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VISIBLE/NEAR-IR REFLECTANCE SPECTROSCOPY FOR THE CLASSIFICATION OF POULTRY CARCASSES

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ABSTRACT

This paper presents the progress of the development of a nondestructive technique for the classification of normal, septicemic, and cadaver poultry carcasses by the Instrumentation and Sensing Laboratory at Beltsville, Maryland, U.S.A. The sensing technique is based on the diffuse reflectance spectroscopy of poultry carcasses.

KEYWORDS: Chicken, Inspection, Quality, Neural-Networks, Principal-Component-Analysis, Mahalanobis-Distance, Pattern-Recognition, Multiple-Linear-Regression, Classifier

INTRODUCTION

In order to assure consumers of product wholesomeness and to protect the public against poultry diseases that are harmful to humans, carcasses of poultry with septicemic disease or those which have not been bled out well must be kept out of the marketplace. Furthermore, high quality poultry products are an absolute necessity for the poultry industry to compete in the domestic and foreign markets. In FY 1991, 6.3 billion birds were slaughtered (USDA, 1992). Among them, 1.2% were condemned and removed from the marketplaces. Of these, 50% were condemned because of septicemia or classification as cadaver.

A cadaver is defined to be the carcass of a chicken that died from any causes other than slaughter (USDA, 1984). It may not have been bled properly. A septicemia condition in chickens is generally a microbial infection commonly caused by either *P. multocida* or *E. coli* (Dhanda and Sen, 1972; Christie and Halliday, 1979; Awad et al., 1973; Harry and Deb, 1979).

Presently, in the United States individual poultry carcasses are visually inspected by federal inspectors at the chicken processing lines. The visual bird-by-bird inspection is labor intensive and prone to human error. A study by the Food and Nutrition Board concluded that error rates may equal a substantial fraction of condemnation rates (Food and Nutrition Board, 1987). Instrument inspection of poultry carcasses will improve the inspection accuracy and reduce inspector's fatigue and discomfort due to repetitive motion of hands and head.

The development of accurate, reliable, and economical sensors is of paramount importance to an improved federal poultry inspection program. The sensing system should be capable of rapidly and correctly detecting carcasses with disease and separating them from normal carcasses on processing lines. Near-infrared spectroscopy has been considered to be a rapid and flexible analytical technique for obtaining information from samples. This technique is rapid, requires minimal sample preparation, and is robust (Davies, 1990). The position and shape of an absorption feature at different wavelengths is indicative of the chemistry of the material and its interactions with the environment. The intensity of the absorption feature is related to the amount of material present in the sample under study.

Recent advances in spectrophotometric interpretation have occurred with the development of analytical and objective methods and in the utilization of computer-aided assessment of the data. The objective of this paper is to report the research results of applying reflectance spectroscopy in the visible/near-infrared regions for separation of septicemic and cadaver poultry carcasses from the normal carcasses.

DIODE-ARRAY SPECTROPHOTOMETER

Figure 1 shows the silicon diode array spectrophotometer system used in this study. Light from a 150 watt halogen light bulb was focused on the circular end of a fiber optic bundle (0.8 cm in diameter). This light traveled through the fiber optic bundle (2.5 m long) and exited in the center of a concentric optical probe. The probe was set at a distance of 2 cm away from the carcass. This was a result of testing for maximum light returned from the poultry carcass.

After interacting with and reflecting from the carcass, the light energy was collected by a concentric ring of optical fibers (0.5 mm thick at a diameter of 1.85 cm). The collected energy was transmitted back through the same fiber optic cable to the entrance slit (250 μ wide) of the spectrograph.

A Jarrell-Ash MonoSpec 27[1] spectrograph with a holographic grating of 150 G/mm and a dispersion of 24 nm/mm was used in this study. At the exit of the spectrograph was a Tracor Northern TN-6112 1024-element silicon diode detector. The diode array in conjunction with the grating provided a 0.5911 nm per diode element resolution. The detector array was thermoelectrically cooled to 20°C to reduce dark current and purged with dry air to prevent condensation on the photodiode detector window.

