SNAPSHOT MULTISPECTRAL AND HYPERSPECTRAL DATA PROCESSING FOR ESTIMATING FOOD QUALITY PARAMETERS

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ABSTRACT

Multispectral and hyperspectral imaging systems have proven capabilities in estimating critical food quality parameters for a number of food processing and inspection tasks. In this paper, we have developed a processing pipeline for multispectral and hyperspectral snapshot video sensors, towards detecting certain critical quality parameters like freshness, spoilage levels and storage temperatures. In particular, a set of pre-processing modules are detecting clear meat or salad observations and then a classification algorithm is responsible for detecting and labelling accordingly each pixel or sample. The experimental results and performed quantitative validation indicate the quite promising potentials of the developed approach.

Index Terms— *Classification, Food Quality, Inspection, Meat, Salad*

1. INTRODUCTION

Snapshot multispectral and hyperspectral sensors are gaining a lot of attention recently mainly because they don't require the constant movement of the camera or the movement of the observed object comparing with the push-broom/ line-scanning ones. Still their main limitation is the spatial resolution (or the acquisition frame rate) as well as their radiometric quality in terms of noise to signal ration, distortions, vignetting, *etc.* which depending on the sensor require radiometric and geometric corrections for any further processing and analysis [1], [2], [3]. Such snapshot/ frame hyperspectral imaging systems, which can acquire hypercubes at video rates, have already been employed for several applications.

Regarding food quality inspection, multispectral and hyperspectral imaging systems, mostly in laboratory environments have been employed and studied a lot. Specific spectral regions have been identified for contributing significantly in various applications in food quality estimation, inspection and food sorting tasks [4],[5].

Rapid detection rates and the non-invasive character are among the advantages of hyperspectral and multispectral imaging for inspection of raw and processed meat. The food processing industry can exploit advanced imaging systems, that are getting smaller and smaller in size, along with machine learning tools towards the accurate estimation of critical parameters including authenticity, quality, freshness, *etc.* [6], [7], [8]. However, there are still important challenges towards large scale experiments that can simulate more realistic scenarios not in absolutely controlled laboratory environments.

To this end, in this paper, we have integrated a set of multispectral and hyperspectral sensors, towards validating their performance on the challenging tasks of minced meat spoilage detection and rocket salad temperature storage estimation. In particular, the multispectral and hyperspectral snapshot video data are processed in an automatic pipeline, which includes the required radiometric corrections as well as the detection of clear meat or salad observations. Then a classification algorithm is detecting the freshness or temperature levels at pixel or sample level. Several experiments were performed with minced meat and rocket salad (*Eruca sativa*) which highlight that the developed approach has high potentials in estimating critical food quality parameters.

2. MATERIALS AND METHODS

The deployed sensors for the experiments included two snapshot hyperspectral mosaic cameras and a multispectral-UV progressive scan camera. In particular, the first two were IMEC's Mosaic Snapshot Sensors and the third one the PIXELTEQ'S SpectroCam™ Multispectral Imaging system. The snapshot cameras were sensitive in the spectral regions of 470-620nm (with 16 spectral bands) and 600-1000nm (with 25 spectral bands), respectively. The FWHM was for all bands around 10-20 nm. These two CMOS sensors have recurring mosaic pattern of 4x4 and 5x5 filters, with each element sensitive to a different spectral region (4x4 = 16, 5x5 = 25). The two sensors have an active area of 2048x1024 and 2045x1080 pixels. Thus, each spectral band (raw data) has a spatial resolution of 512x256 or 409x216, respectively.

The PIXELTEQ'S SpectroCam delivers 8 multispectral bands in the spectral range of 350nm-900nm with a spatial resolution of 1392x1040 pixels. All the hyperspectral bands are being captured incrementally through exchanging rapidly spectral filters delivering up to 15 frames per second.

Fig. 1. The multisensor system including multispectral and hyperspectral sensors was deployed in the laboratory with controlled light conditions and reflectance boards in the field of view.

The developed methodology followed in general the same pipeline regarding both meat and salad samples (Figure 2). In particular, the spectral data were acquired and then, for the two snapshot hyperspectral sensors, the spectral bands were reconstructed at the original image size 2048x1024 and 2045x1080 pixels respectively, through an interpolation-based procedure [9].

