Design of a System That Uses Optical-Fiber Sensors and Neural Networks to Control a Large-Scale Industrial Oven by Monitoring the Food Quality Online

Marion O'Farrell, Elfed Lewis, Colin Flanagan, William B. Lyons, and N. Jackman

***Abstract*—An optical-fiber sensor-based system has been designed to assist in the controlling of a large-scale industrial by monitoring the color of the food product being cooked. The system monitors the color of the food as it cooks by examining the reflected visible light, from the surface and/or core of the cooked product. A trained backpropogation neural network acts as a classifier and is used to interpret the extent to which each product is cooked with regard to the aesthetics of the food. Principal component analysis is also included before the neural network as a method of feature extraction. This is implemented using Karhunen–Loeve decomposition. A wide range of food products have been examined and accurately classified, demonstrating the versatility and repeatability of the system over time. These products include minced beef burgers and steamed chicken filets.**

***Index Terms*—Artificial neural network (ANN), back propagation learning, color classification, feed forward networks, food processing industry, Karhunen–Loeve decomposition, optical fiber sensor, pattern recognition, principal component analysis (PCA), spectral classification, spectroscopy.**

I. Introduction

THE *online* measurement of the color of food internally and externally has already been shown to be an invaluable parameter in the process control of large industrial ovens. These ovens are normally fully loaded and would benefit greatly from a control system that would accurately monitor the product so that it is cooked to a color that is optimum for sales. Errors in the cooking of a single batch of food would result in a loss of the batch and large financial losses for the company. Apart from discarding food, there is also an energy-waste issue with the over-cooking of products, which could also result in significant financial losses.

The system, described in this paper, is based on optical-fiber technology and is intended for accurate measurement of food color. It is not intended as a replacement for measuring the core temperature. Previous work by the same authors [1], [2] shows that an optical-fiber temperature-measuring probe can also be included in the system. The core temperature is essential for providing assurance that all bacteria have been eliminated but it cannot provide any information regarding the aesthetics of the product. For example, a whole chicken can be cooked to a safe level regarding temperature, but the external color can be pale and washed out giving the impression to a customer that it is not properly cooked because it does not look "nice." Therefore, a good solution involves combining the two measurements, i.e., color and temperature. The color measurement would be used in a control loop and would enable the adjustment of certain controllable parameters, such as airflow, temperature, plenum tube height (explained below), or conveyor belt speed. This paper concentrates on the color measurement system and how the color is inspected both internally and externally, thus relating it to the degree to which the product cooked.

The environment into which the optical-fiber system is placed is demanding on the equipment with high temperatures and high volume of steam and oil droplets present in the oven's atmosphere. The belt also has to be cleaned frequently and rigorously using an enclosed wash system comprising high-pressure water jets and hot water. However, in order to maintain even stricter hygiene conditions, the oven also undergoes an entire unit cleaning on a fortnightly/monthly basis. This procedure is one of the reasons that a robust optical-fiber system was necessary, as it would not be affected in the same way that traditional machine vision systems would be due to the fact that all electrical components can be kept out of the oven, or even the room if required, away from this hostile environment. Machine vision is widely used in process control in the food industry [3]–[5] and can offer online classification with regards color when combined with artificial intelligence [6]–[9]. These systems have proven to be successful but in this particular online setup they are not practical for the following reasons.

- They do not operate well in the environment of high temperatures and regular entire wash downs.
- Vision is impaired by the volume of steam that circulates in the oven and this would produce a distorted image for the sensor camera in the computer vision system.
- They are incapable of examining food internally without first cutting the food open, which is destructive and not viable for an online measurement system.

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M. O'Farrell, E. Lewis, C. Flanagan, and W. B. Lyons are with the Department of Electronics and Computer Engineering, University of Limerick, Castletroy, Limerick, Ireland (e-mail: marion.ofarrell@ul.ie; elfed.lewis@ul.ie; colin.flanagan@ul.ie; william.lyons@ul.ie).

N. Jackman is with Food Design Applications, Ltd., Newtown, Castletroy, Limerick, Ireland (e-mail: njackman@fda.ie).

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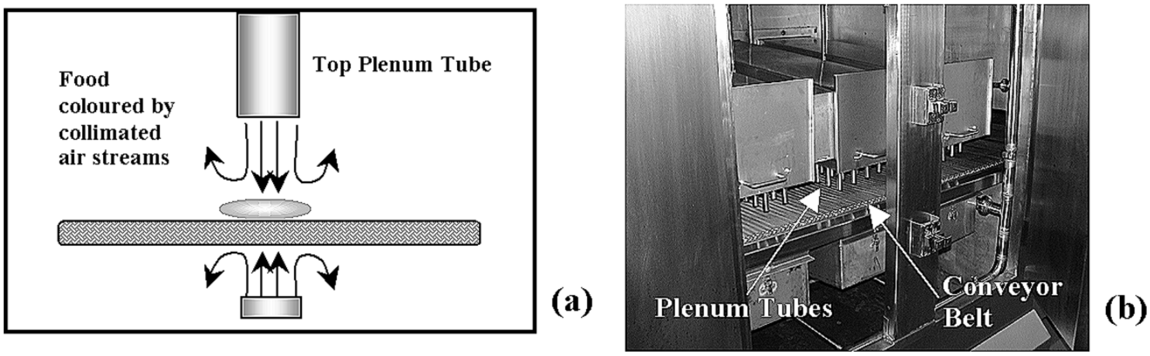

Fig. 1. (a) Diagram of the plenum tubes used to color the food. (b) Picture of the plenum tubes in the oven.

This optical-fiber system uses visible spectroscopy as a method for measuring the color of the food products. Spectroscopy is frequently used as a sensing method in the food industry. It can be used to measure food quality in terms of color [9]–[11], contamination [12], [13], muscle (meat) dehydration or tenderness [14]–[17], and temperature [18]. Although the food is examined in the visible region, the neural network bases its decision on spectral shape, which is more repeatable than simple intensity readings due to the fact that intensity can fluctuate between readings. This gives an added durability to the system. The food types discussed in this paper are fresh minced beef burgers, internal and external, and steamed chicken filets internal.

II. System Setup

The oven used for testing comprises a conveyor belt of approximately 5 m in length and 2 m in width. The conveyor belt is heated from above and below to cook the food and a surface air-blowing technique is incorporated to color the food using plenum tubes. These tubes are located inside in the oven and produce collimated hot air steams that flow across the surface of the product and control how fast the food colors. The process of "food coloring" is described below. The plenum tubes are shown schematically and photographically in Fig. 1(a) and (b).

Cooking is essentially drying the food and as it occurs, a series of chemical reactions take place that cause the meat to change color. In red meat, the protein myoglobin stores oxygen in muscle cells. Myoglobin is a richly pigmented protein. The more myoglobin there is in the cells, the redder, or darker, the meat. A derivative of myoglobin is oxymyoglobin. This is a brighter red that occurs when myoglobin comes in contact with air and is oxygenated. Its color is associated with freshness. Oxymyglobin and myoglobin can coexist in raw meat and they can be changed from one to another. When dark meat is cooked, myoglobin's (and its derivatives) color changes depending on the meat's interior temperature. Rare beef is cooked to 60 °C, and myoglobin's red color remains unchanged. Above 60 °C, myoglobin loses its ability to bind oxygen, and the iron atom at the center of its molecular structure loses an electron. This process forms a tan-colored compound called hemichrome, which gives medium-done meat its color. When the interior of the meat reaches 78 °C, hemichrome levels rise, and the myoglobin becomes dentaured metmyoglobin, which gives well-done meat its brown-gray shade. White meat has a translucent "glassy" quality when it is raw. When it is cooked, the proteins denature and recombine, or coagulate, and the meat becomes opaque and whitish in appearance.

These color changes occur in the visible region of the electromagnetic spectrum. To examine the changes in the spectra at each cooking stage, an Ocean Optics S2000 spectrometer was employed. This was controlled by a host PC running a LabviewVI on Windows 2000 and communicating using USB.

The food is illuminated through six 400-μm core diameter fibers attached to a tungsten halogen white light source, which emits light over the wavelength range 360 nm to 2 μm. One fiber guides the reflected light to the spectrometer. The spectrum of each food sample represents the distribution of reflected light across a wide spectrum of wavelengths in the visible and near infrared. These signals are complex and further complicated by interfering parameters, e.g., localized light absorption due to fatty deposits, burst blood vessels, or bone. It is, therefore, necessary to apply advanced signal processing and pattern recognition techniques to categorize each sample and isolate interfering parameters. One of the main tasks of intelligent interpretation of sensory data is object classification, and neural networks are a popular means of pattern recognition and classification in the face of nonlinearity and are also beginning to play an increasingly significant part in the food industry [8], [10], [19]. Employing the intelligence and generalizing skills of neural networks would mean that the effect of the interfering parameters on the spectrum is taken into account in the training of the network, i.e., the network is still capable of classifying the product correctly in spite of these effects. The software simulator used to implement the neural network for this investigation was Stuttgart Neural Networks Software (SNNS), developed at the Institute for Parallel and Distributed High Performance Systems (IPVR), University of Stuttgart, Stuttgart, Germany.