The diode array detector was connected to a Tracor Northern TN-6200 computer interface. This interface provided a 14 bit analog to digital converter to digitize the analog signals and transferred data to the computer. The computer was used to control the spectrophotometer and to collect and store data. The computer collected data at the full data output rate of the diode array (10 ms for a full wavelength scan) and performed signal conditioning. In this study, reflectance was the ratio of the energy returning from a sample to the energy returning from a reference material (Teflon block).

MATERIALS AND METHODS

The reflectance spectra in the visible and near-infrared regions (500 nm to 1113 nm) of both sides of the breasts of 50 normal, 50 septicemic, and 40 cadaver chicken carcasses were obtained. Spectra were obtained at 0°C and 20°C for all except 30 of the carcasses. For more

[1] Mention of any company or trade name does not imply endorsement of the products by the U.S. Department of Agriculture. It is for purpose of description only.

details, see Chen and Massie (1993). The reflectance measured at each side (right and left breasts) of a carcass was considered to be an independent observation. The conditions of these carcasses were identified in the plants by Food Safety and Inspection Service (FSIS) veterinarians. Details of hardware and the experimental method were described in the previous paper (Chen and Massie, 1993).

The classification algorithms operated on pattern vectors consisting of the reflectances of a carcass at designated wavelengths. The algorithm acquired the knowledge needed to determine the class membership of a vector through a training process. The odd-numbered spectra were used for training all classifiers (training set), while the even numbered spectra were used for verification (test set). In order to develop a technique that is independent of temperature, the spectra collected at 0°C and at 20°C were pooled together.

Multiple-Linear-Regression (MLR) Classifiers

In this technique, a linear function of reflectance was developed to distinguish between each pair of classes: normal vs. septicemic, normal vs. cadaver, and septicemic vs. cadaver. Each discriminant function had the following form:

$$Y=a_0+a_1S(\lambda_1)+a_2S(\lambda_2)+a_3S(\lambda_3)+a_4S(\lambda_4) \qquad (1)$$

where Y is the condition score of the carcasses, $S(\lambda_1)$, $S(\lambda_2)$, $S(\lambda_3)$, and $S(\lambda_4)$ are the reflectances at wavelengths λ_1, λ_2, λ_3, and λ_4, respectively, and a_0, a_1, a_2, a_3, and a_4 are regression coefficients. The first wavelength selected was the one which provided the best coefficient of determination (R^2) in a single term linear regression. Then a second wavelength was found by performing a two-term linear regression with the first wavelength fixed. The first wavelength was then allowed to vary until the R^2 was again maximized. This process was repeated until a best pair of wavelengths was found (not necessarily global optimization). Then third and fourth wavelengths were added and optimized in turn, with the result being an optimal set of four wavelengths in a four-term regression.

For developing the functions to separate the normal from the septicemic and cadaver carcasses, the condition scores of the normal carcasses were assigned a numerical value of 1.0, while the septicemic and cadaver carcasses were assigned a value of 2.0. A scatter plot for the test set was then developed with the x-axis representing the value obtained from the normal vs. septicemic function and the y-axis representing the value from the normal vs. cadaver function. The carcasses predicted as normal were those with both the x- and y-values less than the threshold of 1.5. The same procedure was used to predict a carcass as either septicemic or cadaver.

Principal-Component-Analysis (PCA)/Mahalanobis-Distance (MD) Classifier

The PCA method expresses the spectral vector of any carcass as a linear combination of a set of orthogonal (uncorrelated) vectors, called factors. The first factor, a vector of reflectances, is chosen to account for the largest possible fraction of the variance of the reflectances in the training set. Each successive factor is then chosen to account for the largest possible fraction of the remaining variance. A few factors can usually account for most of the variance. When a spectrum is expressed as a linear combination of these factors, the coefficients are called the factor scores. Each spectrum can be adequately represented by a few scores in factor space instead of many reflectances in wavelength space. The optimal number of factors was determined to be the number which yielded best prediction of the cross-validation set.

