Session 4

At a Glance

1. Sparse image decomposition is a technique to transform an image to a superposition of elementary waveforms for efficient feature recognition.

2. Morphological component analysis (MCA) uses sparsity to separate superimposed features using an over complete representation of the image generated from various elementary waveforms.

3. Applying the MCA technique with two components to a subsample of AIA 193 Å image separates the large-scale active regions and coronal holes from the fine-scale network component.

4. Current work on this project involves finding the optimal dictionaries to represent solar features in different wavelengths and developing a robust noise model to reduce the noise contamination.

For more information, contact
michael.s.kirk@nasa.gov

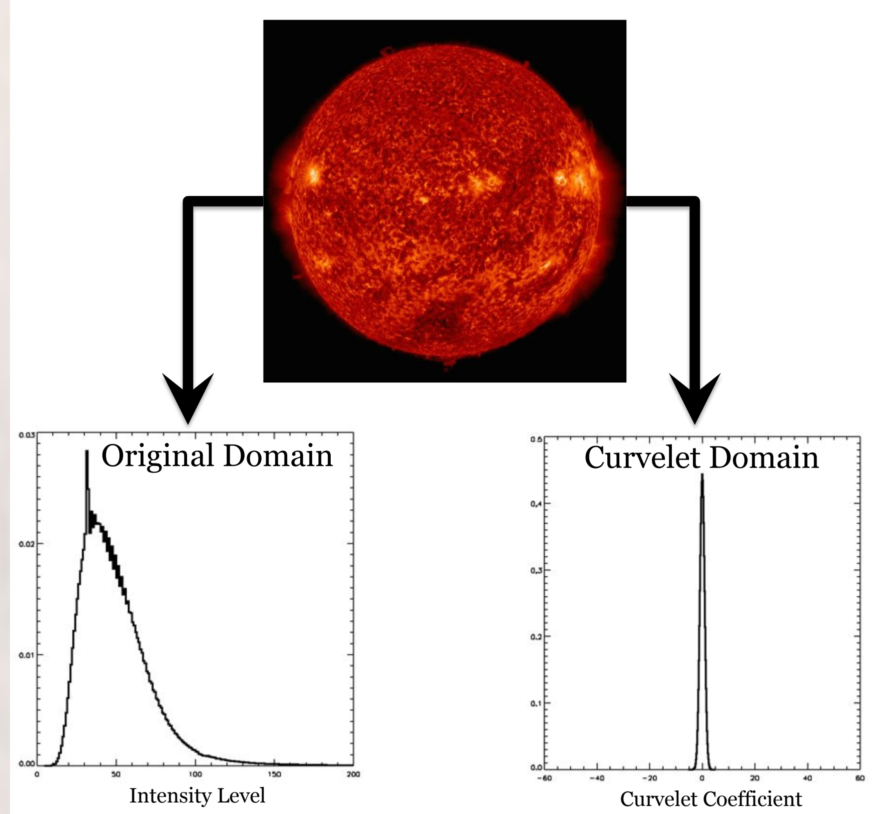
Recognizing Morphological Diversity in Solar EUV Images

Michael S. Kirk [NASA NPP] • C. Alex Young [NASA]

