



Measuring Aging and Water Content in Meat Products

A WHITE PAPER FROM



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1.0 Water Content in Meat

The consumable component of meat, muscle tissue, is approximately 75% water, 20% protein and 5% fat, carbohydrate, and minerals. The proportions vary depending upon type of muscle, the kind of meat, seasonal variability and the intrinsic pH. The water content is higher for leaner cuts. The water content contributes significantly to the eating quality of the product and is an indicator of freshness [1]. The breeding growth and development of the animals, their genotype and diet as well as stresses in pre-slaughter period (i.e. fasting, and different stunning methods) and in post-slaughter period (i.e. chilling, aging, injecting non-meat ingredients and tumbling) are factors in the water holding capacity of meat (WHC) [2].

Some initial studies utilizing spectroscopy and hyperspectral imaging in the visible through near infra-red spectral range (VNIR) have shown promise as a means to non-destructively determine not only the moisture but also fat and protein content as well as marbling, aging, grade and potentially tenderness [3].

2.0 Hyperspectral Imaging

Hyperspectral imaging cameras generate 'hyper-cubes' of data, whereby the spectrum at each pixel in the image is collected. Subtle reflected color differences that are not observable by the human eye or even by color (RGB) cameras are immediately identifiable by comparison of spectra between pixels. A variety of spectral imaging technologies exist.

The most common type of hyperspectral system is the push broom system whereby a line on the object plane generates a 2D pattern on an array sensor. The collection of a complete data cube (2D spatial x 1D spectral) requires mechanical scanning. While the dispersing elements can be made small and each spectrum can be collected in as short as 1ms, the mechanical motion makes these instruments somewhat bulky and prone to misalignment. Furthermore, increased spatial resolution comes at the expense of longer collection times. Push-broom grating systems were the earliest forms of the hyperspectral cameras, initially developed by NASA, mounted on satellites and airborne platforms for research purposes [4].

Band sequential or front staring cameras do not require mechanical scanning. In this technique, a tunable filter that can sequentially select spectral bands is placed in front of the sensor and generates the hyper-cube by collecting complete images at each spectral band-pass. The acquisition time does not depend on the number of pixels, but rather on the number of spectral bands being acquired. These systems are especially attractive for applications requiring high spatial and spectral resolutions with tunable spectral ranges and a small form factor.

Often discussed along with hyperspectral imaging technology are multi-spectral systems, the most popular of which are based on patterned filter arrays. These are an extension of color cameras where the typical Bayer or RGB filters overlaid on the image sensor are replaced with an array of 16 or even more color filters. While no user alignment is needed, and systems can be miniaturized, the spectral resolution is quite limited and comes at the expense of spatial resolution, making this technology inadequate for many critical sample analysis applications.

Fabry-Perot interferometers (FPIs) operate by placing two mirrors parallel to each other. By controlling the reflectivity of the mirrors and their spacing, high-finesse spectral filtering can be achieved. [See figure 1](#). Hinalea Imaging has several front-staring hyperspectral cameras based on this FPI technology, including the 4250 VNIR (400-1000 nm) as shown in [figure 2](#). This camera

captures multi-megapixel images in 300 spectral bands in a few seconds depending on the lighting and exposure requirements. Data from the camera can identify features of interest, both in the spectral and spatial domains and classify these features in the image [5].

