A real time imaging system for assessment and control swine thermal comfort

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A real time imaging system for assessment and control swine thermal comfort

by

Bin Shao

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

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(Communications and Signal Processing)

Program of Study Committee:
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Ames, Iowa

2003

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For the Co-major Program

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For the Co-major Program
To my parents, my wife, and my daughter
with all my love.
# TABLE OF CONTENTS

ACKNOWLEDGEMENTS ........................................................................................................ vi

LIST OF FIGURES ................................................................................................................ vii

LIST OF TABLES ................................................................................................................... ix

ABSTRACT .............................................................................................................................. x

CHAPTER 1. INTRODUCTION .................................................................................................. 1

  1.1 General Statement ........................................................................................................... 1

  1.2 Environmental Factors and Their Effects on Animals’ Productivity ......................... 1

  1.3 Traditional Control Methods and Their Drawbacks .................................................... 2

  1.4 Bioimaging Method and Its Features ........................................................................... 3

  1.5 Challenges and Considerations ..................................................................................... 4

  1.6 Objective of This Study ................................................................................................. 5

  1.7 The Approach .............................................................................................................. 6

CHAPTER 2. LITERATURE REVIEW ....................................................................................... 9

  2.1 Animal Responses to Environmental Factors ............................................................. 9

  2.2 Traditional Environmental Control Methods Used in Agriculture ......................... 10

  2.3 Machine Vision and Its Applications ......................................................................... 10

  2.4 Evaluation of Bioimaging Based Environmental Control ........................................ 12

  2.5 Areas Needing Further Investigation for Real-Time Applications ......................... 15

CHAPTER 3. MATERIALS AND METHODS ........................................................................ 16

  3.1 Image Processing Algorithms ..................................................................................... 16

  3.2 Image Classification Algorithms .............................................................................. 32
3.3 System Architecture .................................................................40
3.4 System Software Design ............................................................47
CHAPTER 4 RESULTS AND DISCUSSION ..........................................57
  4.1 System Simulation with Paper Pigs ...........................................57
  4.2 System Evaluation with Live Animals .......................................61
  4.3 Discussion ........................................................................68
CHAPTER 5 CONCLUSIONS AND RECOMMENDATIONS ....................69
  5.1 Conclusions ........................................................................69
  5.2 Recommendations for Future Work .........................................69
REFERENCES ............................................................................71
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LIST OF FIGURES

Figure 1-1. Bioimaging based system control structure .................................................. 6
Figure 3-1. Original image and its binary image after global thresholding (threshold=128)... 18
Figure 3-2. Illustration of opening operations ...................................................................... 21
Figure 3-3. Erosion, dilation and opening operations ............................................................. 21
Figure 3-4. Opening and blob filling operations of images containing manure pieces ....... 23
Figure 3-5. Illustration of motion detection ......................................................................... 24
Figure 3-6. Pixel neighborhood configurations ..................................................................... 29
Figure 3-7 (a). Postural behaviors of larger pigs under cold and comfortable conditions ..... 34
Figure 3-7 (b). Postural behaviors of smaller pigs under cold and comfortable conditions... 35
Figure 3-8. Feature values of cold and comfortable conditions of different sizes of paper-cut pigs in postural behaviors as shown in figures 3-7 ...................................................... 38
Figure 3-9. Absolute distance between cold and comfortable conditions of the feature elements for postural patterns shown in figures 3-7 ................................................................. 39
Figure 3-10. Feature sensitivity analysis - averaged absolute distance. Refer to table 3-4 for feature set compositions ........................................................................................................ 40
Figure 3-11. System architecture of the real-time image processing system in this study .... 41
Figure 3-12. Matrox Meteor direct data transmission mode ................................................ 44
Figure 3-13. Matrox Meteor pseudo-live data transmission mode ....................................... 44
Figure 3-14. General flow chart of the single value operations for DT3000-PGL ............... 45
Figure 3-15. System software flowchart ............................................................................ 46
Figure 3-16. System timer process ..................................................................................... 48
Figure 3-17. Image acquisition process .................................................................49
Figure 3-18. Image segmentation process ...............................................................50
Figure 3-19. Image motion detection .......................................................................51
Figure 3-20. Feature extraction and classification process ........................................53
Figure 3-21. Updating of animal behavior database using sliding windows ...............54
Figure 3-22. Channel selection operation in pull-down menu ....................................55
Figure 3-23. System configuration dialog box ..........................................................56
Figure 4-1. Paper pigs simulation of thermal behavior under comfort condition ........58
Figure 4-2. Paper pigs simulation of thermal behavior under comfort condition ..........59
Figure 4-3. Some exceptional postural behaviors under comfortable .........................59
Figure 4-4. Classification of animal thermal image under hot condition .....................60
Figure 4-5. An exceptional postural behavior of pigs under cold condition .................60
Figure 4-6. Typical postural behavior of pigs under cold condition ............................61
Figure 4-7. Animal motion detection results- all movements were positively identified ....63
Figure 4-8. Sample image classification results .......................................................64
Figure 4-9. System performance under comfortable condition ..................................65
Figure 4-10. Processing of behavioral images for cold condition .............................66
Figure 4-11. Processing of behavioral images for hot condition ...............................67
LIST OF TABLES

