Agricultural and Biosystems Engineering Publications

Agricultural and Biosystems Engineering

1997

Neural Network Analysis of Postural Behavior of Young Swine to Determine the IR Thermal Comfort

Junqing Shao
Iowa State University

Hongwei Xin
Iowa State University, hxin@iastate.edu

Jay D. Harmon
Iowa State University, jharmon@iastate.edu

Neural Network Analysis of Postural Behavior of Young Swine to Determine the IR Thermal Comfort

Abstract

A novel method that may be used to interactively control the micro-environment for young swine was investigated to classify the thermal comfort state of animals. Early weaned pigs at 13 to 16 days of age were housed in groups of 10 pigs in four environmentally controlled chambers (1.52 m × 1.83 m floor space per chamber). Air temperatures inside the four chambers were set at 24.4°C, 26.7°C, 28.9°C, and 31.1°C, respectively, for the first week , and were reduced by 1.1°C each of the following two weeks. Postural behaviors of the pigs (huddling or spreading) were captured every 40 min with programmable cameras installed above the transparent false ceilings of the chambers. The raw behavioral images were processed by thresholding, edge detection, and morphological filtering techniques to separate the pigs (objects) from their background. The processed images were further subjected to Fourier transformation. The Fourier coefficients of the processed images (8×8 features) were then used as the inputs to a neural network, which classified the environment into cold, comfortable, or too warm category for the pigs. The neural network analysis worked quite well, with 131 out of 136 training images (96%) and 51 out of 65 testing images (78%) properly classified. This study demonstrates that an innovative environmental controller which uses the animal behavior, instead of the conventionally used air temperature, as the input variable, is possible for swine production. It is anticipated that the behavior-based automatic controller would lead to improved animal well-being and production efficiency. Future research needs include development of algorithms for automatic image segmentation of the pigs, exploration of alternative feature extraction methods to improve classification accuracy of the neural network, and development and evaluation of the behavior-based controller prototype.

NEURAL NETWORK ANALYSIS OF POSTURAL BEHAVIOR OF YOUNG SWINE TO DETERMINE THE IR THERMAL COMFORT STATE

J. Shao, H. Xin, J. D. Harmon

ABSTRACT. *A novel method that may be used to interactively control the micro-environment for young swine was investigated to classify the thermal comfort state of animals. Early weaned pigs at 13 to 16 days of age were housed in groups of 10 pigs in four environmentally controlled chambers (1.52 m × 1.83 m floor space per chamber). Air temperatures inside the four chambers were set at 24.4°C, 26.7°C, 28.9°C, and 31.1°C, respectively, for the first week , and were reduced by 1.1°C each of the following two weeks. Postural behaviors of the pigs (huddling or spreading) were captured every 40 min with programmable cameras installed above the transparent false ceilings of the chambers. The raw behavioral images were processed by thresholding, edge detection, and morphological filtering techniques to separate the pigs (objects) from their background. The processed images were further subjected to Fourier transformation. The Fourier coefficients of the processed images (8×8 features) were then used as the inputs to a neural network, which classified the environment into cold, comfortable, or too warm category for the pigs. The neural network analysis worked quite well, with 131 out of 136 training images (96%) and 51 out of 65 testing images (78%) properly classified. This study demonstrates that an innovative environmental controller which uses the animal behavior, instead of the conventionally used air temperature, as the input variable, is possible for swine production. It is anticipated that the behavior-based automatic controller would lead to improved animal well-being and production efficiency. Future research needs include development of algorithms for automatic image segmentation of the pigs, exploration of alternative feature extraction methods to improve classification accuracy of the neural network, and development and evaluation of the behavior-based controller prototype.* ***Keywords.*** *Swine behavior, Image processing, Neural network, Fourier transformation, Environmental control, Animal well-being.*