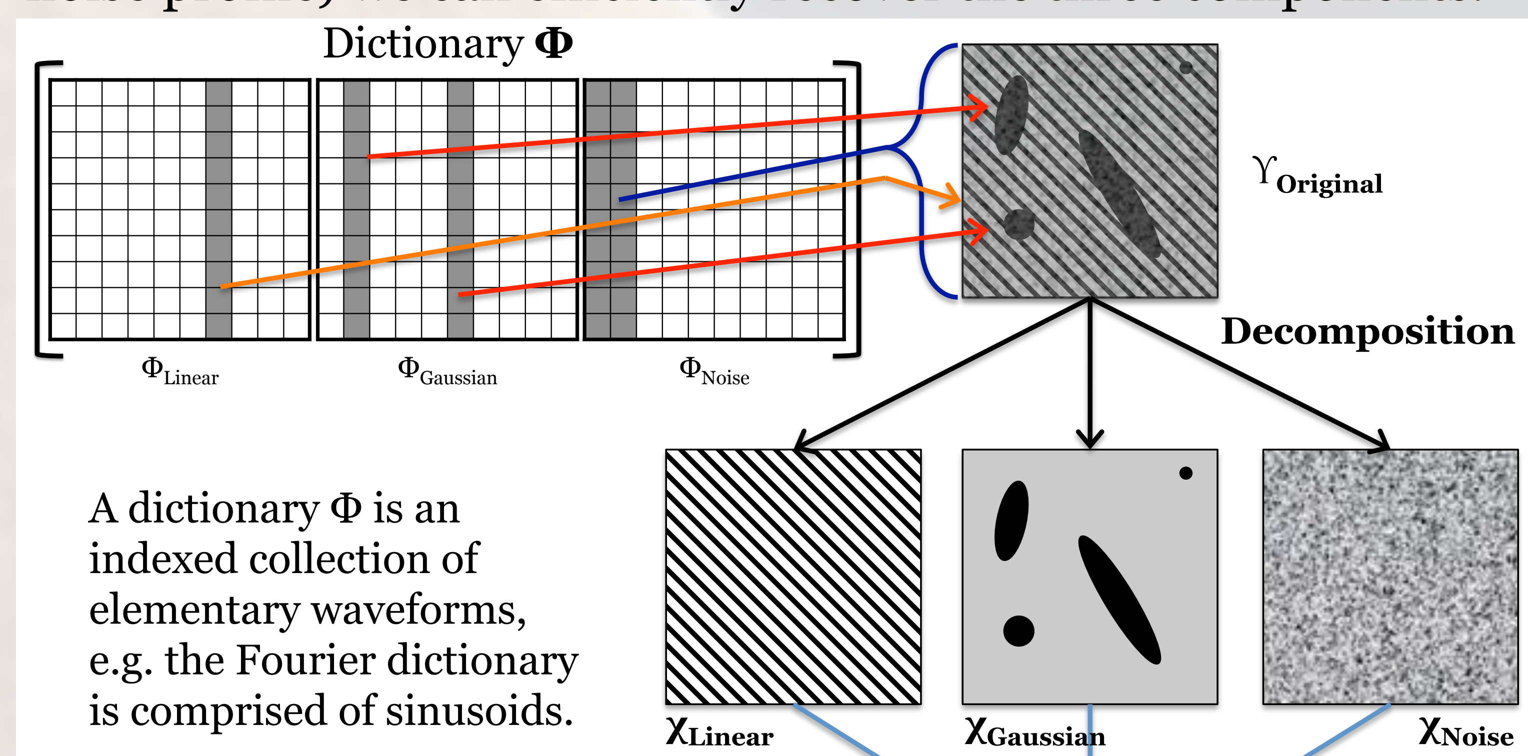
NASA Postdoctoral Program
Administered by Oak Ridge Associated Universities

1. Solar images are complex signals comprised of many different features with distinct characteristics. Any solar image is generally complex in pixel space, but it can become sparse after being decomposed by a specific transform domain. For example, a sine wave can be decomposed using a Fourier transform to be represented by one point. This leads us to ask: **Can we define a set of functions that sparsely define solar features?**

A sparse representation of the Sun:

