5005-C1-20 **Michael B. Wakin*** (wakin@acm.caltech.edu), Applied & Computational Mathematics, Caltech, 217-50, Pasadena, CA 91125. *Dimensionality Reduction of Manifold-Modeled Data via Random Projections.*

We discuss a new approach for nonadaptive dimensionality reduction of manifold-modeled data, demonstrating that a small number of random linear projections can preserve key information about a manifold-modeled signal. We consider the effect of a random linear projection operator $\Phi : R^N \rightarrow R^M$, $M < N$, on a smooth K-dimensional submanifold $\mathcal{M} \subset R^N$. As our main theoretical contribution, we establish a sufficient number M of random projections to guarantee that, with high probability, all pairwise Euclidean and geodesic distances between points on $\mathcal{M}$ are well-preserved under the mapping Φ.

Our results bear strong resemblance to the emerging theory of Compressive Sampling (CS), in which sparse signals can be recovered from small numbers of random linear measurements. Like the fundamental CS bound, our requisite M is linear in the information level K and logarithmic in the ambient dimension N; we also identify a logarithmic dependence on the volume and curvature of the manifold. We also compare and contrast with existing techniques in manifold learning, where dimensionality reducing mappings are typically nonlinear and constructed adaptively from training data. This is joint work with Richard Baraniuk. (Received April 30, 2007)