Proper thermal environmental control is essential to maintain swine comfort, health, and production performance. Air temperature, air velocity, and floor temperature are the main concerns (Boon, 1981; Geers et al., 1986). Most of the environmental temperature control is based on the application of reference values taken from literature (Geers et al., 1991). Although the environmental temperature can be precisely controlled to the proposed values, health problems may occur because the control is not interactive with the thermal needs of the pigs. Better control performance may be achieved if the control is directly based on the comfort behavior of the pigs. A method of quantifying the behavior of the pigs must be provided in order to validate such an interactive control. Wouters et al. (1990) proposed a method based on image analysis of pigs. The behavior of the pigs (huddling or spreading) was judged by the occupation percentage of the pig pixels inside different preset windows in a digitized pen image. By comparing the occupation percentages with reference values, decisions could be made to either increase or decrease the environmental temperature set point. However, the method required the existence of a temperature gradient within the pig pen and depended on pig age.

The objective of this study was to evaluate the feasibility of classifying the comfort behavior of young pigs subjected to simulated production environments by using the spectral characteristics of the processed images of the pig thermoregulatory behavior (huddling and spreading) as inputs to a neural network. This method, if applied to an interactive control procedure, may improve the control performance and well-being of the animals.

The authors are **Junqing Shao,** *ASAE Student Member*, Graduate Research Assistant, **Hongwei Xin,** *ASAE Member Engineer*, Assistant Professor, and **Jay D. Harmon,** *ASAE Member Engineer*, Assistant Professor, Agricultural and Biosystems Engineering Department, Iowa State University, Ames, Iowa. **Corresponding author:** H. Xin, Iowa State University, 203 Davidson Hall, Ames, IA 50011-3080; tel.: (515) 294-9778; fax: (515) 294-2255; e-mail: <hxin@iastate.edu>.

MATERIALS AND METHODS
EXPERIMENTAL MATERIALS

Two groups of 40 piglets, 13 to 16 days old, were assigned to four environmentally-controlled chambers, with 10 pigs per chamber (1.52 m × 1.83 m), in the Livestock Environment and Physiology (LEAP) Research Laboratory of Iowa State University. Air temperatures inside the chambers were set at 24.4°C, 26.7°C, 28.9°C, and 31.1°C, respectively, for the first week, and were reduced by 1.1°C each of the following two weeks. Programmable cameras (Cannon T-70 with command back) above the perforated, transparent ceiling were used to photograph the entire floor of each chamber at 40-min

intervals. The 40-min sampling interval was considered adequate for recording the thermoregulatory behavior of huddling or spreading of young pigs (Heitman et al., 1962; Zhou et al., 1996). A detailed description of the LEAP Research Laboratory can be found elsewhere (Xin and Harmon, 1996).

BEHAVIORAL CLASSIFICATIONS

The behavioral pictures were sorted into three categories according to the position of the pigs: cold, comfortable, or too warm. When the pigs are lying down, their behavior can be classified as on chest, touching, or not touching (Geers et al., 1991). Piglets huddle together under a low environmental temperature. When the piglets took the postural position of nearly touching each other side by side, they were considered to be in the thermal comfort zone (Mount, 1968). The piglets spread apart at a high environmental temperature. Thermal comfort zone has been used as the standard for environmental control.

IMAGE PROCESSING PROCEDURES

To isolate the pigs from the environmental background (floor, feeder, and portion of the chamber walls), the raw images were processed by thresholding, edge detection, and morphological filtering. The results were binary images with the pigs in white and the background in black. In the following analysis, an image is represented by an m × n matrix A, whose elements are expressed as the gray levels denoted as $f(x, y)$ of each pixel.

Thresholding. Thresholding is one of the important approaches to image segmentation. To isolate an object from the background, a threshold T is selected. Any pixel point (x, y) with a gray level $f(x, y) > T$ is assigned as an object point, otherwise, the point is assigned as a background point.

Edge Detection. Edge detection is the most common approach for detecting meaningful discontinuities in gray level. In this study, it was used to detect the boundary between the wall and the floor of the chambers. Edges are where the first derivation of the image is at maximum or minimum.

