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Editorial: State-dependent brain computation

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The brain is a self-organizing system, which has evolved such that neuronal responses and
related behavior are continuously adapted with respect to the external and internal context. This
powerful capability is achieved through the modulation of neuronal interactions depending on
the history of previously processed information. In particular, the brain updates its connections
as it learns successful versus unsuccessful strategies. The resulting connectivity changes, together
with stochastic processes (i.e., noise) influence ongoing neuronal dynamics. The role of such state-
dependent fluctuations may be one of the fundamental computational properties of the brain, being
pervasively present in human behavior and leaving a distinctive fingerprint in neuroscience data.
This development is captured by the present Frontiers Research Topic, “State-Dependent Brain
Computation.”

The Research Topic provides an account of prevailing concepts and theories plus recent
advances on the role of ongoing brain dynamics—reflecting experiences, global brain states, context
and noise—for task-related information processing. Works from the conceptual, experimental
and computational-modeling domains are show-cased, focusing on the following two issues: (1)
Generative mechanisms of ongoing neuronal dynamics, and (2) Principles of interaction between
ongoing dynamics and perceptual or motor processes.

A wide range of spatial and temporal scales encountered in brain dynamics are covered, i.e.,
from microscopic molecular to macroscopic population dynamics and from fast processes evolving
within milliseconds to slow ones taking hours or longer (Table 1). An overview article about state-
dependent learning exemplifies the need for integration of different scales of processing (Ritter
et al., 2015). The role of ongoing alpha oscillations at the microscopic and macroscopic scale for
learning is illuminated in Sigala et al. (2014). In this study, the authors present empirical data along
with computational models that seek to unveil the underlying principles how oscillations interact
with synaptic plasticity. EEG dynamics are also explored in Betzel et al. (2012) where the authors
report fast synchronization dynamics—in the range of tens to hundreds of milliseconds—iterating
amongst a small set of core networks in the resting brain. The authors suggest that these dynamics
may be the neural correlate of resting state BOLD fluctuations. The ability of stochastic dynamic
causal modeling (DCM) for fMRI—a neural field formulation of cortical activity—is probed in
Daunizeau et al. (2012) where EEG spectral changes are predicted from BOLD signal Fast and high
spatial frequency modes as represented in EEG are enslaved by slow and slow spatial frequency
modes predominant in fMRI signals. Using an Ising spin model (Deco et al., 2012) demonstrate
that the dynamic repertoire of the brain, i.e., different spatio-temporal patterns of functional
connectivity, emerges naturally from the neuroanatomical connectivity. It is hypothesized that the
scale-free neuroanatomical architecture maximizes the dynamic repertoire and its accessibility in
TABLE 1 | Different facets of state-dependent brain computation are illuminated in the present Research Topic.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Article</th>
<th>Animal</th>
<th>Function</th>
<th>States</th>
<th>Empirical</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Micro</td>
<td>Banerjee et al., 2012</td>
<td>Macaque</td>
<td>Arm movement/reaching task</td>
<td>LFP</td>
<td>Spike trains, LFPs</td>
<td>Parametric model</td>
</tr>
<tr>
<td></td>
<td>Fernandez-Ruiz and Herreras, 2013</td>
<td>Rat</td>
<td>Rest, stimulation</td>
<td>LFP</td>
<td>LFP</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Humble et al., 2012</td>
<td>–</td>
<td>Memory</td>
<td>Spike trains</td>
<td>–</td>
<td>Spiking neuron models and STDP</td>
</tr>
<tr>
<td></td>
<td>Mark and Tsodyks, 2012</td>
<td>Rat</td>
<td>Spontaneous, sensory stimulations</td>
<td>Different synchrony levels</td>
<td>–</td>
<td>Wilson–Cowan rate model, IF-neurons, Realistic neuronal network with clustered architecture</td>
</tr>
<tr>
<td></td>
<td>Palma et al., 2012</td>
<td>–</td>
<td>Memory</td>
<td>Neuromodulation</td>
<td>–</td>
<td>Spiking recurrent networks</td>
</tr>
<tr>
<td></td>
<td>Quilichini and Bernard, 2012</td>
<td>Rat</td>
<td>T-maze</td>
<td>Neuromodulators</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Bridging micro to macro</td>
<td>Ritter et al., 2015</td>
<td>Human, macaque, rat, in vitro</td>
<td>Learning, rest</td>
<td>Oscillatory LFP EEG BOLD</td>
<td>Yes</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Sigala et al., 2014</td>
<td>Human/young adults</td>
<td>Learning, rest</td>
<td>Oscillatory LFP EEG BOLD</td>
<td>Yes</td>
<td>–</td>
</tr>
<tr>
<td>Macro</td>
<td>Betzel et al., 2012</td>
<td>Human</td>
<td>Rest</td>
<td>EEG, 10–100 ms</td>
<td>EEG</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Daunizeau et al., 2012</td>
<td>Human/patients with epilepsy</td>
<td>Rest, interictal activity</td>
<td>EEG BOLD</td>
<td>EEG, BOLD</td>
<td>Neuronal field model/stochastic DCM, Heuristic model</td>
</tr>
<tr>
<td></td>
<td>Deco et al., 2012</td>
<td>Human</td>
<td>Rest</td>
<td>EEG BOLD</td>
<td>–</td>
<td>Neuronal oscillator model</td>
</tr>
<tr>
<td></td>
<td>Heitmann et al., 2012</td>
<td>Human</td>
<td>Motor</td>
<td>LFP/EEG</td>
<td>–</td>
<td>generic oscillator equations derived from coupled full brain network</td>
</tr>
<tr>
<td></td>
<td>Jirsa and Muller, 2013</td>
<td>Human</td>
<td>Rest, eyes-closed, eyes-open</td>
<td>EEG</td>
<td>EEG</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Miller et al., 2012</td>
<td>Human</td>
<td>Rest and task/stimulation</td>
<td>Band-limited EEG rhythms amplitude modulation</td>
<td>EEG</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Protopapa et al., 2014</td>
<td>Human</td>
<td>Motor and visuo-spatial working memory</td>
<td>EEG functional connectivity</td>
<td>EEG</td>
<td>–</td>
</tr>
<tr>
<td>Not specified</td>
<td>Friston et al., 2012</td>
<td>Human, bird</td>
<td>Sensory stimulation, bird song</td>
<td>Behavioral, simulated neuronal dynamics</td>
<td>–</td>
<td>Generalized Bayesian filtering, generic generative model</td>
</tr>
</tbody>
</table>

