CDP4 Visuo-Motor Integration – Results for SGA2 Year 1 (D2.2.1 – SGA2)

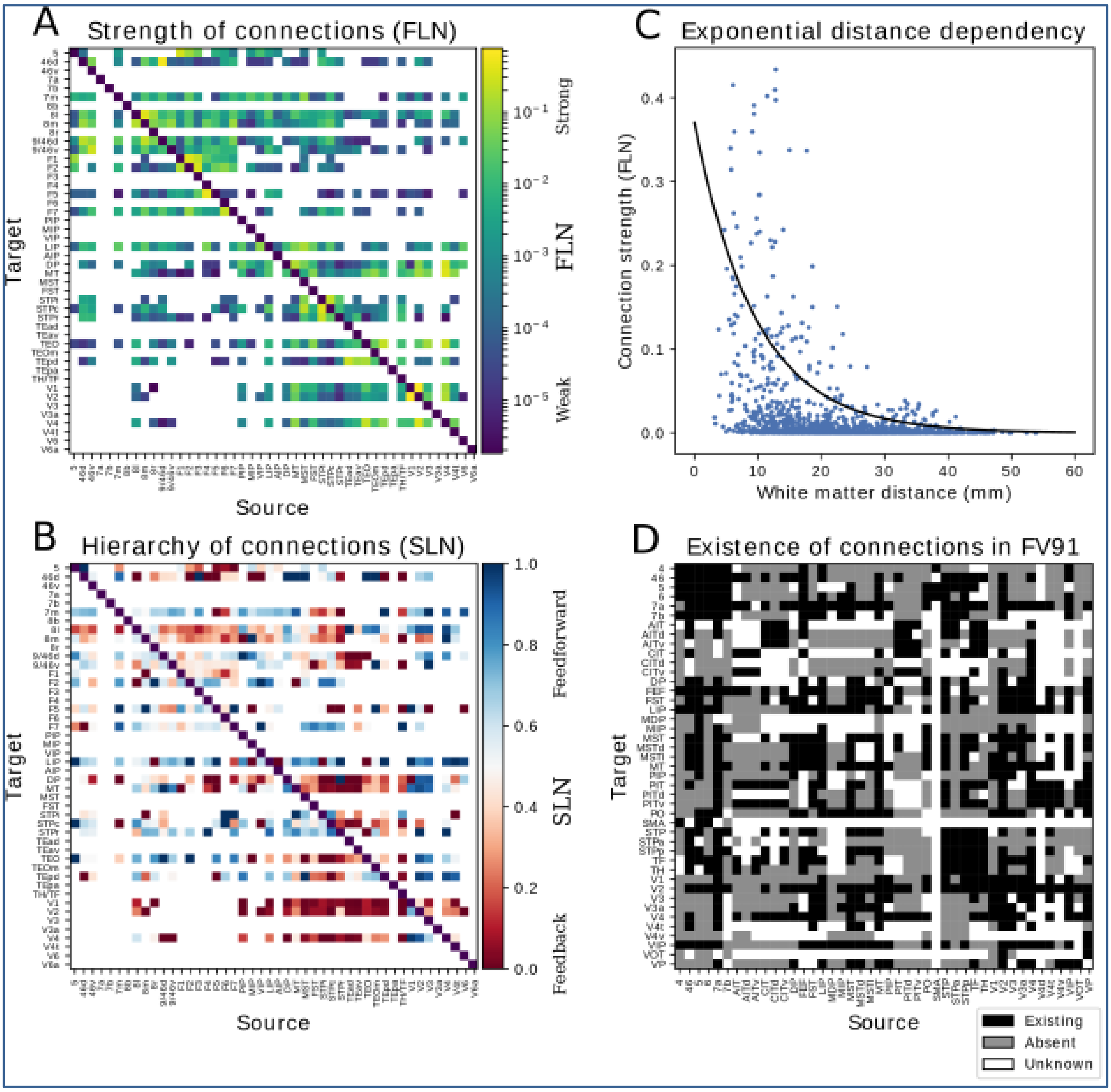

Figure 1: Experimental inter-areal connectivity data from axonal tracing studies in macaque and a predictive relationship.

