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Control interface and tracking control system for automated poultry inspection

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ABSTRACT

A new Vis/NIR inspection system interface was developed to test and implement an automated chicken inspection system for online operation on commercial chicken processing lines. The spectroscopic system demonstrated effective spectral acquisition and data processing for real-time classification of chickens on a 140 bpm processing line. Real-time online testing successfully differentiated between wholesome and unwholesome birds using a neural network classification model with 20 input nodes that correctly classified 94% and 92% of wholesome and unwholesome birds, respectively. This work demonstrates the effectiveness of the Vis/NIR inspection system for accurate real-time product and shackle tracking on commercial chicken processing lines.

1. Introduction

Automated processing systems help the poultry industry to improve product safety, quality, consistency, and increase processing efficiency by increasing line throughputs and reducing wastewater output. Current poultry processing systems are highly automated, including various stages of processing on the kill and evisceration lines as well as additional operations such as cutting and deboning of product. However, safety inspection of poultry carcasses on evisceration lines is one area in which automation is not yet fully utilized. Currently, each chicken intended for sale to U.S. consumers is required by law to be inspected post-mortem by a USDA/FSIS (United States Department of Agriculture/Food Safety and Inspection Service) inspector for its wholesomeness [1]. These inspectors visually examine the exterior body, the interior of the body cavity, and the organs of each bird for indications of diseases or defects. For effective inspection and occupational considerations, each inspector is limited to a maximum working speed of 35 birds per minute (bpm). This current inspection system limits the production efficiency of processing plants that seek to satisfy increasing consumer demand for poultry products by increasing operating speeds and overall throughput. One possible solution to this problem is for poultry processing plants to install on-line instrumental inspection systems that can accurately screen for wholesome carcasses. Inspectors then would only need to “re-inspect” questionable carcasses to prevent wholesome carcasses from being discarded. This approach would dramatically reduce the number of birds requiring direct inspection by humans. An obvious benefit of automated poultry inspection would be improved overall production efficiency for the processing plants.

Live birds are hung on kill lines, which typically operate at 140 or 180 bpm. On a kill line, birds are stunned, bled, scalded, defeathered, and their heads and feet are removed, before they are rehung onto an evisceration line. Typically, birds on a single kill line will be transferred to two separate evisceration lines. Most evisceration lines in the U.S. use either a Stream-line Inspection System (SIS) or a New Efficient Line Speed (NELS) system. Under SIS, an evisceration line operates at 70 shackles per minute with two USDA inspection stations on it, while a NELS evisceration line runs at 91 shackles per minute with three USDA inspection stations. At each inspection station, a USDA/FSIS inspector works with the aid of a helper and a trimmer. Condemnable birds – unacceptable for sale to consumers – are identified by the inspectors and immediately removed from the evisceration lines for disposal.

Implementing an automated inspection system for operation on kill lines requires development of an effective system interface for the inspection system to work with the larger processing line, and would be optimized with the use of an effective tracking control system that can track the progress and fate of any individual bird that enters the processing line. Operating an inspection system on the kill line presents two major benefits. First, with a single rejection point on the kill line, no condemnable birds would enter the evisceration line, allowing for better hygiene and higher line speeds on the evisceration line. Second, working with known technology to remove rejected birds from the kill line, such a system can be easily integrated into product-tracking systems. To operate on the kill line, any automated inspection system must be able to function at speeds of at least 140 or 180 bpm.

Visible/Near-Infrared (Vis/NIR) spectroscopy has been shown capable of detecting systemic conditions manifesting in skin and tissue changes. A Vis/NIR spectroscopy technique was first used to

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classify wholesome and unwholesome chicken carcasses by [2], and was demonstrated capable of separating fixed (stationary) wholesome carcasses from unwholesome carcasses in the laboratory with a classification accuracy of 93% for wholesome and 96% for unwholesome. A Vis/NIR spectroscopic system was later used for classifying chicken carcasses on-site at a slaughter plant [3]. Fresh carcasses were taken directly from the processing line for an offline measurement using a Vis/NIR probe placed in direct contact with each sample for a 2-s stationary reflectance measurement, with a resulting average classification accuracy of 93%. A transportable photodiode array Vis/NIR spectroscopic system was then developed and on-line trials performed at a chicken processing plant [4]. Spectra (470–960 nm) of 1750 chicken carcasses (1174 wholesome and 576 unwholesome) were measured. The instrument measured the spectra of veterinarian-selected carcasses on a processing line running at 70 bpm. Classification models, using principal component analysis as a data pretreatment for input into neural networks, were able to classify the carcasses with a success rate of 95%. The results showed promise for using a Vis/NIR spectroscopic system to separate unwholesome from wholesome carcasses on-line in a poultry-processing environment.

The objective of this work is to demonstrate a Vis/NIR Inspection System interface for effective online poultry wholesomeness inspection under research conditions, and describe the use of the interface with a Tracking Control System appropriate for commercial implementation of the inspection system.