Morphological Filtering. Morphological filtering is an image filtering technique based on the basic morphological operations of dilation and erosion (Gonzalez and Woods, 1992). It is needed for this study because of the nature of the woven-wire floor (i.e., gaps between the floor grids). The operations of dilation and erosion are defined as:

Dilation $\qquad C = A \oplus B = \{ x \,|\, (\hat{B})_x \cap A \neq \varnothing \}$

Erosion $\qquad C = A \ominus B = \{ x \,|\, (B)_x \subseteq A \}$

where $\oplus$ is the dilation operator; Θ is the erosion operator; C is the processed image; A is the image matrix; and B is the element structure matrix.

$$B_x = \{ b + x \,|\, b \in B \}$$

$$\hat{B} = \{ -b \,|\, b \in B \}$$

where b and x are the elements from sets B and C.

As shown in figure 1, a simple physical interpretation of dilation is that it dilates the object by the size of structural element. If the object has holes smaller than the structural element, the holes will be filled. By comparison, the erosion operation (fig. 1) shrinks the object by the size of the structural element. If the object has isolated sparks smaller than the structural element, the sparks will be removed.

By successively applying dilation and erosion, we can fill the internal holes of an object while keeping the outer boundary of the object unchanged. This yields a new operation called closing. Similarly, if the erosion is applied first, followed by dilation, the isolated sparks of the object could be removed; whereas, the outer boundary remains unchanged. This is the operation of opening (fig. 1). Mathematically, the opening and closing operations are expressed as follows,
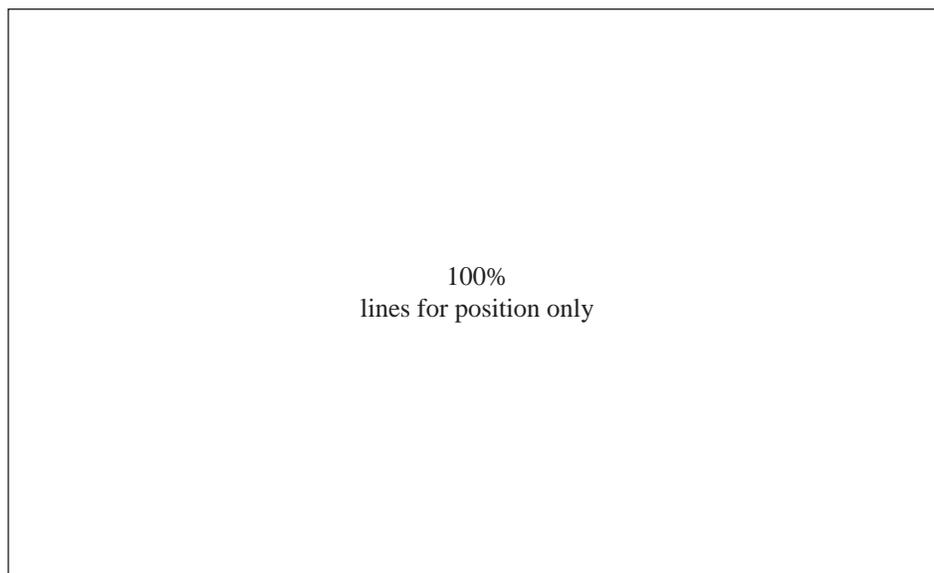
100%
lines for position only

Figure 1–Diagram of morphological filtering operation.

Opening: $A \circ B = (A - B) + B$

Closing: $A \bullet B = (A + B) - B$

Morphological filtering is the combination of opening and closing, $(A \bullet B) \circ B$ or $(A \circ B) \bullet B$. After morphological filtering, a clear image will be obtained with the internal holes filled and the isolated sparks removed.

Feature Extraction and Fourier Transformation. It is impractical to take all the pixels of a binary image as input features to a neural net because of the huge number of pixels in an image. Fortunately most of the energy of an image distributes in a small region of the frequency spectrum (Oppenheim and Schafer, 1989). In many cases, the first few Fourier coefficients are sufficient to hold most of the information of the image. In this study, the first 8×8 Fourier coefficients were selected to be the features of the images to be classified. By doing so, the dimension of the feature could be greatly reduced without affecting the reliability of correct classification. The Fourier coefficients, denoted as $F(u, v)$, are defined as:

$$F(u, v) = \sum_x \sum_y f(x, y)\, e^{-j\frac{2\pi}{N}(ux + vy)}$$

where x and y are spatial domain coordinates; u and v are frequency domain coordinates; N is the size of image, equal to max (m, n); and $f(x, y)$ is the pixel value at (x, y).