(A) Strength of long-distance connections given as the Fraction of Labelled Neurons (FLN) in the M132 parcellation [2]. (B) Hierarchy of the connections provided as the fraction of Supragranular Labelled Neurons (SLN) in M132. SLN is an indicator of feedforward/feedback connectivity [3]. (C) Exponential relationship between the FLN and the shortest distance through white matter. (D) Existence/absence of connections from CoCoMac database [1] for the relevant areas in the FV91 parcellation. See KRc4.1 Output 4.

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Authors:	Mario SENDEN, UM (P117)
Compiling Editors:	
Contributors:	Sacha VAN ALBADA, JUELICH (P20)
SciTechCoord Review:	Martin TELEFONT, EPFL (P1)
Editorial Review:	Annemieke MICHELS, EPFL (P1)
Description in GA:	CDP4 Annual compound deliverable Year 1 Overview of Key Results and Impact achieved in M1 to M12, tailored for presentation to the relevant audiences (research/industry/public) References to HBP/SP/CDP objectives and Use Cases for navigation between multiple Sub-Projects Linkage of Results to components/a set of component fact sheets (lower level information: Component ownership, Technology Readiness level, performed Quality Control checks, etc.)
Abstract:	CDP4 is aimed at understanding the mutual interactions between action and perception with a focus on visual and visually-guided actions such as eye movements and hand-eye coordination. CDP4 is organised around three Key Results splitting it into theoretical (KRc4.1), applied (KRc4.2) and data-driven (KRC4.3) components and combines neuroimaging, neurocomputational modelling, machine learning and robotics. In the current phase, our focus has been largely on theoretical work but progress has been made with respect to the other key results as well.
Keywords:	Visuomotor integration, saccades, object recognition, saliency, multi-area modelling, hemispatial neglect, spiking neuron models, deep learning
Target Users/Readers:	Scientists, Companies and other potential users of HBP results. Neuroscientific community, funders

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History of Changes made to this Deliverable (post Submission)

Date	Change Requested / Change Made / Other Action
13 Mar 2019	Deliverable submitted to EC
22 Jul 2019	Resubmission with specified changes requested in Review Report Main changes requested: • Change 1: Clarify how Output 3 of KRc4.1 links to Outputs 1 & 2 • Change 2: Provide more detail around KRc4.3 Output 1 • Change 3: Clarify the role of KRc4.2 • Change 4: Clarify which datasets have already been used from SPs 1, 2 and 3 in the development of theoretical models • Change 5: Clarify the status of the publications that are currently in Rxiv or BioRxiv format • Change 6: Due to the lack of human data from patient studies for all activities related to CDP4, it is recommended that KRc4.2 be stopped and resources withdrawn or redirected
24 Oct 2019	Revised draft sent by SP/CDP to PCO. Main changes made, with indication where each change was made: • Change 1 Output 3 has been moved to KRc4.3. It fits better with KRc4.3 as the methods developed in Output three can be applied to saliency related user fMRI data there (see Section 5.1.4) • Change 2 We elaborate more on the state of the end-to-end deep reinforcement learning procedure to produce optimal eye movement patterns (see Section 5.1.2) • Change 3 We clarify the role and status of KRc4.2 (postponed until SGA3) in Section 6 • Change 4 We use electrophysiological data recorded as part of T2.5.7 (See Section 4.1.3) • Change 5 These publications have been submitted (See Section 5.2.3) • Change 6 KRc4.2 has been halted until SGA3, resources have allocated to KRc4.1 (See Section 6)
1 Nov 2019	Revised version resubmitted to EC by PCO via SyGMa

1. Overview

Humans are continuously required to interact with a complex, dynamically changing environment. Our brain does thus not operate in a vacuum, but forms a closed loop with the surroundings in which it is embedded. This has important implications for the study of action and perception and their interrelatedness within an ever-changing environment, as one can only be fully understood in context of the others. For example, human vision is only sharp near the centre of fixation and quickly drops with increasing distance from fixation. In order to recognise objects around us, it thus necessary to perform eye-movements and integrate information over several fixations. A by-product of these eye movements is that static objects move across the retina and the perceptual system needs to correct for object displacement and disentangle it from object motion. Eye movements thus need to be understood in terms of object recognition and vice versa. Co-design project 4 (CDP4) is aimed at understanding the mutual interactions between action and perception by combining neuroimaging (using tools such as fMRI), neurocomputational modelling, machine learning and robotics. Our focus lies specifically on visual as well as visually-guided actions, such as eye movements, for object recognition (SGA1 & SGA2) and hand-eye coordination for object manipulation (SGA2: reaching & grasping; SGA3: in-hand manipulations).

