DESIGN OF A DUAL-CAMERA SYSTEM FOR POULTRY CARCASSES INSPECTION

K. Chao, B. Park, Y. R. Chen, W. R. Hruschka, F. W. Wheaton

ABSTRACT. *Two dual-camera systems were developed for on-line inspection of poultry carcasses: one to image the front of the bird and the other to image the back. Each system consists of two identical black and white cameras equipped with interference filters of 540 nm and 700 nm. Both cameras capture spectral images simultaneously. Object-oriented analysis was performed to identify the attributes of individual software components and the relationships among these software components. These individual software components were then organized by the object patterns to form a software architectural framework for on-line image capture, off-line development of classification models, and on-line classification of carcasses into wholesome and unwholesome categories. Model development and testing was performed on 331 chickens independently classified by a veterinarian. For off-line model development, the accuracies for differentiating between wholesome and unwholesome carcasses were 96.2% and 88.5% at 540 nm and 700 nm, respectively, for the front images and 95.7% and 85.1% at 540 nm and 700 nm, respectively, for the back images. On-line classification for 128 new samples combined the filter information within each system, using selected neural network models. The front imaging system gave accuracies of 91%, 98% and 95% for normal, abnormal and combined carcasses, respectively. The back imaging system gave 84%, 100% and 92%.*

Keywords. *Chicken, Computer graphics, Food safety, Inspection, Real-time system, Machine vision.*

During the last three decades, poultry production has greatly increased and the processing speed at slaughter plants has tripled (USDA, 1996). Due to massive production of poultry and the inherent variability and complexity in individual birds, there are great challenges for further improvement of the existing organoleptic inspection methods. Currently, individual carcasses are visually inspected by federal inspectors at poultry processing lines. The visual bird-by-bird inspection is labor intensive and prone to human error and variability. Development of high speed and reliable inspection systems to ensure safe production of poultry during post-harvest processing has become an important issue, as the public is demanding assurance of better and safer food.

Machine vision techniques are useful for the agricultural and food industries, particularly in grading and inspection (Daley et al., 1994; Miller and Delwiche, 1989; Precetti and Krutz, 1993; Sakar and Wolfe, 1985; Tao et al., 1990). Machine vision is the technology that provides automated production processes with vision capabilities when the majority of inspection tasks are highly repetitive, extremely boring, and their effectiveness depends on the efficiency of the human inspectors. Even though machine vision has evolved into a promising technology for agricultural product applications, among the many factors to be considered in on-line application are processing speed, reliability, and applicability for industrial environments. To design an effective vision system for on-line operations, vision hardware functionality need to be considered during the development of vision system software.

Spectral imaging involves measuring the intensity of diffusely reflected light from a surface at several wavelengths. The reflected light contains information about absorbers near the surface of the material. Using intensities recorded in six different spectral bands (540, 570, 641, 700, 720, and 847 nm), the Instrumentation and Sensing Laboratory (ISL) located in Beltsville, Maryland, has developed several spectral image algorithms to differentiate wholesome carcasses from unwholesome carcasses (Park et al., 1996). In this case, comparison of images at two or more wavelengths provides robustness for classifying spectral images. Since the process of analyzing a digital image to identify certain objects is inherently computationally intensive, it is advantageous optically pre-process the image, extracting only those wavelengths which provide useful information.

A pilot-scale facility at ISL was constructed specifically for developing the machine vision based systems for on-line poultry inspection. The facility has been utilized for evaluating individual vision components and testing the workability of spectral imaging algorithms (Park and Chen, 1998).

The objective of this research was to design a real-time machine vision system, including vision hardware and

Article was submitted for publication in July 1999; reviewed and approved for publication by the Information & Electrical Technologies Division of ASAE in May 2000. Presented as ASAE Paper No. 99-3118.

Mention of company or trade name is for purpose of description only and does not imply endorsement by the U.S. Department of Agriculture.

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software components integration, which can be adapted to the on-line processing at poultry slaughter plants. Object-oriented analysis was employed to identify the system's responsibility for individual components. A real-time machine vision inspection system (MVIS) was implemented in the pilot-scale facility. The system's performance was optimized for on-line classification of normal and abnormal chicken carcasses.

