



## **A Unified Framework for Data Assimilation Using Dynamical Graphs of the Information Topology**

**Sai Ravela**

Massachusetts Institute of Technology

The effectiveness of a data-assimilation method depends on its ability to address the issues of nonlinearity, uncertainty and dimensionality. Ensemble-based methods are proving to be useful and several approaches are being developed.

We present a unified framework for ensemble data-assimilation that combines graph-theory with spectral representations to produce state-estimates (with associated uncertainties) efficiently and effectively. The central idea is to decompose the domain into an information-graph. This graph has nodes representing the state in space (the state's dimensions), and scale (multi-resolution) and edges representing their dynamical interactions. The topology of the information-graph is constructed automatically as a subspace approximation of the correlation structure observed in an ensemble of model state forecasts. The information-graph has a dynamical topology and evolves with the system.

For the filtering problem, each node implements a local filter on a very small spatial and spectral subspace. It then uses the graph's connectivity to propagate estimates to other, potentially unobserved, nodes. This inference procedure is carried out using a familiar "forward-backward" sweep whose origins are in two-point boundary value problems and whose relevance extends to arbitrary markov sequences in time. As a result, artifact-free estimates are produced in a computationally optimal manner.

The proposed framework, at once, unifies a myriad filtering approaches including local particle filtering, hierarchical filtering, the Local Ensemble Kalman Filter, Wavelets, multiscale trees, localization and square-root formulations. It also overcomes their limitations, essentially by dynamically capturing the spatial interactions at multiple scales rather than using a single representation for spatial correlations. Further, by modulating the topology on which these interactions lie, information loss associated

with truncating interactions – spectral, spatial or scale – is controlled objectively, rather than in an ad-hoc manner. This approach can be extended (trivially) to smoothing problems, and the methodology holds for either moment or nonparametric characterizations of the underlying distributions. It is highly parallelizable.

We then present results on a new realtime laboratory observatory of large-scale circulation, whose incremental progress has been reported at this venue in previous years. A well-known analog of circulation is the thermally-driven unstable rotating flow. A rotating annulus with a cold center and warm periphery forms an unstable flow and develops a circulation. Clearly, the challenges in assimilating the laboratory system are significantly similar to the large-scale problem, in at least three ways. Nonlinearity: The dynamics are nonlinear and the numerical model is the same as planetary simulations. Dimensionality: The size of the model-state is of the same order as planetary simulations. Uncertainty: The initial conditions are unknown, and we have no perfect model of the physical system. In addition, forecasts must be produced in better than realtime. In our experiments, this translates to a forecast-observe-estimate cycle being completed in better than 10 seconds.

Our observatory has (A) Sensors to take realtime velocity measurements of the evolving physical system, (B) the MIT-GCM to forecast this physical system in realtime, and (C) an ensemble-based assimilation system. We demonstrate effective realtime performance using the proposed scale-space filter by employing time-snapshots of model states to construct ensembles. The computational logistics are uncomplicated and, as a result, we can release datasets to researchers to test their own assimilation methods against the benchmark on a realistic system.