With respect to object recognition, we have identified functional components necessary for this task and developed computational models for each of them. Over the next 12 months, we will train a deep learning architecture to perform object recognition in light of the aforementioned image blow-up and will subsequently translate the computational strategy it develops to biologically realistic brain models.

With respect to object manipulation (reaching), we have set up a robotic arm in a virtual environment and will now train it to reach towards visually striking objects.

2. Introduction

The brain enables autonomous agents to interact meaningfully with a dynamic environment. That is, the brain forms a closed loop with the surroundings in which it is embedded through its sensory-motor apparatus. How the integration of sensory and motor function is achieved and how perception and action mutually affect each other constitute important questions in neuroscience. For instance, the sharp drop-off in visual acuity with eccentricity forces the visual system to perform saccadic eye movements and to integrate information across “snapshots” of the visual scene. These eye movements, in turn, affect perception and they lead to blur, retinal displacements and the requirement to distinguish eye- from object movements. Similarly, tasks such as reaching and grasping require tracking of object and hand location in space as well as continuous translation between coordinate frames (e.g. retinotopic vs body-centred).

Co-Design project 4 (CDP4) fuses computational modelling, deep learning, experimentation and robotics to understand how the brain coordinates such visually-guided actions. To do so, it follows a top-down approach. That is, it starts by identifying and implementing functional components relevant to the task. Implementation may involve developing computational models based on existing neuroscientific data (these modelling efforts occur largely within KRc4.1). It may, however, also involve utilisation of goal-driven deep (reinforcement) learning to let a neural network uncover potential solutions for performing ecologically valid visuomotor tasks (these efforts - largely based on behavioural data and labelled image databases - occur largely within KRc4.3). Subsequently, functional components are integrated into a single large-scale, closed-loop, visuomotor architecture for deployment with robotic systems (KRc4.1). These architectures are continuously refined to increase their biological realism. This occurs in a modular fashion as individual functional components may, for instance, be translated from a rate neuron to a spiking neuron implementation, independent from other components. The architecture may furthermore serve as a virtual patient, to model disorders resulting from damage to the system. The “saccades for object recognition” architecture is especially suited to investigate attention deficits (hemispatial neglect) resulting from stroke (KRc4.2) since it places strong emphasis on attention (saliency) and attention-based decision making (target selection). At the same time, studying hemispatial neglect is important for developing a biologically realistic and ecologically valid visuomotor architecture. As neural information processing requires taking the body and its environment into account, understanding of normal functioning of (components of) the visuomotor architecture requires examination of abnormal performance it produces in light of ablations and disruptions.

Co-Design project 4 is organised around three Key Results (KRs).

KRc4.1: Visuo-motor integration neuronal network model

By collaborative efforts with SP4 and SP7, efficient network simulations in NEST allow to build novel large-scale neural network models that actually perform challenging visuo-motor integration tasks while being based on state-of-the-art knowledge about the architecture of the brain as well as on novel insights from beyond the state-of-the-art sub-millimetre human functional brain imaging. By collaborative efforts with SP10, the visuo- motor integration model runs on the Neurorobotics Platform. The neurorobotics implementation allows to generate realistic behavioural data.

KRc4.2: Lesioning parietal and frontal areas of eye movement model to explain unilateral spatial neglect stroke and TMS treatment effects

The implemented visuo-motor system will integrate simplified modules of about 20 cortical and sub-cortical areas involved in visual stimulus processing, saliency calculation, target selection and motor planning. The established computational-anatomical relationship and asymmetric attention shifting architecture allows to simulate lesions of the model (link to CDP1) that are related to saliency, attention and motor planning producing neurological symptoms observed in unilateral spatial neglect patients. Furthermore, we will have access to neglect patients that are currently treated with TMS stimulation allowing to model reduced inhibition from the contra-lesional hemisphere. The effects of TMS will be integrated in the neural network model.