MATERIAL AND METHODS

SAMPLE COLLECTION

A total of 331 chicken carcasses (167 normal, 54 airsacculitis, 51 septicemia, 26 ascites, and 33 cadaver) were sampled from a poultry processing plant in Maryland over a four-day period in March and a two-day period in April of 1999. The conditions of these carcasses were identified on the plant site by a Food Safety and Inspection Service (FSIS) veterinarian. The carcasses were tagged according to the condemnation conditions and placed in plastic bags to minimize dehydration. Then the bags were placed in coolers, filled with ice, and transported to ISL for the experiments.

DUAL-CAMERA SYSTEMS

Two dual-camera systems were used, one to image the front of the bird and the other to image the back of the bird. For each system, two identical black and white progressive scan cameras (TM-9701, PULNIX Inc., Sunnyvale, California) were used to capture spectral images simultaneously. Each camera was equipped with an optical interference filter (Omega Optical, Inc., Brattleboro, Vermont), at a wavelength of 540 nm or 700 nm, resulting in four images for each bird (front/back, 540/700). Each filter had a 20-nm bandwidth. These two wavelengths had been found previously to give good discrimination results (Park et al., 1996). The size of the CCD sensor in each camera was 6.6 × 8.8 mm (2/3 in. format). The image sensor had 768 (horizontal) × 484 (vertical) active picture elements with an actual resolution of 570 horizontal TV lines. Each camera had a full-frame shutter with asynchronous reset and an interline transfer CCD that provided high speed electronic shuttering to capture images of moving objects. Identical 17-mm focal length C-mount lenses (Xenoplan, Schneider Inc., Kreuznach, Germany) were attached to each camera. Two cameras were touching each other with the lens centers 5.3 cm apart. The cameras were angled slightly to achieve maximal image overlapping. The distance between camera lens and object (the surface of chicken body in the shackle) was approximately 36 cm.

Four halogen lamps (150 W each, USHIO Inc., Tokyo, Japan) with diffusing reflectors (PQ300, Regent Lighting Corp., Burlington, North Carolina) illuminated the poultry carcasses. The four adjustable lamp/reflector assemblies were positioned at the corners of a 30 cm sided square slightly behind the pair of cameras, at 45° angles to the poultry carcass, giving diffused front lighting. The distance from each lamp to the carcass was 50 cm.

For image capture, the IC-RGB frame grabber (Imaging Technology Inc., Bedford, Massachusetts) was configured to operate in a 24-bit true color mode. In this mode, the three 8-bit channels (i.e., red, green, and blue) could be used separately to connect up to three monochrome cameras. The green and blue channels were used in this study to carry image data from the dual-wavelength cameras.

SYSTEM SOFTWARE DESIGN

The machine vision inspection system (MVIS) provides an automated process for on-line poultry carcass inspection. To facilitate the system design, object-oriented analysis (Booch, 1994) was initiated by considering the hardware on which the MVIS must execute. The following strategic decisions were made to expose the issues of the software analysis and design.

1. Host computer equipped with a Pentium II-class processor running Windows NT 4.0 (Microsoft Corp., Redmond, Washington) was used.
2. Images were acquired by a PCI bus image capture card, then passed through to the PC host memory.
3. An on-board (frame grabber) timer was utilized to synchronize the dual-wavelength cameras.
4. Two magnetic proximity sensors (MLC-K60, MagneLink, Hillsbore, Oregon) were used to trigger on-line image capture for off-line training of classification models.
5. A photoelectric proximity sensor (PZ-42, Keyence, Saddle Brook, New Jersey) was used to trigger on-line image capture for on-line classification.
6. Sensor digital inputs were provided through a digital I/O card (PIO-24, Keithley MetraByte, Taunton, Massachusetts), accessible via memory-mapped I/O.
7. The image display device was a PCI bus video card with 8 MB of video memory.

Based on the availability of these hardware components (fig. 1), the MVIS requirements are specified. The MVIS has three primary functions: real-time image acquisition, processing, and on-line classification of poultry carcasses.