A different set of factors was developed for each of the three classes in the training set. Any vector to be classified was tested against each of the three classes. The vector was first expressed in terms of the linear combination of the factors for that class. Then its scores and the residue error not modelled by PCA were used to compute the Mahalanobis distance from the centroid of each class (Galactic Industries Corporation, 1989). The Mahalanobis distance, unlike the Euclidian distance, is measured in units of standard deviation. The Mahalanobis distance provides a measurement of the likelihood of similarities between the vector and the class mean, and it assigns a statistical probability to that measurement. To improve the sensitivity of the classifier, the Mahalanobis distances were further scaled by the Root Mean Square Group (RMSG) size of each class. The RMSG is determined by calculating the Mahalanobis distance for every sample in the training class from the class mean

$$RMSG=\sqrt{\frac{\sum_{i=1}^{n} D_i^2}{n-1}} \tag{2}$$

where D_i is the Mahalanobis distance of vector i from the class mean and n is the number of patterns of the class in the training set. The class with the shortest scaled Mahalanobis distance was assigned to the vector.

To develop this classifier, full spectra of 650 reflectances starting at 504 nm and ending at 888 nm with an interval of 0.5911 nm were used. Software used for this study was "Lab Calc" by Galactic Industries Corporation, Salem, New Hampshire (Galactic Industries Corporation, 1989).

Artificial-Neural-Network (ANN) Classifier

A backpropagation, feedforward neural network model was used to separate the carcasses into the three classes. A neural network is made up of many processing elements called nodes, joined together with weighted interconnections. The nodes are grouped into layers. In the feedforward system the flow of information travels in one direction only, from the input layer to the output layer. In this study one hidden layer was used. The input to each node of hidden and output layers is the weighted sum of the outputs of the nodes in the previous layer

$$I_j=\sum w_{ji}o_i \tag{3}$$

where I_j is the input to the j-node, o_i is the output from the i-node, and w_{ji} is the strength of the connection between i-node to the j-node in the one layer above the i-node layer. The output of each node is determined from the input by the activation function of the node and the bias of the node

$$o_j=f(I_j) \tag{4}$$

where f is the activation function. In this study a sigmoidal activation function f was used:

$$o_j = \frac{1}{1 + e^{-(I_j + \theta_j)/\theta_o}} \tag{5}$$

where the parameter θ_j is used as a threshold or bias and θ_o is to modify the shape of the sigmoid. It should be noted that in implementation, the bias term is considered an extra node with a constant input of 1.0 and is connected to each node in the hidden and output layers. The connection strength of the bias node to each node is optimized in the training time.

The inputs to the input nodes were reflectances normalized to a value between 0 and 1. Each input node corresponded to a wavelength of the spectrum, and each output node represented one of the three decision classes. The reflectances at the 192 wavelengths from 512.9 to 851.6 nm were used as inputs to the network, and $\theta_o = 1$ was used.

During the training phase, the vectors from the training set were presented to the input nodes. If the output pattern of a vector did not match the pattern of the class of the carcass, the connection weights in the net were adjusted in proportion to the difference between the observed and desired patterns using the generalized delta rule

$$\Delta w_{ji}(n+1) = \eta(\delta_j o_i) + \alpha \Delta w_{ji}(n) \tag{6}$$

and where n is the number of update, η is learning rate, and α is a proportional constant. For any output layer node k

$$\delta_k = (t_k - o_k) o_k (1 - o_k) \tag{7}$$

where t_k is the desired output of kth node, and for any internal node j

$$\delta_j = o_j (1 - o_j) \sum \delta_k w_{kj} \tag{8}$$

The weights were modified by an iterative procedure, using equations 5 and 6, which propagated the error back from the output layer to the lower layers. Backpropagation is a gradient search technique which minimizes the root mean square error between desired and actual network outputs. For a more detailed description of backpropagation neural nets, see Pao (1989) and Hecht-Nielsen (1989).