The probe for measuring the external readings is required to have a diameter of 3.5 mm, while the internal probe is only 2.5 mm [Fig. 2(a)]. The internal probe was custom designed to have seven 200-μm fibers and a very narrow stainless steel ferrule so as to take unobtrusive readings, ensuring that none of the food samples need to be discarded due to damage. The contact of the internal probe does not have to be ideal, as the light will either be reflected directly off the internal surface of the product or through some void, possibly containing fatty deposit. Since a major part of the visible spectrum is captured and such effects

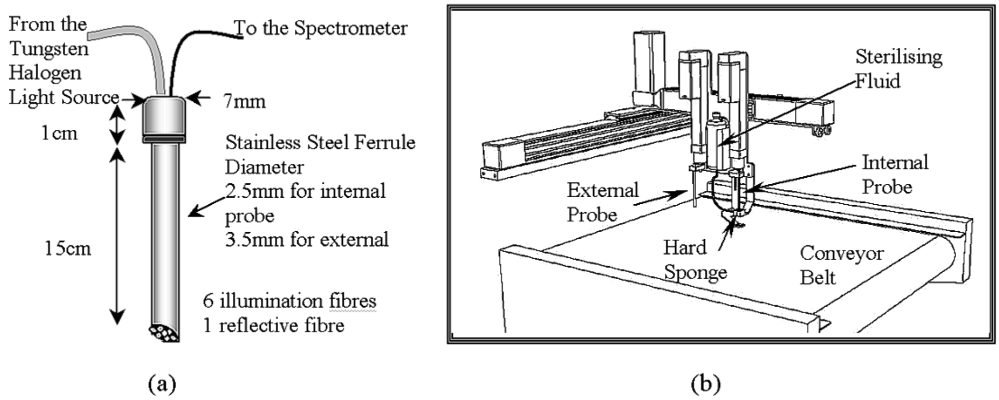

Fig. 2. (a) Probe used for color measurements. (b) The placement of the probes in the oven.

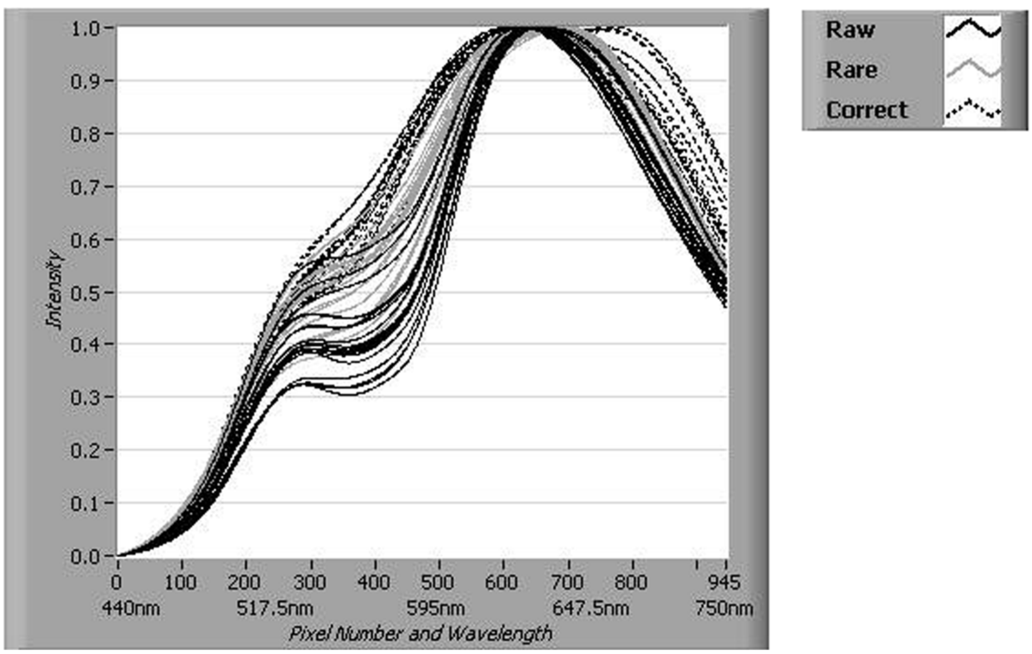

Fig. 3. Spectrograph of each cooking stages color for internal beef burger.

are intensity dependent, this will not pose a problem for the measurement system as the network classifies on specific changes in spectral shape.

The fibers used in the external probe are 400 μm in diameter and the end of the probe includes a 30° window that eliminates specular reflectance from the glossy fat on the meat and allows only the diffuse reflectance, which is representative of the color, to be read. Fig. 2(b) shows the placement of the probes in the oven. There are two probes, internal and external. There is also a sterilizing system, using fluid and a hard sponge, which allows the internal probe to be wiped between each use. Both probes are encased in stainless steel. This material was chosen to allow the probe to be regularly sterilized, something that is essential in the food industry. Its robustness allows the probe to be injected at high speed into the product and puncture without causing damage to the product or itself.

III. Spectroscopic Results

Two food types were examined using the optical-fiber system:

- minced beef;
- steamed chicken.

The fresh minced beef burgers were examined internally and externally. Internally, the beef was examined for the following cooking stages: raw, rare, and well done. Externally, it was inspected so that the color would not be too light or too dark. The steamed chicken filet was examined internally to determine whether it was still pink at the center.

A. Minced Beef

The beef burgers were examined internally at the following cooking stages raw, rare and well done. This data was recorded on the August 21, 2003 and May 20, 2003 with 246 samples per cooking stage. The spectra can be seen in Fig. 3. The y axis shows the normalized intensity at each pixel from the spectrometer (the method and reasons for normalizing the spectra is explained in Section IV, Data Processing) and the x axis shows each pixel value obtained by the spectrometer in the wavelength range 440 to 750 nm. There are 945 pixels intensity values given by the spectrometer in this range.

In the case of external minced beef classification, there were 255 readings taken on the same dates, August 21, 2003 and May

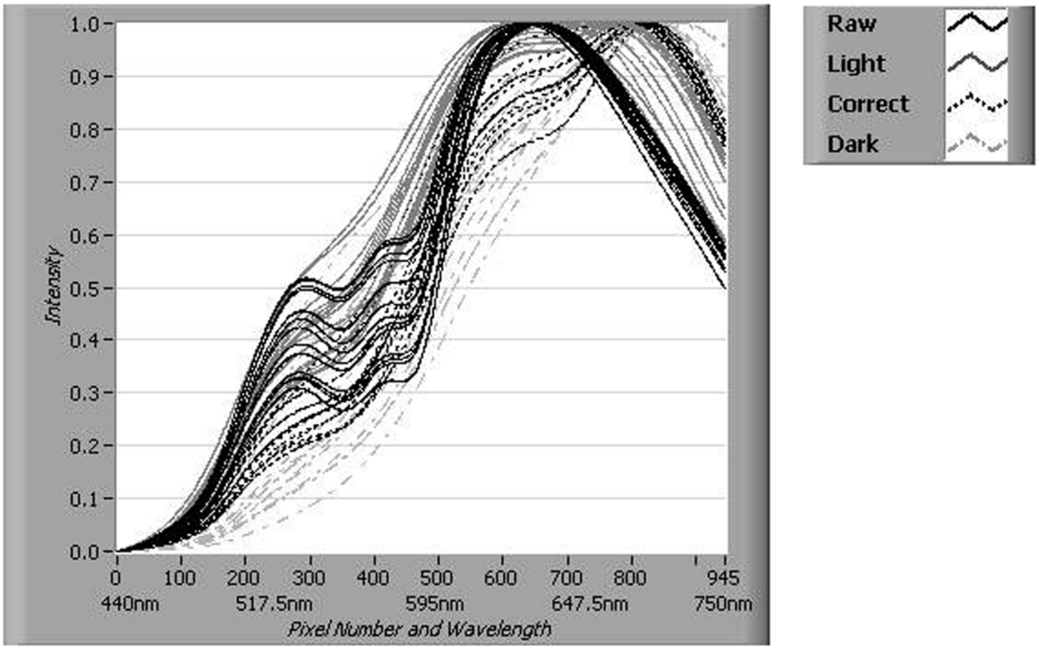

Fig. 4. Spectrograph of each cooking stages color for external beef burger.

