



Enhanced frontoparietal network architectures following “gaze-contingent” versus “free-hand” motor learning

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ABSTRACT

Longitudinal changes in cortical function are known to accompany motor skills learning, and can be detected as an evolution in the activation map. These changes include attenuation in activation in the prefrontal cortex and increased activation in primary and secondary motor regions, the cerebellum and posterior parietal cortex. Despite this, comparatively little is known regarding the impact of the mode or type of training on the speed of activation map plasticity and on longitudinal variation in network architectures. To address this, we randomised twenty-one subjects to learn a complex motor tracking task delivered across six practice sessions in either “free-hand” or “gaze-contingent motor control” mode, during which frontoparietal cortical function was evaluated using functional near infrared spectroscopy. Results demonstrate that upon practice termination, gaze-assisted learners had achieved superior technical performance compared to free-hand learners. Furthermore, evolution in frontoparietal activation foci indicative of expertise was achieved at an earlier stage in practice amongst gaze-assisted learners. Both groups exhibited economical small world topology; however, networks in learners randomised to gaze-assistance were less costly and showed higher values of local efficiency suggesting improved frontoparietal communication in this group. We conclude that the benefits of gaze-assisted motor learning are evidenced by improved technical accuracy, more rapid task internalisation and greater neuronal efficiency. This form of assisted motor learning may have occupational relevance for high precision control such as in surgery or following re-learning as part of stroke rehabilitation.

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Introduction

Neuroergonomics is the study of the brain and behaviour at work (Parasuraman, 2003) and describes the application of neuroscience methodology to better understand the cortical correlates of work-related tasks. In this context, neurocognitive behaviour can be appraised as a means to evaluate training regimes (Voss et al., 2012), detect hypovigilance and fatigue (Hitchcock et al., 2003; Leff et al., 2010), and to evaluate the impact of assistive technologies on the user (James et al., 2010; Tsunashima and Yanagisawa, 2009). Translational applications of neuroergonomic research include the development of technological assistance for adaptive aiding in safety-critical industries such as aeronautics (Rossini et al., 2009), driving (Tsunashima and Yanagisawa, 2009) and surgery (James et al., 2010; Lee et al., 2010), as well as to improve stroke rehabilitation regimens (Moller and Mikulis,

2007). Although plastic changes in cortical activation associated with highly complex motor skills learning in healthy subjects have started to be mapped (Bahrami et al., 2011; James et al., 2011; Leff et al., 2006, 2008a, 2008b, 2008c; Ohuchida et al., 2009; Zhu et al., 2011), the impact of performance enhancing technology on activation-map evolution and functional connectivity adaptation have yet to be delineated. Accordingly, the objective of the present study is to investigate the impact of assistive technology on dynamic changes in functional network architectures associated with the longitudinal acquisition of a complex visuomotor tracking task, designed to emulate ablation on a beating heart phantom.

Regarding complex motor skills acquisition per se, task learning is associated with neuroplastic changes that lead to either up-regulation or down-regulation of regional brain activation (Kelly and Garavan, 2005) and a modulation of the underlying cortical network from a novice to expert state (Halsband and Lange, 2006). Longitudinal changes in regional brain activation commensurate with skills acquisition are well described (Kelly and Garavan, 2005). In the main these comprise response attenuation in the prefrontal cortex (PFC) and increased activation in primary and secondary motor regions and the cerebellum consistent with a re-distribution or re-organisation of the activation map (Debaere et al., 2004; Floyer-Lea and Matthews, 2005; Kelly and Garavan, 2005; Leff et al., 2008b; Puttemans et al.,

Abbreviations: F-P, frontoparietal; PFC, prefrontal cortex; fNIRS, functional near infrared spectroscopy; GCMC, gaze-contingent motor channelling; HbO₂, oxyhaemoglobin; HHb, deoxyhaemoglobin; SD_{RR}, standard deviation of the R-R interval; STAI, state trait anxiety inventory.

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2005). In contrast, little is known about the variations in the interactions between brain regions (nodes) as a result of practice or for that matter as a result of interventions designed to augment learning and enhance accuracy. Yet changes in statistical association between spatially distributed brain activation time series, or “functional connectivity,” (Friston et al., 1993) may hold great promise in understanding individual differences in neural efficiency and learning capabilities (Posner, 2012; Voss et al., 2012).

Only a few motor learning studies suggest that functional connectivity varies from novice to learned states (Coynel et al., 2010; Lin et al., 2012; Steele and Penhune, 2010; Sun et al., 2007). These data suggest that early phases of motor learning are associated with greater connectivity within frontal regions compared to late phases (Sun et al., 2007) and that changes in network integration (Coynel et al., 2010) and modular flexibility (Bassett et al., 2011) accompany skills learning. However, variation in connectivity is likely to be dependent on the brain regions of interest and strengthening of connectivity between motor regions (e.g. cerebellum and primary motor cortex) has been observed (Lin et al., 2012; Steele and Penhune, 2010). These studies applied a unique training regimen and were not designed to characterise differences in network behaviour(s) as a result of alterations in training regimens or modes of learning. For high risk industries in which motor skills acquisition and performance accuracy are integral to public safety (e.g. aviation, surgery, etc.) it is attractive to compare the influence that tailored training regimens and technologies designed to assist learning have on the speed of skills acquisition, evolution in regional activation(s) and efficiency of brain networks. The present study investigates the influence of two different motor training methodologies (i.e. “free-hand” versus “gaze-assisted”) on practice related evolution in functional activation(s) and network architectures. To this end, functional near infrared spectroscopy (fNIRS) was used to capture regional cortical activation. Optical data were subsequently analysed using graph theory, enabling integration between spatially remote neurophysiological events in the brain to be evaluated.