CLASS DIAGRAM DESIGN

The goal of object-oriented design is to decompose a programming task into data types or classes and to define the functionality of these classes. Seven classes developed for the project included *Cue*, *Frame Grabber*, *Device-Independent Bitmaps* (DIBs), *Chicken*, *Neural Network Classifier*, *Document*, and *View* were extracted from the requirements. Within a given inspection cycle, *Cues* control the action of a frame grabber. *Cues* are temporal objects, changing state with time. The *Frame Grabber* is a foundation class used to acquire images from the dual-camera and transfer image data to the host PC memory. The *DIB*s provide a depository for the raw image data. *Chickens* are the participants in the vision inspection system. The attributes (edge position, etc.) and methods (segmentation, etc.) are utilized to represent individual chickens. *Documents* hold the processed data. *Views* are the front-end presentation of the data.

A class diagram is a graphical presentation method to effectively convey design information. The class diagram for the MVIS is illustrated in figure 2. Classes are drawn as boxes, which contain the class name, the names of data fields and operations. Three kinds of connections, aggregation, association, and inheritance, connect the classes. The aggregation relationship occurs when a class

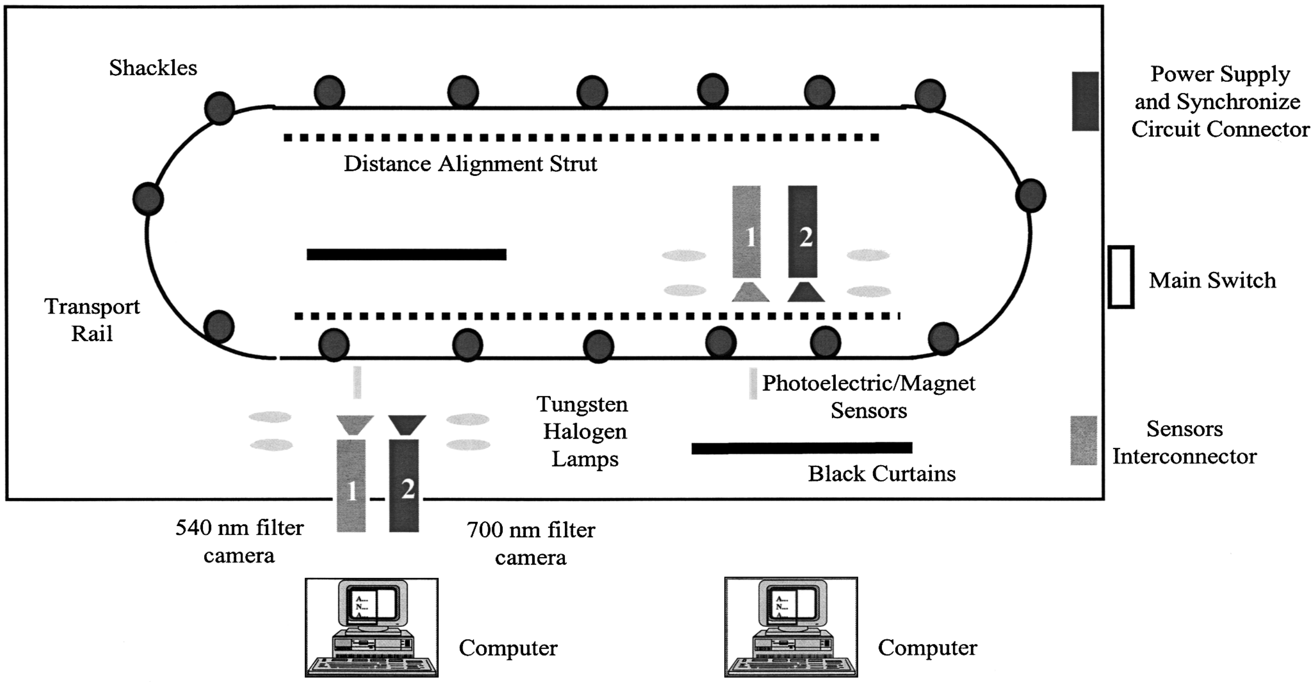

Figure 1–Pilot-scale facility with two dual-camera vision systems.

