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## Hidden Markov Models to study functional dynamic brain states in normal aging

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### INTRODUCTION

According to recent studies exploiting resting state functional magnetic resonance imaging (rs-fMRI), during normal aging, the brain undergoes not only structural but also functional changes [1,2]. Static functional connectivity (FC) analysis revealed a link between aging and the increase of connectivity between resting state networks (RSNs), thus highlighting a more integrated topology [1,3]. However, these studies assume that FC is stationary, disregarding the dynamic reconfiguration of RNSs that has proven to happen even during rest. So far, few studies [4,5,6] have investigated the relationship between aging and dynamic FC, reaching conflicting results.

### MATERIAL AND METHODS

In this work we analyzed rs-fMRI data of 88 subjects from the publicly available MPI-Leipzig Mind-Brain-Body dataset [7], equally distributed in young and old (44 young subjects, age range=20-25 years; 44 old subjects, age range=60-80 years).

MRI data were acquired on a 3T Siemens Magnetom Verio scanner, equipped with a 32-channel head coil. The acquisition protocol included a T1-weighted 3D MP2RAGE (TR=5000ms, TE=2.92ms, FOV=256x240x176 mm<sup>3</sup>, voxel size=1x1x1mm<sup>3</sup>, multiband acceleration factor [MBAccFactor]=3), rs-fMRI scans (TR=1400ms, TE=39.4ms, FOV=202x202mm<sup>2</sup>, voxel size=2.3x2.3x2.3mm<sup>3</sup>, volumes=657, MBAccFactor=4) and two spin echo acquisitions (TR=2200ms, TE=52ms, FOV=202x202mm<sup>2</sup>, voxel size=2.3x2.3x2.3mm<sup>3</sup>).

After state-of-the-art structural and functional pre-processing, a whole-brain functional parcellation of the main RSNs was obtained by means of group independent component analysis [8,9]. Then, following the approach described in [10], the data-driven approach of Hidden Markov Models (HMM) was employed to capture properties of dynamic brain states related to the aging process. The time courses of the selected RSNs were used as input of the HMM.

After performing the model order selection, six states were characterized at the population level in terms of FC patterns, mean BOLD activity and graph metrics and at the single-subject level in terms of time spent in each state and transitions between states.

### RESULTS

We found that two states were mostly occupied by young subjects, whereas three other states by old subjects. Moreover, the transitions between states were not random and followed preferential paths. The graph-based analysis applied on the six FC maps revealed a decrease in node strength with the increase of age in the default mode network and fronto-parietal network, and an overall more integrated topology for those states occupied by old subjects. In particular, an increased connectivity between the dorsal attention network and other RSNs was found in the old-related states.

In conclusion, these results suggest that HMM can be a useful tool capturing the complex and rich functional dynamics changes that occur with aging.

### REFERENCES

- [1] Betzel et al. <https://doi.org/10.1016/j.neuroimage.2014.07.067>
- [2] Damoiseaux. <https://doi.org/10.1016/j.neuroimage.2017.01.077>
- [3] Bagarinao et al. <https://doi.org/10.1038/s41598-019-47922-x>
- [4] Chen et al. <https://doi.org/10.3389/fphys.2018.01852>
- [5] Tian et al. <https://doi.org/10.1016/j.neuroimage.2018.01.040>
- [6] Xia et al. <https://doi.org/10.1002/hbm.24385>
- [7] Villringer. <https://doi.org/10.18112/openneuro.ds000221.v1.0.0>
- [8] Du et al. <https://doi.org/10.1016/j.neuroimage.2012.11.008>
- [9] <http://trendscenter.org/software/gift/>
- [10] Vidaurre et al. <https://doi.org/10.1073/pnas.1705120114>