NEURAL NETWORK CLASSIFICATIONS

Neural networks are increasingly used in many engineering applications as an artificial intelligence classifier. These networks contain densely interconnected nodes via interconnective weights. A neural network must be trained before it can be used to classify the input patterns. The training of a neural network is mainly a procedure of iteratively adapting the interconnective weights until it can properly classify the input patterns (training samples). Through the process, the neurons can learn to recognize certain new patterns and the trained neural net could classify the patterns from unknown classes.

In this study, a three-layer perceptron neural network was used. Figure 2 shows the topology of this neural net. The nodes were aligned into three layers: input layer, hidden layer, and output layer. Each node in the input layer corresponds to a particular feature of the input pattern, in our case, one of the first 8×8 Fourier coefficients of the processed image. Each output node was assigned to represent a particular class of the three behavioral categories. The input pattern is classified to the class whose representative output node has the maximum value.

A back-propagation algorithm (Lippmann, 1987) was used for the neural network training. The back-propagation training algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual outputs of a multi-layer feed-forward perceptron and the desired outputs.

The following steps were needed to train a neural net:
1. Select training sample pattern X_i from each class.
2. Assign the interconnection weights w_{ij} and w_{jl} of the neural net to small random initial values.
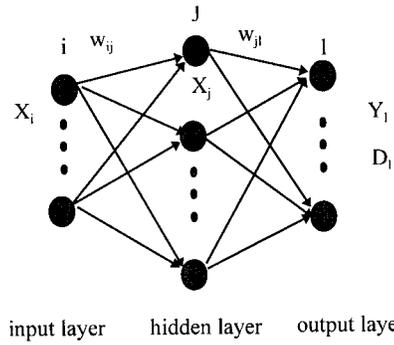

Figure 2–Diagram of a neural network.

3. Input the features of a sample pattern and calculate the actual outputs by the following equations:

$$X_j = f\left(\sum w_{ij}X_i - \theta_j\right)$$

$$Y_l = f\left(\sum w_{jl}X_j - \theta_l\right)$$

where θ_j and θ_l are offsets, which are set to small random initial values, f is a non-linear sigmoidal function in the form of:

$$f(\alpha) = \frac{1}{1 + e^{-\alpha}}$$

where α is a variable. Different values of α can be selected to speed up the learning rate of the neural net.

4. Compare the output Y_l with the desired output D_l and adjust the weights w_{ij} and w_{jl}:

$$w_{ij} \leftarrow w_{ij} + c\,\Delta_j X_i$$

$$w_{jl} \leftarrow w_{jl} + c\,\Delta_l X_j$$

where c is a constant, called learning rate, $0 < c < 1$;

$$\theta_l \leftarrow \theta_l - c\,\Delta_l$$

$$\theta_j \leftarrow \theta_j - c\,\Delta_j$$

$$\Delta_l \leftarrow Y_l(1 - Y_l)(D_l - Y_l)$$

$$\Delta_j \leftarrow X_j(1 - X_j)\sum_l \Delta_l\, w_{jl}$$

5. Input features of another pattern, and repeat steps 4 and 5 until the overall error between the outputs and the desired outputs of the training samples are minimized.

The programs used to perform image segmentation, feature extraction, and the neural network analysis were developed with Matlab, version 4.2c.

RESULTS AND DISCUSSION

BEHAVIORAL CLASSIFICATION AND IMAGE PROCESSING

In this experiment, over 2,000 behavioral pictures of the pigs were taken. Only those containing postural behaviors were eligible for the image analysis, whereas those containing motion behaviors were excluded. Among the eligible pictures, 201 representative pictures were used for training and testing the neural network system.