2. Current automated poultry processing

The first two stages for typical U.S. commercial broiler chicken processing are the Kill and Evisceration lines, which are closed-loop shackle lines on which birds are hung upside down by the ankles; these high-speed lines move the birds through automated steps of processing. Currently, a typical Kill line operates at 180 or 140 bpm and includes stunning, killing, scalding, defeathering, and feet removal. An automated rehanger unit transfers the birds from one kill line to two or more evisceration lines, which may operate at speeds up to 140 bpm. Automated evisceration draws the internal organs out of the body cavities of the birds. The birds then move on to the inspection stations where the body and organs can be examined by human inspectors. Inspectors identify unwholesome birds that must be immediately removed from the line; birds that pass inspection continue to washing, chilling, and additional processing such as sizing and distribution, cut-up and deboning, and product presentation.

For fully automated systems, synchronization is required for the kill line, rehangers, and evisceration lines to work effectively. The kill and evisceration lines each have a fixed number of shackles, and the rehangers must precisely transfer birds from kill to evisceration lines with a minimum of dropped birds for effective production. A tracking control system is used to track broilers throughout this process, providing data for a variety of important purposes including production efficiency, process control, quality control, and food safety mandates. For example, bird counts, pre- and post-process weights, waste/byproduct and product ratios, etc., are routinely compiled for basic production statistics, per day or per shift, to evaluate product yields and operation efficiency, as well as the overall condition of bird flocks received from various growers. Birds rejected at the inspection stations for conditions that can affect food safety are counted, and excessively high reject counts can be cause for investigation into grower operations. High numbers of empty shackles or damaged birds can also be indicators of equipment problems, such as over scalding (excessive temperatures in scalding tanks), malfunctions, or lack of synchronization. Ongoing databases of bird information or operation data can be maintained.

U.S. food safety laws mandate that all chickens sold for human consumption must pass inspection. This is one of the driving forces behind the development of automated poultry inspection systems, since the combination of increasing demand, inspector shortages, and production space limitations puts pressure on poultry processors to increase their operation speeds. The food safety mandates also create peripheral efficiency problems, such as for feet (paw) harvesting. Paws are removed on the kill line, long before the corresponding bodies reach the inspection stations. Current systems most often collect paw batches in hoppers that are held waiting until the bodies pass the inspection station; the occurrence of any single rejected bird at inspection will cause an entire hopper of feet to be discarded, with some significant economic loss. Some other systems maintain extremely long kill lines that continue holding one pair of paws per shackle long after the point where the automated rehanger transferred each broiler body to the evisceration line. The paws on the kill line simply continue to run through an extra holding space until the corresponding body passes inspection; in this case, by tracking the kill line shackles (holding paws) and the evisceration line shackles (holding bodies), a single rejected bird at inspection can be used to trigger disposal of only the corresponding pair of paws. This system minimizes economic loss but requires an expensive investment of extra space and equipment.

3. Visible/Near-Infrared system interface

3.1. Visible/Near-Infrared chicken inspection system

The automated spectroscopy-based inspection system is installed at a fixed point on the kill line and measures Vis/NIR reflectance spectra from across the breast area of each bird. The system acquires Vis/NIR spectral data using quartz tungsten halogen illumination with a bifurcated fiber-optic probe, spectrograph, and a spectroscopic charge-coupled device (CCD) detector. An industrial computer and in-house developed software modules are used to acquire the spectral data for each bird and to process the data in real-time to produce a classification output identifying each bird as being either a wholesome bird or not, before the next bird arrives at the probe. This system was specifically developed to identify birds exhibiting systemically diseased unwholesome conditions, which cannot be sold and must be removed from the processing lines.

The fiber-optic probe (Schott-Fostec, Auburn, NY) consists of one inner and six outer fiber optic bundles. The outer optic bundles transmit light to the bird surface, and fibers of the inner optic bundle returned reflected light to a photo detector. At the measurement end, the outer bundles are angled 10° inward, providing a minimum working distance of approximately 2 cm between probe and bird, with a 200 mm^2 illuminated spot (approximately 16 mm diameter). At the source, the outer bundles take in light from a 100-W quartz tungsten halogen light that is focused on the source ends of the outer bundles using a condensing/imaging lens assembly (*f*/1.8, 33-mm aperture, UV-grade fused silica). The light travels to the measurement end of the probe to illuminate the chicken surface, and after some interaction with meat and skin, reflected light is acquired through the central 7.5-mm diameter aperture and enters the inner optic bundle. The inner optic bundle carries the light to a slit adjusted to be 4-mm high by 50 μm wide and positioned before the spectrograph (MS125, Oriel Instruments, Stratford, CT). With a focal length of 120 mm, a grating ruling of 400 lines/mm, and a fixed-size entrance slit (3-mm high by 10-μm wide), the spectrograph disperses light onto a CCD detector with a 1024×128 pixel array CCD detector (Oriel model 78440). The front-illuminated CCD detector has a pixel size of 26 μm^2 and is thermoelectrically cooled, with a spectral response range from 180 to 1000 nm with a maximum readout time of 300 spectra per second.