A brain graph is a model of the nervous system composed of nodes interconnected by edges (Bullmore and Bassett, 2011). “Nodes” may represent sensors or electrodes (e.g. MEG and EEG), individual voxels (van den Heuvel et al., 2008, 2009), cortical volumes (Bassett et al., 2008) or anatomical regions of interest (Chen et al., 2008; He et al., 2007) (e.g. MRI). Concerning neuroimaging data acquired using fNIRS, nodes may represent optical data acquired at different cortical loci (“channels”). Network “edges” are calculated by generating an association matrix. This matrix is a measure of functional or structural connectivity between the nodes (Bullmore and Bassett, 2011). The association matrix is pruned by application of a threshold to retain the most important functional connections, thereby generating an adjacency matrix. Network econometric data that explore the interactions between brain regions such as clustering coefficient, path length, density and small worldness can be derived from the pruned adjacency matrix. It is then possible to compare graph econometric data between subjects or groups, or to an equivalent “random graph” in order to derive the extent of network small-worldness (Watts and Strogatz, 1998). Although graph comparison is a challenging area of research (van Wijk et al., 2010) and care needs to be taken to ensure that networks are of equal connection density and node number (Bullmore and Sporns, 2009; Bullmore and Bassett, 2011; Rubinov and Sporns, 2010; van Wijk et al., 2010) it is an attractive method to quantify longitudinal variation in neuronal architectures induced by different training methodologies.

This longitudinal randomised controlled study aims to assess the influence of different learning strategies on the evolution in frontoparietal (F-P) activation and F-P network communication. Subjects were randomised to acquire a dynamic visuomotor tracking skill in either “free-hand” mode or following “gaze-contingent motor channelling” (GCMC) (Mylonas et al., 2012) in which motor/instrument control is constrained according to operator gaze fixation as displayed in Fig. 1.

Changes in F-P cortical haemodynamics were monitored using fNIRS. Graph theory was applied to cortical haemodynamic data in order to capture the extent of small-worldness of the task-evoked cortical network and to determine if gaze-assistance results in enhanced neuronal efficiency. The current study was based on three hypotheses:

- (i) First, longitudinal evolution in F-P brain activation is anticipated. PFC attenuation is predicted, co-incident with motor skills learning and consistent with reduced attentional demands that accompany task acquisition (Debaere et al., 2004; Floyer-Lea and Matthews, 2005; Kelly and Garavan, 2005; Leff et al., 2008a, 2008b; Petersen et al., 1998). Localisation of the parietal response to the posterior parietal cortex (PPC) is anticipated commensurate with development of an internal model of task performance (Shadmehr and Holcomb, 1997).
- (ii) Second, a small-world F-P network is predicted which may be modulated with learning-related changes in technical skills acquisition (Coynel et al., 2010; Sun et al., 2007). Small world refers to a network topology characterised by high clustering coefficient and short mean pathlength resulting in low wiring cost and high information processing capabilities. Specifically, cortical networks demonstrate “small-world” properties (Achard et al., 2006; Bassett and Bullmore, 2006; Watts and Strogatz, 1998), which are characterised by high local connectivity or cliquishness coupled with long range connections linking distant network regions (Watts and Strogatz, 1998). Small-worldness is indicative of the brain’s capacity for local processing (functional segregation) coupled with an ability for multi-regional communication, integral for task execution (functional integration) (Sporns et al., 2004; Tononi et al., 1998)
- (iii) Third, it is envisaged that learning-related evolution in F-P activation(s) and network architecture may progress more rapidly to the trained state in gaze-assisted learners, since GCMC stabilises user performance and may result in earlier attainment of technical expertise. Finally, network econometrics have been shown to predict superior performance (Bassett et al., 2009); thus it is conceivable that gaze-assistance, in augmenting technical performance, will result in an F-P network architecture defined by reduced costs and greater efficiency.

Materials and methods

Subjects

Following local research ethics committee approval (project number: 05/Q0403/142), a randomised single blinded trial was conducted. Twenty-one subjects (six female) with no prior nor current history of neuropsychiatric conditions were recruited from Imperial College London [Mean age \pm S.D. = 21.2 \pm 2.4 years]. Subjects were right handed [Edinburgh handedness inventory (Oldfield, 1971), median score (range) = 70 (40–100)]. Subjects gave written consent prior to participation. All participants were task naïve. Exclusion criteria included a history of neuropsychiatric illness, left handedness or prior task experience. Subjects were required to refrain from alcohol and caffeine for 24 hours prior to each data collection point, in order to eliminate any effects on cerebral haemodynamics during the study (Orihuela-Espina et al., 2010).

Group allocation and task paradigm

Subjects undertook the virtual reality visuomotor task by tracking a moving target on the monitor using a haptic manipulator (SensAble Technologies, USA) to control a virtual tool with the aim of localising the moving target as accurately as possible as outlined in Fig. 1. Target trajectory was smooth and cyclic. Subjects were randomised (random number generator) to perform the task either “free-hand” in the