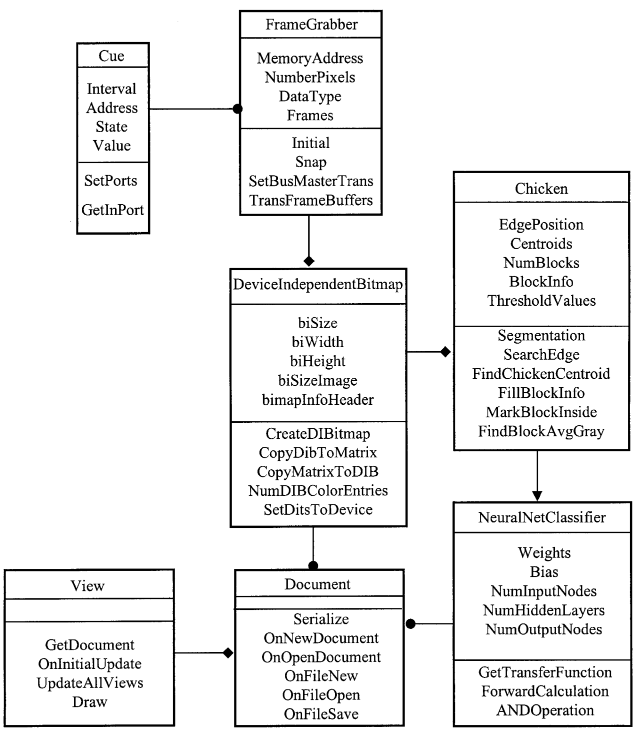

Figure 2–The class diagram for the machine vision inspection system (MVIS).

contains objects of another class. It is denoted by a line with a diamond at the larger class. The association relationship exists between two classes if one uses the other to carry out its tasks. The association relationship is denoted by a line with a circle at the using class. Inheritance is the "is-a" relationship. If every member of a class logically conforms to another class but has additional special attributes, then the first inherits from other. For a class inheriting from a base class, an arrow is drawn from the base class to the derived class.

Cues are time sensitive. Each *Cue* has a time interval during which it is active. The Frame Grabber uses the cue as an indicator to trigger the image acquisition process when an object is passed through the sensors. The main responsibility of a frame grabber is to provide a data structure for acquisition of images. This structure includes the location of the data (memory address), the size of the image (number of pixels), its data type (8-bit byte, 16-bit word, or floating point), and number of frames. A *DIB* is a data field representing the raw image data cached in the frame grabber. Each *Chicken* has two *DIB*s to represent image data acquired through two interference optical filters at wavelengths of 540 nm and 700 nm. The attributes of *Chicken* are defined to describe the intensity characteristics of chicken carcasses. The *BlockInfo* is a user-defined data type, which contains quantitative information such as averaged gray intensity and printable area of individual blocks. *Neural Network Classifier* is a derived class from Chicken. *Neural Network Classifier* inherits information such as number of blocks, averaged gray intensity directly from *Chicken*. These attributes are the inputs to the classifier. The outputs from *Neural Network Classifier* are provided to *Document*. *Document* provides an important operation called serialization to the processed data. The serialization process can save the persistent objects, interrupt the computation, and reload the same data at a later time. *View* displays the data stored in Document. The Document-View structure is directly derived from Microsoft Foundation Class Libraries (Microsoft Corp., Redmond, Washington).

Based on the analysis and design, the MVIS was implemented in the Visual C++ (Microsoft Corp., Redmond, Washington) environment.

OPERATION FLOW

On-line data acquisition occurs for one of two purposes: off-line model development and on-line classification. When acquiring images for off-line model development, a stainless steel plate holding a magnet is hung on each shackle suspending a chicken carcass, marking it for image acquisition and indicating the condition of the chicken. The position of the magnet (high or low) indicates whether the chicken is normal or abnormal. The upper of the two magnet sensors detects the magnet for a marked normal carcass. The lower magnet detects a marked abnormal carcass. These two magnet sensors are connected to a digital I/O board, triggering image capture. When acquiring images for testing on-line classification, chickens are hung in a known normal/abnormal sequence, without magnetic markers, on the pilot-scale line and a photoelectric proximity sensor, also connected to the digital I/O board, triggers image capture when a shackle is sensed.

The real-time image acquisition process uses Cue and Frame Grabber to trigger and synchronize image acquisition. Cue monitors the input status of the digital I/O board and sends a control message to the function level drivers running the frame grabber to initiate an interrupt to the on-board timer to synchronize the dual-wavelength cameras. The images are acquired from the cameras and transferred to the host CPU memory.