Software for the system interface was developed in-house using LabView (National Instruments, Austin, TX). The software addresses four primary functions: system initialization, data collection, data analysis and modeling, and prediction of poultry carcasses. Fig. 1 shows the front panel user interface for the system software. The system initialization module utilizes the 32-bit driver (ATMCD32D.DLL, Oriel Instruments) to initialize the CCD detector and set CCD temperature control, data acquisition mode, exposure time, and data readout mode. After system initialization, the data collection module enables real-time data acquisition and data storage in a database (Access, Microsoft Corp., Redmond, WA). Raw spectra (1024 points) are recorded as percentage reflectance. The spectra are processed in real-time by a 9-point running mean followed by a second difference (S'') calculation according to the formula

$$S_n'' = S_{n-g} - 2 \times S_n + S_{n+g} \quad (1)$$

where S_n is the spectral value at point n, and g is the gap in data points. A gap value of $g = 31$ was selected to produce the effect of the fixed bandpass filter used in related studies [5]. The second difference calculation reduces shifting baseline effects and isolates overlapping peaks. By taking every fifth point from the second difference spectrum, a reduced second difference of 190 data points is produced. Data analysis was performed on these reduced second difference spectra. The Principal Component Analysis (PCA) algorithm [6] was implemented to approximate the spectral vector of each bird with a linear combination of set uncorrelated (orthogonal) vectors:

$$Y \cong a_1 C_1 + a_2 C_2 + a_3 C_3 + \ldots + a_k C_k \quad (2)$$

where Y is the spectral vector, C_k is the kth factor (component), and a_k is the kth coefficient of the linear combination. Coefficients a_1 to a_k are called the scores of the spectral vector. In this way, the dimension of the spectra in a wavelength space can be transformed into a vector space with k dimensions spanned by the k factors. PCA was used as preprocessor to produce principal component scores that were used as inputs to a neural-network based classification model. The classification model used neural networks with the DataEngine V.i function library for LabView (Management Intelligenter Technologien GmbH, Germany) to produce a real-time classification output indicating the bird to be either wholesome or unwholesome.

3.2. Tracking control system

A Tracking Control System (TCS) able to track birds from the beginning of the kill line through the end of the evisceration line is necessary for implementation of the Vis/NIR inspection system on a commercial processing line. Remote monitoring of theVis/NIR inspection system can be by OPC (Object-Linking-and-Embedding for Process Control) between the Vis/NIR system and the programmable logic controller (PLC), which monitors and controls shackle operations throughout the processing plant. Fig. 2 shows key elements of the processing line layout needed to implement automated inspection. The Counting Stations (CS), located on the kill line, automated rehanger, and evisceration line, identify individual birds as they travel through the system to ensure proper data correspondence between the Vis/NIR inspection system on the kill line and verification on the evisceration line. Photoelectric sensors enable each Counting Station to detect and count shackles and to detect whether a bird is occupying a shackle or not. After inspection by the Vis/NIR system on the kill line, birds are physically transferred by the automated rehanger to the evisceration line, and checks conducted using Counting Stations B–F will detect any unsuccessful transfers. On the evisceration line, the birds are vented and drawn before entering FSIS inspection stations where they are examined by human inspectors.

The control system process for tracking birds through the Counting Stations is detailed in Table 1. A default attribute value initially assigned to each bird at the start of the kill line is re-assigned as the bird passes (or does not pass) through later counting stations. The control system must track individual birds and their attributes through to the end of the processing line. At CS-A, each bird is first assigned an ID number and the default attribute value, which is saved in a Microsoft Access database for that individual bird. As it travels from the kill line onto the Rehanger, onto the evisceration line and through the FSIS inspection zone, the bird attribute will be reassigned to wholesome if it passes successfully through to CS-H. If a bird is successfully identified through CS-G but not at CS-H, it is presumed to have been condemned by FSIS inspectors and its attribute is reassigned to unwholesome. If a bird is successfully identified at CS-A, but is not successfully identified at CS-F or CS-G, its attribute is reassigned to lost.

When a bird is in position for inspection on the kill line, the PLC that is tracking the shackles uses OPC to send the bird ID number and a