Based on the reflectance board, every image and spectral band was radiometrically calibrated and the reflectance data were computed. Through a standard background subtraction technique the image region with the meat or salad was detected.
In the case of the minced beef samples, in order to detect and remove pixels belonging to fat, muscle fibers and other undesired parts, an additional detection software module based on the studied statistics across several meat samples, was developed (Figure 3). In the case of the rocket salad samples, the salad detector module was responsible, due to the arbitrary manner of placing the salad leaves, to detect the image region with shadows or holes extracting only pixels that correspond to clear salad leaves.

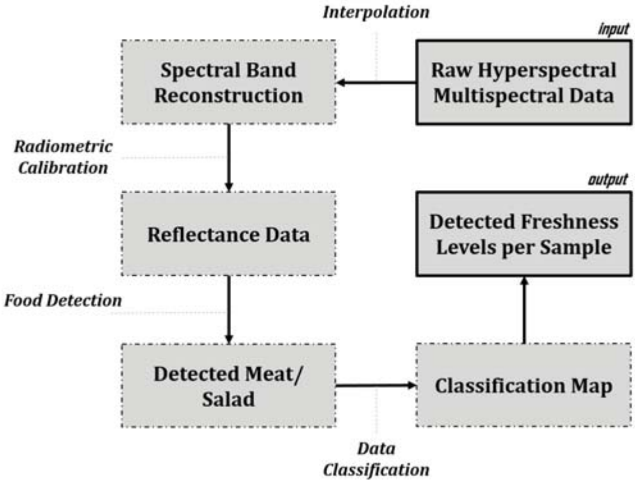

Fig. 2. A flowchart of the developed algorithm for processing the acquired spectral data.

Then a classification procedure was responsible to detect the different freshness levels at pixel level. In order to do so, the samples were divided in 50% training and 50% validation sets. Regarding the classification algorithms, several experiments were performed with SVM (both linear and radial basis function kernels) and Random Forests [10], [11]. The Random Forest (RF) is a meta estimator that fits a number of decision tree classifiers on the various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting. Generally speaking, based on several experimental with all classifiers the RF possessed certain advantages such as a small training time, easy parameterization and relatively higher overall accuracy rates. Therefore, in the next section results based on the RF classifier are presented.

3. EXPERIMENTAL RESULTS AND VALIDATION

3.1. Detecting Meat Freshness

For the detection of minced beef freshness levels (or similarly spoilage levels) two different experiments were conducted on the same dataset. The minced beef samples (two per day) were stored individually in aluminum foil in temperatures lower than 4ºC for different number of days i.e., 1 to 10 days. During the first one, all samples were grouped together and the training and testing sets were formed by diving all pixels into two groups (i.e., 50% training and 50% validation). During the second one, the meat samples were divided into training set and validation set by diving the two per day samples towards a more sample-independent validation.

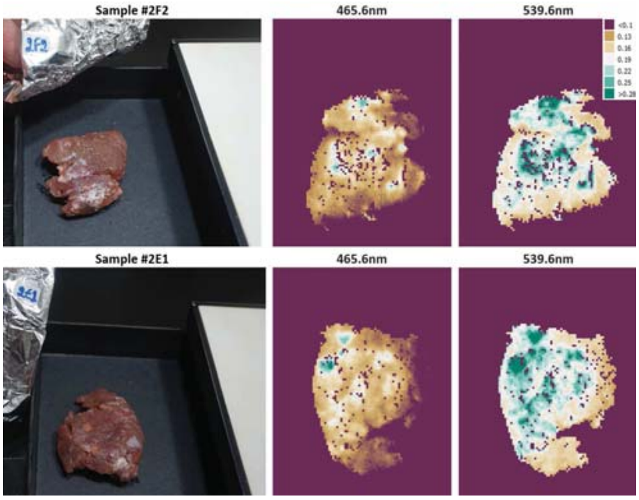

Fig. 3. The detected minced meat at different spectral bands (at 465nm and 539nm).

For the first experiment, ten (D1-D10) different classes were associated with the different freshness levels. The resulting classification map and the corresponding confusion matrix is presented in Table 1. The numbers on the main diagonal are the number of correctly classified pixels in each class. The overall classification accuracy was approximately 94% indicating the successful discrimination between the different classes.