The image processing is performed in real-time (four images per chicken, front/back, 540/700 nm). The size of an original spectral image acquired by the camera is 512 × 480 pixels. The image is reduced to a size of 256 × 240 pixels by extracting every other pixel from the odd lines of the interlaced image. The reduction allowed a shorter processing time, and permitted simultaneous display of two images. The reduced image (object) is segmented from the background using thresholding values of 40 for the 540 nm images and 50 for the 700 nm. Pixels below the threshold were set to zero, and those above retained their original grayscale values. A total of 15 horizontal layers (16 horizontal lines of pixels each) are generated from each segmented image, as shown in figure 3. For each layer, a centroid is calculated from the binarized image. Based on these centroids, each layer was divided into several square blocks with the size of 256 pixels (16 × 16). The numbers of blocks in each layer were {10, 9, 10, 8, 8, 7, 6, 6, 5, 6, 6, 7, 6, 6, and 7} top to bottom, as determined by preliminary studies, for a total of 107 blocks. We call this process “mesh generation.” The averaged intensity of each block is used as the input data to the neural network models. Note that for a very small chicken, the edge blocks could contain several background pixels, passing chicken size information on to the neural net in the form of lowered average intensity.

During off-line training of the backpropagation neural network models, parameters (including weights and biases from the optimized neural network models) are saved in the ASCII data format. Two transfer functions, sigmoid and hyperbolic tangent, are implemented for the on-line classification process. During the on-line classification mode, the photoelectric sensor detects the chicken carcass position along the path of the shackle. Cue then triggers the image acquisition and the image data is passed through the host CPU memory for processing. Immediately following the on-line image processing, one-pass forward mapping of the neural network application is performed to classify the carcasses as wholesome or unwholesome.

PROTOTYPE EVALUATION PROTOCOL

An in-house pilot-scale (60 birds/min) poultry processing line was used to test the dual-camera systems. Images were taken at both 540 and 700 nm wavelengths, one pair of the front, and one pair of the back of each chicken carcass. A total of 203 images (table 1), which were acquired over the four-day period in March 1999, was used to train and select the best neural network models for off-line classification of poultry carcasses. Each feed-forward-back-propagation neural network is configured with 107 input nodes, 10 nodes in one hidden layer, and two output nodes. (The number of hidden nodes follows the standard practice of using approximately the square root of the number of input nodes.) The output nodes' target output is (0 1) or (1 0) depending on whether the sample was identified normal or abnormal by the veterinarian. The analysis method starts with splitting the data into three sets: training (101), testing (55) and validation (47). The neural network models are trained on the training set. The testing set is used to decide which network model and how much training is optimal. The testing set is predicted every 200 iterations of the training cycle, and the network weights are saved if the classification results have been improved. Training is always stopped after 15,000 iterations. The validation set is then used to measure the performance of each optimized model on independent data. The software used for neural network model development was NeuralWorks Professional II/Plus (NeuralWare, Pittsburgh, Pennsylvania). Two back-propagation rules (delta and norm-cum-delta) and two transfer functions (Sigmoid and Tanh) were used for a total of four models (table 2) for each training/testing/validation split of the data. Best models for classification of the front and back of poultry carcasses were selected based on performance evaluation

Table 1. Number of spectral images

	Date	Normal	Abnormal	
Model development	11/3/99 16/3/99 17/3/99 18/3/99	20 25 27 28	28 28 28 19	
Total		100	103	203
Model testing	21/4/99 22/4/99	32 35	30 31	
Total		67	61	128
Grand total				331

Table 2. Neural network models

Model	Learning Rule	Transfer Function
1	Delta	Tanh
2	Delta	Sigmoid
3	Norm-Cum-Delta	Tanh
4	Norm-Cum-Delta	Sigmoid

on the validation set for both normal and abnormal samples.

Samples acquired over the two-day period in April 1999 were used for on-line classification testing of the MVIS. A total of 128 poultry carcasses (67 normal and 61 abnormal) were tested (table 1). Neural network models previously selected from off-line training were implemented to predict the previously unseen poultry carcasses.

RESULTS AND DISCUSSION

OPERATIONS OF MVIS

MVIS was evaluated in on-line operation conditions. It is expected that the dual-wavelength vision system can capture the same chicken simultaneously without any disturbance from other chicken samples on the line. The minimum distance between chickens was 15 cm. Figure 3 illustrates typical images during real-time image processing at 540 nm and 700 nm for both front and back views. Objects (chicken carcasses) were clearly segmented from background. Most blocks were generated inside the boundary of the chicken body as shown in figure 3. Image processing time ranged from 150 to 170 ms, depending on the type of computer used. However, the two images captured at 540 nm and 700 nm were not identical, in the sense of pixel-to-pixel correspondence. This problem occurred because of the configuration of cameras.

