VNIR Hyperspectral Imagery and Machine Learning Based Processing for Temperature Dependent Meat Tissue Characterization

Nicholas Scott, Riverside Research, Dayton Research Center, Beavercreek, OH 45431
Josef Affourtit, MIT, Dept. of Brain and Cognitive Sciences, 76 Massachusetts Ave., Room 46-2005, Cambridge, MA 02139
Sarah Jensen, Savor Safe Food, 6797 North High Street, Columbus, OH 43085

1. Introduction/Motivation:

- HSI technology and machine learning has revolutionized meat quality assessment and food safety through the use of a non-invasive technique and information processing allowing for objective comprehension of product structure.
- A large focus has centered on the NIR and SWIR part of the EM spectrum for meat characterization, but the VNIR also offers promising food structural insight especially for understanding the spectral variability of beef meat as it undergoes the cooking process.
- Of particular importance is the development of a fast, efficient remote sensing technology that captures a small subset of spectral features pertinent to parameterizing temperature dependent meat state. This eliminates information redundancy and facilitates quick state assessment of roasted beef for businesses.
- State-of-the-art machine learning in combination with HSI is applied to meat at various stages of the cooking process. This illustrates how VNIR HSI technology can facilitate temperature-dependent **characterization** leading to the development multispectral technology of remotely sensed meat undergoing heat based chemical change.

2. Methodology:

- A 0.5-inch-thick rectangular lean beef steak occupying 28 square inches of area underwent a two-hour, 350 °F roasting process.
- A pseudo-sunlight spectrum light source along with a light diffuser square box ensuring semi-Lambertian conditions was used to illuminate the steak.
- Six spectral imagery measurements of the steak were made with a Resonon Pika-L HSI camera possessing a spectral bandwidth spanning 300 to 1100 nm every 20 minutes. The camera head was 27 inches from the diffuse box and was tilted at 33° with the horizontal.
- Temperature measurements were made with a metallic probe based digital food thermometer at the measurement times. Measurements tools are shown in Figure 1 and 2.

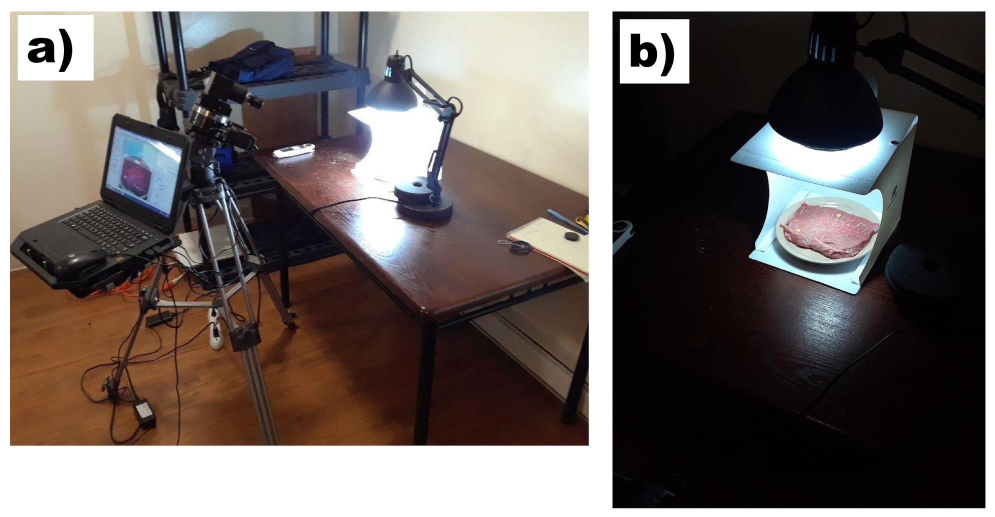

Figure 1: a) Pika-L hyperspectral camera system manufactured by Resonon, Inc., and light source. b) Lambertian diffuser cube and light source.

