End-member extraction in hyper-spectral images for brain tumor localization

Bangalore Ravi Kiran, Bogdan Stanciulescu, and Jesus Angulo

CAOR, CMM, MINES ParisTech, PSL-Research University

MINES ParisTech HELICoiD

Overview

- Helicoid is a EU funded project on HypErspectraL Imaging Cancer Detection.
- Project works on building a complete system [Fabelo et al. 2015] to provide real-time visualization and detection of tumors using hyperspectral images(HSI), during surgery.
- This poster works on algorithms for localization and extraction of tumor tissue endmembers.
- Pure-pixel assumption becomes pertinent here due to the high spatial and spectral resolution of the HSI cameras.

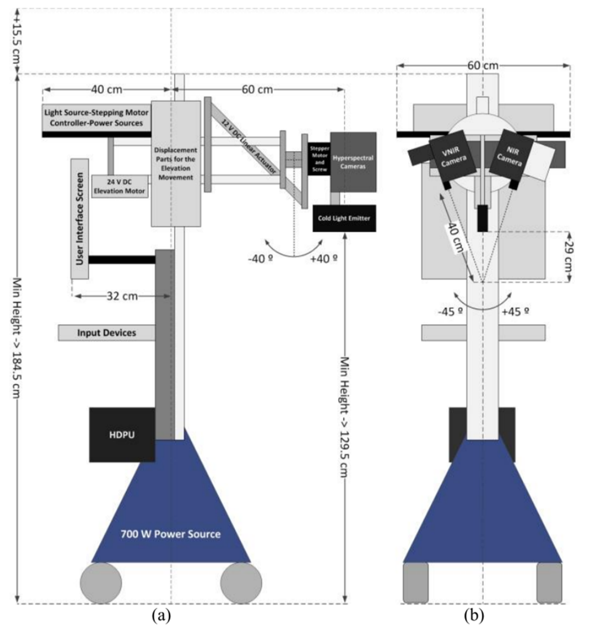
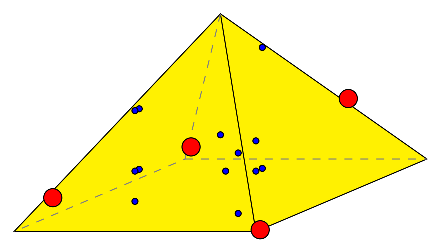
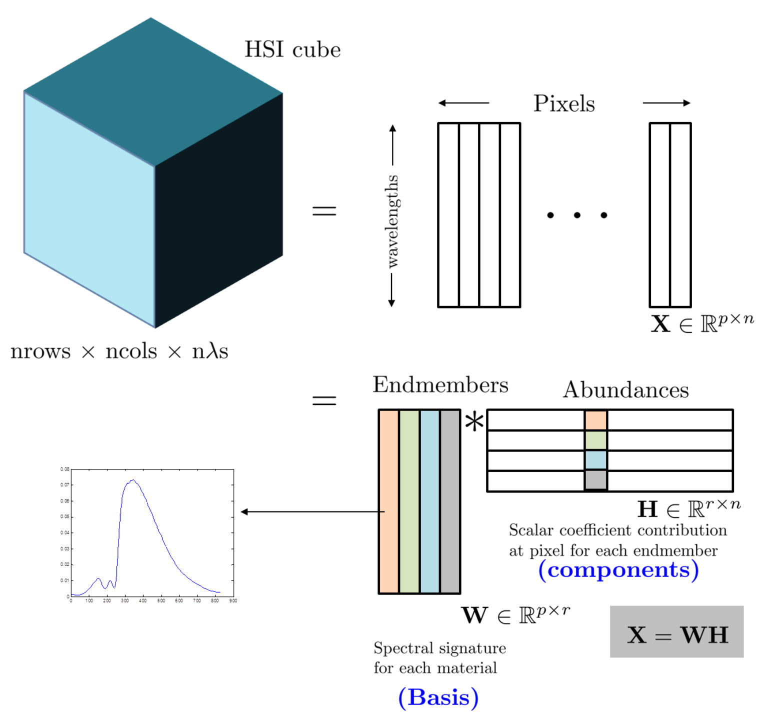


Figure: Side view and Front view. Image reproduced from [Fabelo et al. 2015]. System consists of VNIR-NIR(400-1000nm,900-1700nm) camera image pair with different spectral resolutions and ranges.