The vectors in the cross-validation set were used to terminate the training process at an optimal point. Initially, the accuracy of the neural net in classifying both the training and cross-validation sets improved each time the training set was presented and the weights were adjusted. After repeated training, the accuracy in classifying the cross-validation set reached a maximum, while the accuracy in classifying the training set continued to increase. The best model was the one which classified the cross-validation set most accurately. Beyond this point, the model would have been over-trained, and the neural network would have started to memorize the patterns in the training set rather than generalize the patterns.

The software used was "NeuralWorks Professional II/Plus" by NeuralWare, Inc., Pittsburgh, Pennsylvania. All the patterns in the training set were used for training, and the optimal number of iterations was determined to be the number which yielded best prediction of the test set.

RESULTS

Figures 2-4 show the means and standard deviations of reflectance as a *function of wavelength* for the normal, septicemic, and cadaver carcasses of the training set, respectively. Only spectra of wavelengths between 500 to 890 nm were used in this study, because significant differences in reflectance among the three classes of carcasses were found in this region.

Multiple-Linear-Regression Classifiers

The optimal wavelengths for distinguishing normal from septicemic and cadaver carcasses by the reflectances were 569.7, 542.5, 640.6, and 846.9 nm. For separating the septicemic and cadaver carcasses, the optimal wavelengths were 732.8, 570.8, 731.0, and 735.2 nm.

Table 1 summarizes the prediction accuracy of the test set using the MLR model with the reflectances at the 8 optimal wavelengths obtained with the training set. Table 1 shows that 4 of the normal cases were misclassified as septicemic, while 1 was misclassified as cadaver. Only 6 septicemic and 5 cadaver cases were misclassified as normal.

Of the 250 cases in the test set, 96 were predicted to be normal. Among these, 6 were actually septicemic and 5 were cadaver. This implies that the Type I error rate for predicting normal cases was 6.9% (11 out of 70 cadaver and 90 septicemic cases). Of the 90 normal cases in the test set, 5 were misclassified as abnormal (4 septicemic and 1 cadaver cases). The Type II error rate of misclassifying the normal cases as abnormal was 5.6%. Among the 250 cases in the test set, 82 were predicted to be septicemic. Please note that the Type I error is committed when the wrong samples are assigned to the class while the Type II error is committed when the right *samples in the class are wrongly rejected.* Of the 82, 76 were septicemic cases, 4 were actually normal cases and 2 were cadavers. Of the 90 septicemic cases, 84.4% were correctly identified. Among the 71 classified as cadaver, 63 were correctly predicted, 7 were actually septicemic cases, and 1 was a normal case. The Type I error for classifying the cadaver cases was 11.3%. The Type II error for classifying the cadaver cases was 10.0%; that is, 10 out of the 70 cadaver cases in the test set were misclassified as either normal or septicemic.

The multiple linear regression classifiers based on the 8 optimal wavelengths resulted in 94.4%, 84.4%, and 90% classification accuracies for the normal, septicemic, and cadaver carcasses, respectively. It should be noted that no carcasses were classified to more than one class. However, there was one septicemic case which was not classified to any one class. This septicemic case was barely rejected by the normal, septicemic, and cadaver classifiers. The overall classification accuracy was 89.6% (224 out of 250).

Training and verifying PCA/MD Classifiers

It was found that the optimal number of factors was 6. Table 2 shows the confusion matrix for the verification of the PCA/MD model with 6 factors. It shows that the overall classification accuracy of the test set was 87.2%.

Table 2 shows that, among the 90 normal cases, 6.7% were misclassified as septicemic and none as cadaver. Of the 90 septicemic cases, 4.4% were misclassified as normal and 18.9% as cadavers. Among the 70 cadaver cases, 2.9% were misclassified as normal and 4.3% as septicemic. Among the 160 abnormal cases, 3.8% were predicted as normal cases. Of the 90 classified as normal, 4.4% were septicemic cases and 2.2% were cadaver, i.e., 6.7% were abnormal cases (Type I Error). Among the 150 cases predicted to be abnormal (78 septicemic and 82 cadaver), 4.0% were normal cases. The PCA/MD model classified slightly less accurately than the MLR model.