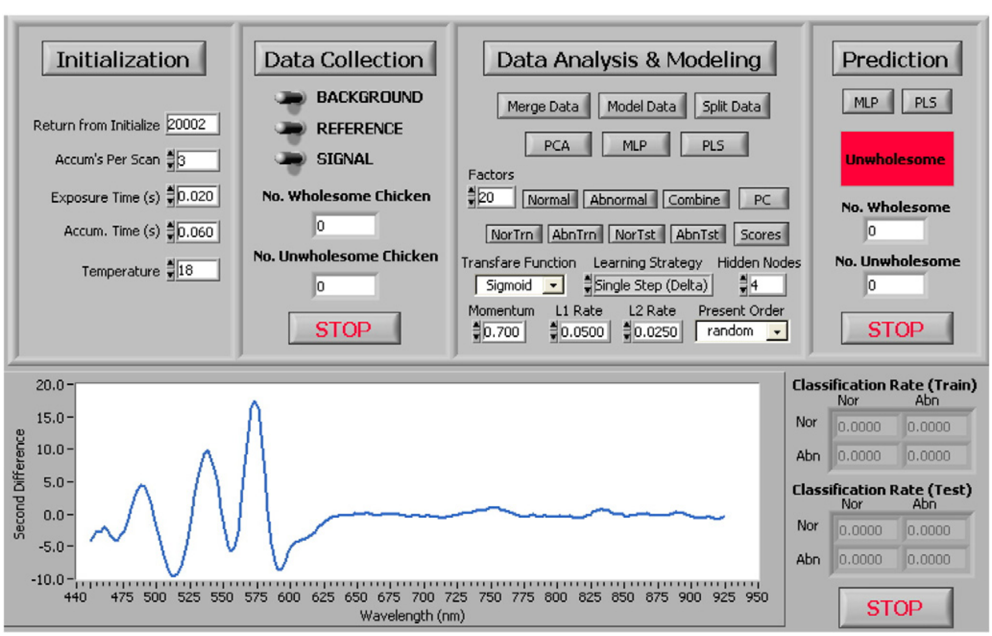

Fig. 1. LabView user interface for Vis/NIR chicken inspection system.

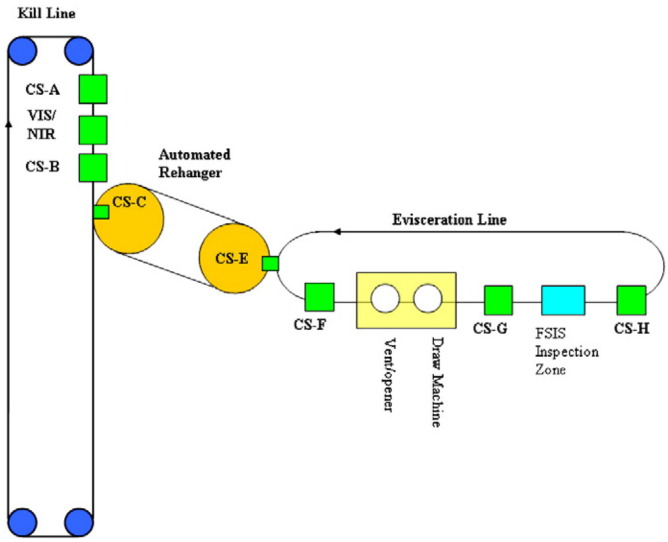

Fig. 2. Schematic diagram of kill and evisceration lines, detailing counting stations (CS) key to operation of the Tracking Control System.

control signal to the Vis/NIR inspection systems via TCP/IP Ethernet data communication protocol. This initiates automated inspection of that bird. This occurs on a bird-by-bird basis, each time prompting the Vis/NIR inspection system to acquire the spectral measurement for each bird, perform spectral preprocessing (smoothing and second difference calculation), and save both original and processed spectral data in a Microsoft Access database with corresponding bird ID and attribute values.

For commercial implementation, the inspection decision produced for each bird by the Vis/NIR inspection system will initiate immediate rejection and removal of condemned birds from the kill line, before the birds reach the Automated Rehanger. For this real-time operation, the system will send the decision signal (accept or reject) to the PLC, which will then remotely trigger mechanical rejection of the bird to occur at or prior to the Automated Rehanger unit. In addition, information from the system can be relayed to a remote central computer managing food safety inspection and quality monitoring issues for the poultry processor.

Table 1 details key points of the TCS for online implementation of the Vis/NIR inspection system. For research, the Vis/NIR inspection system saves a bird classification decision (see * in Table 1) that is saved for performance verification purposes during online experiments. For real-world use, an additional counting station and a rejection point would be installed prior to the location of CS-B, and the classification decision would trigger the transmission of a signal to the bird rejection point for rejecting unwholesome birds before they reach the Automated Rehanger, and the corresponding bird attribute would be reassigned to unwholesome (=0).

Table 1
Tracking control system steps for Counting Stations CS-A through CS-H.

CS-A		
	I	For an occupied Kill Line shackle, assign a bird ID number and default attribute value (=4) to bird.
	II	Load ID and attribute data into the Kill Line data array which stores the information with corresponding Kill Line shackle number.
	III	Send signal to Vis/NIR inspection system—bird is in position for inspection.
Vis/NIR Inspection System		
	I	Receive bird ID number.
	II	Acquire spectral measurement of bird.
	III	*Classify bird as wholesome or unwholesome and save decision data.
CS-B		
	I	Identify the Kill Line shackle entering the Automated Rehanger.
CS-C		
	I	Transfer data array elements for occupied shackle – bird ID number and attribute value – from Kill Line data array to Rehanger data array as the bird is moved from Kill Line shackle to Rehanger carrier.
CS-E		
	I	Transfer data array elements from Rehanger data array to the Evisceration Line data array as the bird is moved from Rehanger carrier to Evisceration Line shackle.
CS-F		
	I	If Evisceration Line shackle is empty despite corresponding Rehanger carrier or Kill Line shackle having been previously occupied (bird was physically dropped), at this point the bird attribute is reassigned (=2) to indicate that the bird was lost. Otherwise, default value remains (=4).
CS-G		
	I	If previously occupied Evisceration Line shackle is detected as empty, the bird attribute is reassigned (=2) to indicate that the bird was lost. Otherwise, default value remains (=4).
FSIS		
	I	Visual inspection is performed by a human inspector.
		a If bird passes inspection, inspector takes no action and the bird remains on the shackle.
		b If the bird does not pass inspection, inspector removes the condemned bird from the shackle for disposal
CS-H		
	I	If the Evisceration Line shackle is still occupied by a bird, the bird attribute is reassigned to wholesome (=1).
	II	If no bird is detected on the previously occupied shackle, the bird attribute is reassigned to unwholesome (=0).