Table 3-1. Initial system settings .................................................................25
Table 3-2. Feature vectors vs. cold and comfortable conditions of 10 images ........36
Table 3-3. Combinations of feature elements for sensitivity analysis .................39
Table 3-4. Average absolute distance (AAD) between cold and comfortable conditions for the different feature combinations listed in table 3-3 ..................39
ABSTRACT

A real-time bioimaging system was developed to detect movement of group-housed pigs and to classify thermal comfort state of the pigs based on their resting patterns. This dissertation describes the background, theory, image features selection and analysis, image classification techniques, system architecture, and system performance with artificial and live pigs.

The system is based on the bioimaging control method: using animal’s thermal behavior as the ultimate biosensor that is used to reflect animal thermal comfortable levels. An automated real time image processing and control system is developed that monitors animal behavior and adjusts external devices according to the image classification results.

The system contains three major components: image capture component that grabs live animal images for analysis and display purposes; image processing component that detects animal movement and analyzes its thermal behaviors; and external device control component that adjusts environmental temperature to keep the temperature within the thermoneutral zone (TNZ). The system operates on a real-time basis with multiple input channels. It also displays live animal images and system control states for selected channels.

The system contains a rich set of image features, including image moment invariants, run-length frequency, animal body occupation ratio, and animal group shape compactness that are extracted as feature vectors. Different image classification methods were also investigated and a minimum distance was adopted as the measurement to distinguish the thermal comfort states of cold vs. comfortable. The system was designed to be body weight
independent, and a sliding window was employed to update reference image feature sets so that classification is always based on the most recent information.

A great amount of work was dedicated to investigating image features and developing system software. The system was initially simulated with paper pigs, followed by testing with live pigs in groups. The testing results showed that this system was able to effectively detect animals' movement, and correctly classify animal thermal behavior into cold, comfortable, or hot conditions. The testing results also showed that the system was able to adapt itself to different animal body weights and provide correct classification results.

Rather than providing an academic prototype, the system is commercial application oriented. It provides real-time configurations so that users can modify system variables such as animal group size, image threshold value, channel selection and temperature set points on the run. To improve the system performance, the system software was developed in Visual C++/MFC on Windows platform, which optimizes the system processing time and provides user-friendly graphical interface.

**Keywords:** Animal thermoregulatory behavior, image processing, pattern recognition, real-time system, thermal comfort, environmental control, animal well-being, bioimaging.
CHAPTER 1. INTRODUCTION

1.1 General Statement

Machine vision techniques have been widely applied in agriculture applications, and most of them are based on image processing and pattern recognition theories. Some systems are even embedded with learning abilities to adapt to dynamic processes. Others take the advantage of neural networks as the classification tool to deal with nonlinear classification problems.

1.2 Environmental Factors and Their Effects on Animals’ Productivity

Environmental factors are critical in animal production processes. Animals under comfortable environmental conditions likely achieve the optimal quality and efficiency of production. Investigation of how environmental factors contribute to animal comfort levels has been a major focus of animal well-being and animal environment studies.

