# **1. Theoretical Background and aims**

## 1.1 The benefits of combining EEG and fMRI

Neuronal activity of cognitive or affective processes can be studied from a large variety of measures, thereby revealing unique perspectives on brain activation.

Electroencephalography (EEG) mainly reflects the summation of postsynaptic potentials in pyramid cell populations with a similar orientation at a cortical level (Luck, 2005). Through sufficient coverage of the head surface with electrodes, synchronised activity of these cells can be recorded at a high temporal resolution. Due to the high temporal resolution for observing changes in brain activation on a scale of milliseconds, EEG is often chosen as a direct link to cortical activity. However, EEG is recorded at a relatively large distance from the cells and considerable portions of the original activity spikes fall off outside a 50 µm radius (Henze, Borhegyi, & Csicsvari, 2000). In addition, shorter spike durations with high-frequency oscillations far above 200 Hz decrease the odds of spike summation. Therefore, the skull prevents higher frequency signals from affecting the EEG and the recorded signal predominantly consists of slower Local Field Potentials (LFP). Compared to action potentials of single cells and multi-unit activity (MUA), LFP are bound to temporal and spatial summation. For this reason, EEG only represents summed surface potentials. Furthermore, despite advances in signal source estimation (e.g. Lei et al., 2011), its spatial resolution is severely limited.

While the electromagnetic fields measured in the EEG directly relate to neuronal activity, functional magnetic resonance imaging (fMRI) is based on blood oxygenation. The hemodynamic signal assessed by fMRI is linked to the oxygen consumption of neuron populations. Depending on the type of MRI recording, results show the flow of oxygenated blood in accordance to the metabolic demands of brain regions (Logothetis & Wandell, 2004). For this reason, the signal used in fMRI contrasts is called blood oxygenation level dependent (BOLD). Since the BOLD signal is a correlate of neuronal activity, it is regarded as an indirect measure. Plus, it is confined to a low temporal resolution on a timescale of seconds. In return, functional BOLD contrasts offer a higher spatial resolution compared to other imaging methods, while still operating entirely non-invasively. As such, MRI is a powerful method for studying the spatial dynamic of brain activity and gaining anatomical information without harming patients or test subjects.

Matching up these two methods, it becomes apparent that EEG and fMRI complement each other. Together they combine next to ideal temporal and spatial resolutions (Debener, Ullsperger, Siegel, & Engel, 2006). Both measures require an in depth understanding about its signals’ physiological basis in order to draw reasonable conclusions from experimental results about brain activity. Their respective limitations often decreases the conclusion’s validity. Instead of relying on a selective view with a single method, simultaneous or parallel recordings provide multifaceted insights into brain activation. In spite of the considerable measurement artifacts inflicted by one method on the other (Allen, Josephs, & Turner, 2000; Bénar et al., 2003; Iannotti, Pittau, Michel, Vulliemoz, & Grouiller, 2014), simultaneous recordings yield the greater potential. While free from artifacts, parallel recordings cannot ensure to represent identical psychological processes in test subjects and add other problems, such as training effects, habituation or fatigue.

Perhaps even more notable than the complementing spatial and temporal resolutions in combined EEG and fMRI is the benefit stemming from their physiological relation. Variation in LFP often bears more similarity to changes in BOLD than to recordings of single cell activity or MUA (Logothetis, Pauls, Augath, Trinath, & Oeltermann, 2001). At the same time, it is irrefutable that EEG and fMRI present brain activity from two very different perspectives. Considering their physiological basis, it seems plausible that modulations across experimental manipulations of BOLD and EEG activity often do not align (Im, Jung, & Fujimaki, 2005; Nunez & Silberstein, 2000). Whereas EEG signals only show the result of multiple activity summations across cortical layers, changes in the BOLD signal across time reflect fluctuations of oxygen concentrations in different brain regions.

The fact that the two signals do not align completely can be regarded as an upside and a downside to concurrent EEG and fMRI recordings. Neurovascular decoupling of neuronal activity and cerebral blood flow impedes the validation of a result found in one method but not in the other. When relating, for instance, Event-related potentials (ERP) to functional contrasts, neurovascular coupling would yield both results to be more meaningful. Plus, information from both sides aid the interpretation and integration of results into the greater theoretical background. Then again, neurovascular decoupling might provide as meaningful information as coupling (Rosa, Daunizeau, & Friston, 2010). For one, decoupling could be merely the result of failed signal detection or could be entirely unrelated to experimental conditions. However, it could also be attributed to pathological characteristics (Schridde et al., 2008).