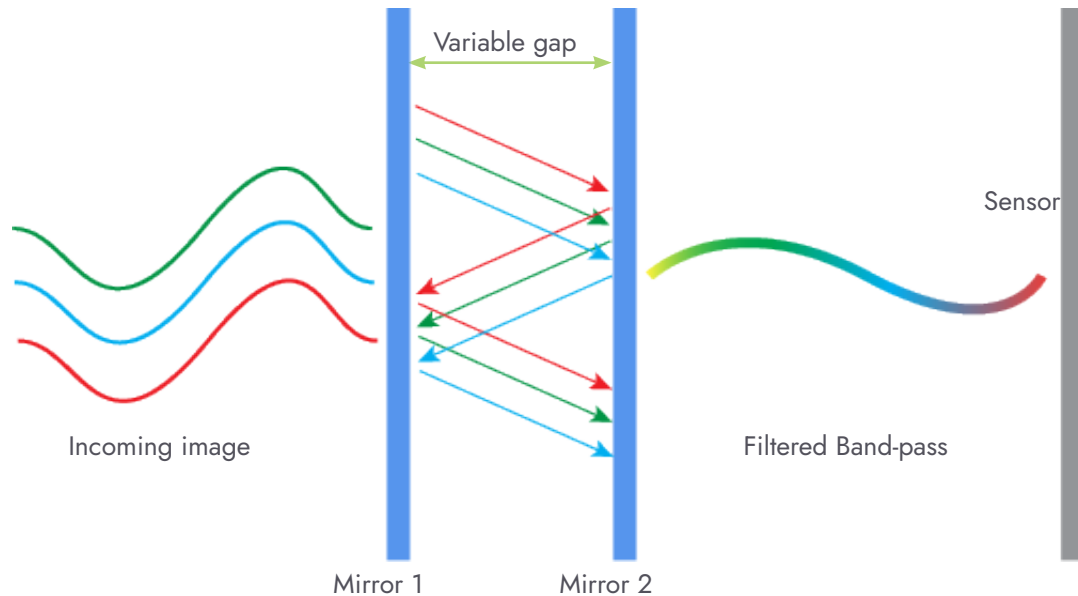


FIGURE 1 Operating Principle Fabry-Perot Filter



FIGURE 2 Model 4250 VNIR (400-1000 nm)

The technology can easily be packaged into form factors and configurations suitable for laboratory bench-top investigations or production line testing. Such an implementation has not been possible for other band sequential techniques (i.e. acousto-optic tunable filters, or AOTFs, and liquid crystal tunable filters) due to cost, reproducibility issues, environmental, and power restrictions. **See figure 3.**



Figure 3: Hyperspectral imaging camera configuration for meat fat and moisture content measurement

3.0 Spectral Image Processing, Unmixing and Classification

To make use of the abundance of data rendered by hyperspectral imaging, various image processing algorithms have been developed. These are essentially mathematical techniques for deconvoluting the multiple spectral emission profiles or species, also referred to as end-members. As with the hardware, these techniques have their origins in satellite remote sensing research.

The most basic and common in microscopy is linear spectral unmixing. This method assumes spectra of each pixel is a linear combination (weighted average) of all end-members in the pixel and thus requires a priori knowledge (i.e. reference spectra). Various algorithms such as linear interpolation, are used to solve “n” (number of bands) equations for each pixel where the “n” is greater than the number of end-members pixel fractions.

Another popular technique, spectral angle mapping, involves a vector representation of observed and target spectra to determine closest relationships in a multi-dimensional space proportional to the number of band passes. Spectral angle mapping is widely used due to its insensitivity to brightness differences. The advent of widely accessible machine learning methods has brought a new and powerful set of tools to this endeavor. Among these include Principal Component Analysis (PCA), a dimensionality reduction technique and K-Means Clustering a type of unsupervised learning algorithm used to find groups in the data based on feature similarity based on feature similarity [7].

4.0 Example of Hyperspectral Imaging Measurement of Moisture Content of Red Meat

A time series study of aging and moisture content of red meat using a Hinalea Visible-Near-Infrared (VNIR) hyperspectral camera (Model 4250) configured as per [Figure 2](#) was performed. Data cubes of samples of ground beef and fillet were captured over the course of two days at three-time intervals with the intent of studying the effects of aging on spectral reflectance properties and consequently moisture content. [See figure 4](#):

