stimuli have been removed. Working memory can be assessed in delayed match-to-sample tasks, in n-back tasks and in delayed discrimination tasks (Luck & Vogel, 1997; Marois & Ivanoff, 2005; Xu & Chun, 2006). Perceptual memory is related to working memory, where the former is concerned with the precision of the stimulus retention (Magnussen, 2000; Magnussen & Greenlee, 1999; Pasternak & Greenlee, 2005). Brain imaging studies of visual perceptual short-term memory have revealed selective activation in early visual areas in occipital cortex and higher visual areas in parietal cortex (Cornette, et al., 2001; Greenlee, et al., 2000). Delay period activations are thought to be a neural correlate of perceptual memory processes, where the information about a reference/sample stimulus should be held on-line for a few seconds until the test stimulus is presented (Pasternak and Greenlee 2005). Recent fMRI studies have revealed that the delay-period activations contain information about the to-be-retained stimulus (Harrison & Tong, 2009; Serences, et al., 2009).

Interestingly, psychophysical studies have shown that the accuracy of delayed spatial discrimination is not affected by manipulations of irrelevant stimulus dimensions. For example, spatial frequency discrimination thresholds were similar for parallel and orthogonal test and reference gratings (Bradley & Skottun, 1984; Magnussen, et al., 1998). Choice reaction times are elevated for orthogonal as compared to parallel gratings in delayed discrimination tasks with reaction times increasing linearly with orientation difference (Magnussen et al., 1998). A systematic effect of angular separation on reaction time between the gratings to be compared with respect to spatial frequency suggests the existence of mechanisms that access feature-specific stores.

In the study by Baumann, et al. (2008) an fMRI experiment was designed to test the idea that visual memory involved a network of channels tuned to spatial frequency and orientation (Magnussen, 2000; Magnussen and Greenlee, 1999). In the study by Baumann et al. (2008) subjects performed a delay spatial-frequency discrimination tasks. On half of the trials, the reference and test gratings had the same orientation, whereas on the other trials the orientations of the reference and test gratings were orthogonal. These authors asked whether the responses to these two different types of trial differ depending on the relative orientation of the reference and test gratings.

The statistical comparison of the conditions with parallel and orthogonal test and reference stimuli only reached significance in the occipital ROI (Fig. 7). A correlation analysis was conducted to compare differences in reaction time for the two conditions with differences in BOLD signal in the two occipital ROI for each individual subject. The results indicated that the occipital BOLD activity correlated significantly with the differences in reaction time ($r = 0.796$, $p \leq 0.001$). This positive correlation between the difference in BOLD responses in the parallel and orthogonal orientation conditions suggest the involvement of these brain regions in the memory task.

Figure 7. Results of the event-related, random-effects group-analysis in n = 14 subjects. Brain areas showing significant activation in the contrast "different orientation > same orientation" are shown by color-coded overlays. Significant clusters surpassing a threshold of $P \leq 0.05$ (corrected for multiple comparisons, cluster-defining threshold $t = 2.0$) are presented. T-values are overlaid onto an a) MNI-normalized sagittal slice (Tailairach plane x = 10), b) MNI-normalized sagittal slice (Tailairach plane x = -10), c) MNI-normalized rendered template. (After Baumann et al., 2008 with permission).

Effects of stimulus uncertainty and workload on performance and brain activity in attention and memory tasks

In the study by Weerda et al. (2006) subjects' performance was compared on the certainty and uncertainty conditions. While the individual extents of the effect of stimulus uncertainty on performance vary from one subject to another, particularly in the colour task, the average effect closely agrees with the prediction of an ideal observer model that assumes stochastically independent processing of information on each dimension. In this model the accuracy of each judgement process is limited by Gaussian noise of internal and/or external origin. The noise arising for the judgement of one stimulus dimension is uncorrelated with the noise perturbing the other process. In the uncertainty condition, information from both dimensions is processed on each trial and the less ambiguous information is selected as the basis for the response. Accuracy is necessarily reduced in the uncertainty condition because the judgment process is perturbed by noise from two sources, rather than from a single source as in each certainty condition. For various reasons (Thomas & Olzak, 1996), the ideal observer may weight information from the two dimensions unequally, resulting in unequal uncertainty effects. However, the root-mean-square of the ratio of d' measures for the two dimensions is independent of any such bias. The findings reported by Weerda et al. (2006) indicate a root-mean squared value of 0.7058 is nearly identical with the model prediction of the inverse of the square root of 2.0

(approximately 0.71). However, in addition to the expected drop in accuracy there was a reliable increase in responses times, suggesting that the effects of the uncertainty manipulation were more complex than the model considers.