the human brain. Critical slowing caused by dynamical instabilities that are triggered by perception is proposed to enable the brain to process sensory perturbations (Friston et al., 2012). Neuronal oscillator models with surround inhibition were shown to generate bistable spatial patterns of activity (Heitmann et al., 2012) and indicate that state-dependent computations
may facilitate rapid switching between motor states, potentially accommodating high speed rather than precision responses. The cross-frequency coupling present in empirical EEG was systematically simulated in a full human brain network model of coupled neuronal oscillators (Jirsa and Muller, 2013) for eyes-open and eyes-closed states of rest condition and the theoretical implications for state-dependent processing discussed. Distinct brain states linked to motor and perceptual visuo-spatial working memory and accompanying specific mental processes are characterized as spatio-temporal functional connectivity patterns in EEG (Protopapa et al., 2014).

On the microscopic scale, spike trains and local field potentials (LFP) dynamics are set in relation (Banerjee et al., 2012) using parametric models with the goal to decode those signals and infer related behaviors. In Fernandez-Ruiz and Herreras (2013) it is pointed out that LFPs are highly variable over time and have flexible spectrums, i.e., the notion of periodic oscillations commonly used to describe brain activity is questioned. These authors propose a method to de-mix LFPs of different sources to determine the true degree of periodicity—a prerequisite for a mechanistic understanding of information transfer in the brain. In a spiking neuronal model with STDP (Humble et al., 2012) demonstrate that simple networks of laterally connected excitatory neurons can self-organize into spatio-temporal pattern recognizers. The potential for representations of more complex nested patterns which implies stronger computational memory capabilities is raised. The flow of information depends on the degree of network synchrony (Mark and Tsodyks, 2012) and an intermediate degree of synchrony is most beneficial for information transfer. The question whether rhythmic entrainment represents a general mechanism of computation in the brain is raised and ways are pointed out how to address this question through empirical work in the future (Miller et al., 2012). The theoretical impact of neuromodulation on memory formation in spiking recurrent cortical networks is systematically evaluated (Palma et al., 2012).

In a perspective article, a systematic account is provided how intrinsic properties of neurons and neuromodulation relates to firing patterns, functional correlations and behavior in rats (Quilichini and Bernard, 2012).

The degree of abstraction in the modeling work presented in this Research Topic varies tremendously, ranging from simplified but biophysically plausible network models to highly detailed neuron models. By placing the different mathematical and empirical aspects in this mutual context, this Research Topic aims to elucidate the principle mechanisms of state-dependent neuronal processing. Developing a framework to link the multiple principles together is arguably the most pressing challenge. With The Virtual Brain (thevirtualbrain.org) simulation framework (Ritter et al., 2013; Sanz Leon et al., 2013) we hope to contribute to this endeavor by enabling researchers to use multiple modeling approaches in a unified framework ensuring reproducibility and comparability of results.

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**References**


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