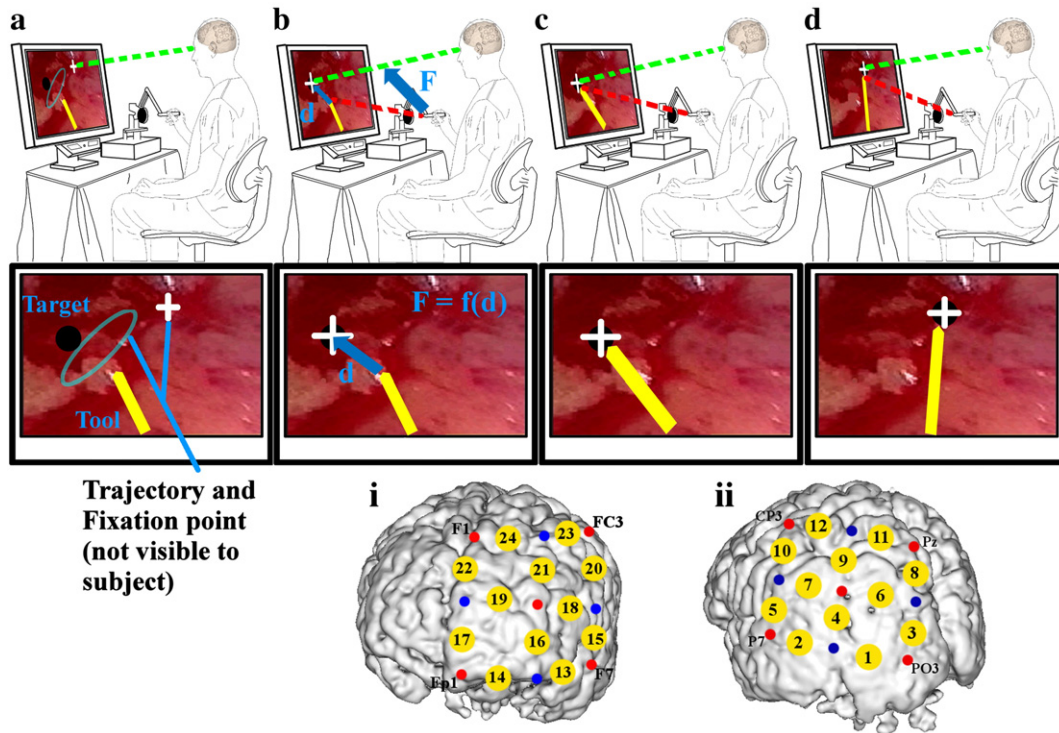


Fig. 1. Task setup. Panels a to d display the task set up and the mode of action of GCMC. Subject is seated and controls the haptic manipulator (right hand) which operates the virtual tool (yellow). Subject gaze behaviour (depicted as white cross, however not visible to subject) is detected with the portable eye tracking system (beneath the monitor) whilst they track the target (black dot) which has a smooth, cyclic trajectory (schematically displayed as light blue ellipse in panel (a)). Subject gaze and the relationship of the tool tip to the haptic manipulator are schematically represented (dashed green and red lines respectively). In panel b, the distance (d) between subject fixation point and the tool tip is calculated and utilised to determine the force (F) required to constrain the tool to the fixation point and thus the target. Therefore the force (F) is a function (f) of the distance (d) between the tool tip and the fixation point. The target is localised with the tool (panel c) and tracked successfully as the target moves (panel d). Optode arrays can be appreciated on the subject which capture cortical haemodynamic behaviour at 12 channel locations overlying the left PFC and PC respectively. Channel location overlain onto a reference MRI atlas is displayed (lower panel) for the PFC (i) and PC (ii). Optode emitters and detectors (red and blue circles respectively) are positioned according to the U.I. 10/10 system (Jurcak et al., 2007) generating 24 channels (numbered yellow circles).

conventional manner (control group) or with gaze-assistance with GCMC (experiment group) (Mylonas et al., 2008, 2012). Subjects randomised to GCMC assistance performed the task in the same manner as free-hand with the exception that their gaze behaviour was extracted in real time using a portable eye tracker (Tobii, Sweden) situated below the task monitor. This information was used to guide force feedback via the haptic manipulator in order to constrain the subject's hand to their fixation point and thus to the target. This technology has been demonstrated to improve technical accuracy beyond that of free-hand performance (Mylonas et al., 2008, 2012).

A block design paradigm was employed with each "session" comprising five blocks of task (20s) interspersed with rest (30s) during which subjects closed their eyes and the screen was blacked out. As the purpose of this study was to assess longitudinal practice-related changes in brain behaviour, subjects repeatedly performed the task on six separate days, resulting in six sessions per subject. A pilot study (unpublished data) determined six sessions to be sufficient to demonstrate learning of the task. All participants received a standardised introduction which precluded any opportunity to practice, ensuring that the most naïve phase of learning was captured. Subjects were blinded to group assignment and to the study objectives. Approximately 2 months after the original test, subjects were recalled for a retention test (session 7) to evaluate skill retention.

Data acquisition and pre-processing

Performance was determined as the distance (pixels) from the tool tip to the target and was averaged over the five blocks of the task to yield a session average. Based upon pilot data the study was powered

to detect a difference of 1.5 SD in technical performance between groups at $\alpha=0.05$ and 90% power, which required eleven subjects in each group.

As depicted in Fig. 1, left hemispheric F-P activity in terms of relative changes in oxyhaemoglobin (HbO₂) and deoxyhaemoglobin (HHb) was detected at 24 channel locations with fNIRS (ETG4000, Hitachi Medical Corp., Japan). Attenuation of light data was converted to relative changes in HbO₂ and HHb using the modified Beer-Lambert law and subsequently decimated to 1 Hz and linearly detrended prior to undergoing data integrity checks as previously described (Orihuela-Espina et al., 2010). Simultaneous heart rate (HR) recording was undertaken with a portable electrocardiogram (Bioharness, Zephyr Technology, USA). HR data were used to derive the heart rate variability (HRV) in terms of the standard deviation of the R-R interval (SD_{RR}) (Taskforce, 1996) as a surrogate for systemic effect and task-induced stress. Concurrently, subject stress was determined with the State Trait Anxiety Inventory (STAI) (Marteau and Bekker, 1992) in order to determine the influence that the systemic circulation and autonomic arousal had upon changes in cortical haemodynamics.

Behavioural data

The influence of group and session on technical performance was determined with a univariate analysis of variance and a post hoc Bonferroni correction was applied (SPSS v18, USA). Performance at practice termination (session 6) was compared with that attained during the retention test (Wilcoxon rank sign) to assess the degree of task retention and hence learning.

Cortical activation and stress

A within-group activation analysis was conducted upon grand-averaged data as follows: for a given NIR channel, baseline haemoglobin data (defined as 5s of data prior to stimulus onset) were compared to task data (defined as data acquired during motor tracking performance) using a Wilcoxon rank sign test. For a given NIR channel, the combination of a statistically significant increase in HbO₂ ($p < 0.05$) coupled to a statistically significant decrease in HHb ($p < 0.05$) was used to define cortical activation. Subsequently, a variable defined as ΔHb was derived for each Hb species and for each channel of data, calculated as the difference between the task and baseline data. ΔHb data were incorporated into a generalised estimation equation with random effect modelling (Intercooled Stata, v10.0 for windows, Stata Corporation, USA) in order to appreciate the influence of group (control versus experimental) and practice session (1–6) on the task-induced changes in cortical haemodynamics. Similarly, generalised estimation equation with random effect modelling was conducted to evaluate the influence of the stress response (i.e. HR and SD_{RR}) on cortical haemodynamic data (i.e. ΔHb) whilst controlling for other variables that may influence the cortical response such as subject, group and practice session. The influence of group (control vs. GCMC), session (1–6) and timing (pre-, during and post-study) on STAI questionnaire response was determined with a univariate analysis of variance and a post hoc Bonferroni correction was applied (SPSS v18, USA).