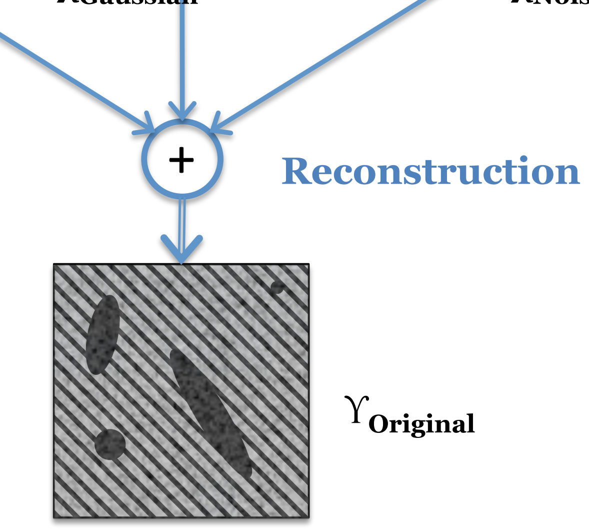


2. Any solar image is a superposition of contributions from different feature types, i.e. the morphological components. Morphological component analysis (MCA) is a method to recover the individual morphological components. For an illustrative example below, the test image contain lines, Gaussian shapes, and noise. Using three dictionaries to define each type of feature (such as ridgelets, wavelets, and an additive noise profile) we can efficiently recover the three components.



A dictionary Φ is an indexed collection of elementary waveforms, e.g. the Fourier dictionary is comprised of sinusoids.