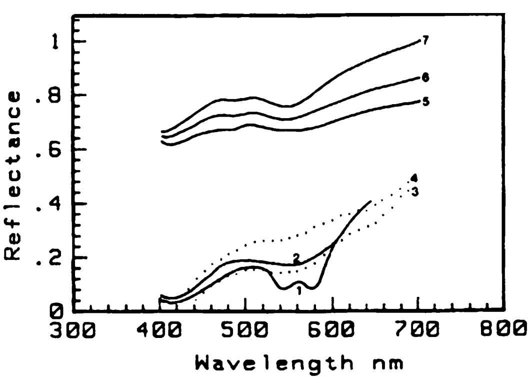

Fig. 5. From [20]: Reflectance of raw and cooked beef. Spectra 1 and 2 are from raw and cooked beef. Spectra 3 and 4 are from cooked chicken leg and breast meat, respectively. Spectra 5, 6, and 7 are taken from cooked pork, lamb, and beef.

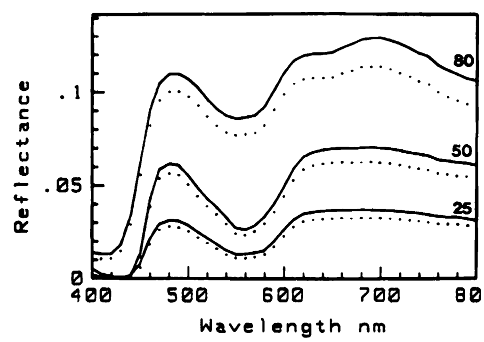

Fig. 6. From [21]. Changes in spectra of mutton as it cooks, at 25° C, 50 °C, and 80 °C.

20, 2003, for each cooking stage that would eventually be classified using the neural network, i.e., raw, light, correct, and dark. The spectra are shown in Fig. 4. These data samples were taken in the visible region between 440 to 750 nm.

In [20] and [21], red meat spectroscopy is discussed. These papers examine reflectance spectra of beef and mutton in their raw and cooked state. This can be seen in Figs. 5 and 6. There is a significant increase of reflectance around 560 nm, and this due to myoglobin and oxymyoglobin (which give meat its red color) being altered chemically to metmyoglobin during the cooking process. While this work is based on pattern recognition of the shape of the spectra, which does not entail looking at the intensity levels, it is possible to subtract the full reflectance spectrum of the tungsten halogen source (obtained from a white surface) from the reflected spectra and obtain a reflectance spectra. The averages of the spectra for each cooking stage are shown in Fig. 7. These spectra demonstrate well the increase of reflectance expected at 560 nm during cooking. While no tests were performed on mutton for this paper, the graph in Fig. 6 is still included since mutton is considered a red meat and it further demonstrates the loss of red, which occurs in the cooking of red meat, and the appearance of brown pigments. While examining the figures, please note that the spectra of Fig. 7 were captured for a wavelength range extending from 440 to 750 nm, whereas the beef spectra of Fig. 5 range from 400–650 nm.

B. Steamed Chicken

In a further separate series of tests, 364 internal records of each of the cooking stages, pink and correct, were taken from chickens that were steamed in the oven. The spectra for the steamed chicken are shown in Fig. 8.

IV. Data Processing

The data processing of the spectra involves two stages. The S2000 spectrometer from Oceanoptics has a high resolution due to its 2048-element linear silicon CCD array (also described as 2048 pixels). This means that the data in the spectra is highly correlated and that there is too much redundant information for

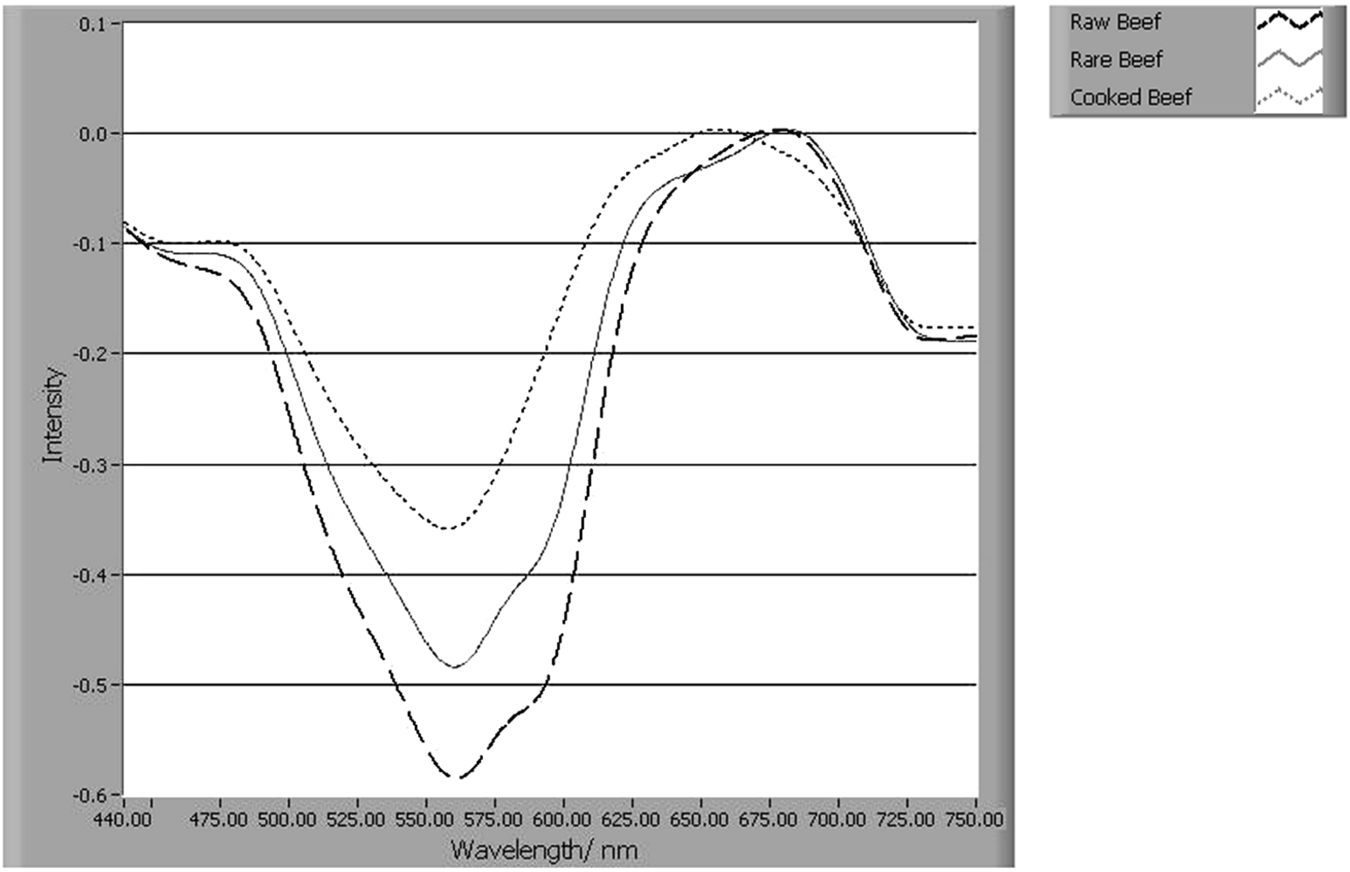

Fig. 7. Average of 246 reflectance spectra of raw, rare, and well-done beef samples.

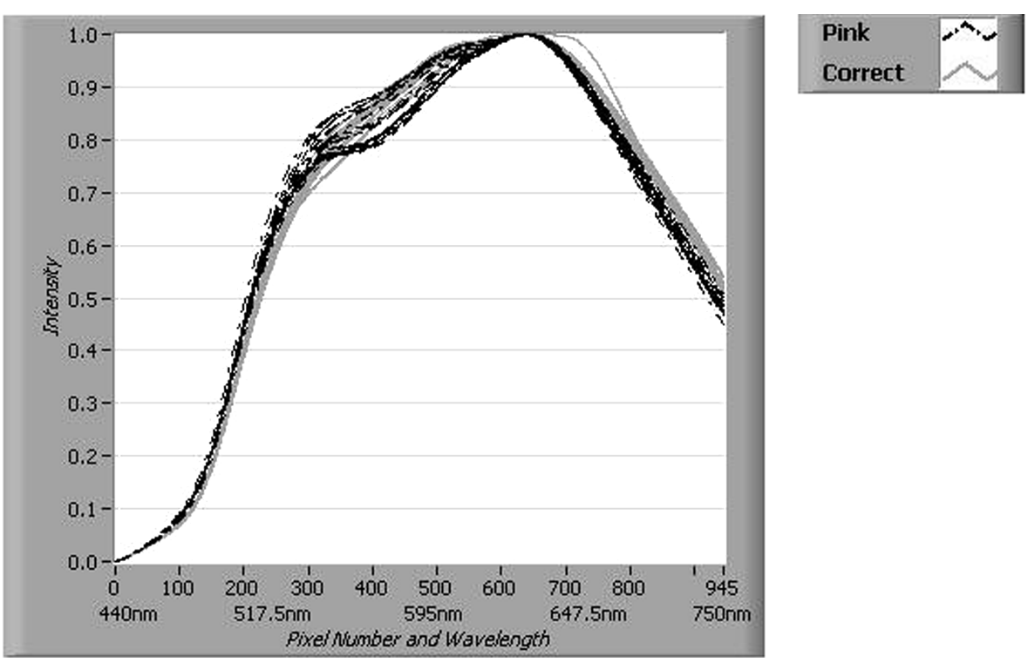

Fig. 8. Spectrograph of internal steamed chicken.

the neural network to use in training. The region of interest for signal changes occurs in the visible spectrum between 440 and 750 nm. By confining the spectral range to this, the data set is reduced to 945 pixel intensity values, which is still relatively high number. Sampling the data along these 945 pixel values can further reduce the data set and analysis has shown sufficient information regarding the shape of the spectra can be maintained taking every nth pixel intensity value from the 945 points. This analysis involved starting with 945 pixel intensity values and then increasing n, each time training and testing the network, until the performance of the network deteriorated due to the fact the insufficient information was held in the training patterns.