Graph construction

Graph construction is outlined in Fig. 2. Group averaged haemodynamic data were derived at each session (1–6). The group averaged timecourse was then cross-correlated in order to generate a functionally connected unweighted, bidirectional graph. Bidimensional cross-correlation $R_{ij}(\tau_t, \tau_{\text{Hb}})$ was utilised as shown in Eq. (1) such that both changes in HbO₂ and HHb were simultaneously considered in determining the functional association between two channels, where τ_t and τ_{Hb} represent the temporal and haemodynamic lag among the signals and subscripts Hb only refer to the haemodynamic signal index and t to the temporal sample index with T being the length of the signals in samples. Over lined symbols represent mean signal value.

$$R_{ij}(\tau_t, \tau_{\text{Hb}}) = \frac{\sum_{t=0}^{\tau-1} \sum_{\text{Hb}=0}^{\tau-1} \overline{\Delta\text{Hb}_i(t, \text{Hb})} \cdot \overline{\Delta\text{Hb}_j(t + \tau_t, \text{Hb} + \tau_{\text{Hb}})}}{\sqrt{\sum_{t=1}^{\tau} \sum_{\text{Hb}=1}^{\tau} \Delta\text{Hb}_i(t, \text{Hb})^2 \cdot \sum_{t=1}^{\tau} \sum_{\text{Hb}=1}^{\tau} \Delta\text{Hb}_j(t, \text{Hb})^2}} \quad (1)$$

The association matrix of the graph is subsequently pruned based according to graph connection density to generate the final network, rendering only those edges that will remain in the graph. Too lenient a threshold may result in retention of edges describing spurious associations between cortical regions and that do not truly represent functional connections. However, too aggressive a threshold may result in the rejection of meaningful cortical connections, under population of the graph and/or node isolation making graph comparison problematic (Bullmore and Bassett, 2011; van Wijk et al., 2010).

In order to rationalise the resultant econometric data, a network from each study group at each practice session was formed leading to 12 graphs in total. The graphs were scaled to ensure equivalent connection densities, thereby facilitating graph comparisons (van Wijk et al., 2010). The connection density was fixed and edges were sequentially removed according to the significance of the functional association (least significant removed first) until the desired connection density was reached (Achard et al., 2006; He et al., 2007).

Graph theory metrics

In order to determine small-worldness, each graph was compared to its equivalent random graph (van Wijk et al., 2010). This was calculated by randomly rewiring the graph as previously described (Watts and Strogatz, 1998). Here the regular graph is built by linking each node (channel) with its topological neighbours in the optode array. From both the session and group specific graphs and the equivalent random graphs, the average pathlength L and L_r and average clustering coefficient C and C_r were calculated. This in turn was used to calculate the small-world index, σ as shown in Eq. (2) (Bullmore and Bassett, 2011).

$$\sigma = \frac{C}{C_r} / \frac{L}{L_r} \quad (2)$$

Network cost $K(G)$ and global efficiency $E_{\text{glob}}(G)$ were calculated using Eqs. (3) and (4). The cost-efficiency of a network is increased in an economical network (Achard and Bullmore, 2007) and therefore is calculated using Eq. (5) and termed “network economy.” At a fixed connection density, the number of connections linking the prefrontal and parietal channels was calculated in order to estimate the connectivity between these regions where i and j represent nodes in the graph.

$$K(G) = \sum_{i \in G} \sum_{j \in G} d_{ij; i \neq j} \quad (3)$$

$$E_{\text{glob}}(G) = \frac{1}{N(N-1)} \sum_{i \in G} \sum_{j \in G} \frac{1}{d_{ij; i \neq j}} \quad (4)$$

(Latora and Marchiori, 2003)

$$\text{Economy}(G) = E_{\text{glob}}^{\text{norm}}(G) - K^{\text{norm}}(G) \quad (5)$$

(Achard and Bullmore, 2007)

Results

One subject withdrew from the study after the second session and two of the remaining subjects were unable to return for the retention test. The six sessions were undertaken on separate days over a median of 8 days. Following data integrity assessments (Orihuela-Espina et al., 2010) a number of channels (127 out of a total of 2880 channels, 4.4%) were excluded due to system noise or artefacts. If a single channel was excluded, the remaining data for that subject/session were still included in the analysis. Unlike previous attempts at employing graph analysis for fNIRS (James et al., 2010), the current approach ensures the maximum retention of individual subject data for group network construction.

Behavioural data

Performance as determined by the distance from the tool tip to the target is illustrated in Fig. 3. It is apparent that accuracy increases with time on the task, manifest as a diminution in this distance across training. Session ($p < 0.001$ $df = 5$, $F = 60.65$), but not group ($p = 0.52$ $df = 1$, $F = 0.41$) was observed to be a predictor for task performance. These predictors explain 36.1% of the variation in performance ($R^2 = 0.361$). Whilst accuracy was observed to be better in the control group initially, the learning curves intersect after the second session as GCMC learners improve to a greater extent than do controls. Therefore, group alone does not predict performance unless session is concurrently accounted for. Eighteen subjects returned for the retention test at a variable time period following final practice [median (range) = 71 (21–116) days]. Despite the variation in the