Non-Negative Matrix Factorization(NMF)



Geometric interpretation of NMF: Simplex on positive orthant, whose vertices are the end-members(red) with which all columns of input matrix $\mathbf{X}$ can be constituted by convex composition. Finding this subset of the positive orthant containt all points is NP-hard. Various approximations studied in literature. Exact NMF can be calculated in the separable case.



Separability condition

- Separability condition states that all columns of $\mathbf{X}$ reside in a cone generated by a small subset of r columns of $\mathbf{X}$.

$$\mathbf{X} = \mathbf{WH} = \mathbf{X}_A H \tag{1}$$

- where the r columns in $\mathbf{W}$ are already present somewhere in $\mathbf{X}$.
- Physically this corresponds to the pure-pixel situation where there is at least one pixel in the scene which corresponds to a reference spectrum of one of the targets.

Spectral Angle Mapper

$$\alpha_i = \arccos\left(\frac{\langle \mathbf{x}, \mathbf{e_i} \rangle}{\|\mathbf{x}\|\|\mathbf{e_i}\|}\right) \quad C(x) = \arg\min(\alpha_i) \tag{2}$$

where $\mathbf{x} \in \mathbb{R}^p$ is any hyperspectral pixel and $\mathbf{e_i}, i \in 1, 2, ..., r$ are the endmember reference spectra. The class $C(x)$ is assigned to any of these pixels x, is the endmember index associated with the least dissimilarity α_i.