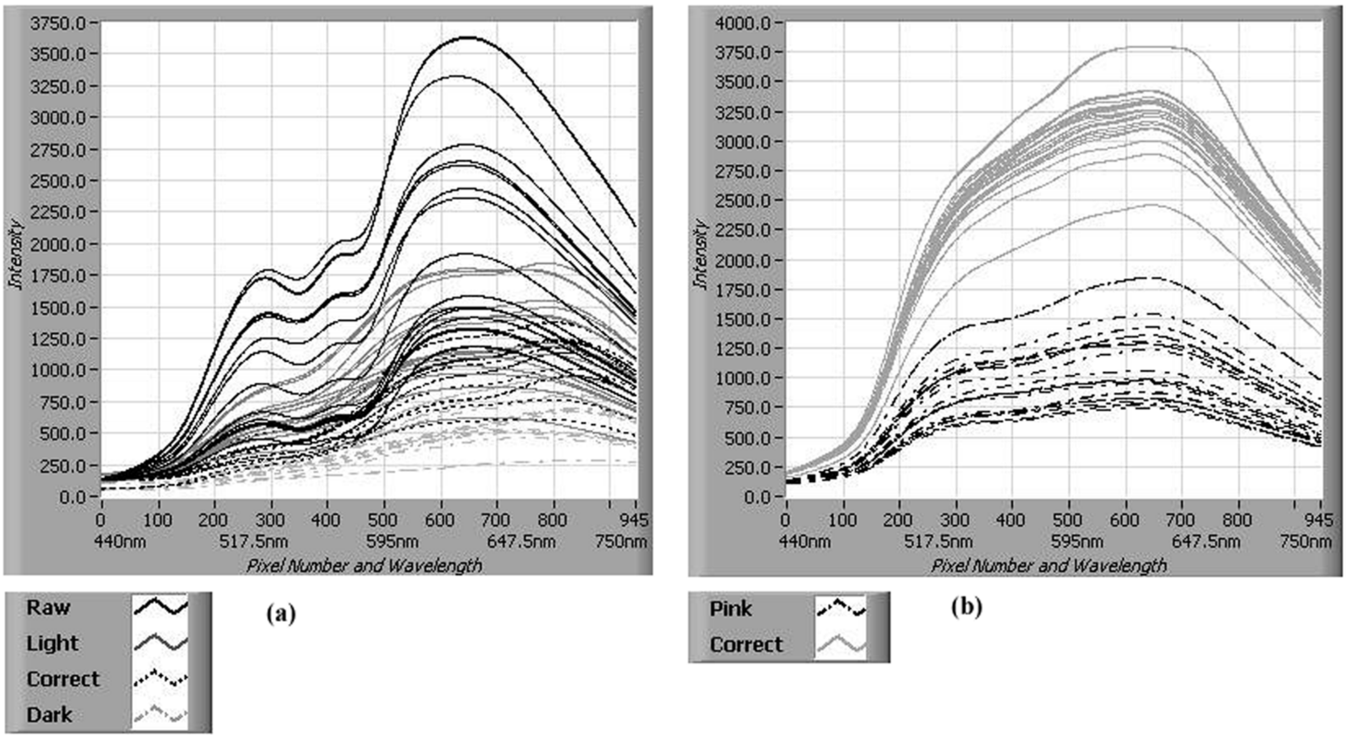

Fig. 9. Spectral data from (a) external minced beef and (b) internal chicken filets before normalization.

The representative data was, in this way, reduced to as few as 25 pixel intensity values.

Second, the data is normalized. This step is critical in reducing intensity errors in the reflected light. Due to the uneven surfaces that are encountered in the different food types, the angle of incidence varies and also the diffuse optical signal that is reflected back to the probe can fluctuate in intensity. This fluctuation can be clearly seen in Fig. 9. For example, the fluctuations for the raw minced beef in Fig. 9(a) vary between a maximum peak value of 487 and a maximum peak value of 3643. Each spectrum is normalized on a scale between 0 and 1 using

$$\text{Normalized Spectrum} = \frac{S - d_{\min}}{\text{Max}(S - d_{\min})} \quad (1)$$

where S is the spectrum and $d_{\min}$ is the minimum data point of that spectrum. $d_{\min}$ varies due to the fact that the baseline level of the spectra from the spectrometer varies with temperature, and normalizing also eliminates this problem for the neural network. The variation at the baseline can be seen to some degree in Fig. 9 (indicated by the arrows).

This problem with intensity was also discussed in [22] where the authors were examining the color of tin cans. Due to the curvature of the cans, there was a problem with oscillating intensities. In this work, an image was taken of the can but instead of using the red, blue, green (RBG) parameters, the authors used the respective differences between them (R-B, G-B, B-R). This is an alternative method to the normalizing of the spectra for eliminating this problem. Fig. 9(a) and (b) shows the spectral data for external minced beef and internal chicken filets before normalization, respectively. These can be compared with Figs. 4 and 8 after normalization has occurred.

V. Neural Networks Analysis

A. Training

Having obtained the data in completely different tests, it was then necessary to build neural networks for each of the food types and classify each cooking stage. The training was performed using SNNS as described earlier. Pattern files (for the training) were generated in a data format compatible with SNNS program and these files were made up of the data displayed in the spectrographs of Figs. 4 and 8.

A multilayer perceptron with one hidden layer was chosen as the network architecture. This feed forward network uses back propagation with momentum as its learning function.

Choosing the size of the hidden layer correctly is essential so that undesired contributions in the input space due to noise are not stored in the weights of the networks. This would result in over-fitting or over-training of the neural network. The size is generally chosen by trial and error, but a good starting point for input neurons with low mutual information would be the following rule of thumb [23]–[26]:

$$J = \sqrt{I \cdot K} \quad (2)$$

where J is the number of units in the hidden layer, I is the number of units in the input layer, and K is the number of units in the output layer. The data used for training in these networks is highly correlated; therefore, the hidden layer was chosen to be less than the value calculated from this formula. The size of the output layer is chosen by the amount of classifications that are required, e.g., for the external of the minced beef there are four units in the output layer, one for each cooking stage: raw, light, correct, and dark.

TABLE I
SIZE OF NEURAL NETWORK FOR EACH FOOD TYPE ALONG WITH VALUES OF THE PARAMETERS η AND μ USED IN TRAINING

Food Type	Input Layer Size	Hidden Layer Size	Output Layer Size	η	μ
External Beef	25	10	4	0.7	0.2
Internal Beef	30	12	3	0.5	0.2
Steamed Chicken	25	10	2	0.5	0.1