Three raw images showing the typical lying behaviors of the pigs under cold, comfortable, and too warm conditions are presented in figure 3. The processed images corresponding to the three raw images are shown in figure 4. For presentation purpose, the pigs are shown in black and the background in white. In these images, the floor boundary is presented and the pigs are extracted from the background. Closing and opening filtering techniques were used to remove the effects of the woven-wire floor because the spaces between floor grids and the black pigs shared the same color. Because some of the pigs were white, the same color as the chamber walls, it was hard to distinguish between the two. Consequently hand-drawn boundaries were used. After edge detection, the boundaries of the floor were separated. If the wall and the pigs had different colors, hand drawing would be avoided.

FOURIER TRANSFORMATION

The Fourier coefficient magnitudes of the images with the first 10×10 frequency elements are shown in figure 5. In order to be invariant to the viewing area of the cameras, the coefficients were normalized by the floor area (in pixel). It is clear that the first 8×8 frequency elements contain most of the image information because the coefficient magnitude near the eighth element diminishes to almost zero.

The differences in the three frequency spectra could be explained as follows. First, each spectrum had a main lobe. The lobe of the cold state was broadest, whereas the lobe of the warm state was narrowest. As it is known in Fourier analysis, a broad lobe in frequency domain implies that the object pixels are concentrated in a small region (i.e., the pigs were huddling together in our case), whereas a narrow lobe implies that the object pixels are spread out within a larger region (i.e., the pigs were lying apart from one another). Secondly, the magnitude of the peak in each graph is the first Fourier coefficient, $F(0,0)$, which represents the average pixel value. Since the image was binary, this average value was the number of object pixels divided by the total pixel number of the image, i.e., the ratio of the area occupied by the pigs with respect to the total image area. Therefore, it is
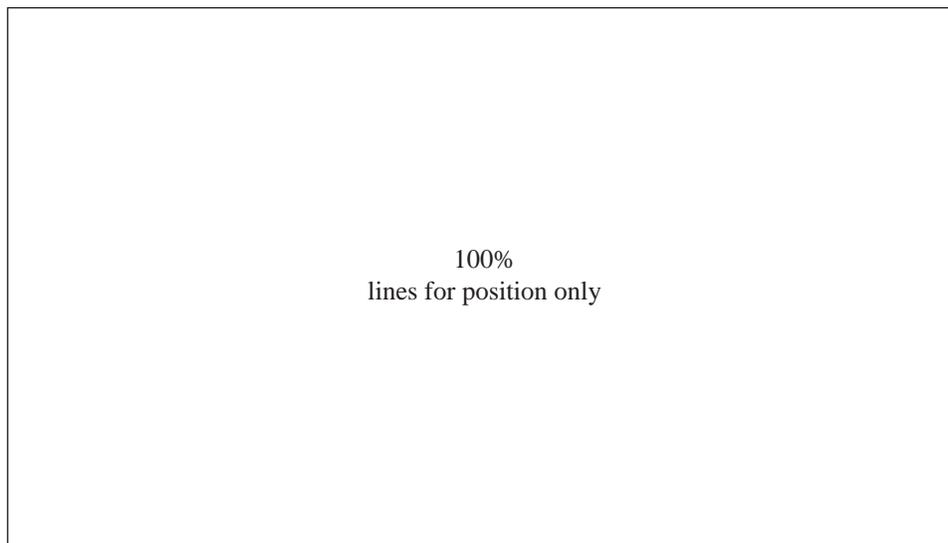
100%
lines for position only

Figure 3–Raw images of early weaned pigs resting under three environmental conditions.

Figure 4–Processed pig resting images.