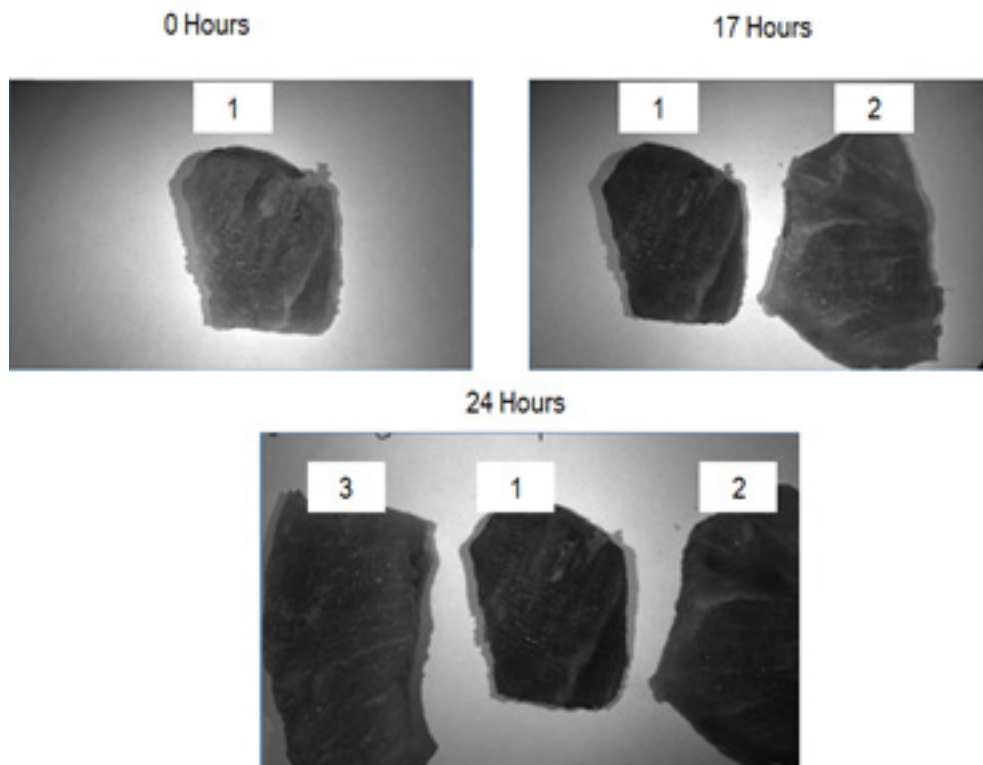


Figure 4: Images of beef fillet at the 630 nm band-pass frame

4.1 Traditional Spectral Analysis

Taking an average of the spectral response of a small area of pixels from the resulting image data-cube, a representative spectral reflectance profile for a given sample can be obtained. A survey of the features indicates a change in the intensity just below 800 nm, a band-pass associated with water content in muscle tissue. The intensity decreases over time which is consistent with the expected moisture loss due to aging. In addition, there is a shift of the entire spectra towards the longer wavelengths. This is consistent with the increased redness in the aged samples, likely due to the deoxymyoglobin transition to oxymyoglobin. These characteristics are seen for individual and groups of fillet and ground beef samples. [See Figures 5, 6 and 7](#).

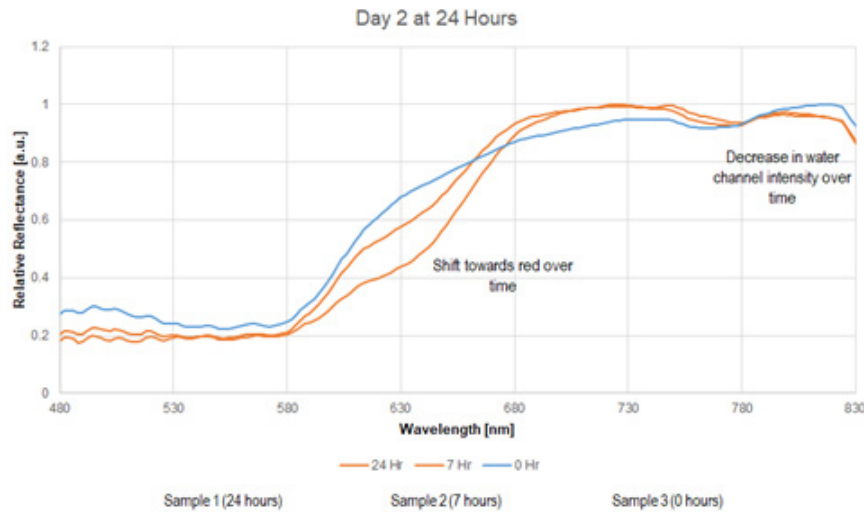


Figure 5: Relative Reflectance Spectra on Day 2 – 24 Hours Elapsed for 3 Fillet Samples