KRc4.3: Application of Visuo-Motor Integration Model to User Input Data

The visuo-motor model integrates state-of-the art architectural and functional knowledge of how the brain controls eye movement (version 1 [SGA1]) and grasping (version 2 [SGA2]) supporting the interpretation of the user's neuroimaging, electrophysiological and behavioural data. Since the visuo-motor integration model is implemented in NEST and linked to a (virtual) robotic system, researchers can run the model with their own visual stimuli as input and compare the predicted behaviour with their own empirical data.

3. Key Result KRc4.1: Visuo-motor integration neuronal network model

3.1 Outputs

3.1.1 Overview of Outputs

1) NEST 2.16.0 (component title: Continuous dynamics code in NEST, leader: Markus DIESMANN, id: C510, type: software)
2) Integrated target selection & saccade generation system (component title: Visuo-motor integration model performing eye movement and reaching tasks, leader: Rainer GOEBEL, id: C2632, type: model)
3) Output 3 was moved to KRc4.3
4) Multi-area model of cortical network at neuronal resolution (component title: Multi-area model of cortical network at neuronal resolution. leader: Sacha VAN ALBADA, id: C730, type: model)

3.1.2 Output 1

Modelling work by researchers at UM in Task T2.2.1 (Visuo-motor integration model performing eye movement and reaching tasks; component id C2632) in collaboration with JUELICH led to further extensions of integration methods for continuous-time population models first introduced in NEST 2.14.0. These extensions have been integrated into the NEST simulator and were released with NEST 2.16.0 as part of Task T7.3.1: Exascale solvers for phenomenological models.

This output has an upstream dependency on component C209 in task T7.3.4: NEST - The Neural Simulation Tool.

3.1.3 Output 2

For Task T2.2.1 (Visuo-motor integration model performing eye movement and reaching tasks; component id C2632), researchers at UM have integrated two previously separate modules of visuo-motor integration, target selection and saccade generation [1], into a unified model. While integration of these models was successful, each module was implemented using different neuron dynamics. Current efforts are devoted to implement both modules using the same dynamics. This provides the opportunity to increase the biological realism of the combined model by choosing for more accurate descriptions of population dynamics than employed previously. For instance, neural populations within the target selection module will be split into excitatory and inhibitory pools. However, while these population models yield valuable insights regarding functional dynamics, the coarse-graining inherent in this approach neglects the possibly rich internal dynamics of neural populations and intricate interactions with other populations on the single-neuron level. Therefore, and to further increase the biological realism, JUELICH started to implement the mechanisms of saccade generation and target selection using functional spiking neural networks (SNNs).

This output has an upstream dependency on component C1857 embedded in Task T4.4.5: Models of sensorimotor integration.

Reference

[1] Gancarz G, Grossberg S, A neural model of the saccade generator in the reticular formation, *Neural Networks* **11.7**, p 1159-1174 (1998)

3.1.4 Output 4

As part of Task T4.2.3 (Multi-area multi-layer spiking cortical models), JUELICH is developing a multi-area model of a cortical network at neuronal resolution (component id: C730) of all vision- and motor-related cortical areas in macaque. The model extends the visual multi-area-model [5, 6], where each cortical area is represented by a full-density model of a cortical microcircuit (component id: C944) [4]. Motor areas differ crucially from visual cortex: they have a less prominent layer 4, a far lower neuron density and different internal connectivity. Therefore, it is pivotal to develop a microcircuit of the macaque primary motor cortex. The motor microcircuit will incorporate the available experimental data for layer resolved density, internal connectivity and subcortical connectivity, among others. To that end JUELICH has started the analysis of the long-range cortico-cortical connectivity. The strength of a connection between two cortical areas can be characterised by the Fraction of Labeled Neurons (FLN) in axonal tract-tracing studies. The hierarchy of the connections can be described by the location of the presynaptic neurons in the source area of the projection via the fraction of Supragranular Labeled Neurons (SLN). As an intermediate result, JUELICH has successfully complemented experimental data with statistical predictions based on intrinsic relationships between the cortical structure (such as white matter distance, log ratio of neuron density and layer thickness) and the connectivity for all known existing connections from the CoCoMac database [1]. As a next step, topological predictive methods will be used to estimate connections where they are unknown. This modelling work provides an understanding not only of neurocomputational properties of local microcircuits but also of their complex interactions in a large-scale network. As such it is crucial for increasing the biological realism of the functional visuomotor architecture of “saccades for object recognition”.