Extensive research has been conducted to investigate the relationships of swine behaviors and productivity to ambient temperatures. This is because air temperature directly affects animal comfort levels and thus influences the quality and efficiency of animal production; and air temperature is readily measurable. There are four modes of heat exchanges between pigs and the environment: conduction, convection, radiation and evaporation (Albright, 1990). Conduction and radiation are the dominant modes in cold conditions, whereas evaporation becomes more important in warm to hot conditions. Animals achieve the optimal production efficiency only in a certain temperature range known as thermoneutral zone (TNZ), where they have the maximum feed efficiency and body weight gain (McGlone et al., 1987, Nienaber et al., 1991, Verhagen et al., 1988). Xin and
DeShazer (1991) reported that when growing pigs were exposed to different temperature/temperature changes, their productivity was significantly different. When temperature falls outside the thermoneutral zone (TNZ), greater changes in temperature will generally lead to more reduction in the animal’s growth performance.

Besides ambient temperature, there are several other factors such as draft, radiation, humidity, group size, floor type and condition, nutrition and health status of the animal that also contribute to the animal’s thermal comfort conditions (Bruce et al., 1979; Boon, 1981; Geer et al., 1991; Riskowski and Bundy, 1990). Because the pig’s thermal condition is affected by the combined factors, a seemingly ideal air temperature might not meet the pigs’ real thermal needs.

Swine are social animals that respond to environmental conditions with different behaviors - their body language. They rest apart when they feel the environment is hot to facilitate heat dissipation. In contrast, when the environment temperature is perceived as cold, pigs huddle together to conserve body heat loss. When pigs feel thermally comfortable, they rest side by side and nearly touch one another (Mount, 1968). Therefore, according to animal resting behaviors, thermal conditions can be classified into three discrete categories: cold, warm, or comfortable conditions. This is the theoretical basis for the bioimaging control method.

1.3 Traditional Control Methods and Their Drawbacks

Most existing systems focus on algorithm development and protocol evaluations, where systems have relatively high classification rate but suffer slow system responses. Consequently, such systems are not desirable for real-time processing and control purposes.
From the control point of view, traditional methods are closed feedback loops. Thermostats are installed inside pigpens, and heating and cooling devices are switched on and off according to sensor readings to maintain the ambient temperature within a desirable range. The simplest control logic is to turn on the heating/cooling devices until the temperature reaches the set point. The advantage of this kind of control system is its simplicity and therefore low cost. But as it was discussed earlier, air temperature is not the only factor that influences animal comfort. Other factors can also affect animal behaviors and there is no measurement to determine the combined thermal condition under which the animals are exposed. The seemingly ideal temperature itself may not meet the animal’s real thermal requirements, and other factors must be taken into considerations as well. Another drawback is that most of the traditional systems adjust temperature setpoint depending on animal age and body size, with younger animals needing higher temperature settings than older ones. As the animals’ thermal needs change with growth, caretakers must adjust temperature settings according to animal age and body size.

1.4 Bioimaging Method and Its Features

Bioimaging control employs a novel theory in which animals are used as the ultimate biosensors. The rationale is that animals interact with all contributing environmental factors with particular postures as discussed above. The new bioimaging method will capture and analyze the animal postural behavior, which will be more interactive and complete than use of any single environmental factor. One prominent advantage of this system is its independence of animal age or body size. Computer imaging techniques can be used to monitor animal behaviors and adjust ambient temperatures according to the postural
behaviors. The animals will in turn reflect the adequacy of the environment through display of their postural behaviors. The disadvantage of this method is its complexity. Appropriate animal behaviors must be selected and classified into distinct categories. As the external devices are turned on/off to achieve the desired environment, temperature increment and rate of change must be carefully selected so that the system functions stably. Lastly, an automatic method must be developed to accomplish this goal.