	Reference data										
Days	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	PA
D1	2161	74	71	8	0	2	0	7	0	1	93.0
D2	31	2360	35	2	0	2	0	0	0	0	97.1
D3	47	36	2100	4	39	193	0	2	1	0	86.7
D4	4	1	5	2381	0	0	0	66	0	0	96.9
D5	4	0	48	1	1962	96	0	0	0	0	92.9
D6	11	7	163	3	85	1590	0	0	0	0	85.5
D7	0	0	0	0	0	0	2084	0	0	0	100
D8	14	2	3	78	0	0	0	2197	63	0	93.2
D9	0	0	0	0	0	0	0	149	1938	0	92.8
D10	0	2	0	0	0	0	0	0	1	2081	99.8
Total	2272	2482	2425	2477	2086	1883	2084	2421	2003	2082	
UA	95.1	95.1	86.6	96.1	94.0	84.4	100	90.7	96.8	99.9	
	Overall accuracy : 93.9%										

Table 1. Hyperspectral Data Classification Results - from fresh (D1) to D10.

In particular, for all considered classes, the User Accuracy was higher than 84%, with most of them at around 95%. The two classes that achieved lower rates at around 85% were D3 and D6. Indeed, a 7% and 10%, respectively of the pixels were mis-classified mainly between the two of them.

In the second experiment a more challenging classification task took place since the training and validation sets were obtained from independent samples. The classification classes were formed by grouping together the meat samples of the first three days (group 1: D1 to D3), of the next three days (group 2: D4 to D6) and of the remaining four days (group 3: D7 to D10).

The resulting confusion matrix for the second experiment is presented in Table 2. The resulting overall accuracy was at 70.4%. As it was expected, the group that was more easily discriminated by the classifier was group 3, the one with the higher spoilage levels, the higher bacterial growth after seven or more days of storage. For this particular class the User and Producer accuracies approximately 96% and 89%, respectively.

Relatively lower classification accuracy rates were obtained for the first two groups i.e, 66% and 51% regarding PA and 58% and 55% regarding UA. As expected, the vast majority of the mis-classification cases were observed between these two classes (group 1 – group 2).
Moreover, it should be noted that, if we consider the per sample classification scores (not the per-pixel ones), then the developed procedure managed to correctly identify (at a 100% rate), all the considered validation samples (through a majority voting process). Indeed, in all cases the per-class accuracy rates at pixel level were higher than 50% and therefore at sample level it was feasible to correctly identify between the three freshness/ spoilage levels.

	Reference data			
Days	Days 1-3	Days 4-6	Days 7-10	PA
Days 1-3	4545	2293	43	66.1
Days 4-6	2997	3394	291	50.8
Days 7-10	360	542	7541	89.3
Total	7902	6229	7875	
UA	57.5	54.5	95.8	
	Overall accuracy : 70.4%			

Table 2. Hyperspectral Data Classification Results - 3 freshness groups (D1-3), (D4-6), (D7-10).

3.2. Detecting Rocket Salad Storage Temperature

The main goal in this experiment was to detect the different storage temperature levels of a rocket salad (Eruca sativa). To this end, several rocket salad batches in sealed plastic bags were stored for five days in four different temperature conditions. In particular, they were stored at 4^{o}C, 8^{o}C and 12^{o}C, as well as in a dynamic temperature environment, in the range between 4^{o}C and 12^{o}C. The aim was to simulate more realistic conditions, as a refrigerator can be opened several times per day affecting the storage temperature.

Therefore, the four different classes correspond to the different storage temperature levels. The dataset was split in half to 50% training and 50% validation sets.

The resulting classification and the corresponding confusion matrix is presented in Table 3. The achieved overall accuracy rate was at 79.0%. In particular, the =fresher samples stored a 4ºC environment, were detected with higher accuracy rates with a Producer and User accuracy above 90%. The other two classes with stable temperatures (8ºC and 12ºC) were detected with a 72% and 76% PA and with a similar 71% and 76% UA, respectively. The class stored in dynamic temperature conditions, was associated with the most mis-classification cases, mainly being confused with the classes stored at 8ºC and 12ºC as expected.

