Implementing Evolutionary Optimization to Model Neural Functional Connectivity

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Motivation

As computational brain activity models improve, they can explain more observed neural activity, and may eventually be used for diagnosis and design of treatments of brain disorders. However, all currently developed models have many parameters that thus far have only been manually tuned. Optimizing these parameters computationally could not only improve the models overall but also allow for personalized models. However, standard gradient-based optimization methods do not work here due to restrictions of physics and biology as well as stochasticity of the models.

Methods

The reduced Dynamic Mean Field (DMF) model (Deco et al. 2013):

- separates cortical surface into local function-based areas based on Structural Connectivity
- approximates activity per region as simplified spiking model using nonlinear stochastic differential equations
- calculates Functional Connectivity from pairwise correlations of activity per region

$$\frac{dS_i(t)}{dt} = -\frac{S_i}{\tau_s} + (1 - S_i)\gamma H(x_i) + \sigma v_i(t) \tag{1}$$

$$H(x_i) = \frac{ax_i - b}{1 - \exp(-d(ax_i - b))} \tag{2}$$

$$x_i = wJ_N S_i + GJ_n \sum_j C_{ij} S_j + I_0. \tag{3}$$

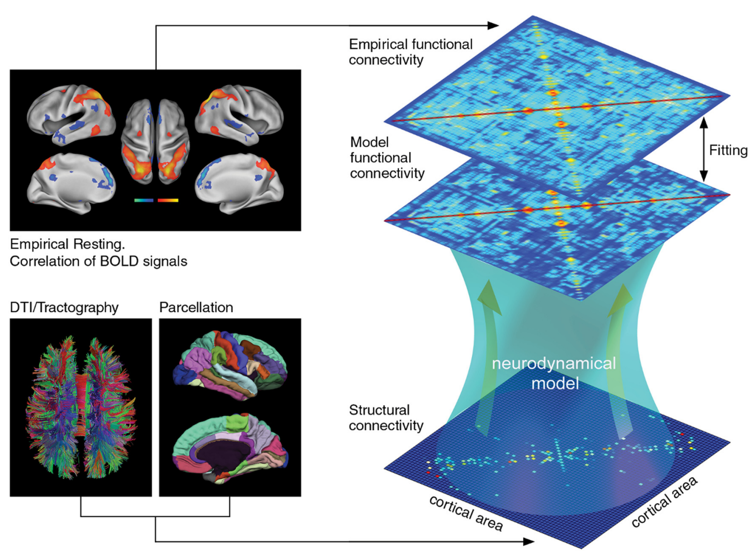

Figure 1: Fitness evaluation process for a single parameter set (Deco et al. 2013).

In the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) (Hansen 2016), the population is described by a covariance matrix for a multivariate normal distribution. Individuals in each generation are sampled from this distribution, and their resulting fitnesses are used to adapt the covariance matrix toward more successful individuals before selecting the next generation of individuals.

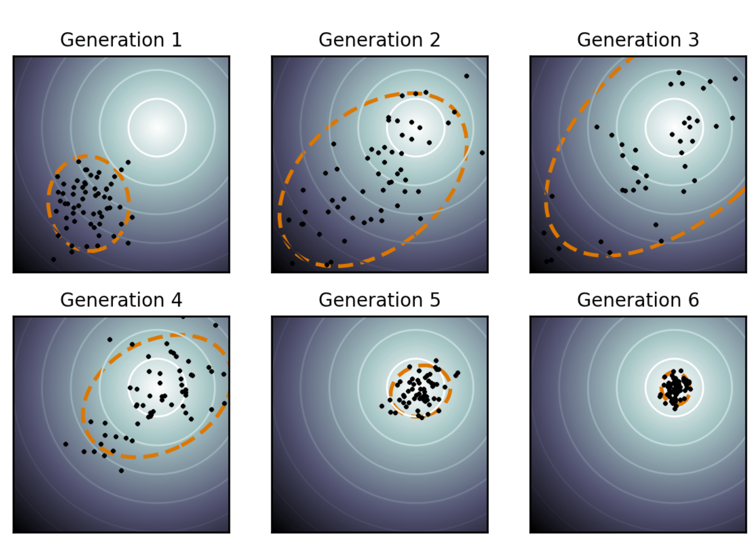

Figure 2: Visual example of CMA-ES in two dimensions.

In this application, individuals were sets of 9 global continuous parameters ($a, b, d, \gamma, \tau, w, J_N, I_0$, and G) and fitness was the correlation coefficient of the model-generated FC to the empirically measured FC.

Data

- SC data was collected from and averaged over five healthy right handed males using diffusion spectrum imaging (DSI) and parcellating the cortex into 66 regions (Deco et al. 2013).
- FC data was collected from and averaged over 24 healthy young volunteers using resting state fMRI with the same parcellation as above, finding the pairwise correlation of resting state BOLD activity between all regions (Deco et al. 2013).