Figure 4 illustrates the real-time image processing during real-time classification for the back of chicken carcasses. On-line neural network classification that

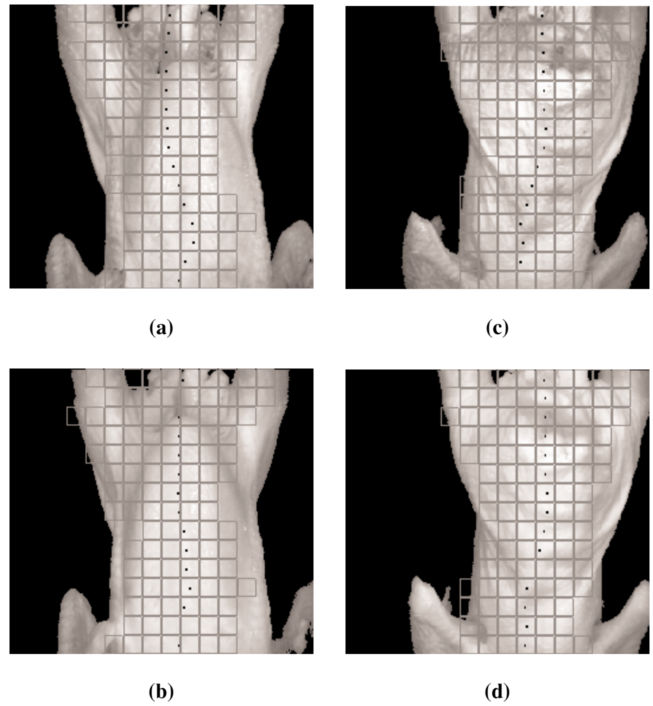

Figure 3–Real-time image processing form the MVIS. Centroid and mesh generation during image capture for off-line training. (a) front at 540 nm, (b) front at 700 nm, (c) back at 540 nm, (d) back at 700 nm.

