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

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Summary and Implications

A new method of classifying thermal comfort of young pigs was investigated that may be used to interactively control the micro-environment. The method uses the spectral features of swine postural images as inputs to a neural network which then classifies the corresponding thermal environment as cold, comfortable, or too warm for the pigs. The results show that the method has great potential as an interactive control tool to improve swine well-being and production efficiency. Further research and implementation of the algorithms for development of the innovative, behavior-based swine environmental controller are warranted.

Introduction

Proper thermal environmental control is essential to maintain swine comfort, health, and performance. Environmental control has primarily been based on maintaining certain reference air temperatures taken from the literature. However, air temperature is only a part of the microenviornment which is also greatly contributed by factors such as air velocity and floor condition (Geers et al., 1986). Thus, although the air temperature can be precisely controlled to the proposed values, the pigs may still experience health problems because the control is not interactive with the behavior of the animals. To be interactive, a method of quantifying the behavior of the pigs must be provided (Geers et al., 1991). Wounters et al. (1990) proposed a method based on image analysis of pigs. The huddling or spreading behavior of the pigs 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 special temperature gradient within the pig pen and was dependent on pig age.

The objective of this study was to evaluate the feasibility of classifying the comfort state of young pigs by using the spectral characteristics of their postural images as inputs to a neural network.

Materials and Methods

Experimental Materials

Two groups of 40 piglets at 13 to 16 days of age were housed in four environmentally-controlled chambers, with 10 pigs per chamber (1.52 m. by 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 above the transparent ceilings were used to photograph the entire floor of each chamber at 40-minute intervals. The 40-minute sampling interval had been shown 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 setup can be found elsewhere (Xin and Harmon, 1996).

Behavioral Classifications

The behavioral images of the pigs were classified into three categories according to the position of the pigs: cold, comfortable, or too warm. The postural behaviors that correspond to the cold, comfortable, and too warm environment are characterized by huddling together, spreading apart, and nearly touching each other side by side, respectively (Mount, 1968; Geers et al., 1991). Maintaining the thermal comfort condition has been the standard for environmental control.

Image Segmentation

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

Fourier Transformation and Feature Extraction

It is impractical to include 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 by 8 Fourier coefficients were selected to be the classification 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.

Neural Network

Neural networks are increasingly used in engineering applications as an adaptive classifier. These networks contain densely interconnected nodes via interconnection 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 automatically and iteratively adapting the interconnective weights until it can properly classify the input patterns (training samples). If the training samples are representative, the trained neural net could classify new patterns from unknown classes.

In this study, a three-layer perceptron neural network was used. Figure 1 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, i.e., the first 8 by 8 Fourier coefficients of the processed image. Each output node was assigned to represent a particular class. The input pattern was classified to the class whose representative output node had the maximum value.

Figure 1-Diagram of a neural network.
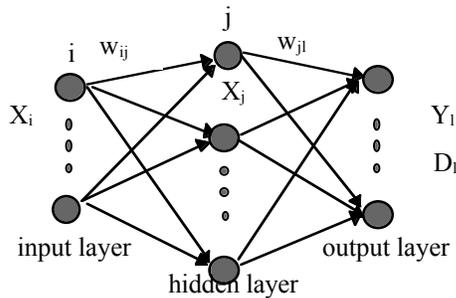
A back-propagation algorithm (Lippmann, 1987) was used for the neural network training. The back-propagation training algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual output of a multi-layer feed-forward perceptron and the desired output.

Results and Discussions

Behavioral Classification and Image Segmentation

Three raw images showing the typical postural behaviors of the pigs under cold, comfortable, and too warm conditions are shown in Figure 2. The corresponding processed images are shown in Figure 3. 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 floor because the spaces between floor grids and the black pigs were the same color. Because some of the pigs had the same white color as the chamber walls, it was difficult to distinguish between the two. Consequently hand drawn boundaries were added. After edge detection, boundaries of the floor were separated.

Fourier Transformation

The spectral magnitudes of the first 8 by 8 Fourier coefficients are shown in Figure 4. In order to be invariant to the viewing area of the cameras, the coefficients were normalized by the floor area (in pixels). It can be noted that the first 8 by 8 frequency elements contain most of the image information because the spectral 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, with the broadest lobe for the cold state and the narrowest lobe for the warm state. It is known in Fourier analysis that a broader lobe implies concentrated object pixels (huddling pigs in this case), whereas a narrower lobe implies spread object pixels (spreading pigs in this case). 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 the object pixels divided by the total number of the image pixels and equal to the ratio of the area occupied by the pigs to the total image area. Therefore, it was reasonable for the cold state spectrum to have lower values of $F(0,0)$, compared with the comfort or warm states. 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, the pigs were lying apart from 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 can be concluded that the first 8 by 8 Fourier coefficients contained proper features to reflect the differences of the three behavioral states. A neural network based on these features can give proper classification of the 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 body weight, the neural network could still produce the correct classification based on the other 63 coefficients and their interrelationships. The independence of the method from pig age and body weight will greatly simplify the classification of the animal behavior and improve environmental control.

