A NEW INFORMATION THEORETIC APPROACH TO QUANTIFY FMRI FUNCTIONAL CONNECTIVITY

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INTRODUCTION: In resting state fMRI (rs-fMRI), an important challenge for the interpretation of functional connectivity is to quantify the process of synchronization between regional fMRI signals whose periodicity is initially unknown. It is furthermore desirable to measure how much information is shared. Based on the concept of information theory, transient information (TI) has recently been introduced as a quantity to measure the uncertainty in synchronization in relation to the information that is shared [1]. In this preliminary study, we explored the value of TI for the quantification of functional connectivity in rs-fMRI.

THEORY: Given two detrended and binary rs-fMRI signals $\vec{s}_1$ and $\vec{s}_2$, we wish to determine how random the chain of fluctuations in the signals appears when increasing sizes of blocks are considered. Under the assumption that $\vec{s}_1$ and $\vec{s}_2$ derive from a single source, we define the block entropy $H(L) = -\sum_{L=1}^{M} \Pr(\vec{s}_1^{\,L}, \vec{s}_2^{\,L}) \log 2 \Pr(\vec{s}_1^{\,L}, \vec{s}_2^{\,L})$, where $\vec{s}^{\,L}$ represents a block of L consecutive symbols in $\vec{s}$ and the summation runs over all block length L. Furthermore, the information that $\vec{s}_1$ and $\vec{s}_2$ share is given by the excess entropy E [1], which is equivalent to the mutual information between $\vec{s}_1$ and $\vec{s}_2$. TI is then the difference between H(L) and E taken over all L blocks and reflects how difficult it is to synchronize the two signals. The sketch in Figure 1 depicts the relationships between H(L), E and TI.

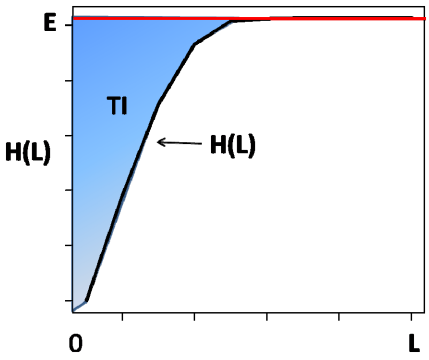

Figure 1. Schematic plot of block entropy H(L) growth versus block size L. The shaded area is the transient information TI.

METHODS: We applied the theory to rs-fMRI data of the Alzheimer's disease Neuroimaging Initiative (ADNI). The rs-fMRI parameters were: 3 Tesla MRI, 7 minutes scan, TR/TE = 3000/30 msc, 3x3x3mm spatial resolution. In addition, we used the corresponding high resolution T1 images for anatomical registration. Preliminary data were obtained from three randomly selected normal subjects. The rf-fMRI signals were selected from two regions involved in the default mode network [2], i.e. posterior cingulate cortex (PCC) and precuneus (PRE) and from a "reference" region, i.e. the putamen (PUT). TI were calculated for the pairs (PCC vs PRE) and (PCC vs PUT).

RESULTS: Figure 2 shows the block entropy H(L) and the transient information TI(L) as a function of L from pairwise comparisons of rs-fMRI signals the 3 regions. The H(L) plot indicates that PCC and PRE synchronize faster than PCC and PUT. The TI(L) plot indicates that the synchronization between PCC and PUT is more difficult than between PCC and PRE. This trend was consistently seen in other subjects.

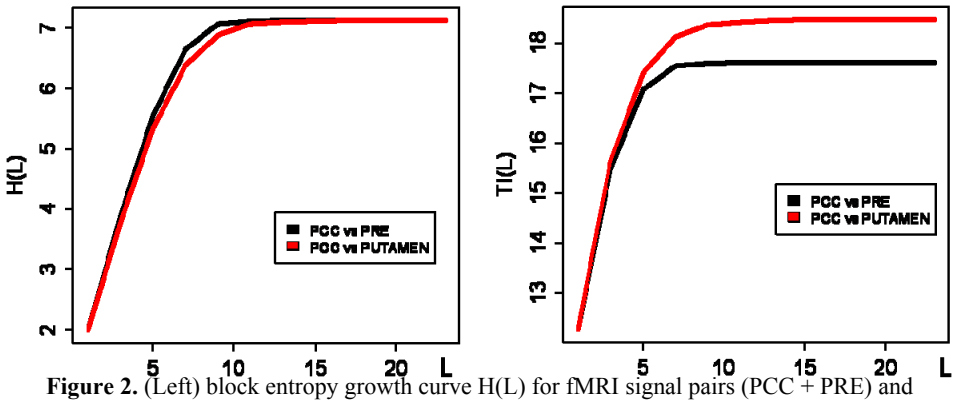

Figure 2. (Left) block entropy growth curve H(L) for fMRI signal pairs (PCC + PRE) and (PCC+PUT); (Right) the corresponding transient information growth curve TI(L) for the two signal pairs.

Conclusion: To our knowledge, this is the first attempt of quantifying the synchronization between rs-fMRI signals while simultaneously evaluating the amount of information that signals share. The preliminary finding that PCC synchronized faster with PRE than with PUT may indicate that PCC and PRE are better connected since they belong to the default mode network. Moreover, the finding that the synchronization between PCC and PRE is easier than between PCC and PUT further indicates that there is less randomness within the network. Transient information could provide a new metric for rs-fMRI to quantify functional connectivity and to study functional networks in healthy brain and disease.

REFERENCE: [1] Feldman, et al., Advances in Complex Systems 7:329-355(2004). [2] Raichle, et al., Proceedings of the National Academy of Sciences 98 (2): 676–82 (2001).