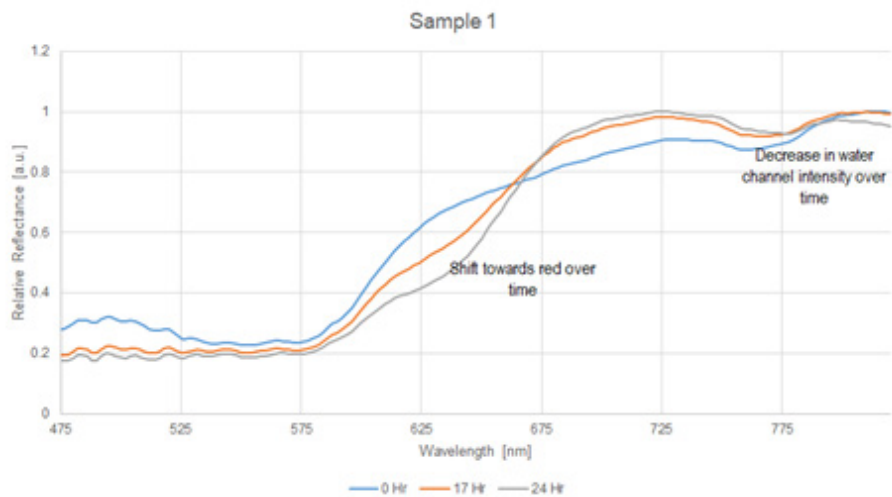


Figure 6: Beef Fillet Sample 1 Over Time

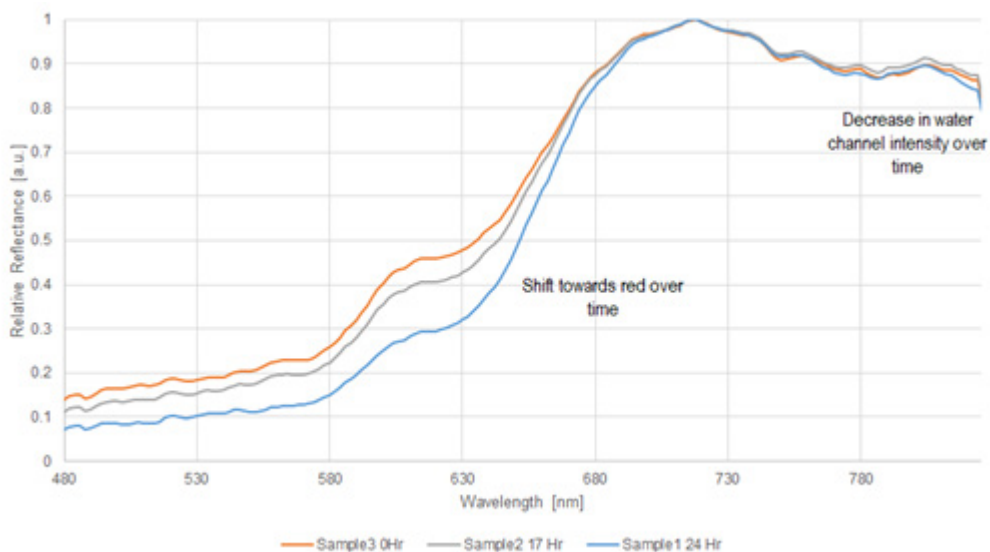


Figure 7: Relative Reflectance Spectra on Day 2 – 24 Hours Elapsed for 3 Ground Beef Samples

Figure 8 shows a clear spectral shift towards longer wavelengths (red) and a broadening (whitening) trend was observed along with some detail structural changes particularly in the 600-700 nm range. These results are consistent with published spectral and statistical studies [6].