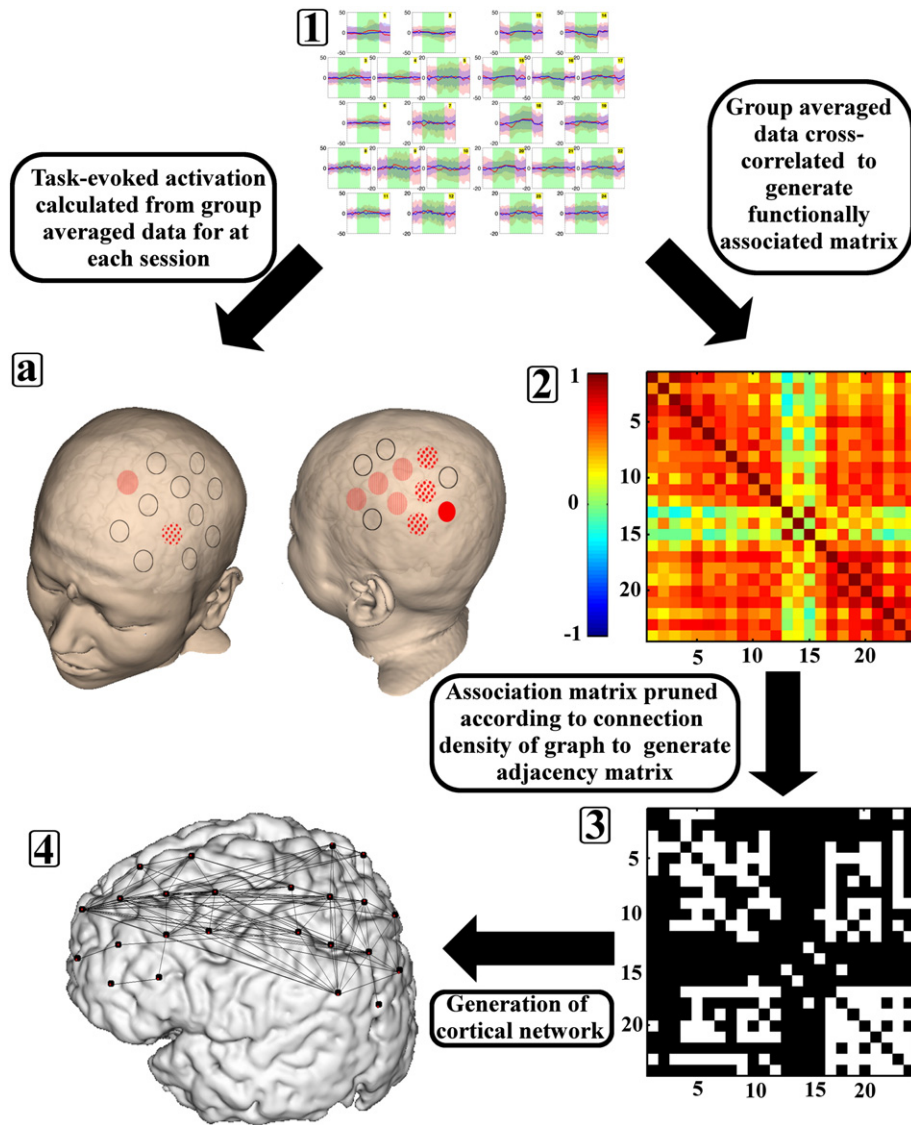


Fig. 2. Flow of data analysis and graph construction. Following pre-processing and conversion to relative changes in HbO₂ and HHb, haemodynamic data are averaged across the five task blocks and over all subjects in each group for each session. This yields a grand averaged timecourse (1). The five sample baseline is compared with the task-averaged Hb value in order to determine task-evoked increases/decreases in HbO₂ and HHb. This is subsequently displayed overlying channel locations on a reference MRI atlas (a). For graph generation, both Hb species in the grand averaged time course are bidimensionally cross-correlated in order to generate the association matrix (2). In turn, this is pruned to generate the adjacency matrix (3) using the threshold. In the current study, the association matrix is pruned according to the connection density of the graph with least significant connections removed first. From the adjacency matrix (3), the undirected, weighted cortical network (4) is generated. Graph econometrics such as network cost, efficiency and economy can be subsequently derived.

timing of the retention test, performance during retention was not significantly different from that during the final training session in either group [control group accuracy (median (range)): final session: 22.0 (15.4–36.2) vs. retention test: 22.9 (13.9–32.3); $p = 0.4307$]; [GCMC group accuracy (median (range)): final session: 16.8 (10.9–38.0) vs. retention test: 15.84 (11.9–23.9); $p = 0.9404$]. This indicates retention of skill at a median of 71 days.

Cortical activity

Fig. 4 illustrates between-group longitudinal changes in cortical activation associated with technical skills acquisition. Naïve performance (first session) was associated with PFC and parietal cortical (PC) activation, regardless of study group allocation. However, rapid attenuation in PFC and PC activation was only observed in the GCMC group. In contrast, after limited practice (session 3) persistent

PFC activation (channels 14, 16 and 21–23) and spatially broader PC activation were observed in subjects randomised to free-hand learning. Attenuation in PFC and PPC activation only occurred toward practice termination (session 6) in unassisted learners. Longitudinal learning-related changes in parietal excitation comprised a spatial contraction in the number of activating channels within the PPC. However, residual activation in the PPC appeared to be magnified. Longitudinal changes in PC activations transpired more swiftly in gaze-assisted learners. As displayed in Table 1, session and cortical region (PFC versus PC) were independent predictors of ΔHbO_2 . Additionally, ΔHbO_2 decreased as the sessions progressed, implying an overall attenuation in the magnitude of the cortical response across practice. Relative to the PFC, a greater cortical response was seen in the PC, which is in line with PFC attenuation and magnification of PPC excitation. “Group” was not an independent predictor of changes in cortical haemodynamics. Therefore, differences in cortical haemodynamics

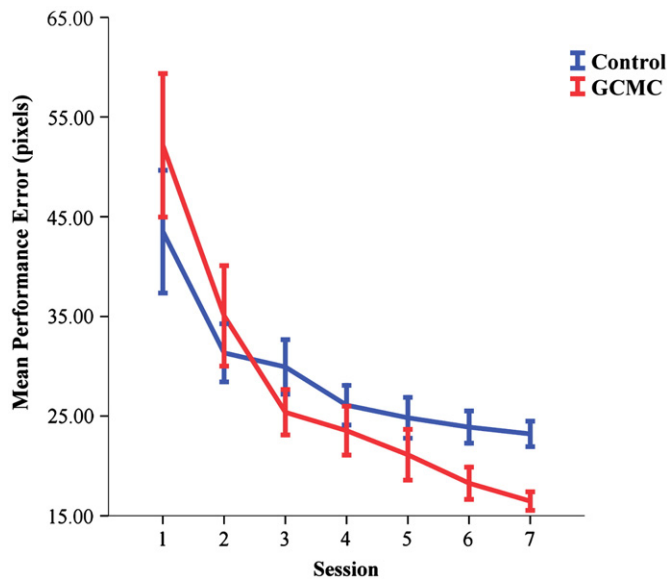


Fig. 3. Subject performance across six task sessions and the retention test (session 7, which occurred a median of 71 days after session 6). Data represent mean and 95% confidence intervals (error bars) for subjects in control (blue) and GCMC (red) groups. Initially, performance is better in the control group until the learning curves intersect after the second session. Subsequently, GCMC users demonstrate improved performance. There is no significant difference between performance at practice termination (session 6) and the retention test (session 7), indicating task learning.

were mediated by temporal fluctuations across sessions and modulation according to cortical region (PFC versus PC).