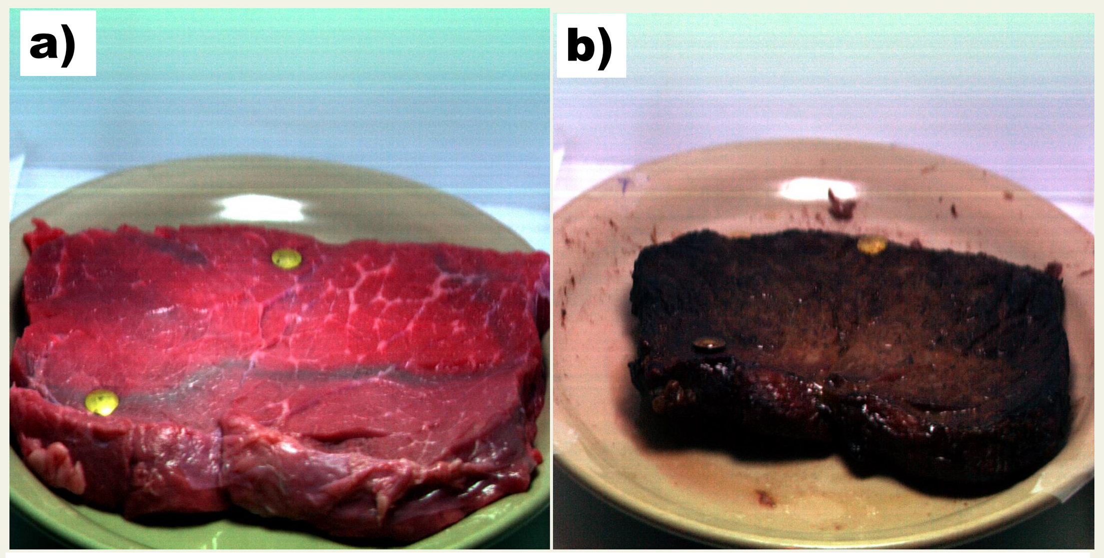

Figure 2: RGB imagery of beef steak a) before roasting and b) after roasting. Temperature of raw meat and cooked beef at measurement times are 60 °F and 180 °F respectively.

3. Hyperspectral Imagery Data and Spectral Analysis:

- Mean spectral profiles for raw and cooked beef predominantly exhibit spectral variability over the 400-900 nm spectral range. Raw beef exhibits a greater mean spectral amplitude than cooked beef.
- Noticeable spectral features appear as local maxima near 430, 530, 600, 700, 775, and 810 nm. A local spectral minimum at 550 nm appears accentuated for the raw beef when compared to the cooked beef.
- Covariance based virtual dimension estimates show that optimal number of spectral bands is 12 for both raw and cooked beef. Six
- PCA bands scattered over the first 16 PCA bands contain strong signal texture information for the raw beef while only 3 PCA bands contain information for the cooked beef. This small number suggests significant texture structure can be captured by a multispectral band sensor.

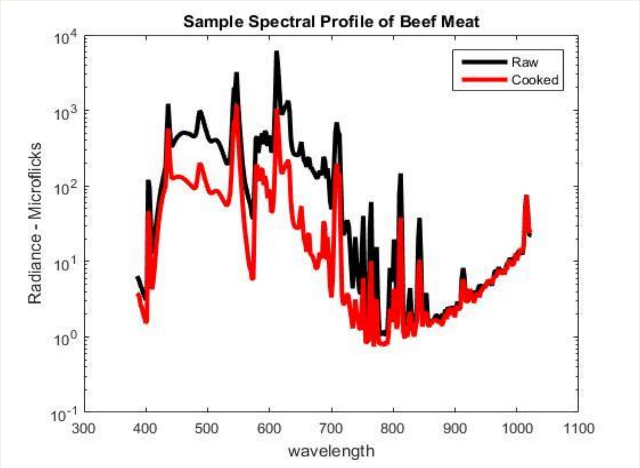

Figure 3: Spectral profiles averaged over 10000-pixel realizations for raw and cooked beef.

- Nonnegative matrix factorization (NMF) can eliminate speckle noise from the imagery and shows clear tissue texture segmentation for both raw and cooked beef states in different spectral bands. NMF eigenvector mean spectra for both states show that 435 (blue), 547 (green), and 612 (orange) nm appear as dominant physical bands which also characterizes the light source photonic structure. As the beef cooks less energy appears in the orange band while the combination of green and orange bands (comprising brown) increases in spectral power. This spectral transformation is consistent with the roasting process.