4. In-plant online testing of Visible/Near-Infrared interface

4.1. Procedures

Collection of spectral data to use for classification model development was performed over a two-week period on-site at a commercial chicken processing plant. Spectral data was acquired for totals of 900 wholesome birds and 852 unwholesome birds. Chicken carcasses on several commercial processing lines were identified as wholesome or unwholesome at six FSIS inspection stations, placed onto portable racks by inspectors' assistants, and these small batches (up to 20 birds at a time) were immediately transported to a nearby room for experimental online spectral data acquisition. The carcasses were manually hung onto the shackles of a 17.7 m overhead conveyor running through a closed rectangular loop (6.7×3.1 m). The overhead conveyor, equipped with a variable frequency-controlled drive system, was preset to operate at a line speed of 140 bpm for this experiment. Prior to spectral measurement of the chicken carcasses, reference and background measurements were taken. To establish a spectrally flat, repeatable, high energy reference, a reference spectrum was collected by placing the fiber optic probe 2 cm from the surface of a 10×10 cm square, 14-mm thick Spectralon reflectance target (Labsphere, Sutton, NH) that provided approximately 99% effective diffuse reflectance throughout the wavelength region examined. A background measurement was taken, to compensate for the zero energy signal, by placing the optical probe 2 cm from the bottom of an enclosed black cylindrical Teflon sample cell with the light source turned off. Spectra were recorded as percent reflectance according to the following formula:

$$\%\ \text{Reflectance} = \frac{100 \times (\text{sample reflectance} - \text{background})}{(\text{reference} - \text{background})}. \quad (3)$$

The CCD detector, controlled through the system software (interface shown in Fig. 1), accumulated 3 scans per measurement, with full vertical binning resulting in 1024 data point for each spectral measurement. The single-scan exposure time was 20 ms; consequently, a single chicken carcass was scanned over a total time of 60 ms. A photoelectric sensor (Model QS30LDLQ, Banner Engineering Corp., Minneapolis, MN) was used to synchronize the data acquisition with bird position in the field of view. Afterwards, the FSIS veterinary medical officer examined the wholesome or unwholesome condition of each bird, including specific postmortem conditions, and each diagnosis was recorded for correlation to the spectral database.

4.2. Classification modeling

The raw spectra were recorded as percentage reflectance, consisting of 1024 points spaced 0.5009 nm apart, from 431.0 to 943.5 nm. A 9-point running average and second difference with gap = 31 points was applied to each spectrum. Selection of every 5th point further reduced each spectrum to 190 points (450.6–924.0 nm).

The full development data set of 900 spectra for wholesome birds and 852 for unwholesome birds was divided into three subsets for development of neural-network-based classification models: training, test, and validation. Every third spectrum, starting with the first in order of collection, was used for training; every third spectrum, starting with the second, was used for testing; and every third spectrum, starting with the third, was used for validation. This division produced three separate datasets, each containing 300 wholesome and 284 unwholesome spectra. Principal component analysis was then applied, using principal components calculated for the training set to produce scores for each spectrum in the training, testing, and validation sets.

The scores were then used as inputs into a feed-forward-back-propagation neural network. Neural network classification was tested using 10, 20, and 30 input nodes. The corresponding numbers of hidden nodes were derived based on the square root of the input nodes, i.e. 3, 4, and 5, respectively. All 3 neural network configurations produced 2 final output nodes. The output nodes were (0 1) or (1 0) depending on whether the sample was identified to be wholesome or unwholesome by the veterinarian. For each of the 3 neural network configurations, 4 classification models using combinations of two learning rules and two transfer functions were tested—delta and cumulative delta, and tanh and sigmoid [7], as shown in Table 2.

Each of the neural network classification models was trained using scores from the training set; the neural network weights produced by each iteration was evaluated using the test data set, for the determination of the network weights of each model using the savebest procedure (NeuralWorks Professional II/Plus, NeuralWare, Inc., Pittsburgh, PA). The validation set scores were then used to measure the performance of the each model, independent of the training and testing datasets, to select one of the 12 models—i.e. the specific combination of learning rule, transfer function, and number of input nodes to the neural network.