100%
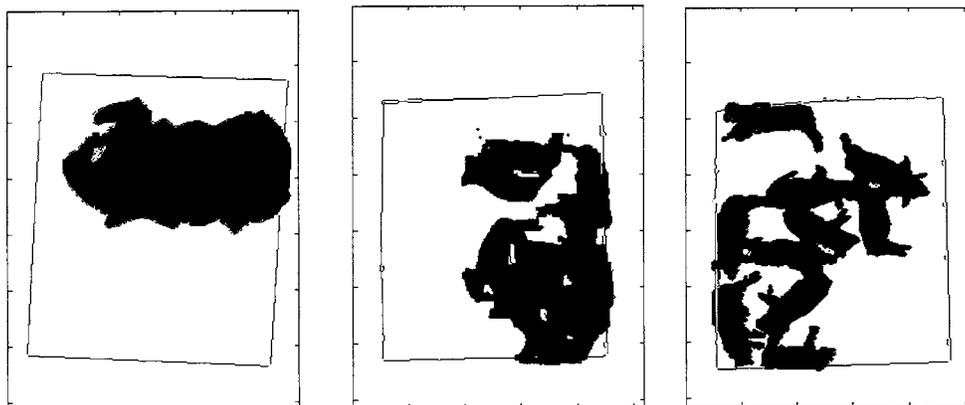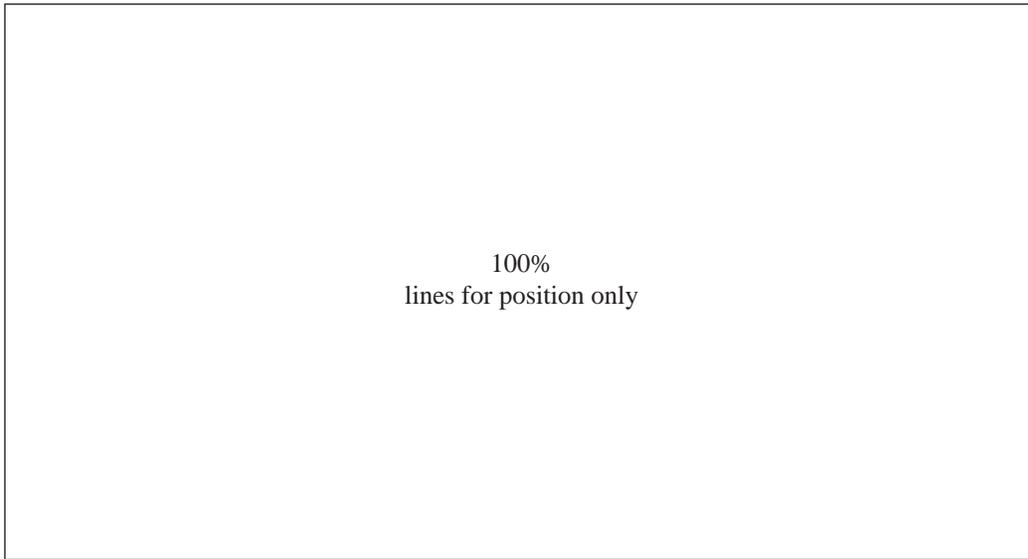lines for position only

Figure 5–Fourier coefficients of the processed pig resting images.

reasonable for the cold state spectrum to have lower value of F(0,0), compared with the comfortable or warm state. However, F(0,0) alone was not enough to classify the behavioral category because the values may be similar for pigs barely touching one another (comfortable) and pigs spreading apart (too warm). Thirdly, for the too warm state, because the pigs were lying apart form one another, the pixel values of the corresponding image changed more rapidly in the spatial domain, thus resulting in larger values in the higher frequency region compared with the other two states.

From the preceding analysis, it seems that the first 8×8 Fourier coefficients contained proper features to reflect the differences of the three behavioral states. A neural network based on these features could generate the proper classification of pig comfort behavior.

Because the Fourier coefficients were based on not only the occupation percentage, but also the geometric properties of the image, the features are nearly independent of the age or body weight of the pigs. Even though the value of F(0,0) may be affected by the body weight, the neural network could still produce the correct classification based on the other 63 coefficients and their interrelationships. Compared with the work by Wouters et al. (1990), the independence of this method from pig age or body weight would greatly simplify the classification of the animal behavior and complications of engineering design of the pig pen.

PERFORMANCE OF THE NEURAL NETWORK

This study used a three-layer neural network, sixty-four (8×8) features as input nodes, 30 nodes in the hidden layer, and three classifications (cold, comfortable, and too warm) as output nodes. The input features were normalized by the floor area (in pixels).