References

[1] Bakker R, Wachtler T, and Diesmann M. CoCoMac 2.0 and the future of tract-tracing databases. Front Neuroinformatics 6:30, 2012.
[2] Markov NT, Ercsey-Ravasz MM, Ribeiro Gomes AR, Lamy C *et al.* A weighted and directed interareal connectivity matrix for macaque cerebral cortex. Cereb Cortex 24:17-36, 2014.
[3] Markov NT, Vezoli J, Chameau P, Falchier A, Quilodran R *et al.* Anatomy of hierarchy: Feedforward and feedback pathways in macaque visual cortex. J Comp Neurol 522:225-259, 2014.
[4] Potjans TC and Diesmann M. The cell-type specific cortical microcircuit: Relating structure and activity in a full-scale spiking network model. Cereb Cortex 24:785-806, 2014.
[5] Schmidt M, Bakker R, Hilgetag CC, Diesmann M, and van Albada SJ. Multi-scale account of the network structure of macaque visual cortex. Brain Struct Func, 223:1409-1435, 2018.

[6] Schmidt M, Bakker R, Shen K, Bezgin G, Diesmann M, and van Albada SJ. A multi-scale layer-resolved spiking network model of resting-state dynamics in macaque visual cortical areas. PLOS Comput Biol, 14:e1006359, 2018.

3.2 Validation and Impact

NEST 2.16.0 has been validated by implementing existing models within its framework and evaluating the consistency between original model simulations and those performed using NEST 2.16.0. Agreement was excellent.

3.2.1 Potential Use of Outputs

Extension of the NEST framework to include rate-based neuron models (Output 1) allows for the implementation of functionally performant large-scale models using this publicly available, widely used, and actively developed simulation tool. This allows researchers to develop biologically plausible spiking neuron models and functionally realistic rate neuron and mean field models within the same framework and hence facilitates gradual transitions between as well as integration of these (respectively bottom-up and top-down) modelling approaches.

3.2.2 Publications

The main publications for this KR are:

1) (P1760) Senden, M., Schuecker, J., Hahne, J., Diesmann, M. & Goebel, R. [Re] A neural model of the saccade generator in the reticular formation. *ReScience* **4,** (2018). Output 1
2) (P1036) Schmidt M, Bakker R, Hilgetag CC, Diesmann M, and van Albada SJ. Multi-scale account of the network structure of macaque visual cortex. Brain Struct Func, 223:1409-1435, 2018. Output 4
3) (P1457) Schmidt M, Bakker R, Shen K, Bezgin G, Diesmann M, and van Albada SJ. A multi-scale layer-resolved spiking network model of resting-state dynamics in macaque visual cortical areas. PLOS Comput Biol, 14:e1006359, 2018. Output 4

3.2.3 Measures to Increase Impact of Outputs: Dissemination

An executable formal model description of the multi-area model of all vision-related areas of macaque cortex (Schmidt *et al.*, 2018a,b) was made available on GitHub (https://inm-6.github.io/multi-area-model/), enabling others to build on the code. A tutorial video was published on YouTube, available in the HBP Education channel (https://www.youtube.com/watch?v=NGAqe78vmHY) and via the NEST simulator website (http://www.nest-simulator.org/), and has already received >1000 views. Output 4

4. Key Result KRc4.2: Lesioning parietal and frontal areas of eye movement model to explain unilateral spatial neglect stroke and TMS treatment effects

4.1 Outputs

4.1.1 Overview of Outputs

1) Dynamical model of hemispheric asymmetry in attentional control (component title: Lesioned visuo-motor model with asymmetric attention modules for left and right hemisphere, leader: Rainer Goebel, id: C2633, type: model)

4.1.2 Output 1

As part of Task T2.2.2 (Lesioned visuo-motor model with asymmetric attention modules for left and right hemisphere; component id C2633) researchers at UM are developing a quantitative dynamic model of hemispheric asymmetry in attentional control. The current, early, version of the model comprises the interconnected dorsal and ventral fronto-parietal networks consisting of left and right frontal eye fields and posterior parietal cortices. Hemispheric asymmetry in the frontal cortex is implemented in accordance with Heilman's Hemispatial theory [1,2] while in the parietal cortex it is implemented in accordance with Kinsbourne's opponent processor model [3].