The selected neural network classification model was then used for online classification of birds on a 140 bpm commercial chicken processing line, with the assistance of the FSIS Veterinary Medical Officer for performance verification. Because the real-world incidence of systemically diseased unwholesome birds is low (approximately 0.2% of birds processed), this in-plant testing was performed over a period of 2 weeks in order to collect adequate numbers of unwholesome birds from one chicken processing line for model testing. The FSIS Veterinary Medical Officer observed individual birds on the processing line to identify wholesome and unwholesome birds, the condition of which could then be recorded and correlated to the spectral measurements acquired for each bird. An additional color sensor was positioned at shackle height, to detect steel pendants placed on the shackles of wholesome and unwholesome birds as they passed through the spectral measurement area. Differently colored panels on the pendants identified the corresponding birds as being either wholesome or unwholesome, as evaluated by the FSIS Veterinary Medical Officer. Spectral measurements and bird evaluations were acquired for a total of 1442 chicken carcasses (721 wholesome and 721 unwholesome) used to evaluate the selected classification model.

Table 2
Neural network models.

Model	Learning rule	Transfer function
1	Delta	Sigmoid
2	Delta	Tanh
3	Cumulative delta	Sigmoid
4	Cumulative delta	Tanh

5. Results and discussion

The average reflectance spectra of wholesome and unwholesome chickens on the 140 bpm closed-loop line are shown in Fig. 3. With the exception of baseline variations, the spectra of wholesome and unwholesome chickens were similar. The overall vertical offset of any particular spectrum was caused by variable scatter and surface reflectance as well as small variations in probe-to-sample distance, which have little effect on category characteristics. To reduce the visual impact of shifting baseline effects and to isolate overlapping peaks, second difference spectra (calculated with a gap size of 15.5 nm) were calculated for all wholesome and unwholesome chicken spectra. Fig. 4 shows the mean second difference spectra calculated for wholesome and unwholesome chickens on the closed-loop processing line. The wholesome and unwholesome second difference spectra showed the most distinct differences in absorption band peaks at 458, 490, 540 and 574 nm and valleys at 514, 556, and 592 nm, and to a lesser extent at 716 and 816 nm.

For well-bled meat, meat surface coloration is largely the result of the relative amounts of three forms of myoglobin, i.e. deoxymyoglobin, metmyoglobin, and oxymyoglobin [8]. The deoxymyoglobin and oxymyoglobin components coexist with metmyoglobin in both wholesome and unwholesome chicken meats and the three forms of myoglobin can inter-convert and may degrade through oxygenation, oxidation, and reduction reactions when external processes such as cold storage, cooking, and irradiation are applied [9], [10]. The absorption bands around 458, 490, 540, and 574 nm represent the effects of various conformational structure of myoglobin, while the absorption bands at 740 and 835 nm could be a combination of lipids, water, and various forms of myoglobin absorptions. These absorption areas form a major base for spectral differentiation of wholesome chicken from unwholesome chicken.

PC 1 and PC 2 scores for the closed-loop training set are plotted in Fig. 5. The PC 1 scores show wide variation for both wholesome and unwholesome chicken spectra. However, for the PC 2 scores, a pattern is evident in which the wholesome scores are positive and the unwholesome scores are negative, with some slight overlap.

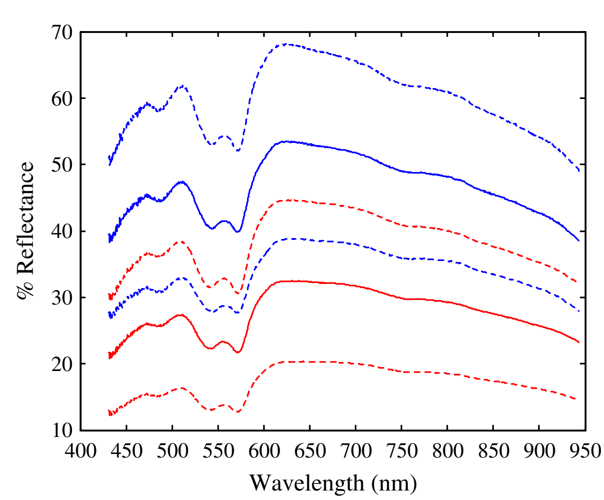

Fig. 3. Mean reflectance spectra (solid lines) of wholesome (blue) and unwholesome (red) chicken carcasses, with one standard deviation envelope (dotted lines).

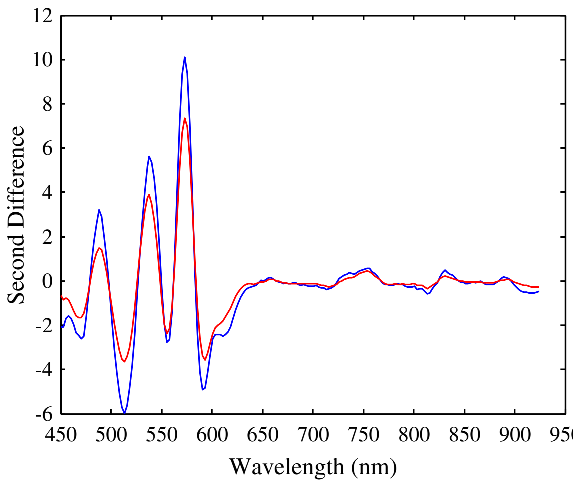

Fig. 4. Mean second difference spectra of wholesome (blue) and unwholesome (red) chicken carcasses.