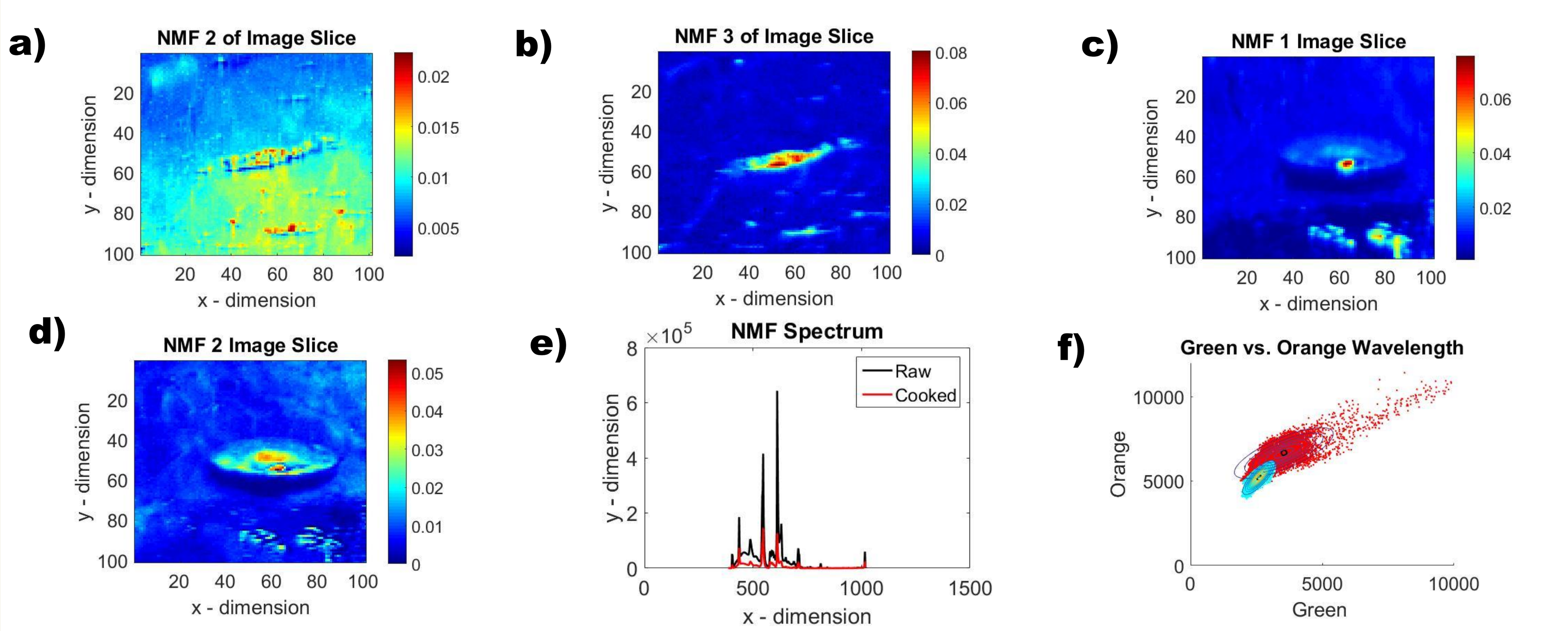

Figure 4: a)-b) NMF image slices for raw beef sub-image. **b)-c)** NMF image slices for cooked beef sub-image. Image chips are 100 by 100 pixels. Texture of beef clearly captured in 3 NMF spectral bands with other bands containing noise for raw and cooked beef. Oval shape is marble meat texture containing mixture of fatty and lean tissue. ROIs capture the same area. **e)** NMF eigenvector spectra show dominant physical spectral bands. Units of axes in nm. **f)** GMM of the pixel data for the green and orange spectral bands for the raw beef. Contours designate estimated data clusters.

