Alignments in functional connectivity networks

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1 Introduction

Alzheimer's disease (AD) is a brain disconnection syndrome [5], where functional connectivity can detect disconnection in pre-dementia stages [8]. Functional connectivity networks created from functional magnetic resonance imaging (fMRI) and electroencephalogram (EEG) are susceptible to signal noise from a combination of biologic artefacts (eg. eye movement) and environmental sources (eg. electrical interference) [6].

A particular challenge for EEG is volume conduction, whereby a signal from a single source propagates through biological tissue to be detected simultaneously by multiple sensors (channels). The imaginary part of coherency (iCOH) provides a measure for connectivity that avoids this signal contamination, by ignoring correlation between signals with zero or π-phase lag [7]. This removes false instantaneous activity with connectivity denoting synchronised signals at a given time lag, but it does come at the cost of erasing true instantaneous activity. We propose a network assessment, eigenvector alignment (EA) [2, 4], that is robust to noise and connectivity erasure by evaluating pairwise relationships (alignments) from the pattern of functional connectivities.

2 Methodology

EA was introduced to study fMRI connectivity networks in AD [2]. The methodology is similar to that of cosine similarity, which is applied as a data clustering metric for machine learning among other applications. For EA, the nodes – representing regions of interest (ROI) or EEG sensors – are embedded in a Euclidean space defined by the connectivity network's dominant eigenvectors. Employing a selection of only the most dominant eigenvectors ensures that the nodes are aligned according to the network's most prominent pathways [3]. Figure 1 demonstrates that low iCOH connectivity values (eg. between sensors 88 to 96) can still achieve small alignment angles (i.e. close alignment), as close alignment indicates similarity in the connectivity pattern. The three sensor groupings (marked by colour) have close in-group alignments, while between group alignment angles are large as these groups form separate clusters in the Euclidean space (Fig. 1 **C**).

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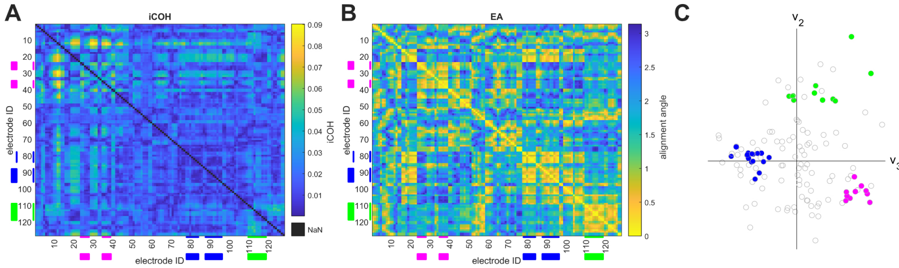

Fig. 1: The (**A**) iCOH connectivity matrix, (**B**) eigenvector alignment matrix, and (**C**) sensor node embedding, in an eigenvector defined Euclidean space, are presented for a 128-channel EEG recording of a control subject. Colour denotes node groupings in (**C**) with the related sensor IDs highlighted in (**A**) & (**B**), where v_2 & v_3 are the 2nd & 3rd eigenvectors, respectively.

3 Results

Since iCOH removes true instantaneous activity to mitigate against volume conduction, some of the lowest iCOH connectivities will map to erased true connectivities. In Fig. 2 **A** the lowest iCOH connectivities are altered to demonstrate how EA results can remain robust to even dramatic changes to a minority of connectivities, indicating that alignments between sensors can still be reliably determined after connectivity erasure.

EA's exposure of network structure relies on connectivity patterns rather than magnitudes, therefore recording conditions that are known to significantly alter functional connectivity – such as eyes open versus closed in resting state fMRI [1] – can still be directly compared. EA finds similar significant changes in alignment when comparing control and AD subjects for both eyes open and closed resting state fMRI recordings. In particular, Fig. 3 displays that the cerebellum undergoes the same notable changes in eyes open and closed; a reduction in decreased alignments in AD with those that remain primarily associated with frontal ROI, and increased alignments in AD extending further forward in the brain to connect with the planum polare in eyes closed (Fig. 3 **B**) and the planum polare, temporal pole, and Heschl's gyrus in eyes open (**D**). The planum

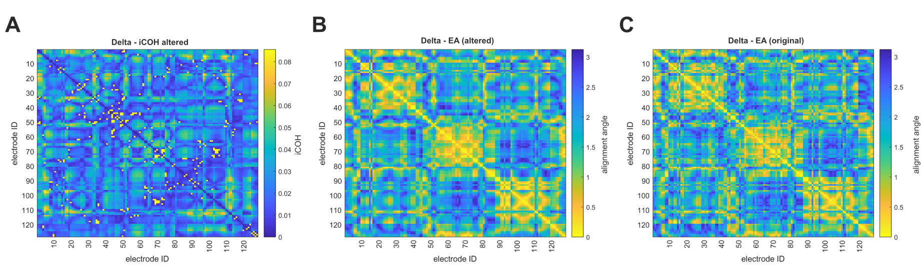

Fig. 2: In (**A**) the iCOH matrix has $\sim 2\%$ of the lowest iCOH values set equal to the maximum recorded value for a control subject's delta frequency $(0.1-4\,\text{Hz})$ 128-channel EEG recording. In (**B**) the EA matrix is based on the iCOH matrix (**A**), while in (**C**) the EA matrix is based on the original, unaltered, iCOH matrix.

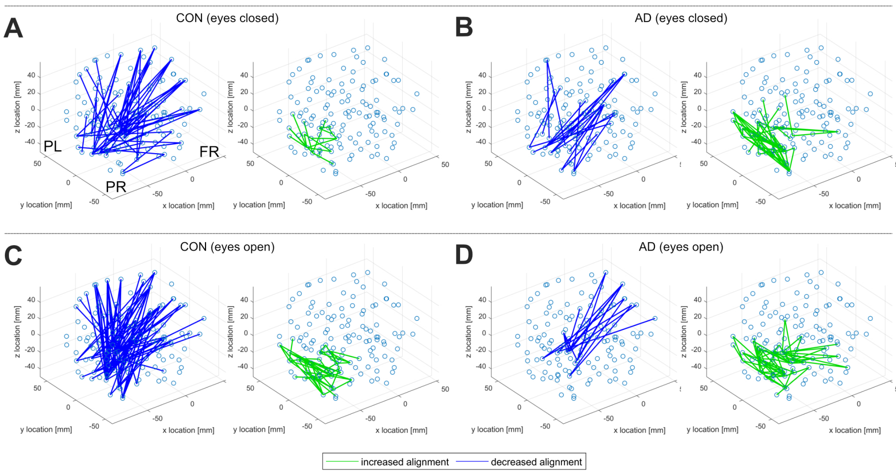

Fig. 3: Significant alignments of the cerebellum from resting state fMRI data for (**A**) 10 CON subjects, eyes closed, false discovery rate (FDR) = 0.05 (**B**) 10 AD subjects, eyes closed, FDR = 0.05 (**C**) 39 CON subjects, eyes open, FDR = 0.005 (**D**) 34 AD subjects, eyes open, FDR = 0.005. The posterior left (PL), right (PR), and frontal right (FR) are marked in **A** to guide orientation.

polare and Heschl's gyrus are notable ROI in AD, as they experience some of the most notable alignment change in resting state functional connectivity networks [2].

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