Examination of the loading weights (not shown) for PC1 and PC2 found the loadings to be similar to the second difference spectra. Loading weights are the regression coefficients at specific wavelengths for each PC and show the relative contribution of those wavelengths to the amount of spectral variation for which that accounts. Of particular interest in the spectral region near 490 nm—this region has been correlated to metmyoglobin, which is found in greater amounts in unwholesome meat than in wholesome meat, and is thought to be a degraded form of oxymyoglobin and deoxymyoglobin [11].

Fig. 6 shows the Root Mean Square Error of Cross-Validation (RMSECV) for the closed-loop training data set. With one-sample-out cross-validation, the error decreased with each additional PC, with the last significant incremental decrease in error occurring with PC 5.

For 10-, 20-, and 30-input neural networks, Table 3 shows the testing set and validation set results for each of the four models. Using as inputs the scores calculated from 10 PCs, the overall classification accuracies ranged from 83% to 90%. With 20 input nodes, the classification accuracies improved, with Model 1 (delta learning rule and sigmoid transfer function) achieving the best accuracies. For the test data set, 96% of wholesome carcasses and 92% of unwholesome carcasses were correctly classified by Model 1, for an average accuracy of 94%. For the validation set, 95% of wholesome and 92% of unwholesome carcasses were correctly classified by Model 1, for an average accuracy of 93.5%. With 30 input nodes, the classification accuracies did not increase significantly. In general, the models using the delta learning rule performed better than those using the cumulative delta learning rule. It was also noted that the classification accuracies of Model 4, using the cumulative delta learning rule with the hyperbolic tangent transfer function, were consistently lower than those of the other three models.

Classification Model 1 was used for in-plant online testing of the inspection system interface. The full data set of 1442 chicken spectra measured online (721 wholesome and 721 unwholesome) was divided into three sets, for model training (521 wholesome and 521 wholesome), testing (100 wholesome and 100 wholesome), and validation (100 wholesome and 100 unwholesome). Results for the validation set, which was used to measure model performance

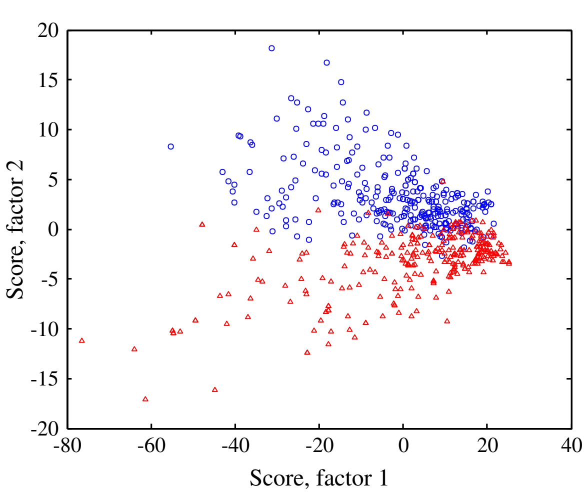

Fig. 5. PCA score plot of components 1 and 2 for wholesome (circle) and unwholesome (triangle) chicken carcasses.

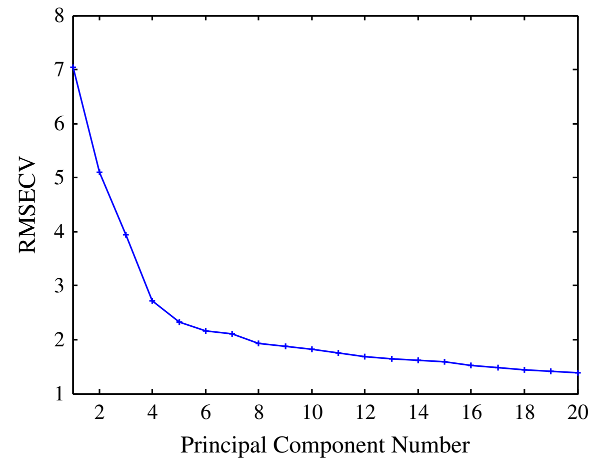

Fig. 6. Cross validation RMSECV curve for training set data.

Table 3
Classification accuracies resulting from 10, 20, and 30 input nodes to the neural network.