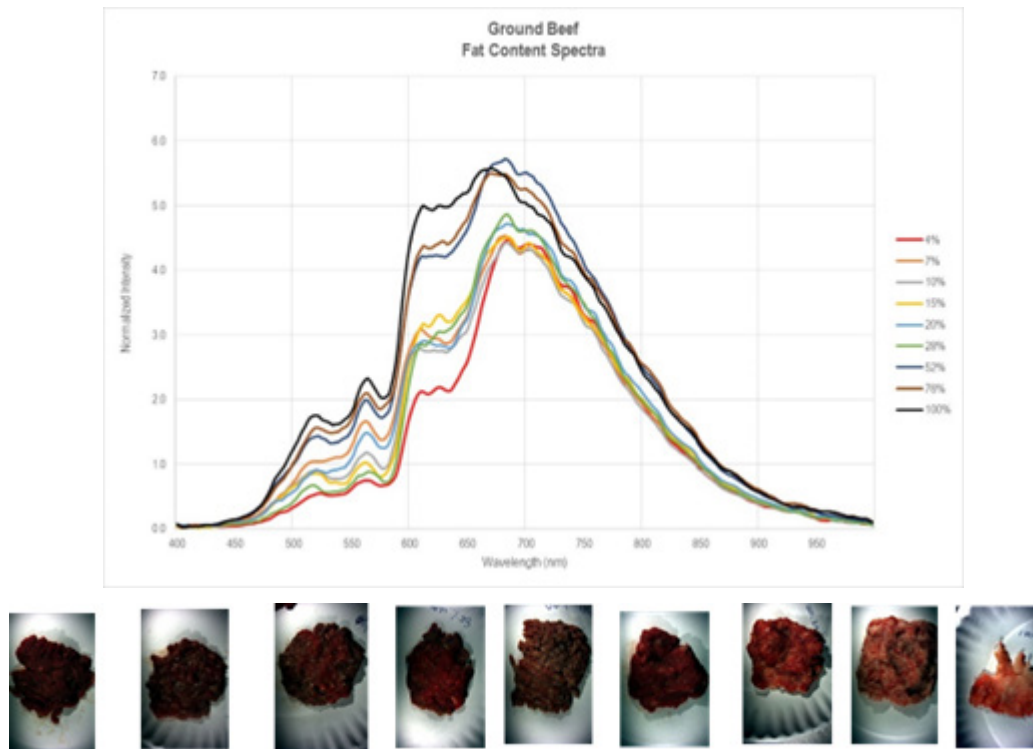


Figure 8: Images and averaged spectra of lean ground beef with varying proportions of added minced fat

4.2 Improved Spectral Analysis using Hyperspectral and Machine Learning

While analysis of individual spectra can provide specific characteristics of a single region or area of a sample of meat, it is an inefficient way to evaluate or inspect the entire product. The full value of hyperspectral imaging is in providing quickly actionable information for the entire product. To do this, the classification techniques discussed in 2.0 are leveraged. Applying machine learning techniques such as PCA to identify the most likely end-members and K-Means Clustering to group or classify them, for example, can improve the visualization of these components markedly. In **Figure 9**, the spectra for each pixel are first normalized to remove illumination non-uniformity, a PCA was then used for dimension reduction and a K-means algorithm used to classify and false color the end-members. Hence, each color in the image represents one cluster. An example spectrum for that cluster is also shown on the right. **Figure 10** shows the ground beef sample classified by a super-pixel segmentation method (PSMPS) in Gerbil [7].

