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Interest-Points for Hyperspectral Images

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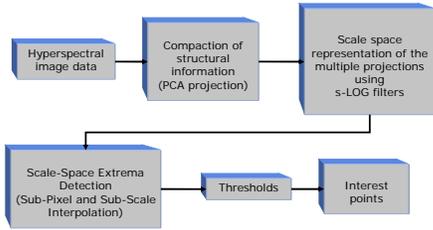
INTEREST POINTS FOR HYPERSPPECTRAL IMAGES



GOAL

The idea of interest point detection is extended from monochromatic (grayscale) images to multi-spectral and hyper-spectral images, where the structural information is distributed over several bands or layers.

IP Detection Framework



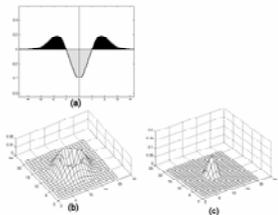
□ Hyperspectral data is projected on the directions of top N principal directions (spanning highest N variances).

□ The normalized projections are fed to s-LOG filters which maps the data in $\square^{2 \times N} \rightarrow \square^2 \times \square_+$ where the spatial dimension is 2, N is the number of projections used and \square_+ indicate the positive real axis for scale.

□ The extrema in scale-space is detected, followed by subpixel and subscale interpolation using second order Taylor series expansion.

□ Empirical thresholds on the Gaussian curvature and the ratio of Principal curvatures along space give the interest points.

s-LOG filters (splitted Laplacian of Gaussian filters)



s-LOG are derived from a Laplacian of Gaussian with a variable width. Shown in (a) are positive and the negative coefficients in light and dark shades respectively of a LOG filter with 1 standard deviation. This filter is split into two parts based on the sign of the coefficients and then normalized to unit weights. Panel (b) shows s-LOG+ filter formed by using only the positive coefficients of LOG in 2D. (c) s-LOG- formed by using only the negative coefficients of LOG in 2D.

These filters are applied on each layer of the projection. Two pixel vectors are formed by stacking the N responses of the s-LOG+ and s-LOG- at each pixel location. The spectral distance between these vectors (using the modified Earth Mover's distance) give the response of the s-LOG filter at that pixel location.

Earth Mover's Distance

The EMD between two spectra $\mathbf{g}_1 = \{(\lambda_{i1}, g_{i1}) \dots (\lambda_{im}, g_{im})\}$ and $\mathbf{g}_2 = \{(\lambda_{i2}, g_{i2}) \dots (\lambda_{2m}, g_{2m})\}$ is defined in terms of an optimal flow $F = (f_{ij})$ which minimizes,

$$W(\mathbf{g}_1, \mathbf{g}_2, F) = \sum_{i=1}^m \sum_{j=1}^m f_{ij} d_{ij}$$

Subject to

$$f_{ij} \geq 0, 1 \leq i, j \leq m$$

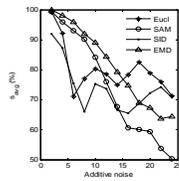
$$\sum_{j=1}^m f_{ij} \leq g_{i1}, \sum_{i=1}^m f_{ij} \leq g_{i2}$$

$$\sum_{i=1}^m \sum_{j=1}^m f_{ij} = \min(\sum_{i=1}^m g_{i1}, \sum_{i=1}^m g_{i2})$$

and $d_{ij} = d(\lambda_{i1}, \lambda_{j2})$ is some measure of dissimilarity between the bin λ_{i1} and λ_{j2} , and m is the number of spectral bands. Then the Earth Mover's distance between \mathbf{g}_1 and \mathbf{g}_2 for the optimal flow f_{ij}^* as

$$\delta_{EMD}(\mathbf{g}_1, \mathbf{g}_2) = \frac{\sum_{i=1}^m \sum_{j=1}^m f_{ij}^* d_{ij}}{\sum_{i=1}^m \sum_{j=1}^m f_{ij}^*}$$

Stability of EMD in presence of noise



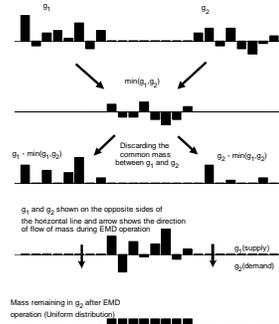
The figure shows the stability s_{emd} (%) of the EMD in retaining the rank-order of the distances between a group of spectra, as a function of the variance of additive noise added to each spectrum. The comparison with Euclidean, Spectral Angle Mapper (SAM) and Spectral Information Divergence (SID) clearly shows that EMD is more consistent in handling noisy spectra.