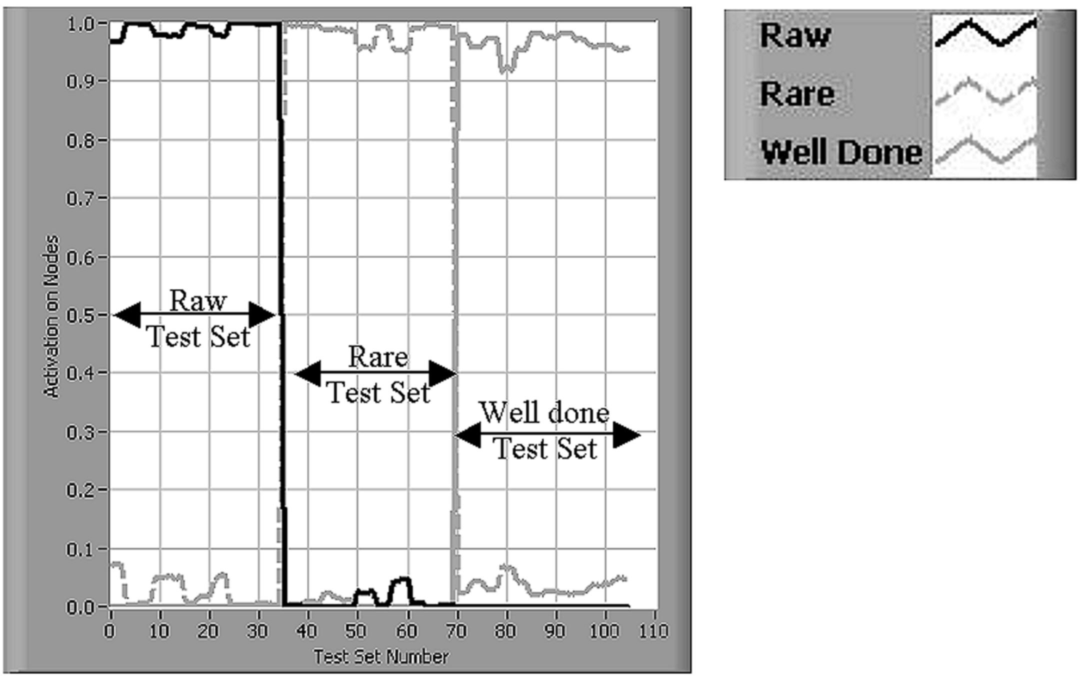

Fig. 10. Activation on output units of the neural network for internal beef burger. The samples were taken on the same day that the training data was taken but were not used in training.

Haykin [27] discusses that when choosing optimum learning η and momentum α constants that the following rule may be used: The η and α that, on average, yield convergence to a global minimum in the error surface with the least number of epochs. A neural network is tested with various combinations of η and α ($\eta = 0.01, 0.1, 0.5, 0.9$ and $\alpha = 0, 0.1, 0.5, 0.9$) to observe their effect on the convergence. It was decided to apply the same experiment to the training data for the food products to determine the most suitable values for η and α. It was found that the best convergence for both products occurs when α is between 0.5 and 0.9, and when η is between 0.1 and 0.5. The final size of each network is summarized in Table I along with the value of η (learning rate) and μ(momentum term), which are parameters required for the back propagation with momentum learning function and used in training.

The neural network was trained until it reached a global minimum. However, since it is not always optimal to try to find the absolute minimum point of the criterion [28], it was also decided to train a neural network employing cross validation using the early stopping rule [27], [29]. In the case of the network trained using the early stopping rule, the training set was divided in the ratio 50:50 for training/cross validation. Both trained networks were then tested using independent data acquired on different days. It was found that the neural networks that were trained using both methods, i.e., until a global minimum was reached and early stopping, performed identically during testing.

B. Testing

A network, which gives good generalization, must perform well with data never previously encountered during the training. For the immediate testing of a neural network, data was separated from the data used for training exclusively for testing purposes. An example of this is seen in the case of the internal testing of the beef burger. The graph in Fig. 10 demonstrates the activation on the output layer of the neural network. The x axis of the graph represent the test sample processed by the network. In this case, 105 samples were tested, i.e., 35 from each of the cooking stages, raw, rare, and well done. The y axis is the corresponding activation in the output units for each sample, e.g., for test sample 1 (which is a raw reading) the raw output is 0.97, the rare output unit is 0.07, and the well-done unit is 0.

However, to fully test the neural networks for each food type, it was essential to collect data from the same product but in a completely separate series of tests, e.g., on a different day. Table II shows the dates on which samples were taken for training and for testing. It also indicates the amount of samples

TABLE II
INFORMATION ON WHEN AND HOW MUCH DATA WAS TAKEN FOR BOTH TRAINING AND TESTING

Food Type	Date training data was taken (2003)	No. of samples per cooking stage used in training	Date testing data was taken (2003)	No. of samples per cooking stage used in testing
External Beef Burger	Aug 21 & May 20	255	Oct 8	380
Internal Beef Burger	Aug 21 & May 20	246	Oct 8	236
Steamed Chicken	May 20	364	Aug 21	365

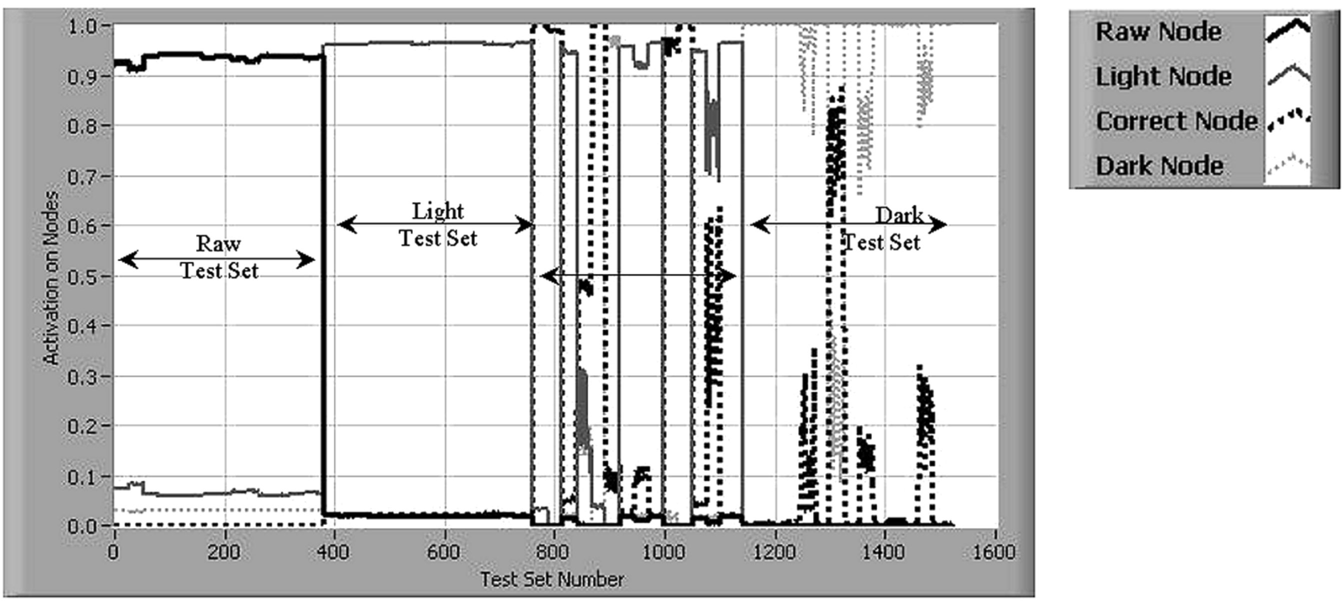

Fig. 11. Activation on output units of the neural network for external beef burger for 380 × 4 samples taken on October 8.

per cooking stage that were taken on those dates. The test results of each of the products are considered in the following sections.

1) External Beef Burger: Fig. 11 shows the test results sampled externally from the beef burger.

The above result is interesting in that at first it looks as though the network could not classify the last two stages, correct and dark, accurately. This raises questions regarding the viability of the technique. In this case, there is a possibility that the food will end up overcooked. When these samples were tested, the probe was placed at random on the burgers to see how the classifier performs as it would in reality, whereas when collecting the training data, the different colors have to be specifically picked out so that the training set is accurate.

Fig. 12 compares the spectral data taken from a correctly cooked burger that was classified as light with the training data for both the light and correct stages. It is clear that it is actually the same spectral shape as the light stage and not the correct stage, so the neural network is classifying correctly.

The reason behind this anomaly lies in the visual appearance of the food. Fig. 13(a) is a photograph of all four of the cooking stages. In the case of the raw and light stages, the color is uniformly distributed across the product and gives an even color appearance. In the correctly cooked case, a mottled effect is apparent that is a mixture of two colors. The correct stage, therefore, appears to have light stages color mixed into it. This is due to the uneven surfaces that are present in the minced beef and there is a tendency that the bumps on the surface color at a faster rate [Fig. 13(b)].

Examining the overcooked stage, it can be seen that there are some readings taken from overcooked burgers that are classified as correct. These samples are compared to the training data used to train the correct and dark stages in Fig. 14.

It is evident that the test spectra best resemble the dark stage and this is especially seen in the circled data of Fig. 14, where the correct stage actually has some absorbance around 660 nm that disappears as the product is further cooked and darkens. This dip is not evident in test spectra 1221–1324, and, therefore, they should be classified as dark, resulting in a misclassification of 103 of the dark test spectra.