1.5 Challenges and Considerations

Pioneer works on bioimaging method have been focusing on the feasibility investigation and algorithms development (Shao et al, 1997; Hu et al, 2000). In this study we focused on developing/implementing the assessment and control system on a real-time basis with live animals. There are some challenges that must be overcome to achieve this goal. The first challenge comes from the live animals. Unlike selected images, live animals move in performing various activities, and may change their resting patterns even at the same thermal condition. In order to classify animal behaviors effectively, image acquisition intervals must be carefully selected so that the CPU is not exhausted while enough behavioral information is captured. Too short time intervals don’t detect animal behavior changes, and complex algorithms also need more time to complete. Conversely, too long time span would miss animal behavioral changes, and consequently fail to control or maintain the thermal needs of the animals.

Another consideration in image acquisition is noise reduction, where average of images can be used to reduce white noise level. However, manure must be eliminated from the image by a defined algorithm. Motion detection is another challenge in the real world
application. Since only the images that contain animals at rest can be used to represent thermal conditions, a motion detection algorithm must be developed to select appropriate images. The challenge of motion detection partially comes from the criteria used to determine animal movement. Small movements such as animal breathing or leg kicking/stretching should be omitted, but significant movements such as position changes should be reported promptly and accurately. A carefully selected algorithm and criteria should maintain system stable while respond promptly.

The most challenging issue and the most noteworthy feature of this study is the animal body size independency. Traditional studies focus on classification of fixed size animal thermal behaviors, where time dependent changes were not considered (Shao et al., 1997; Geer. et al., 1991). Thus a system that performs well for certain age/size of animals may not apply to another group of animals. In this study, carefully selected features and the employment of self-learning ability minimized animal body size dependency. Another consideration in developing real-time commercial systems is the balance between algorithm complexity and computation time. The system should be implemented to be fast enough to respond to animal thermal behavior changes while maintaining adequate classification accuracy.

1.6 Objective of This Study

In this study, our purpose was to develop a real-time assessment and control system that monitors and classifies pig behaviors and adjusts the environmental temperature setpoints accordingly to meet the animals' thermal needs. Specifically, the system should be able to distinguish the thermal conditions of being cold, comfortable or hot based on the
animals' behaviors with a fast system response. Since animal growth is a dynamic process, the system's analysis method needs to be animal body weight or size independent, so that it can monitor animal behaviors throughout the growth cycle. In doing so, a learning ability needs to be incorporated into the system software so that it can teach itself to adapt animal size and behavioral changes over time.

1.7 The Approach

To approach this goal, the above classification theory can be accomplished automatically by computer imaging techniques. Animal images are continuously captured into image buffer. By taking complex image processing and pattern recognition algorithms, thermal behaviors of the animals can be precisely classified into one of the three thermal comfort states. This classification system can also further adjust the external devices to keep the environmental temperature inside the true TNZ. Advanced algorithms are also capable of learning animal body size changes, thus adjusting critical variables in pattern recognition algorithms. The only exception is that the classification results might fall in uncertain conditions at some points, where the images were ignored and no actions would be taken. The following diagram depicts the system structure.

Figure 1-1 Bioimaging based system control structure.
In this study, we focus on system design, image segmentation, image motion detection, image feature selection and analysis, image classification techniques, external device control algorithm, hardware implementation, and software development.

**System design:** The system is designed to operate on the Windows NT platform with user friendly interface so that users can configure and interact with the system on a real-time basis. Live animal images are also displayed on TV or computer monitor, for users observation.

**Image segmentation:** Animals are extracted from their background so that their thermal behaviors can be analyzed. Various image segmentation algorithm and their pros and cons are discussed.

**Image motion detection:** Motion detection algorithm and criteria are established to select appropriate images showing animals at rest. The selected images are then fed to image feature extraction subsystem.

**Image feature extraction:** Images are represented by carefully selected image features to improve classification performance and to eliminate the dependency of animal body size.

**Image classification:** Animal thermal behaviors are classified into different thermal conditions by their feature sets. The temperature setpoint is adjusted based on the classification result.

**External device control:** In this study, we focus on developing device control algorithms. Environmental temperatures are adjusted by adjusting/fine-tuning setpoints in the system software.
System software: The ultimate goal of this study is to provide a commercially applicable automatic control system for animal behavior assessment and control. Control algorithms and decisions are implemented in system software. System software is designed and developed such that it can be configurable with user-friendly graphical user interface (GUI). As a real-time system, the software analyzes animal behaviors and displays live animal images along with the system status.