	Wholesome carcasses	Unwholesome carcasses	All carcasses	
10 input nodes				
Model 1	92	88	90	Test
	90	89	89.5	Validation
Model 2	91	88	89.5	Test
	91	87	89	Validation
Model 3	90	88	89	Test
	89	84	86.5	Validation
Model 4	91	78	84.5	Test
	90	76	83	Validation
20 input nodes				
Model 1	96	92	94	Test
	95	92	93.5	Validation
Model 2	95	92	93.5	Test
	94	92	93	Validation
Model 3	93	92	92.5	Test
	94	91	92.5	Validation
Model 4	93	90	91.5	Test
	91	89	90	Validation
30 input nodes				
Model 1	95	93	94	Test
	94	92	93	Validation
Model 2	95	92	93.5	Test
	95	91	93	Validation
Model 3	94	92	93	Test
	93	92	92.5	Validation
Model 4	90	90	90	Test
	91	90	90.5	Validation

Table 4
Classification results for real-time chicken inspection, validation set of 200 carcasses.

	Chicken condition: wholesome	Chicken condition: unwholesome
Classification result: wholesome	94	8
Classification result: unwholesome	6	92

independently from the training and testing datasets, are shown in Table 4. For the validation set, 94 wholesome and 92 unwholesome carcasses were correctly classified, for an average classification accuracy of 93%. Type I error (economic loss risk) occurs when wholesome carcasses are incorrectly identified as unwholesome. Type II error (public health risk) occurs when unwholesome carcasses are incorrectly identified as wholesome. For the validation set, Type I error was 6% and Type II error was 8%. Both Type I and Type II errors must be considered for sorting purposes: (1) whether wholesome birds identified as unwholesome (Type I error) will be thrown out with the unwholesome birds on a rejection line, or will be re-examined or reprocessed by human inspectors, and (2) whether there is to be an additional human inspector to catch unwholesome birds mistakenly identified as wholesome (Type II error) on the processing line.

An effective real-time inspection system must have the capacity for rapid spectral measurement, data processing, and classification computation within a limited time window. This study demonstrated that the Vis/NIR inspection system interface is capable of handling high speed spectral data acquisition, processing, and decision output that will be necessary to commercial implementation.

6. Conclusions

A new Vis/NIR inspection system interface was developed in order to conduct research to test and implement an automated Vis/NIR chicken inspection system for online operation on commercial chicken processing lines. The Vis/NIR spectroscopic system was developed using modularized software components and was demonstrated capable of collecting and processing real-time spectral measurements for chickens on a 140 bpm processing line. Data analysis and modeling demonstrated that the system can successfully differentiate between wholesome and unwholesome birds, using a neural network classification model with 20 input nodes that correctly classified 94% and 92% of wholesome and unwholesome birds, respectively. This work demonstrates that with Vis/NIR Inspection interface can effectively allow the laboratory-developed Vis/NIR spectroscopy-based inspection system to operate on commercial poultry processing lines requiring accurate real-time bird and shackle tracking on kill line and evisceration line.

References

[1] USDA, A Review of the Slaughter Regulations Under the Poultry Products Inspection Act, Regulations Office, Policy and Program Planning, FSIS, USDA, Washington, D.C, 1984.
[2] Y.R. Chen, D.R. Massie, Visible/near infrared reflectance and interactance spectroscopy for detection of abnormal poultry carcasses, Trans. ASAE 36 (3) (1993) 863–889.
[3] Y.R. Chen, R.W. Huffman, B. Park, M. Nguyen, Transportable spectrophotometer system for on-line classification of poultry carcasses, Appl. Spectrosc. 50 (1996) 910–916.
[4] Y.R. Chen, W.R. Hruschka, H. Early, A chicken carcass inspection system using visible/near-infrared reflectance: in plant trials, J. Food Process Eng. 23 (2) (2000) 89–99.
[5] K. Chao, Y.R. Chen, W.R. Hurschka, F.B. Gwozdz, On-line inspection of poultry carcasses by a dual-camera system, J. Food Eng. 51 (3) (2002) 185–192.
[6] S. Wold, M. Sjostrom, 1977, in: B.R. Kowalski (Ed.), Chemometrics: Theory and Application, American Chemical Society, Washington, DC, 1977, pp. 242–282.
[7] D. E. Rumelhart, G. E. Hinton, R. J. Williams. Learning internal representations by error propagation. In *Parallel Distributed Processing*, volume 1:Foundations, D. E. Rumelhart, J. L. McClelland, and the PDP Research Group (Eds.), Cambridge, MA: MIT Press, (1986) 318–363.
[8] H.J. Swatland, A review of meat spectrophotometry (300 to 800 nm), Can. Inst. Food Sci. Technol. J. 22 (1989) 390–402.
[9] Y. Liu, Y.R. Chen, Y. Ozaki, Characterization of visible spectral intensity variations of wholesome and unwholesome chicken meats with two-dimensional correlation spectroscopy, Appl. Spectrosc. 54 (4) (2000) 587–594.
[10] Y. Liu, X. Fan, Y.R. Chen, D.W. Thayer, Changes in structure and color characteristics of irradiated chicken breasts as a function of dosage and storage time, Meat Sci. 63 (3) (2003) 301–307.
[11] Y. Liu, Y.R. Chen, Two-dimensional correlation spectroscopy study of visible and near-infrared spectral variations of chicken meats in cold storage, Appl. Spectrosc. 54 (10) (2000) 1458–1470.

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