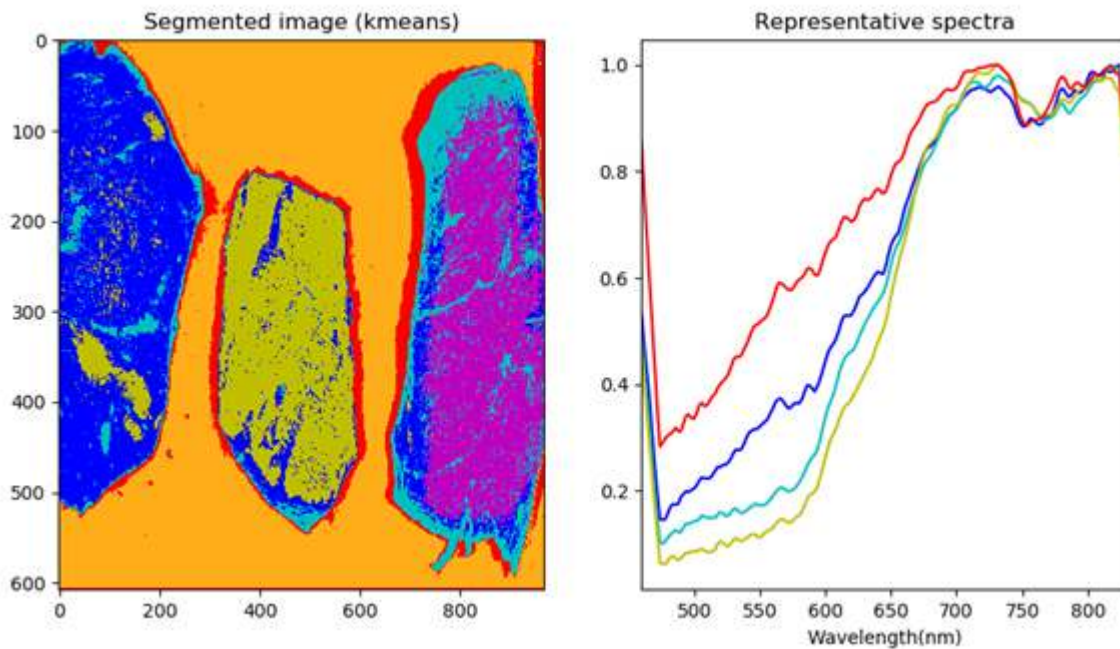


Figure 9: (Left) filet samples at 24 hours elapsed. Spectra for each pixel are first normalized to remove illumination non-uniformity, a PCA with 10 components was then used for dimension reduction and a K-means algorithm with 6 clusters, initialized randomly used to classify and false color the end-members. Hence, each color in the image represents one cluster. (Right) An example spectrum for that cluster.

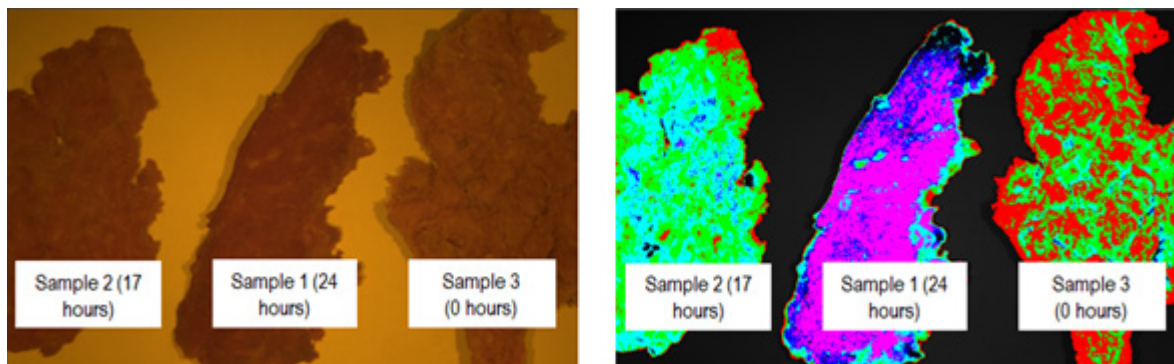


Figure 10: Ground beef samples at 24 hours. Elapsed classified using super-pixel segmentation method (PSMPS) in Gerbil. Note higher end-member (green and red false colors) overlap between Sample 2 and 3 (7 hours apart).

Similarly, images can be classified or segmented using machine learning algorithms by spectral components or end-members associated with each level of fat content. False coloring these grouped end-members shows a consistent trend associated with increasing percentages of fat with respect to lean red meat in the samples below.

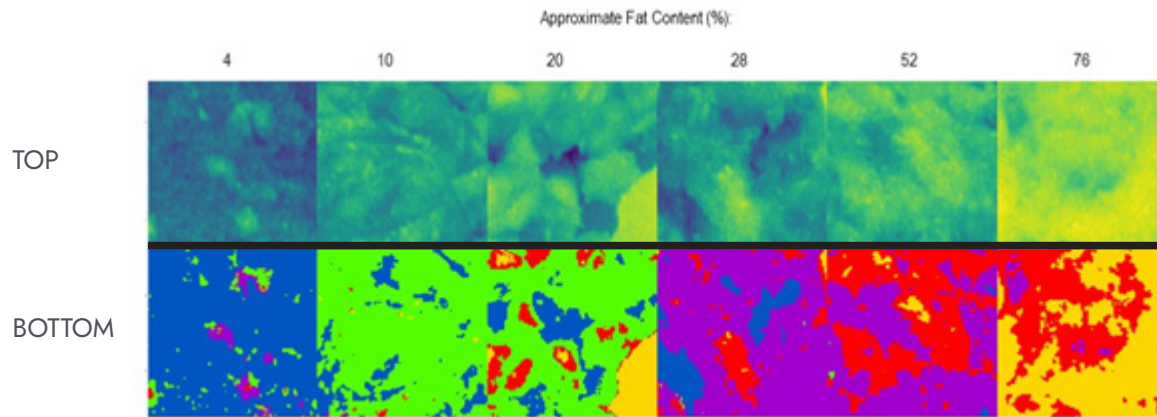


Figure 11: Ground beef samples with varying percentage of fat content (top) classified using K-Means clustering algorithm to cluster or group by similarity to the former image (bottom).