The results of behavioral classification by the neural network are shown in table 1 for each of the three categories. One hundred and thirty six pictures were used in the training procedure, and 65 pictures were used in the testing procedure. In reference to visual examination, the neural network properly classified 131 out of the 136 (96%) training images, and 51 out of the 65 testing images (78%).

The 136 training images consisted of 46, 48, and 42 images, respectively, from cold, comfortable, and too warm category. The training results showed that 45 out of the 46 (98%), 47 out of the 48 (98%), and 39 out of the 42 (93%) behavioral images were correctly classified for cold, comfortable, and too warm state, respectively. The 65 testing pictures consisted of 24, 22, and 19 images, respectively, from cold, comfortable, and too warm state. The testing results showed that 21 out of the 24 (87%), 19 out of the 22 (86%), and 11 out of the 19 (58%) images were correctly classified for the cold, comfortable, and too warm state, respectively. The neural network results thus showed that Fourier coefficients have a good potential to be used as features for the pig thermal behavioral classification. Meanwhile, the less distinctive spectral characteristics of behaviors between the comfortable and too warm categories led to a lower classification rate for the too warm category. The result thus calls for exploration of alternative feature selections to improve classification accuracy of the neural network. Furthermore, the pitfalls of manually segmenting the pigs and selecting eligible postural behaviors must be overcome by automatic segmentation and selection processes.

Table 1. Results of neural network classification as compared to visual examination

	Visual (No.)	NN* (No.)	NN* (%)
Training Images			
Cold state	46	45	98
Comfortable state	48	47	98
Too warm state	42	39	93
Total	136	131	96
Testing Images			
Cold state	24	21	88
Comfortable state	22	19	86
Too warm state	19	11	58
Total	65	51	78

* NN = Neural Network.

Conclusions

An innovative method of environmental control for growing swine was investigated. The method uses the spectral features of swine postural images as inputs to a neural network, which classifies the corresponding thermal environment as cold, comfortable, or too warm for the animals. The results showed that the method has great potential as an interactive control tool for improving animal well-being and production efficiency. Further development and implementation of the image processing and control algorithms and hardware are warranted.

References

Boon, C. R. 1981. The effect of departure from lower critical temperature on the group postural behavior of pigs. *Animal. Prod.* 33:71-79.

Geers, R., V. Goedseels, G. Parduyns and G. Vercruysse. 1986. The group postural behavior of growing pigs in relation to air velocity, air and floor temperature. *Appl. Anim. Behav. Sci.* 16:353-362.

Geers, R., H. Ville, V. Goedseels, M. Houkes, K. Goossens, G. Parduyns and J. Van Bael. 1991. Environmental temperature control by the pig's comfort behavior through image analysis. *Transactions of the ASAE* 34(6):2583-2586.

Gonzalez, R. C. and R. E. Woods. 1992. *Digital Image Processing*. New York, N.Y.: Addison-Wesley Publishing Company.

Heitman Jr., H., G. L. Hahn, T. E. Bond and C. F. Kelly. 1962. Continuous versus periodic observation in behavior studies with swine raised in confinement. *Animal Behavior* 10:165-168.

Lippmann, R. P. 1987. An introduction to computing with neural nets. *IEEE ASSP Mag.* (April):4-22.

Mount, L. E. 1968. *The Climatic Physiology of the Pig*. Baltimore, Md.: Williams and Wilkins.

Oppenheim, A. V. and R. W. Schafer. 1989. *Discrete Time Signal Processing*. Englewood Cliffs, N.J.: Prentice Hall Inc.

Wouters, P., R. Geers, G. Parduyns, K. Goossens, B. Truyen, V. Goedseels and E. Van deer Stuyft. 1990. Image-analysis parameters as inputs for automatic environmental temperature control in the piglets houses. *Computers and Electronics in Agriculture* 5:233-246.

Zhou, H., H. Xin and D. S. Bundy. 1996. Sampling rate for measurement of piglet thermoregulatory behavior. *Transactions of the ASAE* 39(6):2259-2260.

Xin, H. and J. D. Harmon. Responses of group-housed neonatal chicks to posthatch holding environment. *Transactions of the ASAE* 39(6):2249-2254.