**DeepSkyFusion**

The originality of the DeepSkyFusion research project lies in the design and implementation of new methods for multisource data fusion through Bayesian inference. To avoid information loss, both spectral and spatial super-resolution are required in some cases. Image data fusion involves automatic registration and spatial/spectral resampling, which is an ill-posed inverse problem that requires a good understanding of the image formation process.

**Goals and objectives**

Optimally combine all observations into a single image-like model

- Increase the spatial resolution if needed
- Increase the spectral resolution if needed
- Compute the uncertainties (inverse covariance matrix)

Enhance the image quality (optional)

**Related issues:**
- Automatic image registration
- Dynamic range expansion
- Astronomical image modeling
- Image formation process (”rendering”)
- Optimal spatial/spectral sampling
- Uncertainty simplification/formatting
- Compatibility with existing analysis tools
- Large data set (VO) processing...

**Multisource data fusion through Bayesian inference**

Reconstruct a single model from multiple observations
- Use a directed graphical model framework (Bayesian networks)
- Perform accurate camera calibration within this framework
- Efficiently account for missing data
- Develop efficient optimization procedures
- Perform model selection (best spatial/spectral resolution)

**Image models: image formation and priors**

Likelihood: Image formation model
- Use accurate resampling based on B-Splines and band-limited signal theory
- Take into account physical parameters (telescope, atmosphere, sensor, ...)
- Use real noise statistics: probabilistic part of the image formation process

**State of the art**

Multiple observations of the same object

- Different position, orientation, resolution, exposure time, SNR, spectral depth...

Problems: Information redundancy, missing data

Existing solutions:
- Simple image registration & coaddition/mosaicing
- Drizzling (Hubble Space Telescope)
- Super-resolution
- Multiframe restoration
- Weighted average of the analysis results

**Benefits**

- Provide a single, optimal image to replace all observations for a more accurate analysis
- Use all available physical information (instrument modeling)
- Use super-resolution capabilities (spatial, spectral)
- Error estimation (uncertainties)
- Possible model comparison, selection

**Recursive inference & inverse covariance simplification**

Recursive inference: add one image at a time
- Allow for model updates instead of batch processing
- Propagate uncertainties: use current posterior as a prior for the next inference step

Covariance selection: simplify the inverse covariance
- Get a first order Markov structure (no long-range interactions)
- Minimize a distance between multivariate normal distributions
- This way the recursive inference is greatly simplified

**Image resampling model**

Output pixel size = input pixel size / resampling factor

**The proposed graphical model**

Prior model
- camera pose
- camera resolution
- PSF parameters
- sensor sampling grid
- n observations

Marginalization
- camera pose parameters
- sensor parameters
- PSF
- n observations

Observations
- spatial kernel
- noise
- sensor parameters
- n observations

Recursive model
- inverse problem
- graphical model
- n observations

Marginalization
- prior model parameters
- inverse problem parameters
- spatial kernel
- noise
- sensor parameters
- n observations

Recursive inference
- add one image at a time
- allow for model updates instead of batch processing
- propagate uncertainties: use current posterior as a prior for the next inference step

Covariance selection: simplify the inverse covariance
- get a first order Markov structure (no long-range interactions)
- minimize a distance between multivariate normal distributions
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**Theory**

The hierarchy of tasks necessary to the project

**Multisource Data Fusion and Super-Resolution from Astronomical Images**

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**Image mosaicizing**

Super-resolution from multiple undersampled images

Error minimization problem

Simplified graphical model and Bayesian inference through marginalization

**Image formation model**

1. Deterministic image formation process
   - Deformation (geometric mapping f, param. θ) and (additive noise α, w)
   - Convolution with the Point Spread Function (PSF) h
   - Sampling on a discrete pixel grid m

   For each sensor:
   \[ y_j = (f(l_j) + h(l_j) + \alpha), \] where \( \lambda_j \) is function of \( f, h \)

2. Probabilistic image formation process
   - Prior: Gaussian noise statistics for deterministic and undetermined variance
   - Posterior: given observations

Prior: a prior pdf of astronomical images
- Prior models used for regularization purposes (image reconstruction - ill-posed inverse problem)
- Use simple Markov model in the fusion process (allow for subsequent denoising if needed)
- Take into account stars as point sources over a smooth background (Clean-like method)