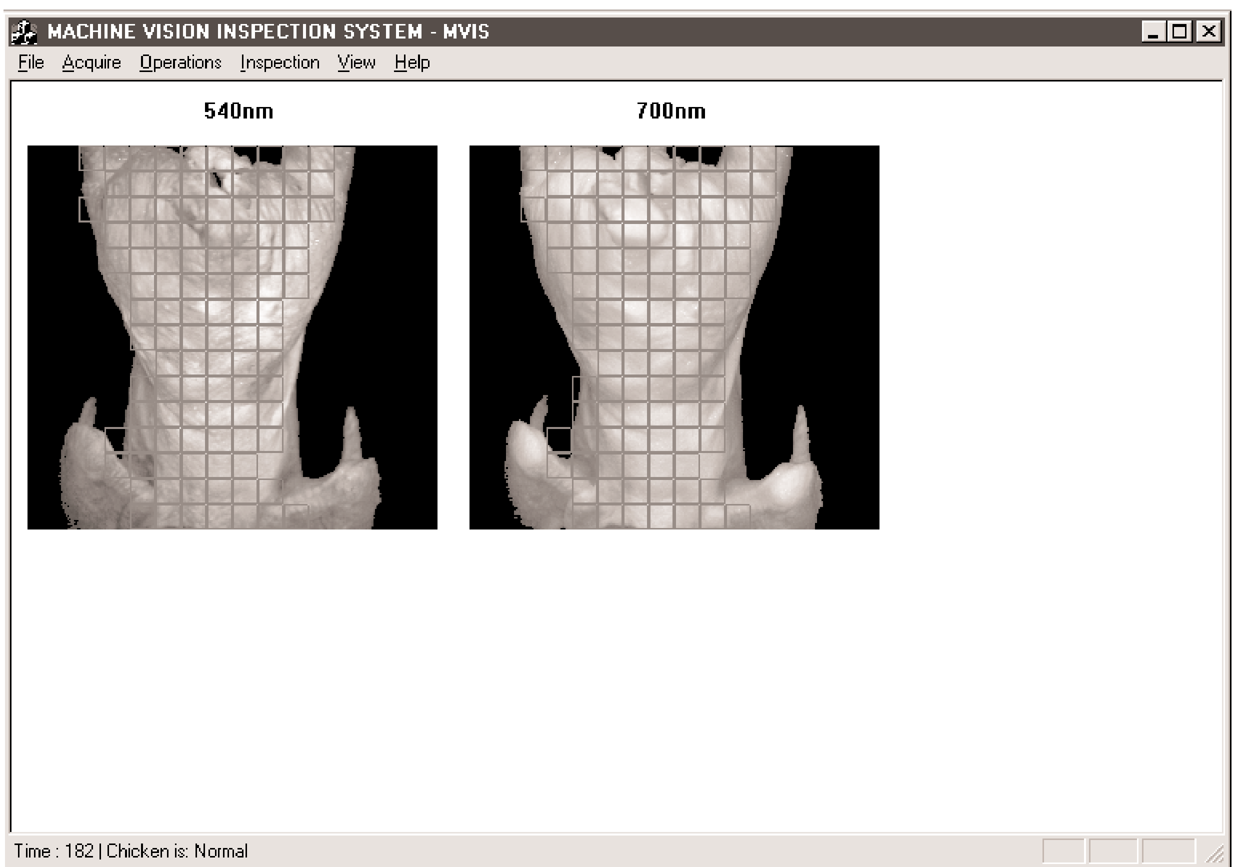

Figure 4–MVIS running for on-line classification of back of chicken carcass predicted to be normal.

utilized inputs from real-time mesh generation was running during the whole process without losing a single frame. Real-time display of processed images also performed reliably. The Document/View structure is used in the visual-programming environment. As shown in figure 4, a document class holds processed information with one view displaying that information as two images and another presenting it as a text. The on-line classification times were counted from 200 to 220 ms for front views and 180 to 200 ms for back views, indicating an achievable inspection rate of 180 chickens per minute by the MVIS. (The front PC CPU was 200 MHz; the back was 233 MHz.)

Off-line Training of Neural Network Model

The four neural network models were tested to select the optimum to use for on-line classification of poultry carcasses. The test results for each model using the front spectral images at 540 nm are shown in table 3. The fraction predicted correctly for testing and validation are included for each of the four models, with the chicken carcasses from normal and abnormal subsets of the *testing* and *validation* sets, and from the normal and abnormal combined. (Training results always approach 1.000 and are not reported.) The classification accuracy to identify normal carcasses was 100% for the four models for both testing and validation data sets. The separation of the abnormal chickens was not as good (87-97%). These results do not show one model as conclusively better, but they do show the combined accuracy to be on the order of 95% correct classification for the validation set. For the on-line classification test, Model 2 was chosen arbitrarily over the equal-result Model 4.

Table 3. Fraction predicted correctly during off-line training using front spectral images at 540 nm

	Carcasses			
Model	Normal	Abnormal	Total	
1	1.000	0.971	0.984	Testing
	1.000	0.875	0.942	Validation
2	1.000	0.971	0.984	Testing
	1.000	0.917	0.962	Validation
3	1.000	0.971	0.984	Testing
	1.000	0.875	0.942	Validation
4	1.000	0.971	0.984	Testing
	1.000	0.917	0.962	Validation

Table 4. Fraction predicted correctly during off-line training using front spectral images at 700 nm

	Carcasses			
Model	Normal	Abnormal	Total	
1	0.889	1.000	0.952	Testing
	0.929	0.708	0.827	Validation
2	0.889	1.000	0.952	Testing
	0.929	0.750	0.846	Validation
3	0.963	0.914	0.935	Testing
	0.929	0.833	0.885	Validation
4				
	0.778	0.971	0.887	Testing
	0.929	0.750	0.846	Validation

Table 4 shows corresponding results using front spectral images at 700 nm. The results clearly indicated that Model 3 was best with 88% correct on the validation set with the combined samples and 83% on the abnormal. It is expected that the testing success rate should be higher than that of the validation. However, as shown in table 4, the validation success rates for models 1, 2, and 4 are better than that of testing. We have no explanation for this, but it could be caused by insufficient testing, or by the front 700 nm images being more uniform in the validation set.