System hardware: System hardware is integrated with third party components. We also adopt low-level drivers from hardware vendors.

A significant amount of work was dedicated to software design and development. The advantage of this system compared to other systems is that it doesn’t rely on animal body size and it can be used on a real-time environment with live animals. The body size independence eliminates the formidable work to adjust system configurations by having the system teach itself to adapt to animal body size changes. The real-time feature makes this system both academically sound and commercially practical.
CHAPTER 2. LITERATURE REVIEW

2.1 Animal Responses to Environmental Factors

Animals respond to environmental conditions with specific behaviors, and the environmental factors, on the other hand, influence animal comfortable levels and production performance. There are numerous factors that affect animal comfortable conditions such as air temperature, relative humidity, air flow velocity, floor type, nutrition, and group sizes (Bruce, 1981). The environment condition is the combination of these factors. Among these, air temperature is most important because it directly affects animal behaviors and thus production performance. Generally a seemingly ideal temperature reading might not meet animal’s real needs. All environmental factors must be considered.

Mount et al. (1974) investigated animal postural behaviors and their thermal conditions, and stated that pigs will huddle together when ambient temperature is too low. Huddling at cold environments helps to reduce the exposed body surface, thereby reducing body heat loss. On the other hand, Hahn et. al. (1987) stated that when pigs are under heat stress, they will try to stay apart and extend their bodies. The increased body exposure helps to dissipate extra heat. If the effective thermal environment is inside the thermoneutral zone (TNZ), animals will comfortably rest side by side and nearly touch each other (Boon, 1981). These thermal behaviors form the basis for the bioimaging control addressed in this study.

Environmental conditions directly affect animal production performance. Xin and DeShazer (1991) investigated pigs response to temperature changes. Their results showed that increased cyclic temperature changes tend to reduce animal performance when the mean temperature is outside TNZ. Nienaber et al. (1991) investigated the relationship between
feeding behaviors and environmental temperature. In their experiment, pigs were treated under three thermal conditions: TNZ, cold (TNZ-4°C), and extreme cold conditions (TNZ-12°C). Their study showed that as the temperature decreases, animal’s rate of eating adjusted to metabolic weight decreases. Lindvall (1981) investigated the effect of animal group size and floor materials, and revealed that animal’s average daily gain (ADG) decreases as the pig number increases in the pigpen. Verhagen et al. (1988) investigated the relationship between environment conditions and the animal metabolic rate. Pigs were treated under different combinations of temperature and draught conditions. Their study concluded that animal’s heat production increases when draught conditions were imposed.

2.2 Traditional Environmental Control Methods Used in Agriculture

As discussed above, ambient temperature is the most important factor and it is usually used as the method to control environmental conditions. This is because that temperature directly influences animal comfortable levels and it is easy to measure. The objective of this control is to maintain the environmental temperature inside the TNZ. A simple logic is to turn on heating or cooling devices by comparing the temperature reading with the setpoint. The advantage of this method is the simplicity, although the seemingly ideal temperature reading may not reflect the animal’s real thermal needs, which is the result of the combination of all the environmental factors. A more accurate method is needed.

2.3 Machine Vision and Its Applications

Various systems involving machine vision techniques have been introduced during the past decades. Steenhoek et al. (2001) reported their evaluation results of using image processing analysis to classify seed corns based on their roundness and flatness. They used
simple neural networks with backpropagation learning algorithm as classification tools. Lida et al. (2000) estimated nitrogen content possessed in rice plant using a CCD camera with band pass filters. In their study, they compared different filters (535nm and 670nm wavelength), and found out that the pictures taken with the 535 nm wavelength filters can precisely estimate the nitrogen content.