- Gaussian mixture modeling using the orange and green spectral bands do not show sharp data clusters but rather a linear trend between the spectral bands.
- A significant drop in spectral energy in the green and orange bands as well as a centering and stiffening of the linear trend is visible as the meat surface becomes more homogenous due to the roasting process. The equal spectral contributions of green and orange spectral band energy is due to relinquishing of water and fat, and browning as the beef meat undergoes the cooking process.

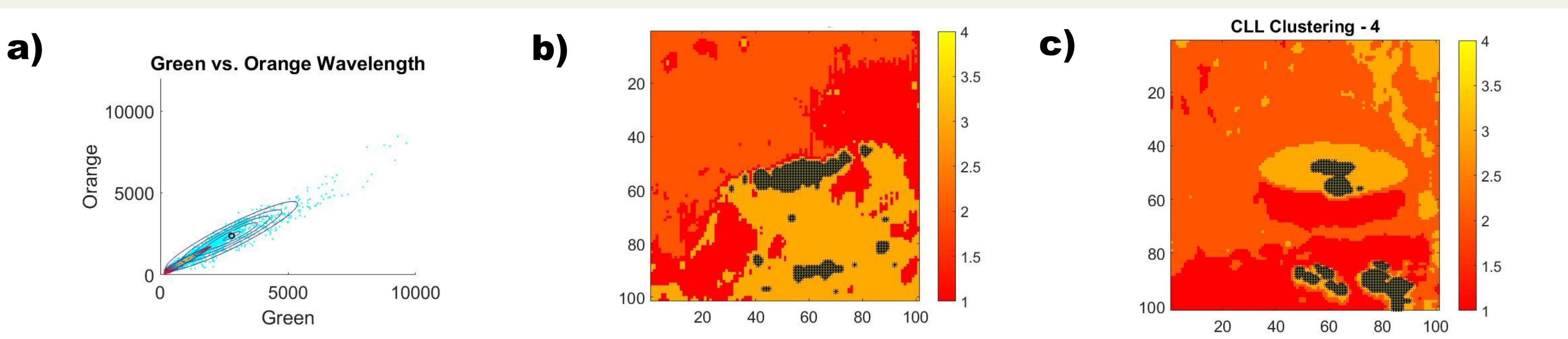

Figure 5: a) GMM of the pixel data for the green and orange spectral bands for the cooked beef. Contours designate estimated data clusters. CLL clustering heat map using the first 35 PCA spectral bands for the **b)** raw beef and **c)** cooked beef. Units of xaxis in nm.

Summary

- **NMF estimates demonstrate that a 3-band spectral feature set comprised of blue, green, and orange bands dominates the raw and cooked imagery. An MSI camera could be based on this feature set.**
- **Machine learning shows the roasting process is characterized predominantly by specific blue, green, and orange band *reduction* in spectral amplitude. The orange band has maximal value and decreases the most as the green, and orange achieve near equal spectral amplitude levels.**

4. Competitive Leaky Learning Analysis and Distance Metric Results :

- CLL clustering is a neural network-based algorithm where spectral pixel vectors "compete" with each other to see which ones are the most similar to previous input vectors. With each iteration spectral vectors become more affiliated with certain weight vectors allowing for imagery clustering.
- CLL clustering is successful in exhuming **texture modulation** of the beef steak surface for raw and cooked conditions consistent with the imagery shown in the NMF image slices.
- Clusters 2 and 3, using the raw beef imagery, possess a Kullback-Lieber divergence (KLD) and Bhattacharyya distance (BD) of 2.94 and 0.182 respectively which decreases to 0.8 and 0.06 respectively. This is shown in Figure 6.