Table 5 shows the success rate when the back spectral images at 540 nm are utilized as inputs to the four models. The results indicated that Model 1 was best, giving an accuracy of 95% for the combined validation set, and 89% for the abnormal validation set. Table 6 shows the comparison of the four models using back spectral images at 700 nm. Model 1 was selected because validation accuracy for the combined carcasses was highest, and the separate normal and abnormal classifications were high.

On-Line Classification of Poultry Carcasses

For each combination of 540/700 nm and front/back, the best model from the offline training was chosen (table 7). Then a separate online test result was made for the front and for the back poultry carcasses. In each case,

Table 5. Fraction predicted correctly during off-line training using back spectral images at 540 nm

	Carcasses			
Model	Normal	Abnormal	Total	
1	1.000	0.964	0.981	Testing
	1.000	0.895	0.957	Validation
2	0.963	0.964	0.964	Testing
	0.821	0.895	0.851	Validation
3	0.926	0.971	0.945	Testing
	0.929	0.895	0.915	Validation
4	0.963	0.929	0.945	Testing
	0.929	0.842	0.894	Validation

Table 6. Fraction predicted correctly during off-line training using back spectral images at 700 nm

	Carcasses			
Model	Normal	Abnormal	Total	
1	0.963	0.893	0.927	Testing
	0.857	0.842	0.851	Validation
2	0.926	0.857	0.891	Testing
	0.857	0.789	0.830	Validation
3	0.963	0.893	0.927	Testing
	0.857	0.789	0.830	Validation
4	0.926	0.927	0.927	Testing
	0.786	0.895	0.830	Validation

Table 7. Models used in on-line classification testing

	Wavelength (nm)	Model
Front	540	2
	700	3
Back	540	1
	700	1

Table 8. Fraction predicted correctly during on-line classification testing

		Normal	Abnormal	Total
Day 1	Front	0.87	1.00	0.93
	Back	0.68	1.00	0.84
Day 2	Front	0.96	0.97	0.97
	Back	1.00	1.00	1.00
Day 1 + Day 2	Front	0.91	0.98	0.95
	Back	0.84	1.00	0.92

the 540 and 700 nm results were combined using an AND operation to give a single prediction. That is, a carcass is predicted normal only if the data from both filters result in normal prediction. Table 8 shows these final online test results. We have separated it into day 1 and day 2 because of a problem with the back lighting, noticed and corrected at the end of the first day. For testing unwholesome carcasses, nearly perfect scores (only one unwholesome carcass was misclassified as wholesome) were achieved. However, the classification accuracy on the first day for wholesome carcasses was 87% for the front and only 68% for the back. The back light correction accounts for part of the increase in performance from day one to day 2.

In general the results for the online test are better than expected, especially the remarkable 100% for the back images on the second day. This is probably because the online classification chickens formed a sample set with characteristics closer to the average of those of the offline training set. That is, the range of intensities within corresponding blocks in the normal (or abnormal) set was probably smaller in the on-line classification. Also, the means of normal and abnormal images were at least as far (if not further) apart in the on-line set.

Summary and Conclusions

Dual-camera systems were designed specifically for on-line poultry inspection. Object-oriented analysis was performed to integrate vision hardware components with the inspection algorithm development. The software for the machine vision inspection system (MVIS) was implemented in the Microsoft Visual C++ environment. Operations including real-time imaging acquisition, processing, off-line model development, and on-line classification were tested in a pilot-scale facility using two dual-camera systems: one for the front and the other for the back of poultry carcasses. Based on these tests, the following conclusions were made.

1. The hardware and software were tightly integrated. The real-time image acquisition and processing occurred without failures, showing the system to be reliable.
2. The inspection algorithm was effective for off-line classification of poultry carcasses. Combined (normal and abnormal) accuracies for classification of carcasses were 96.2% and 88.5% at 540 nm and 700 nm, respectively, for the front images and 95.7% and 85.1% at 540 nm and 700 nm, respectively, for the back images.
3. Models developed were successful for on-line classification of samples collected a month later, showing model development to be robust. Classification accuracies were 95% for the front images and 92% for the back.
4. The design method delivered a successful system that is now ready to be tested in in-plant trials.

In this report, training and testing were based on the images attained on an in-house pilot scale poultry line. The system was designed to be easily transported to and placed at a commercial poultry processing line.

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