Cortical networks and small-world properties

As is depicted in Fig. 5 cortical network econometric data (i.e. cost, efficiency, economy, etc.) are strongly influenced by the stage and mode of learning. Econometric data of average clustering (C) and mean pathlength (L) are displayed in Table 2. These are normalised according to the equivalent random graph (Watts and Strogatz, 1998) and are used to calculate the small-world scalar: σ . It is evident that normalised global efficiency, normalised cost and economy of the F-P network are improved as a result of gaze-assisted motor learning. This implies that gaze-assisted learners developed a pattern of F-P network communication that was more efficient and less costly than that of free-hand learners. Small-worldness behaviour is indicated when $\sigma > 1$ and was observed in all practice sessions apart from the final in both groups. The loss of small-worldness may relate to an increase in mean pathlength coinciding with a simultaneous reduction in the number of functional connections between the PFC and PC in the final session in both groups (Table 2). Moreover, final session PFC redundancy is evident from the activity-related analysis (refer to Fig. 4). It is conceivable that as activity within the PFC attenuates, its functional association with the PC may well decrease, especially since activations in the PPC are magnified. This effect occurs in tandem with a trend towards a reduction in network efficiency, economy and an increase in cost towards the final session accompanied by the loss of small-worldness.

Systemic effect, and stress

Mean heart rate was not a predictor for variation in ΔHbO_2 [coefficient = 0.006, confidence interval (−0.003 to 0.015), $p = 0.163$] or ΔHHb [coefficient = 0.004, confidence interval (−0.001 to 0.009), $p = 0.158$]. However, SD_{RR} was a predictor for ΔHbO_2 [coefficient = 0.027, confidence interval (0.016 to 0.037) $p < 0.001$].

With regard to the STAI questionnaire, group ($p < 0.001$ $df = 1$, $F = 20.34$) and timing (pre-study period, task period and post-study period) ($p = 0.006$ $df = 2$, $F = 5.21$) were predictors of a change in STAI questionnaire response. These predictors explain 13.9% of the variation in STAI response ($R^2 = 0.139$). Post hoc analysis demonstrated a significant reduction in subjective stress (increase in STAI) in the post-study period compared to task period [STAI response median (range) as follows: task period = 21 (12–24) vs. post study period = 23 (13–24), $p = 0.003$]. Practice session was not a predictor for change in STAI responses ($p = 0.07$ $df = 5$, $F = 2.07$). Critically, this means that HR was not a predictor of changes in cortical haemodynamics and subjective stress (STAI responses) was stable across practice sessions and therefore unlikely to be solely responsible for dynamic changes in brain behaviour. Moreover, the contribution of stress to changes in cortical haemodynamics, if at all, may manifest through HRV dependent influence on changes in HbO_2 alone.

Discussion

In the present study, a neuroergonomic paradigm has been employed in order to investigate left F-P cortical activity as subjects acquire a simulated surgical task with and without robotic assistance in the form of gaze-contingent channelling. fNIRS was utilised to detect local changes in cerebral haemodynamics associated with brain activation. The primary findings are that gaze-assisted motor learning leads to improvements in technical skill, more rapid evolution in regional cortical activation indicative of task internalisation, and a more efficient/economical F-P network architecture than free-hand learners.

Additionally, we have observed a loss of small worldness toward practice termination regardless of the mode of learning. There are a number of possible explanations/hypotheses that may account for learning related escalations in network costs, reduced network efficiency and the loss of small world behaviour at practice termination observed in both GCMC and control groups: (1) the relative PFC redundancy coupled to enhanced PPC activation at practice termination means that functional correlations are likely to be weaker at the end of practice than at the beginning. In the present study, this is evidenced by a reduction in the number of connections between frontal and parietal regions. Simultaneously, the network pathlength increases and in so doing reduces the small world index. (2) Technical accuracy in both study groups appears to be continuing to improve and subjects' performance has yet to reach asymptote. It is possible that had we continued to study subject's beyond six trials conceivably longitudinal improvements in F-P network efficiency along with a return to small worldness may have been observed. (3) Finally, longitudinal changes in network architectures are challenging to contextualise given the lack of motor learning studies that specifically and systematically address longitudinal plasticity in cortical networks evaluated using graph theory.

These results exhibit congruity with established theory of learning related neuroplasticity which suggests that expertise development is associated with attenuation in PFC activity (Kelly and Garavan, 2005; Leff et al., 2008a; Petersen et al., 1998; Puttemans et al., 2005). One theory is that attention and control centres in the PFC are necessary to support novel task demands during unskilled, effortful performance but are no longer necessary and subsequently "pruned" as a result of practice-dependent changes in executive control (Petersen et al., 1998). The residual PPC activity is indicative of the development of an internal model of the task (Shadmehr and Holcomb, 1997), dynamic monitoring of arm movements (Mulliken et al., 2008) and sensorimotor integration (Buneo and Andersen, 2006; Buneo et al., 2002). Therefore, longitudinal redistribution of activation comprising PFC down-regulation and PPC up-regulation suggests expertise acquisition, development of an internal model of the task and residual reliance on the PPC for effective spatial transformations between gaze-detected targets and precise motor