References:

[1] Heilman, K.M., Abell, T.V.D., 1980. Right hemisphere dominance for attention. Neurology 30 (3), 327.

[2] Heilman, K.M., Valenstein, E., 1979. Mechanisms underlying hemispatial neglect. Ann. Neurol. 5 (2), 166–170.

[3] Kinsbourne, M., 1977. Hemi-neglect and hemisphere rivalry. Adv. Neurol. 18, 41–49.

4.1.3 Output 2

JUELICH has begun to integrate spatial attention into the visual multi-area-model. This work uses electrophysiological data recorded from areas V6/V6A in macaque monkeys acquired within SP2 (T2.5.7) to build correlates of visual spatial attention and attentional shifts into a spiking model covering these areas as well as V1, V2, V4, PO (human homologues of V6/V6A), IT (divided into six areas), LIP, and FEF. In the current stage this model comprises a single hemisphere. However, as a demonstrator in SGA3 it will be extended to include a second hemisphere to model attentional asymmetries.

4.2 Validation and Impact

4.2.1 Potential Use of Output

The dynamic model as well as a bi-hemispheric visual-multi-area model may be used to study potential therapies for hemispatial neglect based on efforts of re-balancing activity in the two hemispheres such as non-invasive brain stimulation.

5. Key Result KRc4.3: Application of Visuo-Motor Integration Model to User Input Data

5.1 Outputs

5.1.1 Overview of Outputs

1) Image blow-up algorithm (component title Brain-constrained deep learning modules for visuo-motor integration tasks, leader: Rainer GOEBEL, id: C2634, type: model)
2) Deep convolutional autoencoder for saliency computation (component title Brain-constrained deep learning modules for visuo-motor integration tasks, leader: Rainer GOEBEL, id: C2634, type: model)
3) Mental imagery (component title: Feedback interactions in monkey and human, leader: Wim VANDUFFEL, id: C2468, type: dataset)

5.1.2 Output 1

Researchers at UM have developed an algorithm which resamples images in accordance with ganglion cell distributions in the human retina. This work falls within T2.2.4: Brain-constrained deep learning modules for visuo-motor integration tasks (component id C2634). Resampling leads to image blow-up such that central regions in the image are enlarged while distant regions are compressed. By incorporating this distortion into convolutional neuronal networks, these networks become more biologically realistic in two related aspects. First, visual acuity and spatial frequency preference of the networks exhibit eccentricity dependence. Second, networks exhibit cortical magnification as most of their units are devoted to central vision. These aspects are currently being validated by training a convolutional neural network on an orientation discrimination task of resampled (distorted) grating stimuli.

Human-like acuity drop-off with increasing distance from fixation requires convolutional networks to explore a visual scene by taking snapshots from different fixations and integrate this information in order to recognise objects. Researchers at UM are currently developing an end-to-end deep reinforcement learning procedure to produce optimal eye movement patterns in light of the aforementioned distortions. As a first step, the recurrent attention model (RAM) has been implemented. This convolutional neural network is able to classify objects based on glimpses (cut-outs of the visual scene, no further distortion) by consecutively selecting locations for upcoming glimpses in a goal-directed fashion. Currently this network is being trained to identify objects by making fixation decisions in light of resampled (distorted) images rather than glimpses. In parallel, researchers at UM are developing alternative neural network architectures with distinct ventral (what) and dorsal (where) pathways.

Exploiting the "policy gradient" deep reinforcement learning method in combination with convolutional and recurrent neural networks, the model will take a distorted snapshot of an image as input and exploit the information present to learn and generate sequences of saccade-like shifts in overt attention. In addition, by the end of SGA2 (month 24) the model will be able to integrate a sequence of snapshots into an overall coherent "mental" representation that can be classified. In general, the model will autonomously learn where to look, and to identify what it is seeing.