2) Beef Burger Internal: The internal color of the beef burger was also monitored. It is evident from the circled areas of the graph in Fig. 15 that there is a bit of uncertainty in the classifier when tested with some samples. This was not a huge concern as the classifier is still giving the highest activation on the proper unit, but it must be taken into consideration that it is dropping below 0.75. However, it can be explained in Fig. 16(a) and (b). Here, the difference between the data used to train the

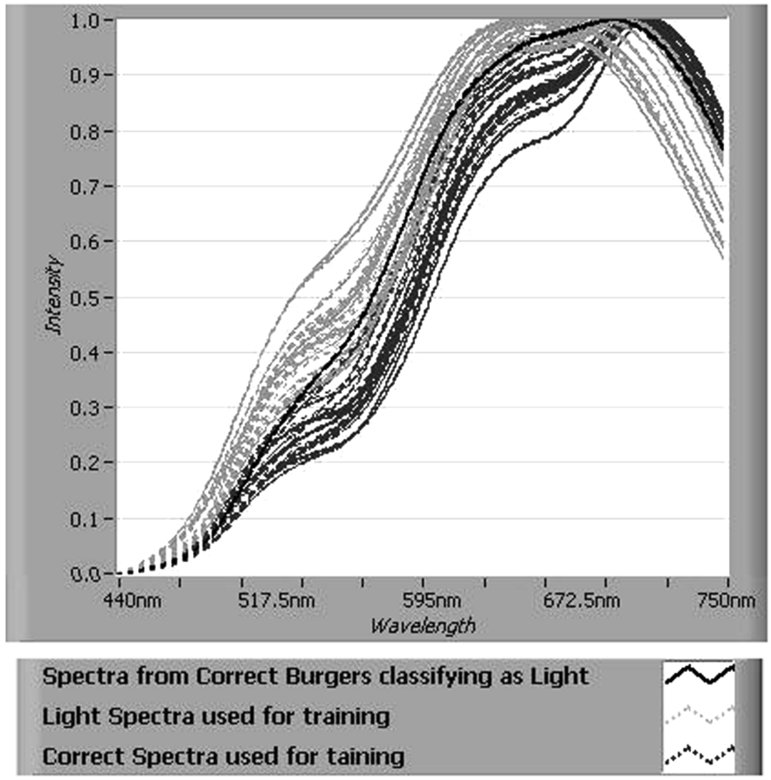

Fig. 12. Data taken from a correctly cooked burger that classifies as being light.

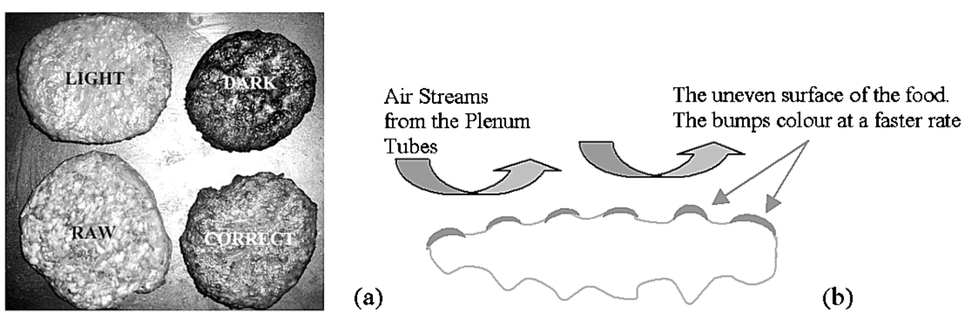

Fig. 13. (a) Photograph of minced beef burgers. (b) The uneven coloring of food.

network in May and August is compared with the data used to test it on October 8 with the spectra causing an activation below 0.75 on the well-done output unit [Fig. 16(a)] and on the rare output unit [Fig. 16(b)] highlighted in black. It is possible to state that the reason for this lower activation is that there are slight differences between these test spectra and the training set in each case, and, therefore, the network is generalizing.

3) Steamed Chicken: Finally, the steamed chicken neural network was tested to see if it could classify between pink and white meat internally. The activation on the outputs of the network is seen in Fig. 17, and it was very clear in its classification between the two stages.

A specially developed algorithm in LabVIEW was used to implement the trained neural network to make real-time measurements possible. There are certain limitations to the SNNS software once the network has been trained, in that it has to be opened using X-win32 and the data has to be passed into the network in special pattern files, which are not feasible in real time. This is possible when training but is a cumbersome method for testing. Therefore, when the network has been trained, the final weight terms are used to generate the neural network in LabVIEW and this means that the data captured from the spectrometer can be sent immediately to the neural network VI (LabVIEW programs are called virtual instruments or VIs) for classification.

VI. Discussion

The original data from the spectrometer contains 945 pixel intensity values in the visible region, and this must be reduced because 945 input nodes would constitute an intolerably high dimension. As discussed in the previous chapter, using every nth pixel intensity value along the x axis reduced the data. By doing this, it was possible to reduce the pixel intensity values to as low as 25, which is quite a significant reduction and may indicate that the spectral data is highly correlated with high redun-

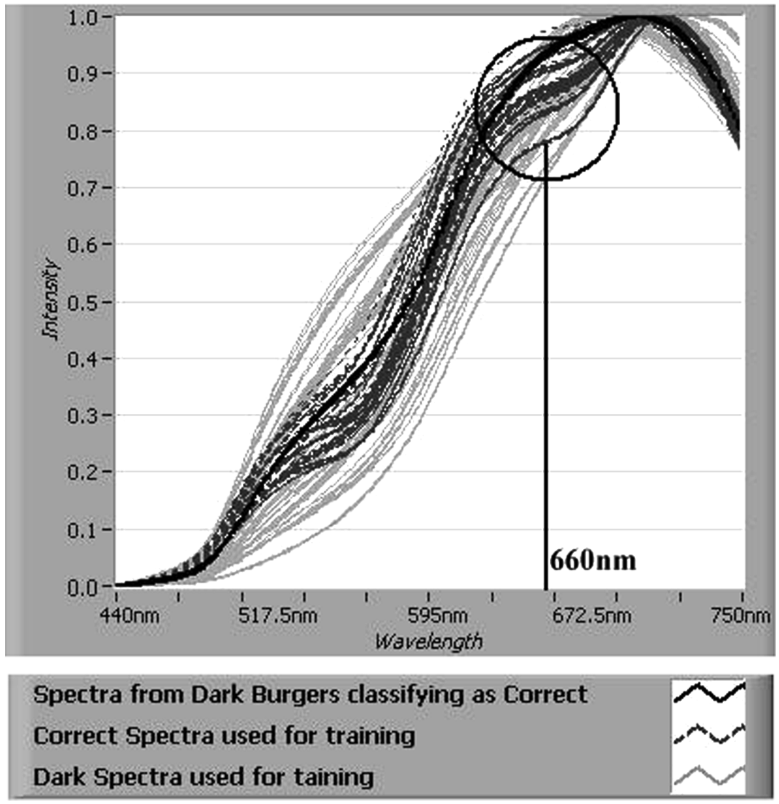

Fig. 14. Comparing the test data, which were taken from a dark burger, that are classifying as correct with the data used in training.

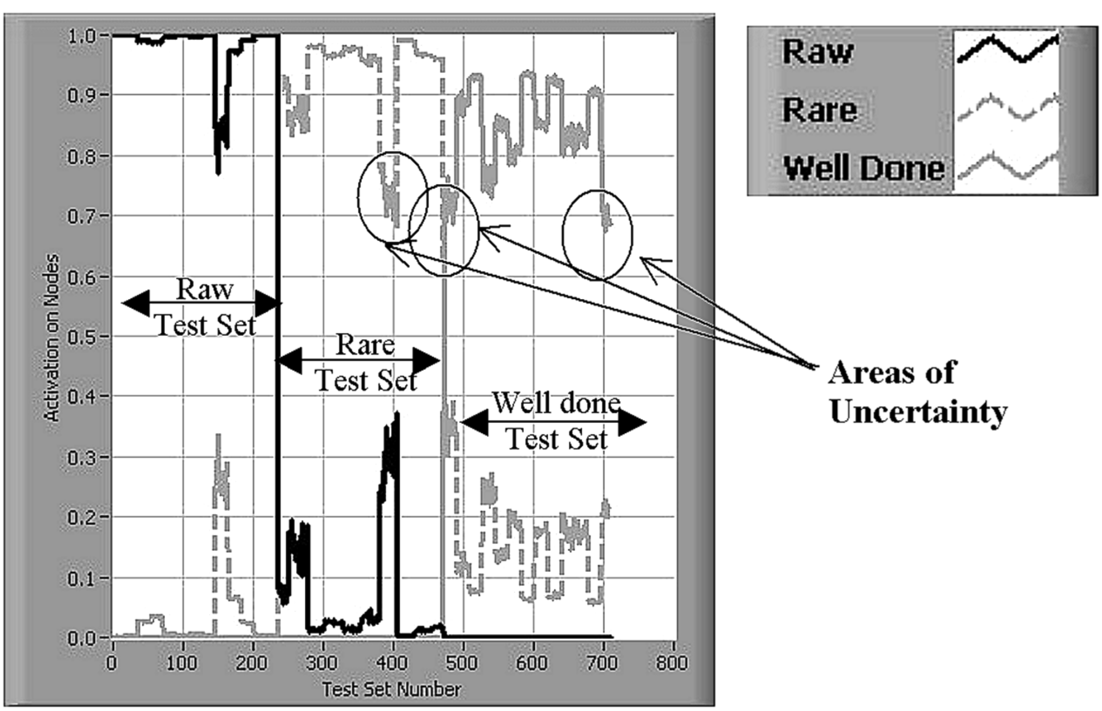

Fig. 15. Activation on output units of the neural network for internal beef for samples taken October 8.

dancy when used to classify with respect to the spectral shape. It was decided to investigate a different way of reducing the dimensions of the solution space and extract features in the data to improve the data that is input to the neural network. There are a number of articles in the area of face recognition [30], [31], which indicate that a different method could be used for feature selection prior to training the neural network. The approach utilizes principal component analysis (PCA) to reduce the input data dimensionally and eliminate the redundant information more efficiently.