Segmentation using Spectral Angle Mapper

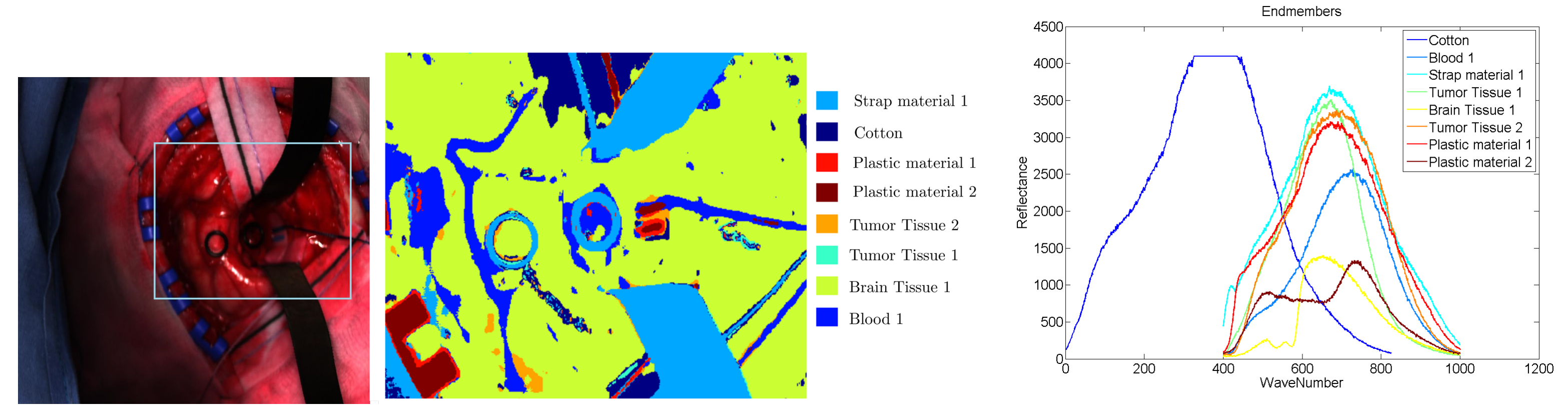
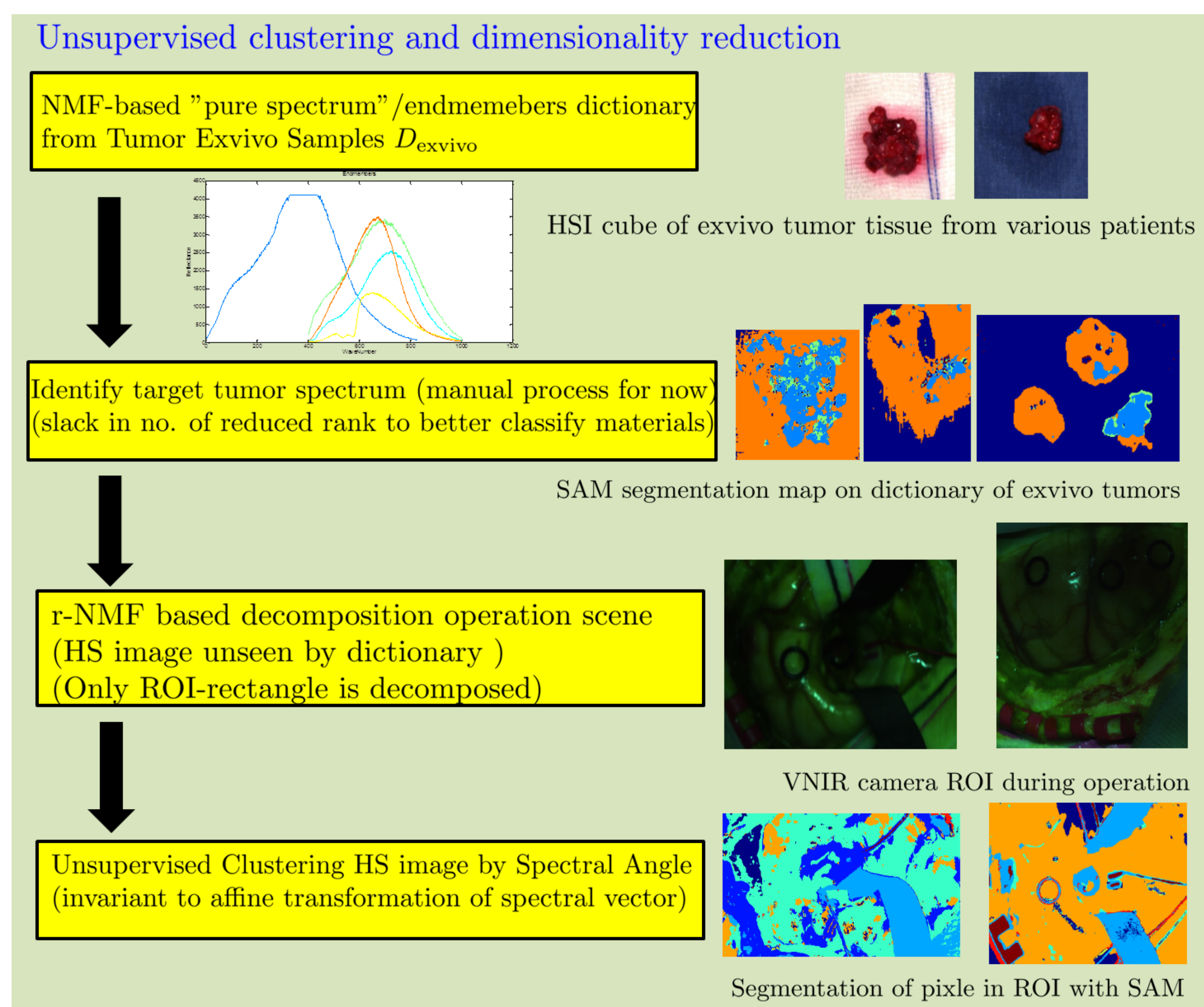


Figure: RGB Image with Region under study in blue rectangle. Segmentation generated using SAM to cluster hyperspectral pixel vectors w.r.t endmembers generated by NMF. The labels assigned (tumor classes, tissues) are temporary and were used to study the stability of clusters across various In-vivo images. Right: r = 7-Endmember spectra in the Region of interest(ROI).