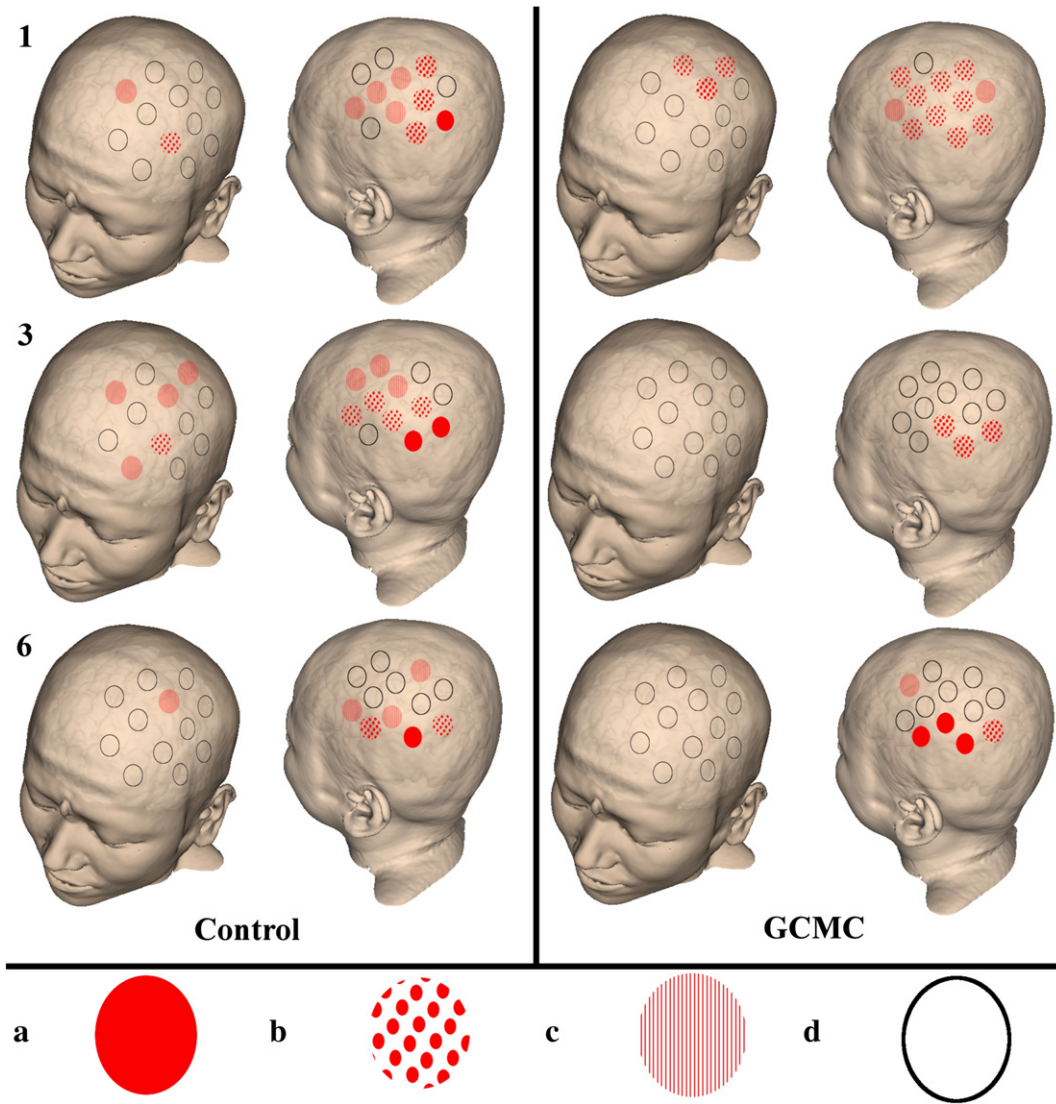


Fig. 4. Groupwise statistical analysis of longitudinal changes in cortical activity across sessions 1, 3 and 6 for control (left) and GCMC (right) subjects. Approximate channel locations are indicated by colours representative of the pattern of activity: (a) ΔHbO_2 increase and coupled ΔHHb decrease (both species reaching significance); (b) ΔHbO_2 increase and coupled ΔHHb decrease (one species reaching significance); (c) ΔHbO_2 increase and coupled ΔHHb decrease (neither species reaching significance); (d) no paired increase in ΔHbO_2 decrease in ΔHHb . Attenuation in PFC activity and focussing of activity within the PPC can be appreciated.

Table 1
Influence of subject group, cortical channel, practice session and cortical region (PFC vs. PC) on ΔHbO_2 .

HbO ₂	Variable	Coefficient	s.e.	z	p > z	95% C.I.
	Group	1.796423	1.111874	1.62	0.106	-0.3828089 to 3.975656
	Channel	-0.016795	0.0306889	-0.55	0.584	-0.0769442 to 0.0433541
	Session	-0.2314645	0.053448	-4.33	0.000	-0.3362207 to -0.1267083
	Region	2.344992	0.4362594	5.38	0.000	1.489939 to 3.200045
	Constant	2.267051	1.699034	-1.33	0.182	-5.597097 to 1.062994
	σ_u	2.4616349				
	σ_e	11.228495				
	rho fraction of variance due to u_j	0.04585821				

tracking. The greater attenuation in PFC excitation observed in GCMC versus free-hand learners may also reflect the influence of saccadic activity on the magnitude of excitation within frontal eye-fields. Generation of saccades (Schall, 2002) and corrective saccadic behaviour (Murthy et al., 2007) have both been demonstrated to lead to activation in the frontal eye field, a region located in the PFC. Saccadic cross-referencing between the tool-tip and target is likely to be more prominent in free-hand learners compared GCMC learners who by definition were required to regard the target in order to aid tool localisation. Therefore, it is conceivable that gaze-assisted visuomotor control ameliorates some of the prefrontal burden on the operator by reducing saccadic related activation.

It is important to appreciate variation in cortical network behaviour in order to better understand learning-related changes in brain integration associated with skills acquisition. Evidence suggests that modular flexibility within a network may predict subsequent performance whereas activation changes alone may not (Bassett et al., 2011). The findings in the current study are in line with other research demonstrating reduced connectivity between the PFC and other brain regions in conjunction with motor task learning (Sun et al., 2007) and reduced cortical network integration with time on task (Coynel et al., 2010).