5.0 Summary

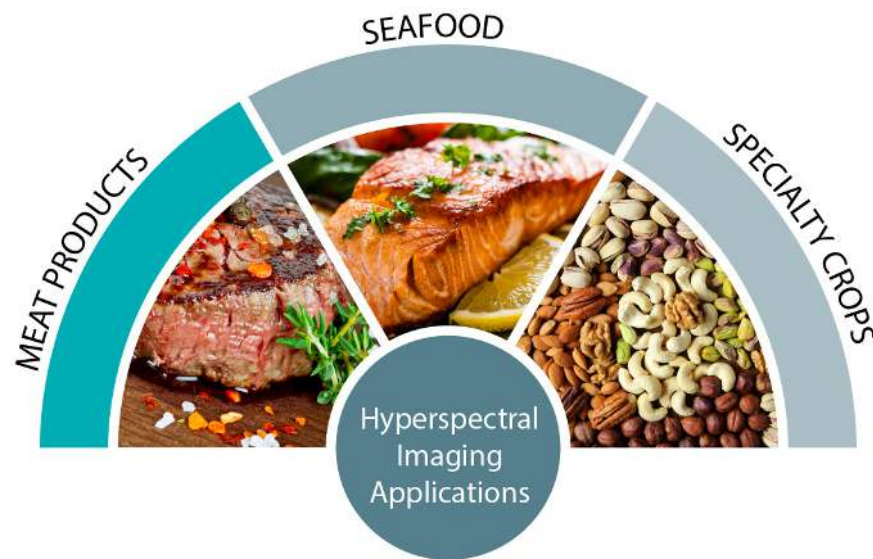
In addition to spatial information which can be useful for size sorting and other machine vision tasks, by identifying distinctions in images which are not only invisible to the eye but also to color (RGB) cameras and even multi-spectral ones, hyperspectral imaging systems can provide rapid assessment of product quality metrics such as moisture, aging, protein and fat content, marbling and more.

In the examples discussed, the Hinalea is able to detect a decrease in intensity near 800 nm, indicating a loss of water content or moisture over time. In addition, a red shift of the spectral profile over time likely due to deoxymyoglobin transition to oxymyoglobin was also seen. The classified images show end-member overlap due to time-proximity. These tools represent a means by which intuitive actionable information can be obtained at the operator level. There is also potential for further refinement in the automated decision making and product sorting process.

A unique combination of portability and the ability to dynamically change spectral range and band-pass capability of hyperspectral imaging technology means that the same instrument can be configured for a wide variety of parameters. For example, particular points of interest along an inspection line to both optimize accuracy while reducing the time to capture images. Finally, the cost advantages of the technology relative to other hyperspectral imaging solutions also vastly improves access for all such potential uses.

6.0 References

1. USDA/FSIS, "Water in Meat and Poultry", Food Safety Information, May 2011
2. M.J.A. den Hertog-Meischke , R.J.L.M. van Laack & F.J.M. Smulders (1997) "The water-holding capacity of fresh meat", Veterinary Quarterly, 19:4, 175-181, DOI: 10.1080/01652176.1997.9694767
3. Firtha, Ferenc, Anita Jasper and László Friedrich. "Spectral and Hyperspectral Inspection of Beef Ageing State." (2012)
4. C. H., Poole, G. H., Parker, P. E. and Gottwald, T. R.(2010) 'Plant Disease Severity Estimated Visually, by Digital Photography and Image Analysis, and by Hyperspectral Imaging', Critical Reviews in Plant Sciences, 29: 2, 59 — 107, DOI: 10.1080/07352681003617285, <http://dx.doi.org/10.1080/07352681003617285>
5. Hod Finkelstein, Ron R. Nissim and Mark J. Hsu, TruTag Technologies Inc., "Next-generation intelligent hyperspectral imagers"
6. Gerbil Hyperspectral Imaging and Visualization Framework, <http://gerbilvis.org/>



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