This model assumes that operators carry out the same cognitive processes in the uncertainty condition as in the certainty conditions, except that both sets of processes are carried out in parallel. If this were the case, it might be expected that any area that shows activity during one or both of the certainty conditions would also show activity in the uncertainty condition. The results reproduced in Fig. 2 and 3 (see above) fails to support this conclusion. Although several brain areas appear to fulfil this expectation, there are several areas that are either only active in one or both of the certainty conditions or only in the uncertainty condition. These results suggest that the subjects employ different cognitive processes in the uncertainty condition than those used in either of the certainty conditions. This would mean that observers do not simply perform both discriminations in parallel in the uncertainty condition, but rather restructure their cognitive approach. The cortical activity pattern during uncertainty would therefore not simply be the union of areas active during both certainty conditions, but would rather contain activity in entirely new areas as well as lack activity in other areas.

The differential contrasts, which make direct statistical comparisons between certainty and uncertainty conditions, provide pertinent information about the differences in neural activity between *selective* and *divided* attention. The results of these contrasts suggest a link between the behavioural and functional imaging data in that subjects differ in their cognitive strategies in conditions with stimulus uncertainty. Subjects exhibiting a relatively small psychophysical uncertainty effect seem to have carried out the same cognitive processes during the uncertainty condition as during the two certainty conditions, as indicated by the very few differences in cortical activity between these conditions.

The findings reported by Raabe et al. (2006) suggest that simulated driving scenarios can be used to test the effects of workload on the pattern of brain activity evoked by visual and auditory stimuli. High work loads lead to smaller amplitude of the P3-component in auditory oddball detection tasks. High workload also has an impact on the pattern of brain activity revealed with functional MRI for these same tasks. The results of this study open up the area of ergonomics and engineering psychology to methods used in cognitive neuroscience. Applications on these findings are provided by studies of Schrauf & Kincses (add some ref. here) by using the neural effects of workload evoked by auditory stimuli in several real driving scenarios. It is now possible to track the brain activity of a person while they engage in fairly complex cognitively demanding tasks.

The results reported by Baumann et al. (2008) suggest that early visual areas are involved in the neural mechanisms underlying visual working memory. Observers can discriminate between the spatial frequency of two sequentially presented gratings, even when these have orthogonal orientations. The brain activity evoked by these discrimination tasks with parallel and orthogonal gratings differs, however, and these differences point to more activation in the condition where spatial frequency information has to be shared over different orientation channels (i.e., those tuned to orthogonal orientations). The task is completed and high performance levels are maintained, but subjects require slightly more time to do the task and early visual areas are more active (Baumann et al., 2008).

Conclusions

Taken together, the results reported by Weerda et al. (2006) provide support for the idea that visual attention can be directed to select stimulus dimensions during discriminations tasks. Stimulus uncertainty reduced the performance on these tasks and the extent of these performance drops can be modelled by considering the effects of noise when the subject has to monitor two versus just one source of information. Workload can be conceptualized in terms of signal detection theory as an increase in noise or an increase in the number of sources that need to be monitored. In a similar fashion as that observed for stimulus uncertainty, changes in workload will affect performance and the brain activations in cortical regions involved in the underlying sensory and cognitive processing. The effect of workload on performance in a simulated driving task has been studied using fMRI. Here the effects of workload on the cortical response to an auditory oddball stimulus were shown to be reduced by increase workload (Raabe et al., 2006). The validation of this effect on drivers' workload estimations was performed by using EEG in a car in real driving scenarios. Several field studies show a reduced cortical response to the auditory stimulus while the drivers demand on driving skills or secondary tasks are increased (add ref here).Visual working memory helps us to hold material "online" even long after the stimuli are no longer present. Working memory allows us to operate on sensory representations to perform discrimination task for stimuli no longer present. The neural correlated of working memory have been studied using fMRI combing with delayed spatial-frequency discrimination tasks. A comparison of a grating's spatial frequency was made for parallel or orthogonal gratings (Baumann et al., 2008), and the differential contrasts between these conditions revealed additional focal activation in extrastriate cortex when orthogonal gratings were compared. These findings suggest that the neural mechanisms that underlie visual working memory act on early representations of simple stimulus dimensions like orientation and spatial frequency.

Taken together, psychophysical studies of stimulus uncertainty, ergonomic studies of workload and neurocognitive studies of visual working memory all point to a complex network that supports information processing when the capacity of our sensory and cognitive systems are at their limit.

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