Workflow



Markers using Rx Anomaly Detector

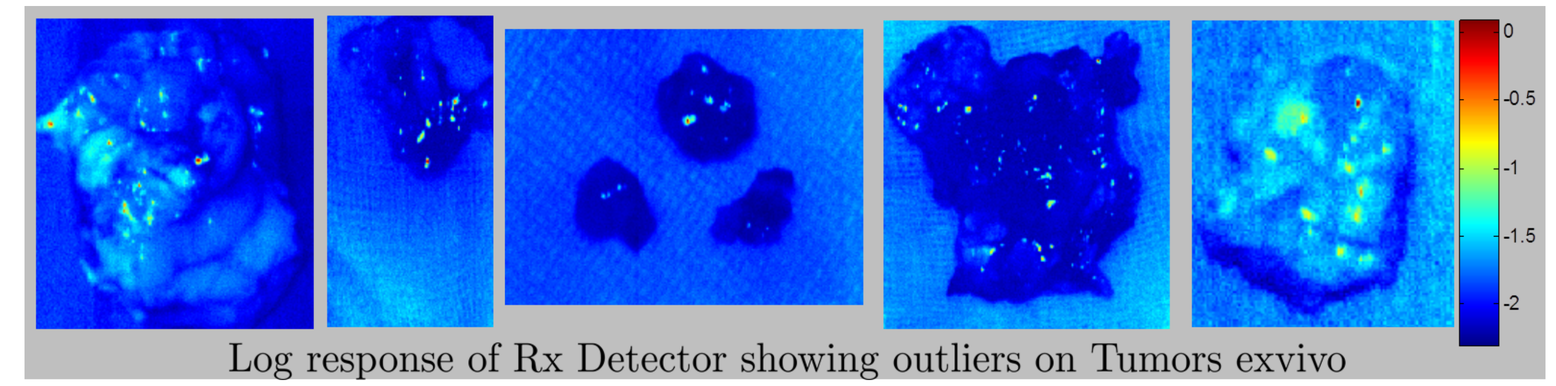


Figure: Rx detector shows anomaly/outlier locations. Potential tumor locations identified.

- Robust Rx detector localizes potential tumor tissue signatures [Santiago-Angulo 2012].
- Finite k (around 1000) random projections on to unitary sphere.
- Can serve as robust marker to extract tumor tissue spectral signatures.
- Rx detector sensitive to variety of materials in the scene.
- Works well in homogenous scenes.

Conclusion

- Obtaining ground truth for tumors with endmember variability is very tough.
- Variability due to lighting conditions, patient, tumor grades.
- Separable NMFs are low complexity algorithms but sensitive to variability.
- Speckle appears as outlier which is undesirable, mixing model fails.

Future Work

- Robust unsupervised clustering algorithms using the covariance of spectrum.
- Better dissimilarity measure (SAM is good but not robust).
- Using NIR information jointly to detect tumor tissue targets better.
- Robust separable NMFs.
- Filter speckle noise.

Bibliography

- Fabelo et al. HELICoiD Demonstrator for Intraoperative Brain Cancer Detection using Hyperspectral Images (2015).
- Manolakis, Dimitris and Shaw, Gary, Detection algorithms for hyper-spectral imaging applications, Signal Processing, IEEE (2002).
- Hoyer, P.O.: Non-negative matrix factorization with sparseness constraints. JMLR (2004).
- Velasco-Forero, S., Angulo, J.: Robust rx anomaly detector without covariance matrix estimation. (WHISPERS)(2012)
- Nicolas Gillis, Stephen A. Vavasis, Fast and Robust Recursive Algorithms for Separable Nonnegative Matrix Factorization (2012).

http://www.helicoid.eu/

ravi.kiran@mines-paritech.fr, bogdan.stanciulescu@mines-paristech.fr, jesus.angulo@mines-paristech.fr