(a)

(b)

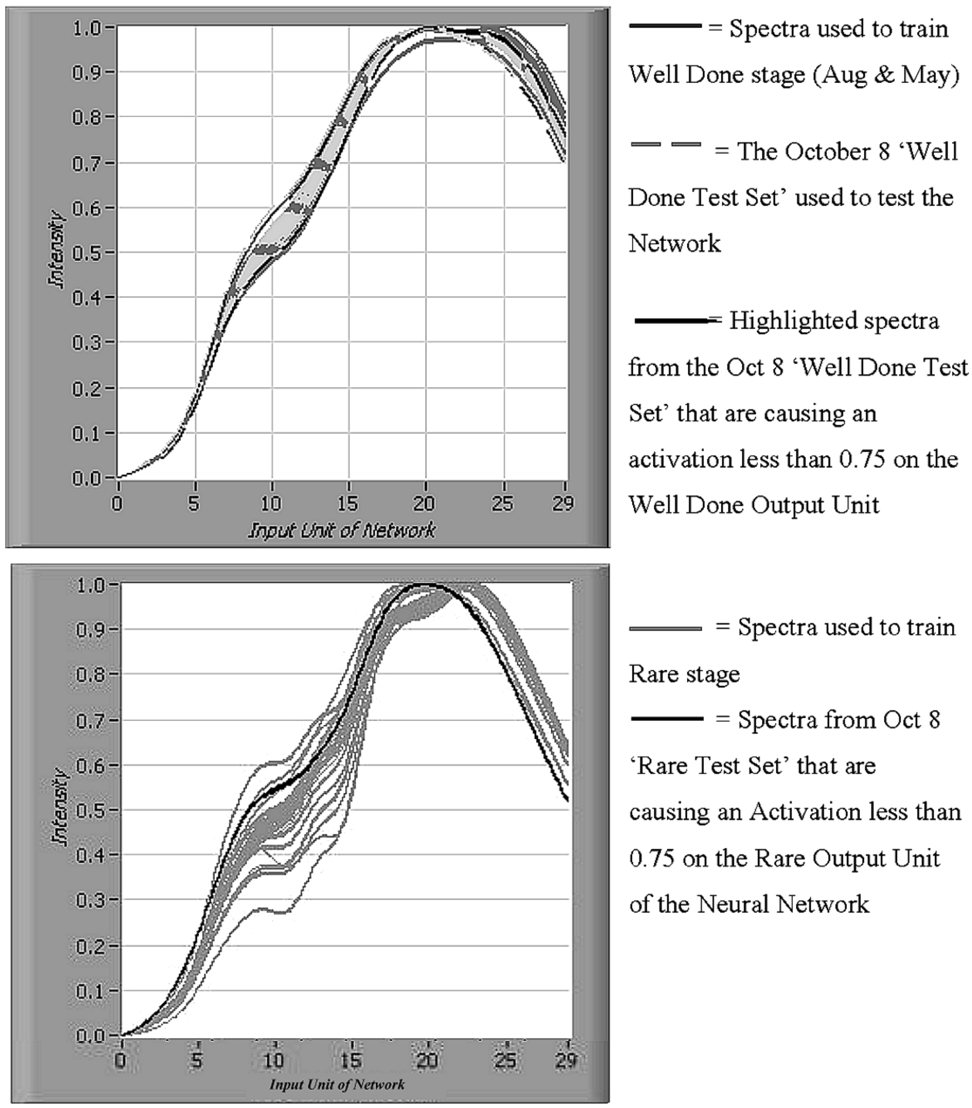

Fig. 16. Examining the test samples that are causing an activation less that 0.75 on (a) the correct output unit and (b) the rare output unit.

VII. PCA Analysis Using Karhunen–Loeve Decomposition

When using neural networks, for example, with the external beef burgers, where it is necessary to have 25 inputs, the data processor converts 25 points to a single point in a 25-dimensional space and resolves the classification in this space. With Karhunen–Loeve decomposition, it is possible to reduce the dimensions of this solution to a smaller subspace by only including significant data and, thus, eliminating redundant or highly correlated information. PCA generates a set of eigenvectors from the subspace whose linear combination gives an approximation to the original vectors, which span the larger dimensional space.

The 25 spectral intensity values of the beef burger neural network input layer were originally selected from the 945 spectral intensity values between 440 and 750 nm. This means that a solution space of 945 dimensions exists at the outset and this is far too large.

By calculating and the plotting the eigenvalues of the covariance matrix of the dataset it is possible to choose the corresponding eigenvectors (forming the subspace) used to represent the data. The aim of selecting the amount of eigenvalues is that the selected amount should cover around 99% of the variance. Table III shows the percentage variance for eigenvalues 940–945.

Selecting four eigenvalues gives a total variance of 99.175 and selecting three eigenvalues gives a total variance of 98.18%. Choosing a fifth eigenvalues could imbalance the representative data since now there are two eigenvalues, 942 and 941, which are close in value and containing very little variance but given the same importance as eigenvalues 945, 944, and 943. It was decided to maintain four eigenvalues.

Since it is impossible to plot data in four dimensions, Figs. 18 and 19 show the first three dimensions plotted for each spectrum in the training set for the beef burgers, with 255 spectra samples per class and the test set with 380 spectra samples per cooking stage, respectively.

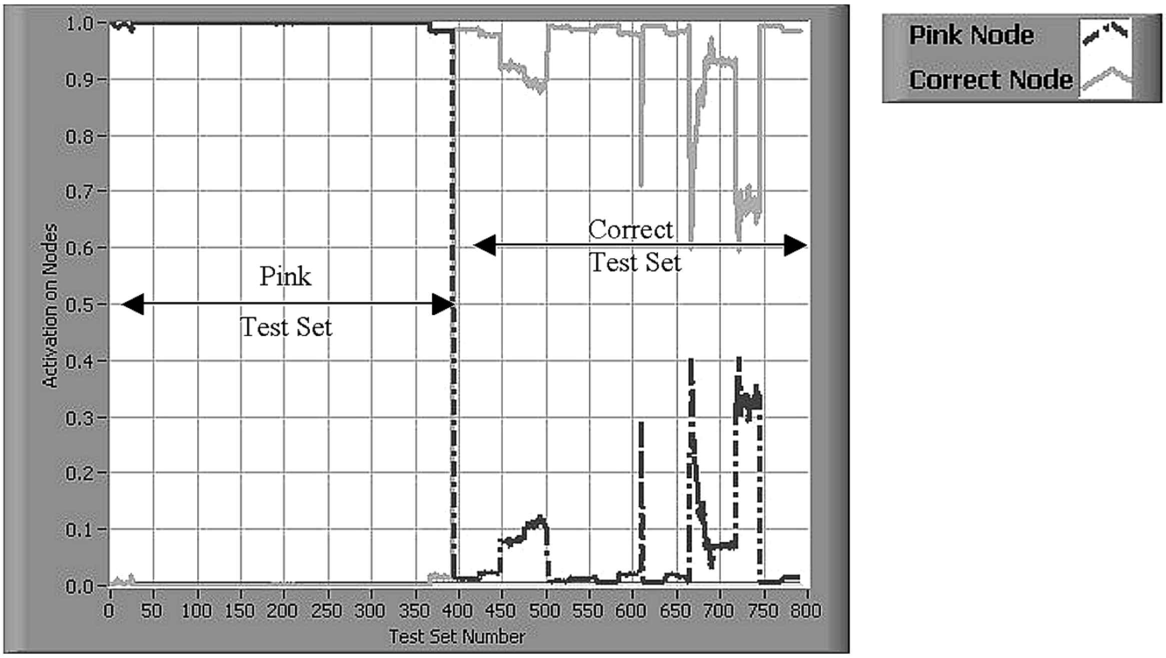

Fig. 17. Activation on output units of the neural network for internal steamed chicken for samples taken August 21.