References:

[1] Mnih, V., Heess, N., Graves, A., & Kavukcuoglu, K. (2014). Recurrent Models of Visual Attention. 2204–2212.

5.1.3 Output 2

For Task T2.2.4 (Brain-constrained deep learning modules for visuo-motor integration tasks; component id C2634) researchers at UM further refined the deep convolutional autoencoder for saliency computation, first developed during SGA1. Specifically, an Atrous Spatial Pyramid Pooling (ASPP) module was added which utilises several convolutional layers with different dilation factors in parallel to capture multi-scale image information and global context. By dilating convolutional kernels, their receptive field sizes can be expanded in a computationally efficient manner without introducing additional parameters to the learning task. Here, three of these layers were laid out in parallel and combined with the activation maps from both a pointwise convolutional operation and global average pooling. The ASPP module was then applied to the extracted high-level features of a pre-trained image classification architecture, which allowed the network to encode semantic representations at multiple spatial scales and thus predict salient image regions more holistically. A qualitative evaluation demonstrated the re-weighting of feature importance in complex scenes via the multi-scale model component. This has resulted in improved approximations of empirical fixation maps.

5.1.4 Output 3

For Task T2.5.5 (Feedback interactions in monkey and human; component id C2468), researchers at UM have conducted a submillimetre fMRI study in humans at 7T investigating the spatial specificity of feedback arriving in early visual cortex during visual mental imagery of letter shapes. By successfully reconstructing imagined letter shapes, these researchers provided new evidence in favour of detailed topographic organisation of feedback. Specifically, it was shown that feedback and feedforward processing show the same retinotopic organisation. Furthermore, the study revealed that utilisation of a denoising autoencoder greatly enhances reconstruction quality and can serve as a pretraining procedure when designing classifiers able to identify imagined letters from brain activity.

These results illustrate the possibility to project cortical activity into the visual field even in the absence of physical stimuli and hence to visualize high level processes such as mental imagery or, of high relevance to CDP4, attention. Indeed, the tools for reconstruction developed for and validated by this study will be essential to read out spatial activity distributions related to salience from posterior parietal cortex and to compare these against predictions made by the convolutional autoencoder (Output 2).

5.2 Validation and Impact

The ASPP module extension of the deep convolutional autoencoder (Output 2) has been evaluated by comparing the performance of the architecture with and without this module on the test set of the MIT saliency benchmark. This evaluation revealed that ASPP module lead to significant performance improvements.

5.2.1 Actual Use of Output(s)

The extended saliency detection model (Output 2) has been used by researchers at UPFL who integrated it into a cortical model for visual segmentation (Task T10.2.1: Active perception and scene understanding; component id C2704).

The reconstruction tools developed for and validated by Output 3 are used to test predictions of saliency distributions in response to natural images within posterior parietal cortex measured with 7 Tesla (submillimetre) fMRI. This work is currently ongoing.

5.2.2 Potential Use of Output(s)

The image sampling (blow-up) algorithm resamples images to reflect ganglion cell placement in the human retina. As such it might be relevant to increase the biological realism of models of the human retina. Efforts to design a highly biologically plausible retina model are currently ongoing within SP4, notably Task T4.4.2 (Network model of the retina responding to complex stimuli; component id C2296).

An end-to-end deep reinforcement learning procedure to produce optimal eye movement patterns in light nonlinear image sampling offers new opportunities for robotic applications. These systems may be outfitted with cameras whose sensor placement mimics the human retina. This would allow for very large coverage of the visual field while at the same time allowing for sharp vision near fixation. However, similar to humans such systems would need to produce eye movements and the architecture developed within CDP4 can be utilised for this purpose.

Apart from their immediate scientific relevance, the results of Output 3 further open new avenues for brain computer interfaces (BCIs). Specifically, a denoising autoencoder can be used to pretrain a classifier purely based on perceptual data before fine-tuning it on imagery data. This may be utilized for the development of content-based BCI letter-speller systems which may be particularly suitable for communication in cases where voluntary muscle movement is impaired (e.g. locked-in syndrome).