However, in a similar way with the previous experiments, when moving from pixel-based detection to a per-sample storage temperature detection task, through for example a majority voting process, all samples are being successfully identified (at a 100% detection rate). Indeed, in all cases, the per-class accuracy rates at pixel level were higher than 67% and therefore, at sample level, it was feasible to correctly identify the different storage temperature conditions.

	Reference data				
^oC	4^oC	8^oC	12^oC	Dynamic temp	PA
4^oC	543213	1118 3	1902	4472	96.9
8^oC	26738	404735	60412	67391	72.4
12^oC	14971	62236	424832	57987	75.9
Dynamic temp	17904	93035	74531	374458	66.9
Total	602826	571189	561677	504308	
VA	90.1	70.8	75.6	66.9	
	Overall accuracy : 79.0%				

Table 3. Detecting at the 5th Day (after 134 hours) the o C that the salad was stored.

4. CONCLUSIONS

In this paper, we have developed a processing pipeline for multispectral and hyperspectral snapshot video sensors, towards detecting certain critical quality parameters like freshness, spoilage levels and storage temperatures. A set of pre-processing modules are employed, to detect clear meat or salad observations and then a classification algorithm is responsible for detecting and labelling each pixel or sample. The experimental results and performed quantitative validation indicated that the developed approach is a highly promising one.

5. REFERENCES

[1] Honkavaara, E., Saari, H., Kaivosoja, J., Polonen, I., Hakala, T., Litkey, P., Makynen, J., Pesonen, L., 2013, Processing and assessment of spectrometric, stereoscopic imagery collected using a lightweight uav spectral camera for precision agriculture, Remote Sensing, vol. 5, no. 10, pp. 5006-5039.

[2] Vakalopoulou M. and Karantzalos K., 2014. Automatic Descriptor-Based Co-Registration of Frame Hyperspectral Data, Remote Sensing, vol. 6, no. 4, pp. 3409-3426.

[3] Kandylakis Z., Karantzalos K., Doulamis A., Doulamis N., 2015. Multiple Object Tracking with Background Estimation in Hyperspectral Video Sequences, IEEE Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing.

[4] Pu, H., Kamruzzaman, M., Sun, D-W., 2015. Selection of feature wavelengths for developing multispectral imaging systems for quality, safety and authenticity of muscle foods-a review," *Trends in Food Science & Technology*, Vol.45(1), pp.86-104.

[5] Cheng, J-H., Nicolai, B., Sun, D-W., 2017. Hyperspectral imaging with multivariate analysis for technological parameters prediction and classification of muscle foods: A review, *Meat Science*, Vol.123, pp.182-191.

[6] Ropodi, Athina, Panagou, Efstathios Z., Nychas, George-John E., 2017. Multispectral imaging (MSI): A promising method for the detection of minced beef adulteration with horsemeat, Food Control, Vol. 73, Part A, pp.57-63.

[7] Feng, C-H., Makino, Y., Oshita, S., García Martín, J. F., 2018. Hyperspectral imaging and multispectral imaging as the novel techniques for detecting defects in raw and processed meat products: Current state-of-the-art research advances, *Food Control*, Volume 84, Pages 165-176, 2018

[8] Estelles-Lopez, Lucia, Ropodi, Athina Dimitris Pavlidis, Jenny Fotopoulou, Christina Gkousari, Audrey Peyrodie, Efstathios Panagou, George-John Nychas, Fady Mohareb, 2017. An automated ranking platform for machine learning regression models for meat spoilage prediction using multi-spectral imaging and metabolic profiling, Food Research International, Vol. 99, Part 1, pp. 206-215.

[9] Wang G., Garcia D., Liu, Y., de Jeu, R. Dolman, A. J., 2012. A three-dimensional gap filling method for large geophysical datasets: Application to global satellite soil moisture observations, Environmental Modelling & Software, Vol. 30, pp.139-142.

[10] Keerthi S.S. and Lin C.J., 2003. Asymptotic behaviors of support vector machines with Gaussian kernel. Neural Computing, Vol. 15(7), pp. 1667-1689.

[11] Breiman, L., 2001. Random Forests, Machine Learning, Vol. 45(1), pp.5-32.