Performance of the Neural Network

This study used: a three-layer neural network, 64 (8 by 8) features as input nodes, 10 nodes in a hidden layer, and three classifications (cold, comfortable, and too warm) as output nodes. The input features were normalized by the floor area (in pixels). One hundred thirty-eight pictures were used in the training algorithm, and 23 pictures were used in the testing procedure. The mean square error was 0.04. One hundred thirty-six out of 138 images (98%) were properly classified in the training data, and 19 out of 23 images (83%) were properly classified in the testing data. The method thus showed great potential as an interactive control tool to improve swine well-being and production efficiency. Further research and development of the control algorithms and hardware seem to be warranted.

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Figure 2-Raw images of SEW pigs resting under three environmental conditions.
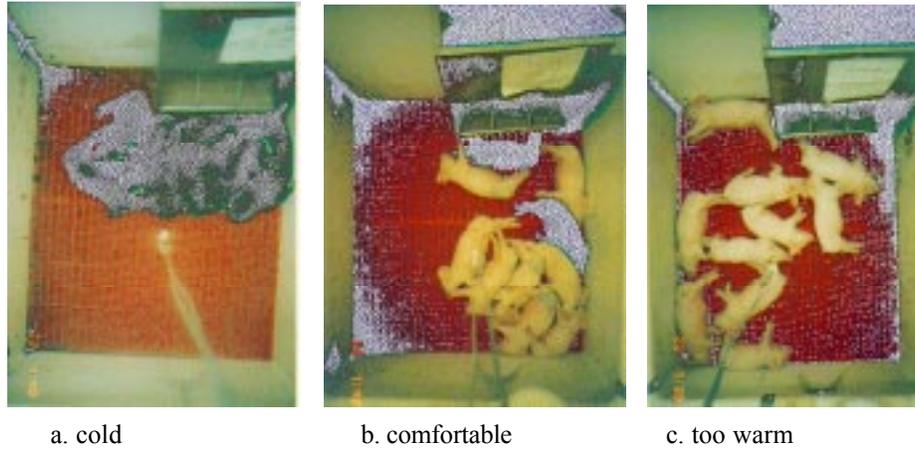

a. cold   b. comfortable   c. too warm

Figure 3-Processed SEW pig resting images shown in Figure 2.

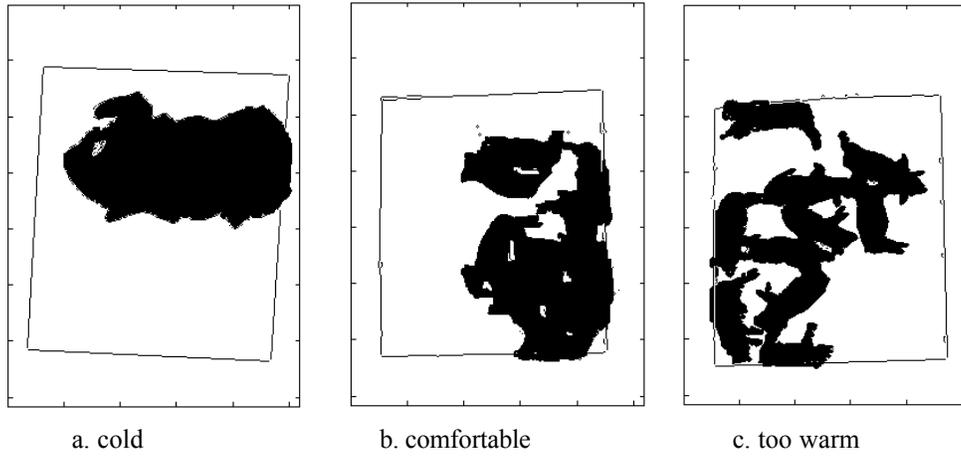a. cold   b. comfortable   c. too warm

Figure 4-Fourier coefficients of the processed SEW pig resting images shown in Figure 3.

a. cold   b. comfortable   c. too warm