5.2.3 Publications

The main publications for this KR are:

(P1761) Kroner, A., Senden, M., Driessens, K., & Goebel, R. (2019). Contextual Encoder-Decoder Network for Visual Saliency Prediction. https://arxiv.org/abs/1902.06634 - this work has been submitted to the *Neural Networks* - Output 2

(P1640) Senden, M., Emmerling, T. C., van Hoof, R., Frost, M. A. & Goebel, R. Reconstructing imagined letters from early visual cortex reveals tight topographic correspondence between visual mental imagery and perception. *Brain Struct. Funct.* 1–17 (2019). Output 3

5.2.4 Measures to Increase Impact of Output(s): disseminations

The saliency detection model (Output 2) has been made available on github: https://github.com/HBPNeurorobotics/embodied_attention

The results of Output 3 have been extensively shared on twitter and are the subject of invited talks at several labs such as the computational neuroscience group at the Universitat Pompeu Fabra in Barcelona, Spain.

6. Conclusion and Outlook

Over the past 12 months all parties involved in CDP4 have made significant progress with respect to Key Result KRc4.1. This has not only led to a number of publications, including new insights with respect to mental imagery which may have important implications for the development of letter-speller BCIs, but also to further extensions of the NEST simulator which have been made available to the scientific community with the release of version 2.16.0. With respect to the development of a large-scale visuomotor architecture most progress was made by integrating existing functional components on the one hand and performing simulations of multi-scale spiking neural network models on the other. The ability to simulate large, interconnected, networks of biologically plausible neurons together with the continued development of functionally performant visuomotor systems will prove crucial over the upcoming months to implement a neural architecture of visuomotor integration. While Key Result KRc4.1 is thus on a good track in general, little progress has been made towards performing behavioural visuomotor experiments using a neurorobotics implementation of the architecture. However, both target selection and saccade generation models, as well as the saliency architecture (KRc4.3), have been embedded in the Neurorobotics Platform and the collaboration between UM and FZI (SP10) has been strengthened in order to deliver first experimental results within the next six months. Specifically, in order to integrate all functional modules related to the “saccades for object recognition” closed-loop architecture, CDP4 stimulated SP10 to develop the Integrated Behavioral Architecture (IBA) framework for the NRP. The IBA is a software framework, the main function of which is to enable compositionality of various brain functions and circuits. Through this framework, neuro-computational components can be integrated into the NRP as part of a modular, expandable cognitive architecture, in order to evaluate their functional performance through embodied simulation.

KRc4.2 is an important component of the FLAG-ERA BRAINSYNCH-HIT partnering project which started in 2018 and is thus relevant for the HBP. Furthermore, KRc4.2 fits within the over-arching story of CDP4 as the modelling work carried out within KRc4.2, development of a model of hemispheric asymmetry in attentional control (Output 1) and integration of spatial attention into the visual multi-area-model (Output 2) are directly related to work in KRc4.3 (models of saliency computation & target selection) and KRc4.1 (multi-area model), respectively. While work on this key result has begun it is still in an early stage. This is because an expected dataset of neglect patients has not yet been received since approval of BRAINSYNCH-HIT had taken longer than expected. In line with suggestions made by the EC, we will put KRc4.2 on hold and focus our efforts on KRc4.1 and KRc4.3 until the end of SGA2. We submitted our plan to continue the work on KRc4.2 into SGA3 as part of WP3 (demonstrator) in order to fulfil our role in the BRAINSYNCH-HIT partnering project to the SIB.KRc4.3 has made good progress. Both the image blow-up algorithm and the autoencoder have reached a mature state. Furthermore, the autoencoder is actively used by other researchers in the HBP, mostly by SP10. In the upcoming 12 months the autoencoder will be used to generate predictions of saliency distributions in response to natural images within posterior parietal cortex measured with 7 Tesla (submillimetre) fMRI. The image distortion algorithm has not yet been used by other groups but constitutes an important first step towards developing an end-to-end deep reinforcement learning procedure to produce optimal eye movement patterns in light of the aforementioned distortions. Such a system will become an important source of predictions of behavioural data in eye movement experiments.