Results

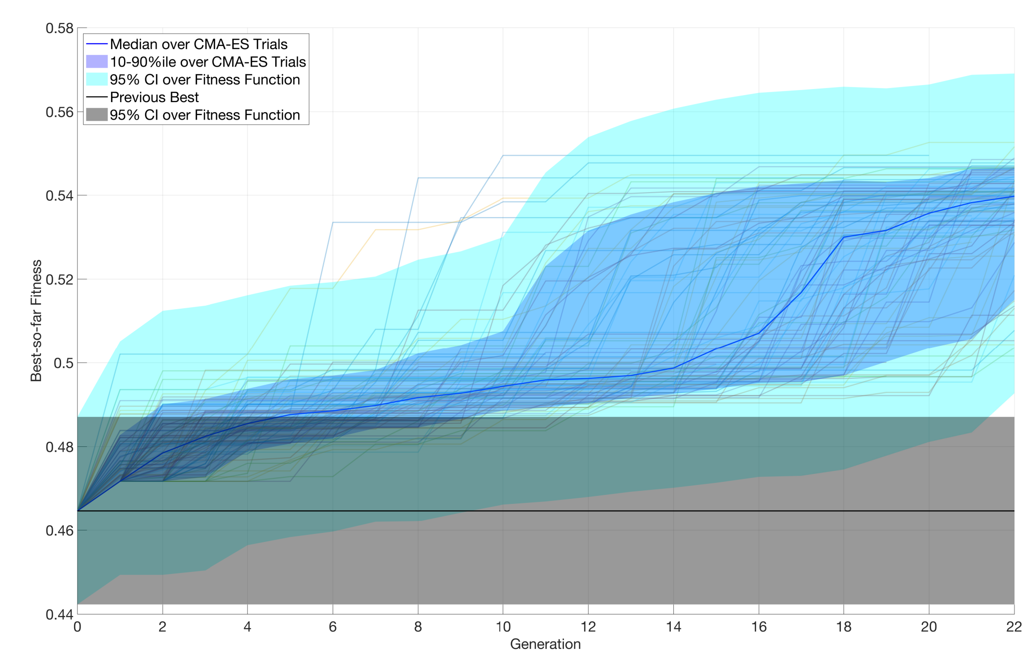

Figure 3: Best fitness seen in each generation of each of 104 individual trials and averaged over all trials, compared to baseline fitness. 95% CI represents uncertainty of fitness function. The parameter set of each trial with the best overall fitness are saved as solutions, generating 104 new parameter sets that have significantly higher fitness.

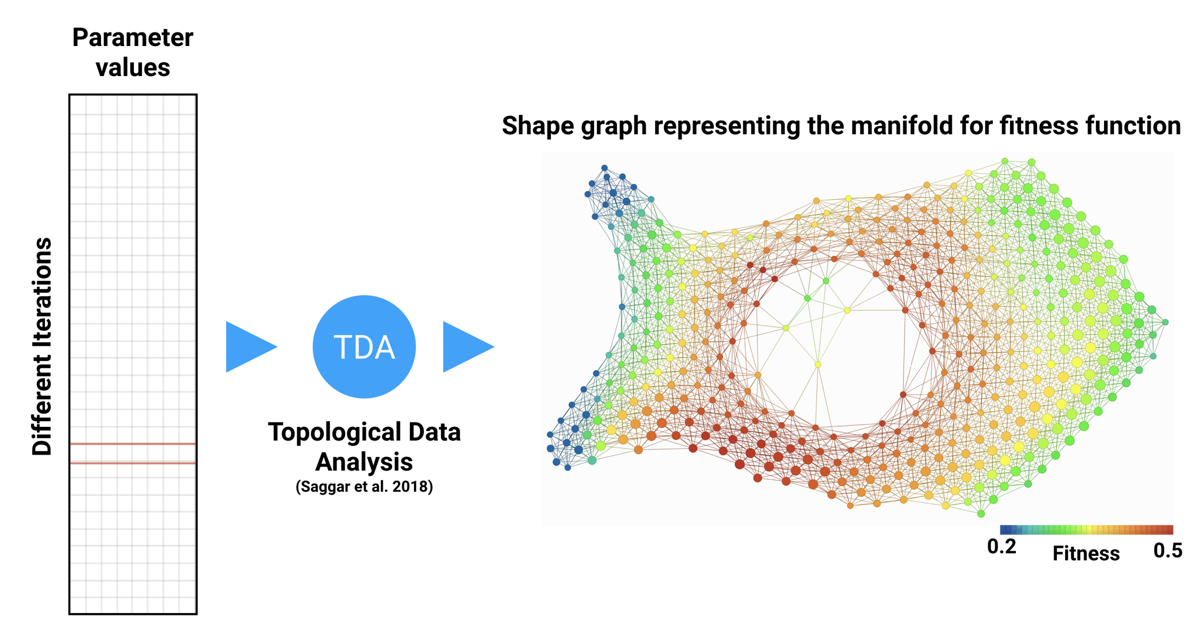

Figure 4: Mapper: Topological Data Analysis of all 10^5 parameter sets explored in CMA-ES trials visualized as clusters in two-dimensional space, colored by average fitness of cluster (Saggar et al. 2018).