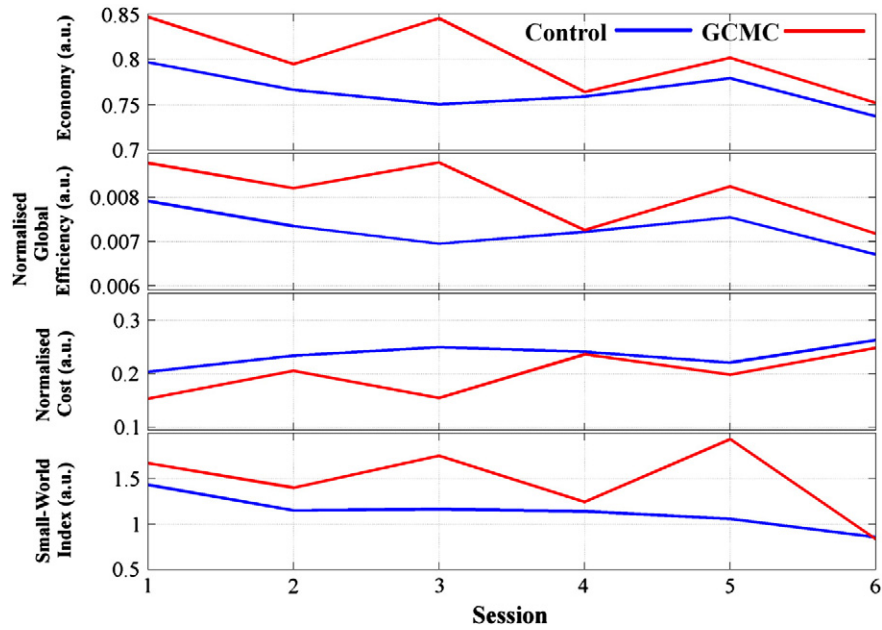


Fig. 5. Cortical network econometrics for control (blue) and GCMC (red) subjects across the 6 task sessions. It can be appreciated that network economy and efficiency is improved with GCMC and network costs are reduced. The small-world index is greater with GCMC and both groups display a small-world index > 1 until the final session. Efficiency, economy and the small-world index display a decreasing trend across the six sessions and cost increases. This occurs in tandem with attenuation in PFC activation.

However, unlike the training protocols in these studies which assessed network behaviour at only two (Sun et al., 2007) or three time points (Coynel et al., 2010), the current study assessed cortical network behaviour at every practice session. A more comprehensive analysis such as this enables practice-related changes in brain behaviour to be delineated more precisely. Moreover, the current approach enables practice-related changes in brain behaviour to be contrasted between two different modes of task learning, and therefore may determine the optimal mode based upon neuronal efficiency. In this study, subjects performing with gaze-assistance were more accurate at learning termination, and demonstrated more rapid activation map plasticity manifest as PFC attenuation and magnification of PPC excitation.

Analyses of dynamic changes in functional cortical networks may afford an improved understanding of the impact of different training regimes on task learning (Voss et al., 2012). One application of graph analysis, as in the current study, is in determining the optimal learning strategy from the perspective of network cost and efficiency. In this setting, brain behaviour is studied in order to appreciate the cortical resources required during task execution to ascertain whether or

not assistive technology is helpful in ameliorating the burden of task demands. Importantly, technology capitalising on the user's gaze behaviour to constrain motor performance enhanced the progression toward an "expert" pattern of brain activation and did so with an improvement in network economy and a reduction in network cost and normalised global efficiency. The behavioural corollary of improved network architectures is superior learning capabilities manifest as more rapid gains in technical performance. Many graph theoretical metrics exist (e.g. network modularity and network motifs) and additional work in this field might further capitalise on these metrics to investigate the impact of assistive technology on brain behaviour at work.

Conclusion

The current study highlights the potential role of functional neuroimaging in characterising the effects of assistive technologies on the user's brain. This neuroergonomic study demonstrates that gaze-assistance technology leads to more rapid acquisition of motor tracking skills and to the development of a pattern of cortical excitation that

Table 2

Network econometrics of average clustering coefficient and mean pathlength (normalised equivalent random network) utilised to calculate small-world index, normalised global efficiency, normalised cost, economy and the number connections between prefrontal and parietal regions.

Session	Average clustering coefficient ^a	Mean pathlength ^a	Small-world index	Number of F-P connections	Normalised global efficiency	Normalised cost	Economy
Control	1 4.2071	2.9374	1.432253	41	0.00792	0.20314	0.80478
	2 3.7422	3.2517	1.150844	43	0.007351	0.23344	0.77391
	3 4.0494	3.4785	1.164122	40	0.006952	0.24928	0.75768
	4 4.001	3.5086	1.140341	35	0.00722	0.2408	0.76642
	5 3.1069	2.9383	1.05738	35	0.007553	0.2207	0.78686
	6 3.481	4.0705	0.855177	25	0.006709	0.26255	0.74416
GCMC	1 3.2619	1.9538	1.669516	33	0.008784	0.15323	0.85556
	2 3.8609	2.7566	1.400602	43	0.008215	0.20528	0.80293
	3 4.5567	2.6008	1.752038	42	0.008796	0.1548	0.85399
	4 3.3168	2.6711	1.241736	36	0.007258	0.23579	0.77147
	5 4.6115	2.3856	1.933057	39	0.008254	0.19813	0.81013
	6 3.593	4.3075	0.834127	27	0.007179	0.24779	0.75939

^a Average clustering coefficient and mean pathlength normalised with respect to equivalent random network (Watts and Strogatz, 1998).

more swiftly progresses to the trained state, than that of free hand learners. Gaze assistance not only improves technical performance but results in a brain network whose architecture facilitates more efficient functional communication. For high precision industries such as surgery improved neuronal efficiency during motor performance may result in liberation of resources for the operator to attend to other safety critical aspects of the procedure (e.g. decision making).

Study limitations

The authors acknowledge the following limitations with the current study. First, although subject heart rate was monitored throughout, scalp blood flow was not recorded and changes in scalp flow are known to influence cortical haemodynamic data (Orihuela-Espina et al., 2010; Saager and Berger, 2008; Tachtsidis et al., 2008; Takahashi et al., 2011). Nevertheless, changes in optical attenuation within scalp layers are known to be affected by the optode source-detector separation. Specifically, phantom simulation studies reveal a greater contribution of scalp layers to NIR signals with shorter source-detector separations than was used in the current series of experiments (Hoshi et al., 2005; Takahashi et al., 2011). As illustrated in laboratory experiments conducted by Takahashi et al. (2011) and Hoshi et al. (2005) using multilayered phantoms the partial optical pathlength contribution of the brain tissues to the total optical pathlength may be as low as 5–22%. Theoretically, changes in scalp flow may have contributed to the observed “functional” changes in cortical haemodynamics observed during free hand and gaze assisted learning. However, it should be noted that unlike the current study in which both haemoglobin species are simultaneously considered in connectivity analysis and activation accepted only in the presence of anticipated changes in both HbO₂ and HHb species, phantom simulations evaluating the contribution of changes in scalp flow have focused solely on the HbO₂ response. Second, optical imaging enables activity from approximately the outer centimetre of the cortex to be detected at channel locations. Accordingly, brain regions not imaged but task-relevant may have been excluded. However, this is mitigated by targeting NIR optodes to regions known to be relevant to task execution and is offset by the benefits that optical imaging confers in terms of flexibility, relative resistance to motion artefact and the ability to study learners in real world environments that is currently not possible with fMRI.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <http://dx.doi.org/10.1016/j.neuroimage.2012.08.056>.

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