As a result, approaches for combined EEG-fMRI recordings allow analysing shared and discrete signal variation (see Fig. 1) in these methods (Herrmann & Debener, 2007). Highlighting neurovascular coupling and decoupling promises new insights for the study of physiological foundations of EEG and fMRI as wells as experimental investigations of cognitive processes.

Event-related

Unrelated

**EEG**

**fMRI**

Fig. 1. Illustration of variance proportions in EEG and fMRI signal attributed uniquely to EEG (red) or fMRI (blue) and event-related neurovascular coupling (striped) or event-unrelated coupling (not striped shared area) from Herrmann and Debener (2007).

## 1.2 Multivariate analysis of fMRI and EEG data

## 1.3 Multimodal data fusion

Despite the short time combined EEG and fMRI has been emerging as a research field, there is already a wealth of literature for statistical analyses. Recently, multimodal data fusion has received attention most of all (Multert & Lemieux, 2009).

This approach stands opposed to the isolated (i.e. ERP, frequency analyses, fMRI contrasts, connectivity analyses) and asymmetric types of data analyses, such as EEG-informed fMRI and fMRI-informed EEG. In all of these cases one of the two methods takes precedence over or excludes the other (Huster, Debener, & Eichele, 2012). Further, each of these analyses only uses part of the data. The main advantage of data fusion is that it represents a multivariate approach which takes into account almost all available information.

A popular method for fusing different kinds of medical imaging and EEG data is the joint Independent Component Analysis (jICA) (Calhoun, Adali, & Liu, 2006; Calhoun, Liu, & Adali, 2009; Eichele et al., 2008; Kyathanahally, Franco-Watkins, Zhang, Calhoun, & Deshpande, 2016). As with ICA in single modalities, a generative model with an unknown, linear mixing process of signal components is assumed to underlie the data. The jICA also aims at identifying maximally independent components contributing to the signal by unmixing signal parameters. However, a spatiotemporal decomposition is performed on at least two different data modalities. In terms of ERP and fMRI data, spatiotemporal decomposition refers to the ERP time course and voxel intensity. Moreover, the jICA adds a strong constraint by assuming that sources associated with the two data modalities modulate the same way across subjects. Therefore, only sources with identical linear covariation are extracted from the unmixed data matrix. Correspondingly, beta weights are assigned to pairs of components from both data modalities (see Fig. 2). When extracting complementary components from ERP time courses and fMRI contrasts, each time point in the extracted ERP time course is assigned a combination of the associated fMRI voxels, adding spatial to the temporal data.



Fig. 2. Illustration of jICA with coupled feature matrix of multimodal datasets and in a shared data matrix (left) and in an umixed matrix with shared beta weights (right) from Calhoun and Adali (2009).

The likelihood function used in the jICA is similar to the usual ICA as well. The joint unmixing data matrix W of two datasets and from the same sample of test subjects N is estimated so that the likelihood L(W) is maximal. In the estimated unmixing matrix each dataset has the dimensions N and voxels () or ERP time course (). The basic estimation of L(W) is

,

where the vectors and represent observations for sample n = 1,… , N in the matrices and (Calhoun & Adali, 2009).

With this framework for multimodal data fusion Kyathanahally et al. (2016) were able to detect decision making components underlying simple to more complex Delay Discounting Tasks. Joint components identified in simpler tasks with certain rewards could predict parts of activation patterns found in more complex tasks with reward and punishment uncertainty, indicating that decision making processes might occur in an additive fashion.

Although data fusion attempts to use all the available information, the jICA framework puts limitations to this principle. First of all, the constraint of identical modulation of features restricts the amount of data going into signal components. This constraint is necessary to only focus on shared data sources. It can be relaxed by either choosing different datatypes or assuming correlated instead of identical modulation of the datatypes (i.e. parallel ICA). Moreover, while the authors advise to use the jICA as a second level analysis on single subject data (e.g. Calhoun & Adali, 2009), other approaches have gone further by performing second level data fusion on single trials (Debener et al., 2006; Huster et al., 2011; Murta, Hu, Tierney, Chaudhary, & Walker, 2016).

## 1.3 Aims of this study