TABLE III
CALCULATING THE VARIANCE FOR EACH EIGENVALUE FOR EXTERNAL BEEF

Eigenvalue number	945	944	943	942	941	940
Eigenvalue variance: F_{Ei}	76.70%	18.19%	3.2%	1%	0.61%	0.1%

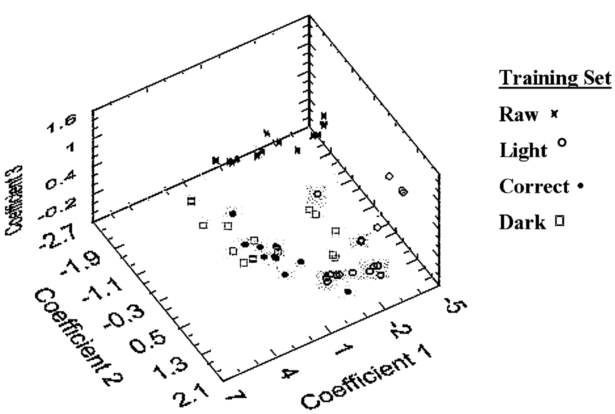

Fig. 18. Distribution of the training dataset, for fresh minced beef, when the first three principal components are plotted against each other.

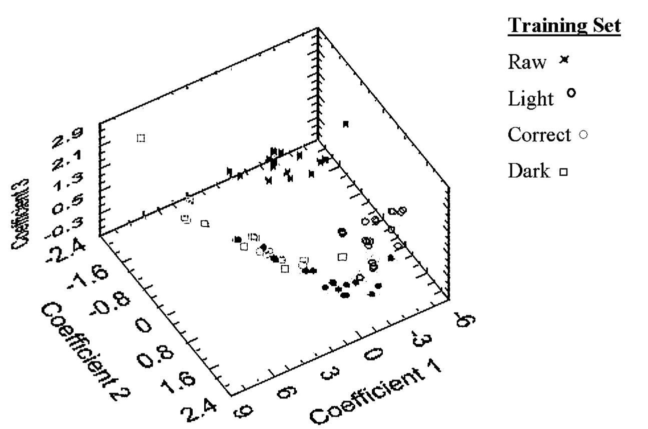

Fig. 19. Distribution of the testing dataset, for fresh minced beef, when the first three principal components are plotted against each other.

Using PCA, the representation of each spectrum has been condensed to four data features, thus reducing the solution space to four dimensions. These four points can then be used to form the input layer of a new neural network of size 4-4-4. The performance of this neural network using the test set from October 8 can be seen in Fig. 20.

The network classifies in much the same way as the original 25-10-4 neural network, except for the dark cooking stage. In this, the network all of the data was classified as dark, which corrects the misclassification of the 25-10-4 neural network. It is, therefore, clear that by employing feature extraction techniques the performance of the neural network is significantly improved.

VIII. CONCLUSION

A series of experimental tests have been conducted to assess the quality of food products as they cook online in a large-scale industrial oven. A fiber-optic-based spectroscopic technique, coupled with signal processing through an artificial neural network (ANN) has been developed for the purpose of

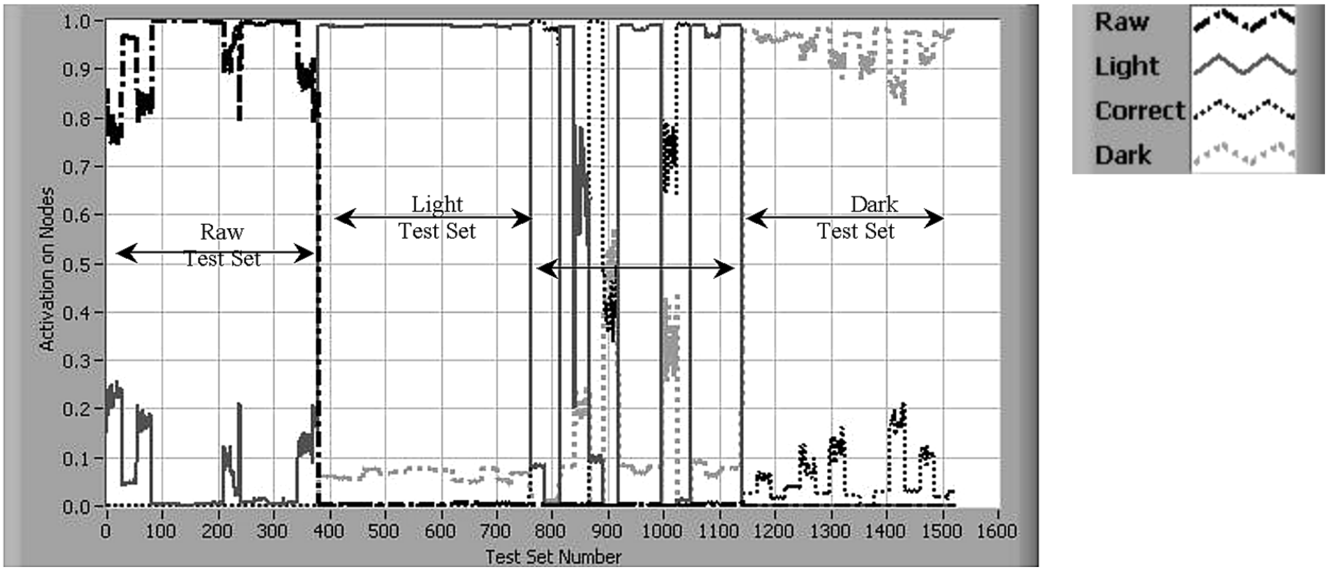

Fig. 20. Activation on output units of the neural network, after PCA analysis, for external beef burger for 380 × 4 samples taken on October 8.

the recognition and classification of the various colors of the cooking stages of the food samples. The results of this work have shown good classification and could result in a very useful sensor for the food industry, but could also be applied to other areas of color measurement.

The application of standard ANN directly to the data has resulted in successful classification of food products in most cases. There do exist some cases where the classification is not 100% accurate, as was the case with the discrimination between correctly cooked and dark stages of the externally monitored beef burger.

A further method (PCA) has been investigated that eliminates redundant information and allows the number of input units in the neural network to be greatly reduced. The most important effect, however, was the increase in accuracy seen in the output classification when PCA precedes the ANN, especially in the case of the external minced beef neural network.

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Marion O’Farrell was born in Limerick, Ireland, in 1979. She received the B.Eng. degree in electronic engineering in 2001 and the Ph.D. degree from the University of Limerick in 2004 for work on intelligent optical fiber sensors in the food industry.

She currently holds a post doctorate position at the University of Limerick. Her research interests include optical fiber sensors, color sensing, the online measurement of food quality, neural sensor systems, and optical fiber temperature sensing.

Elfed Lewis was born in Holyhead, U.K., in 1959. He received the B.Eng. degree in electrical and electronic engineering and the Ph.D. degree, for work on high-speed photography and spectroscopy of electric circuit breaker arcs during the current zero phase from the University of Liverpool, Liverpool, U.K., in 1981 and 1987, respectively.

He was a Development Engineer with BICC Telecom Cables, Prescot, Merseyside, U.K., in conjunction with University of Liverpool, developing chromatic modulation-based optical fiber sensors for a wide range of applications. In 1989, he joined Liverpool John Moores University, where he initiated the research activity in optical fiber sensors. The group investigated sensors for environmental monitoring, including water contamination and pH. In 1996, he joined the University of Limerick, Limerick, Ireland, where he is currently Head of Department Electronic and Computer Engineering and Director of the Optical Fiber Sensors Research Group, which he founded in 1996. The group is primarily engaged in investigating sensors for environmental monitoring (e.g., water quality, vehicle exhaust emissions, UV light intensity, etc.), food quality assessment, and parameters associated with high-power microwave sources (e.g., electric fields, electron beam proximity, etc.).

Colin Flanagan received the B.Eng. degree in electronic engineering, the M.Eng. degree in computer engineering, and the Ph.D. degree from the University of Limerick, Limerick, Ireland, in 1986, 1988, and 1991, respectively.

He is a Senior Lecturer with the Department of Electronic and Computer Engineering, University of Limerick. His research interests include neural sensor systems, computer architecture, and network processors.

William B. Lyons was born in Dublin, Ireland, in 1973. He received a N.C.E.A. Diploma in electronics (product development) from the Dundalk Institute of Technology, Ireland, in 1993, and the B.Eng. degree in electronic engineering and the Ph.D. degree for work in the area of multipoint optical fiber sensors utilizing artificial neural network pattern recognition techniques to separate out cross-coupling effects from the University of Limerick, Limerick, Ireland, in 1998 and 2002, respectively

He worked in the semiconductor industry for SVGL as an Install and Qualification Engineer.

N. Jackman, photograph and biography not available at the time of publication.