Training and verifying Artificial Neural Network Classifiers

Different schedules of η and α for the hidden and output layers were tried to obtain the highest accuracy of classification. The training schedule of the best result among the runs was found to start with $\eta = 0.9$ and $\alpha = 0.6$, and remained constant up to the learning count of 35,000. Both η and α were reduced to 0.2 at the learning count of 35,000. The learning rate η was again reduced to 0.01 at 55,000, and further reduced to 0.001 at 80,000. The accuracy of classification of the test set reached a maximum (91.6%) at a training count of 65,001 and after that, the accuracy started to drop and reached 88.8% at the count of 80,000, when the learning was terminated.

Table 3 is the confusion matrix for the validation (and verification) of the ANN model with 192 input nodes. It shows that the overall classification accuracy of the test set was improved to 91.6%. Table 3 shows that, among the 90 normal cases, 5.6% were misclassified as septicemic and none as cadaver. Of the 90 septicemic cases, 4.4% were misclassified as normal and 10.0% as cadavers. Among the 70 cadavers, 4.3% were misclassified as normal and none as septicemic. Of the 90 normal cases, 5.6% were misclassified as abnormal (Type II Error), while among the 160 abnormal carcasses, 4.4% were predicted as normal cases. Of the 92 classified as normal, 4.3% were septicemic cases and 3.2% were cadaver, i.e., 7.6% were abnormal cases (Type I Error). Among the 158 cases predicted to be abnormal (81 septicemic and 77 cadaver), 3.2% were normal carcasses. The model performed better than the MLR model.

DISCUSSION

The Mahalanobis Distance (MD) method used in the PCA/MD model is an improved MD classifier. It did not assume identical covariance matrices for the three classes as it was generally assumed in MD classifier. The Mahalanobis distances were further scaled by the Root Mean Square Group (RMSG) size of each class to improve their sensitivity. However, the MD classifiers were linear classifiers, and they sometime could not achieve the same classification accuracy as the ANN classifiers, which are non-linear classifiers.

The MLR method does not guarantee that every carcass will be assigned to a unique class. In fact, there was one carcass in the test set that the MLR model could not identify as belonging to any of the three classes. The ANN model uses a broad spectrum of inputs (192 wavelength inputs), and covers a broader range of wavelengths and it does not need a wavelength search. Because of the noise in the training set spectra, the wavelengths selected by the MLR method may change from one training set to another training set, or one instrument to another. Classifiers utilizing a broader range of spectra without an optimal wavelength search are less sensitive to wavelengths bias in the instrument, and thus are easier to transfer from one instrument to another. If drift or differences between instruments require the model to be re-trained, a single neural net model is much easier to handle than one that requires both an MLR to find the optimum wavelengths and a neural net to do the classification.

CONCLUSIONS

This paper presented the development of a nondestructive technique for the classification of normal, septicemic, and cavader poultry carcasses. A diode array spectrophotometer equipped with a fiber optic probe was used to obtain reflectance spectra of the breasts of poultry carcasses in visible and near-infrared regions. The methods and the results of three classification techniques, the Multiple-Linear-Regression, Artificial-Neural-Network (ANN), and Principal-Component/Mahalanobis-Distance Methods were presented. The ANN classifiers performed the best among the three classifiers. The overall classification accuracies are: ANN, 91.6%; MLR, 89.6%; and PCA/MD, 87.2%.

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Table 1. Summary of the prediction of the test set using MLR model with 8 wavelengths.