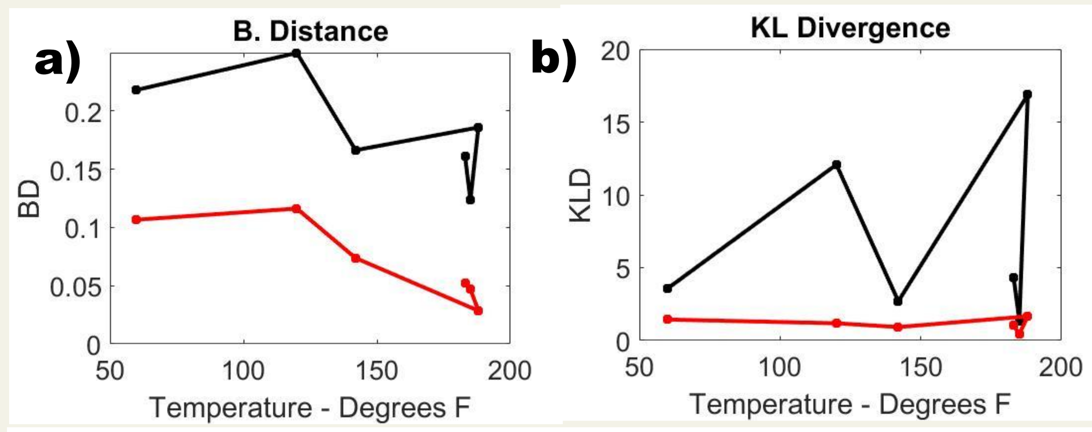

Figure 6: a) BD and b) KLD metrics for the second and third cluster groups over the six-measurement coarse of the roasting process. The clusters groups using the first 35 PCs and the 3 NMF derived real spectral bands are shown in black and red respectively.

- The decreasing BD value between different cluster areas on the steak surface is consistent with the **homogenization** of meat tissue as the difference between cluster areas decreases with the roasting process.
- The trends of the PCA-based BD and NMF-based BD are similar suggesting that similar clustering power can be achieved using the 3 spectral bands found from the NMF spectrum. **This suggests a smaller spectral bandwidth proxy is possible.**
- The ability of the roasting process to be tracked spectrally with changes in temperature suggests that a remote sensing MSI sensor could **in principle** be constructed to capture heat modulation of beef.

5. Meat Interior Spectral Amplitude Results:

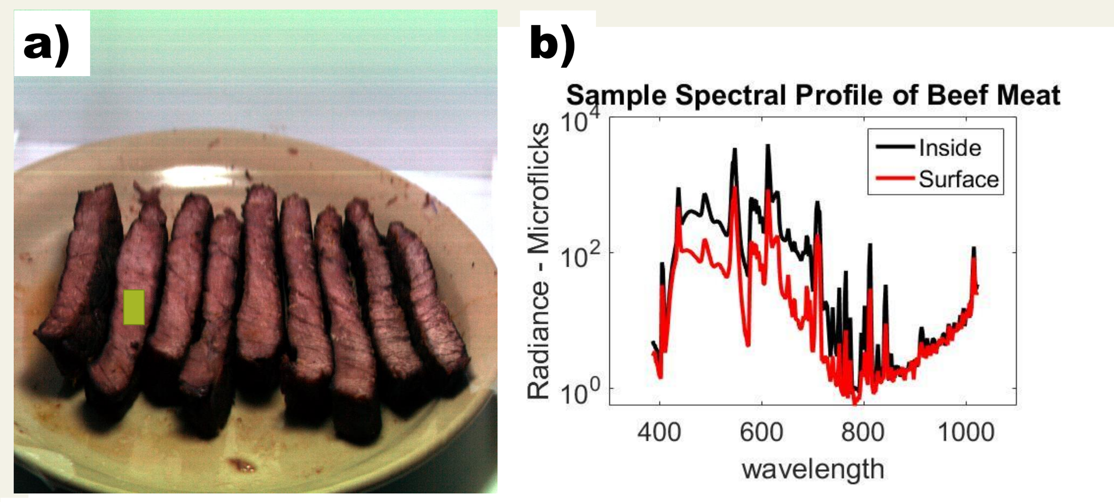

Figure 7: a) RGB image of meat interior. **b)** Average energy spectrum over green rectangle in image for meat inside. Outside meat surface spectrum for same piece of meat shown. Average taken over 2500 pixels. Units of x - axis in nm.

- Interior of meat shows the orange band (612 nm) to have slightly higher energy than the green band (547 nm) whereas the blue band is very low. This spectral structure is close to that observed on the meat surface but lower in amplitude.
- More data realizations could allow for a regression parameterization of the temperature with spectral energy allowing for remotely sense meat state assessment (e.g. rare, medium-rare, and well done).