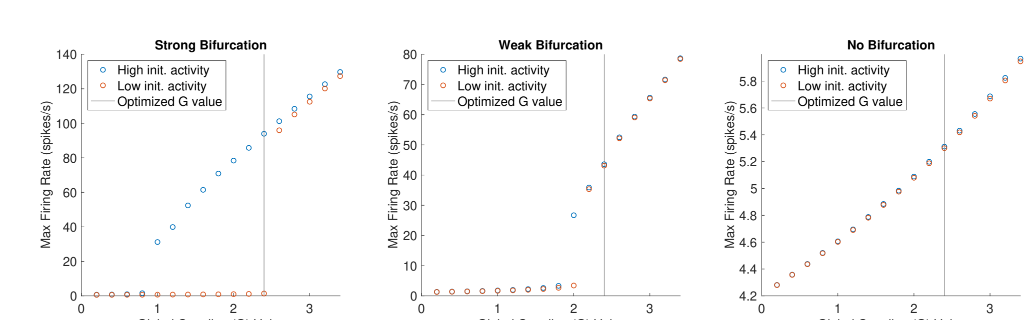

Figure 5: A sample of each level of bifurcation. Of the 104 best parameter sets, 8 had strong bifurcation, 9 had weak bifurcation, and 87 had no bifurcation.

Results (continued)

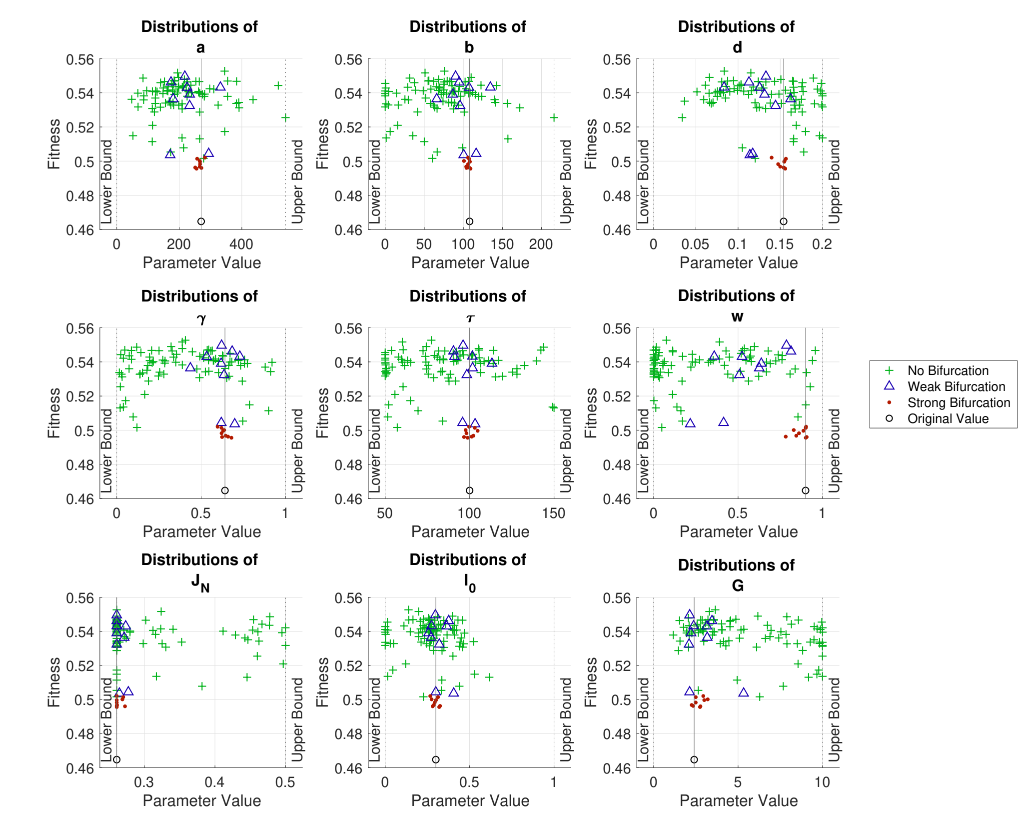

Figure 6: Fitness vs. distribution of each parameter of each of the best parameter sets found per trial. Parameter values are colored by their level of bifurcation.

Extensions and Challenges

- Collect individualized data with finer parcellations (360) so parameters may be optimized on a per-subject basis or aggregated with less over-fitting.
- Study importance of bifurcation as chance of over-fitting decreases.
- Investigate new and more complex brain activity models.
- Allow heterogenous parameters so each region has its own parameter set, optimizing thousands of continuous parameters.
- Develop new evolutionary optimization algorithms that incorporate non-continuous parameters that cannot be evolved with CMA-ES.
- Increase parallelization within evolutionary algorithm to utilize massive compute power to make all above extensions possible.
- Compare evolutionary strategies with bayesian optimization and other optimization techniques on speed and efficacy as number of parameters and parameter types both increase.

Acknowledgements

This work was supported in part by an NIH Director's New Innovator Award to M.S. (DP2 MH119735) and in part by the National Science Foundation under grant DBI-0939454.

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Updated October 13, 2019