		Total	Normal	Septicemia	Cadaver	Not Identified	Type II % Error
Actual	Normal	90	85	4	1	0	5.6
	Septicemia	90	6	76	7	1	15.6
	Cadaver	70	5	2	63	0	10.0
Type I % Error			11.5	7.3	11.3		

Table 2. Confusion matrix for verification obtained from PCA/MD model.

		Total	Normal	Septicemia	Cadaver	Type II % Error
Actual	Normal	90	84	6	0	6.7
	Septicemia	90	4	69	17	23.3
	Cadaver	70	2	3	65	7.1
Type I % Error			6.7	11.5	20.7	

Table 3. Confusion matrix for verification obtained from neural network model with 192 inputs, 13 hidden nodes and 3 output nodes, using Sigmoid threshold function.

		Total	Normal	Septicemia	Cadaver	Type II % Error
Actual	Normal	90	85	4	1	5.6
	Septicemia	90	4	77	9	14.4
	Cadaver	70	3	0	67	4.3
Type I % Error			7.6	4.9	13.0	

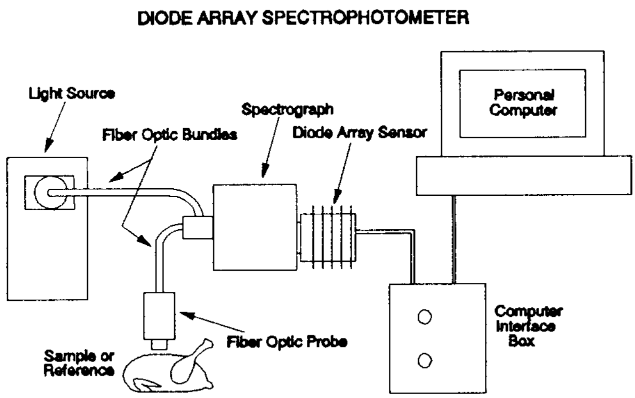

Figure 1. A schematic diagram of the diode array spectrophotometer system.

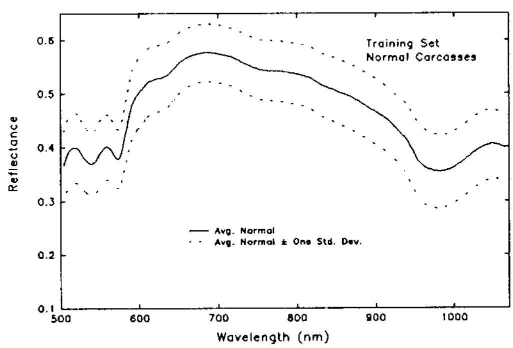

Figure 2. Mean and standard deviation of the spectra of the normal carcasses.

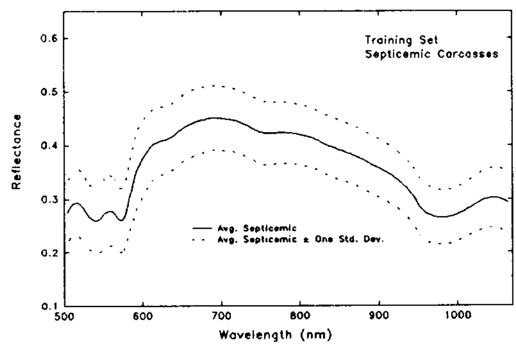

Figure 3. Mean and standard deviation of the spectra of the septicemic carcasses.

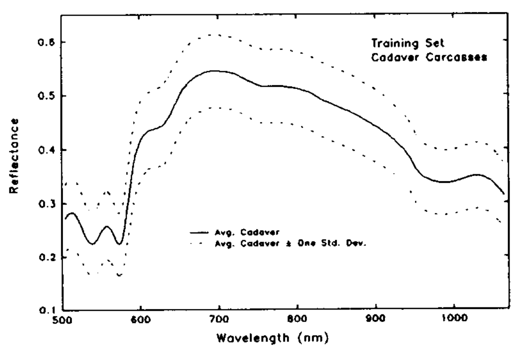

Figure 4. Mean and standard deviation of the spectra of the cadaver carcasses.