$$\Upsilon = \sum_{k=1}^{K} \chi_k = \sum_{k=1}^{K} \Phi_k a_k$$

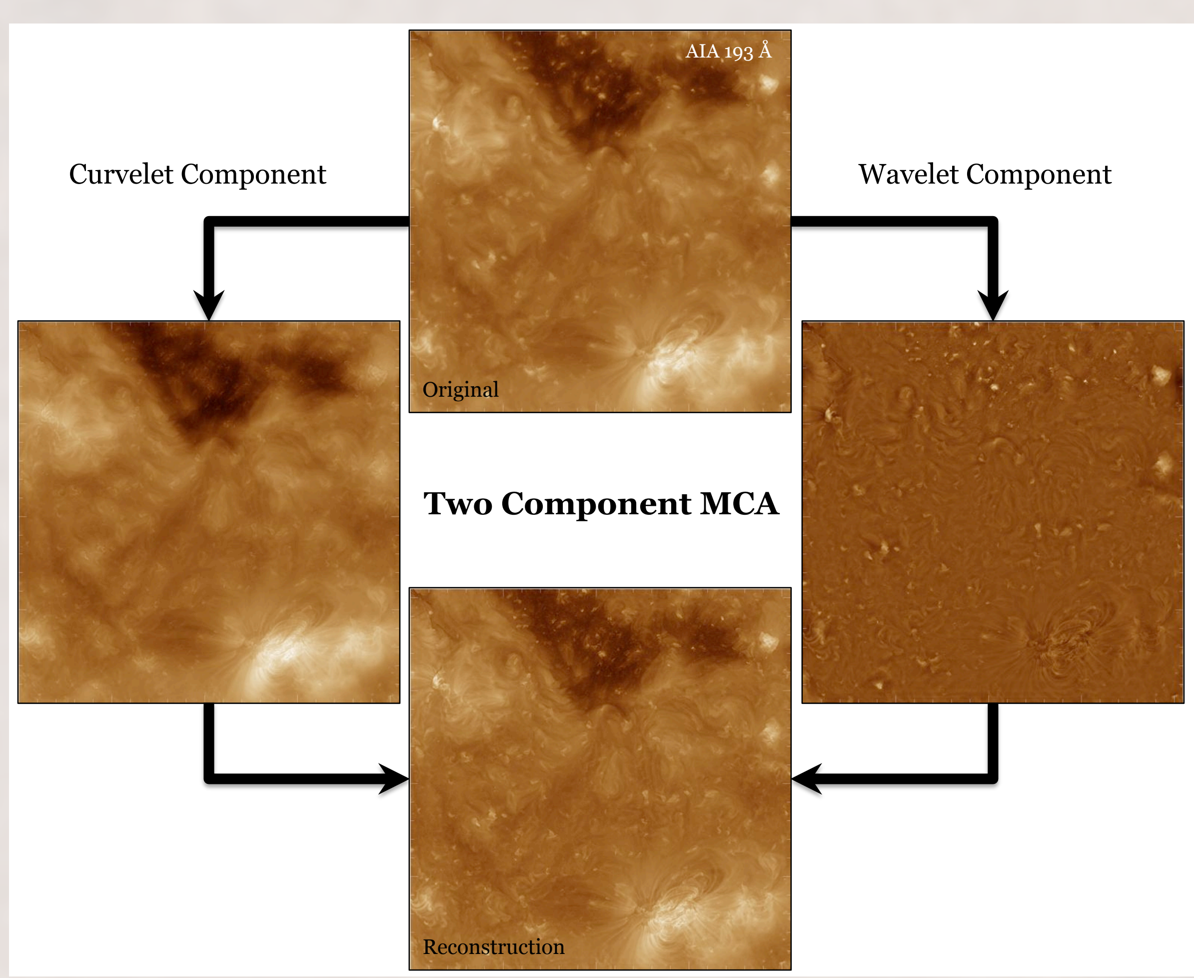


The original image ϒ is decomposed into individual components χ_k which are defined by sub-dictionaries.

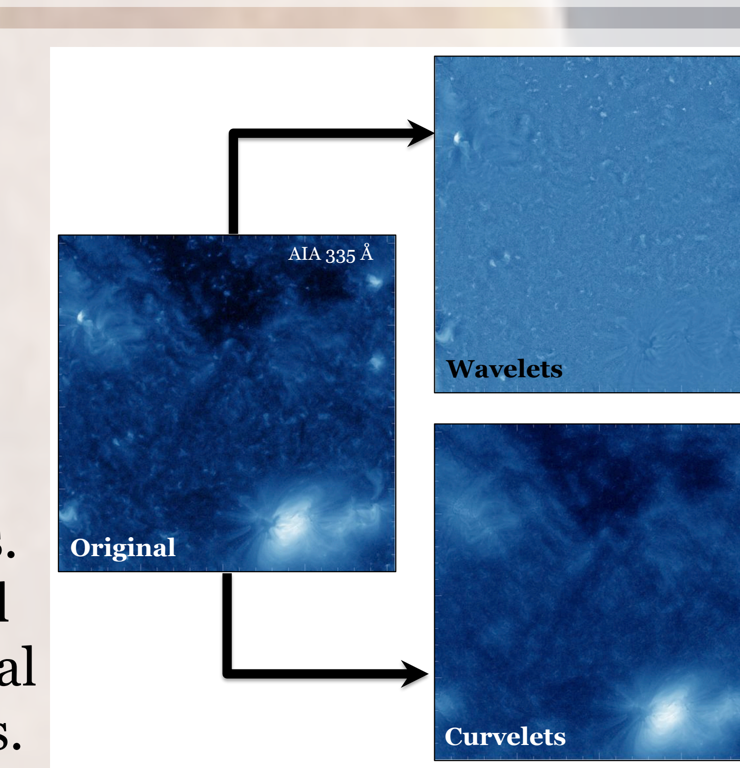
3. To separate a solar *texture* from an underlying piecewise smooth solar *background*, we use an iterative MCA approach on a subsample of an SDO AIA 193 Å image. This example was chosen to include both a coronal hole as well as a quiescent active region. To decompose the sample, we chose two defining dictionaries: a curvelet transform and a 2D undecimated wavelet transform. The wavelet component contained about 10% of the original intensity, while the curvelet component contained 90%. The MCA successfully separates the large scale features (active regions and coronal holes) from the fine scale variations. This technique also employed a quadrature mirror filter to segregate the spatial frequencies. A thorough explanation of the techniques:

Starck, J.-L., Elad, M., and Donoho, D.: 2004b, Redundant multiscale transforms and their application for morphological component analysis, *Advances in Imaging and Electron Physics* 132, 288–348.

Starck, J.-L., Elad, M., and Donoho, D.: 2005a, Image decomposition via the combination of sparse representation and a variational approach, *IEEE Transactions on Image Processing* 14(10), 1570–1582.



4. Using MCA to quickly parse solar images into their visual components is compelling. Our current work is on the following issues: finding optimal dictionaries; characterizing the noise contamination; efficient application to whole disk images. Analysis of dynamic features will be added to characterize temporal solar morphological components.



Funding for this project was provided by NASA Postdoctoral Program at the Goddard Space Flight Center in association with Oak Ridge Associated Universities

SIPWork VII, August 2014 — La Roche en Ardenne, Belgium