Fast implementation of EMD for unequal total mass

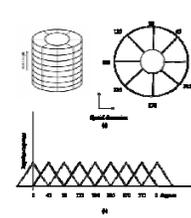
• EMD is not a true metric when the sum total mass of the spectra are not equal. This overcome by moving the equilibrium point of mass transfer from zero to a finite value, which is the difference between the sum total mass of the spectra. The steps are shown in figure for sample spectra \mathbf{g}_1 and \mathbf{g}_2 .

• Also, the number of variables in the mass flow can be reduced to half by the operations shown in figure.

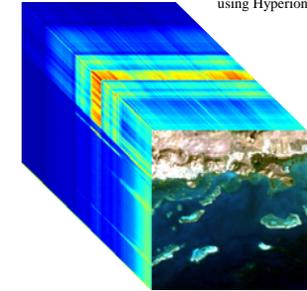
• Also, we use the EMD without normalization by the total flow, since this the total flow changes with the sum total mass.



Spectral descriptors



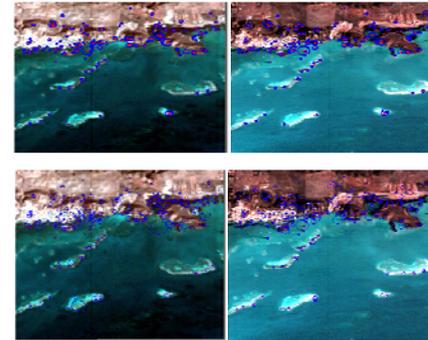
The structure of the spectral descriptor. (a) Shows the spatial and spectral structure of the descriptor. Spatially, it has a central region enclosed by eight radial regions as shown in part (a). The spectral dimension is binned and normalized. (b) Shows the overlapping weights that are used to sample the eight radial bins.



La Parguera Hyperspectral Image size (250x239x118) using Hyperion sensor.



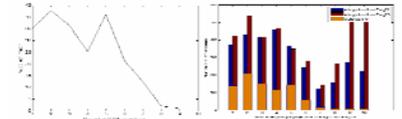
Interest points illustration



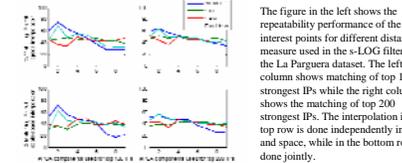
The top row shows all those IPs that are matching in scale and space of the top-300 interest points using the proposed algorithm, while the bottom row shows all the top-300 IPs of La Parguera at 2002 (right) and La Parguera at 2003 (left). The IPs are overlaid on the RGB projection of the hyperspectral image. The circle around each IP indicates the scale at which it is detected.

References

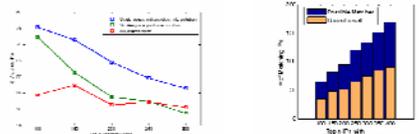
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The figure above shows Key point matching using Lowe [1] on each of the projections of the hyperspectral image.



The figure in the left shows the repeatability performance of the interest points for different distance measure used in the s-LOG filters on the La Parguera dataset. The left column shows matching of top 100 strongest IPs while the right column shows the matching of top 200 strongest IPs. The interpolation in the top row is done independently in scale and space, while in the bottom row is done jointly.



The results of matching IPS for independent and joint scale-space interpolation as compared to no interpolation. The distance measure used in the s-LOG implementation is the modified EMD. The results show that interpolation improves the % of matched IPs.

RELEVANCE TO CENSSIS



An attempt to extend/generalize the CenSSIS registration tool to hyperspectral images by computing stable interest points.

ACKNOWLEDGEMENTS

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