



Data Assimilation by Maximizing Mutual Information

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Fundamental to data-assimilation is an optimization problem, which has overwhelmingly been posed as a least-squares problem that can be synthesized using (1) a Gaussian distribution of uncertainty in observations and state (or decision) variables of interest (2) An observation equation relating system states to observed quantities. Such optimization problems may be posed for a fixed-point, a fixed-interval or in a fixed-lag time-dependent scenario, and constrained using Lagrange-multiplier terms, regularization, entropy or sparsity constraints.

We present a new framework for distributions oriented estimation, which is based on an information measure of similarity (or dissimilarity) between random variables. The mutual information is a measure on the joint distribution of two random variables and captures the reduction in entropy (thus uncertainty) of one variable as a result of knowledge of the other.

Given access to distributions either analytically or via examples (samples, ensemble-members), parametric or non-parametric methods (such as kernel methods) can be used to quantify the mutual information. Thus an optimization problem to solve for decision variables can be posed.

This methodology is particularly useful where (a) distributions are highly non-Gaussian, (b) there is a strongly nonlinear relationship between observed variables and state (or decision) variables. Direct state (or parameter) estimation from radar and Satellite imagery, tracer measurements are thus great candidates for such methodology. Examples will be provided for two highly nonlinear assimilation problems; one involving position errors of coherent structures and the other involving tracer measurements.