In agricultural applications, machine vision techniques are usually combined with pattern recognition methods and neural networks techniques. Wan et al. (2000) developed an automatic grain quality inspection system using three classification methods: range selection, neural network and hybrid algorithms. Their results showed that the range selection method had the highest classification rate but was computationally expensive (slow adjustment); that neural networks had advantages of fast training process but suffered from low accuracy; and that hybrid method needed more time to pass through the classification process but could achieve high classification rate. Hang and Lin (2000) proposed a methodology to estimate the geometric characteristics of big plant phalaenopsis by image processing techniques. A CCD camera was used to capture images and then boundary chain coding and Hotelling transformations were applied to calculate the geometric characteristics. Perez et al. (2000) proposed an algorithm to detect broad-level weeds in cereal crops under actual field conditions. They took near-ground color images to distinguish vegetation and background, and compared the algorithm performance with the human classification rate. Their results showed that it was feasible to use image processing techniques to estimate leaf area of weeds when the camera was moving across the field.

For many agricultural products, quality and shape are usually closely related, and pattern or shape recognition is thus one of the important applications. Ding and Gunasekaran
(1994) developed a computer-vision based feature extraction and classification system to inspect food shape. Heinemann et al. (1994) developed an image processing system to inspect and grade white Agaricus bisporus mushroom with feature extraction algorithms and neural networks. Panigrahi et al. (1998) proposed a computer vision system to classify germplasms based on their shapes. In their method, Euclidean distance and K-means algorithm were used as classification rules.

Animal monitoring and control is another major application field using image processing techniques. Hogewerf et al. (1991) proposed a simple but practical system to record images and take an objective viewing of dairy cow teats. Hu and Xin (2000) developed effective image motion detection and segmentation algorithms for behavior analysis of group-housed pigs. Shao et al. (1998) investigated image features for classification of swine thermal comfort behaviors. Chedad et al. (2000) developed algorithms to quantify the behaviors of pregnant ewes in field conditions.

2.4 Evaluation of Bioimaging Based Environmental Control

Animal behavior-based thermal comfort assessment and control system is a novel method that has the advantages of integrating all the influential factors by using the animal’s behavior as the ultimate biosensor for the environmental conditions (Xin and Shao, 1997). Previous works have been conducted to investigate the feasibility of the behavior-based assessment and control method (Geer. et al., 1991; Wouters, et al., 1990; Xin et al., 1997; Shao et al., 1997; Shao et al., 1998). However, a real-time system that is independent of animal size must be developed before such a system can be used in the industry.
Image processing techniques have been used in behavior-based thermal control systems (Geer et al., 1991; Wouters et al., 1990; Shao, 1997), and several image motion detection and segmentation methods have been developed (Yakimovsky et al., 1976; Skifstad et al., 1989; Gonzales et al., 1993; Hu and Xin, 2000). However, these methods focused on the feasibility and efficiency of image processing, computation time was not of direct concern due to their nature of off-line control.

Geer et al. (1991) studied animal thermal behaviors by machine vision. Animal occupation ratio was calculated and a certain threshold was used to serve as the classification criteria. No further study followed. This pioneer study provided a new area of computer vision and its application on animal environmental control. Needless to say, more work needs to be done to make such a system practical.

Xin and Shao (1997) reported their study of animal thermal comfort level classification by computer imaging. Animals were exposed to different temperatures, and thermal behaviors were recorded. In their study, Fourier coefficients, moments, perimeter, and area were extracted as image features and neural networks was used to classify testing images. Their naïve method resulted in a high classification rate. But it also suffered from high computation cost because of the algorithm complexity.

To improve the classification method, Xin and Hu (2000) examined another method. In this study, they investigated a new algorithm to achieve multi-threshold image segmentation. This new method not only reduced the computation time, but also significantly improved motion detection performance. Light changes were no longer a factor that affects image motion detection.
More algorithms have been developed for motion detection in image processing field such as likelihood ratio method (Yakimovsky, Y., 1976) and Fourier transform method (Gonzales et al., 1993). Skistad et al., (1989) proposed a shading model method. This method was based on that image intensity is the product of illumination and surface shading coefficient, and in a small surface area, the surface shading coefficient and illumination are regarded constant. This implied that the variance of image intensity ratio in a small area is close to zero. Thus this value was selected to compare to a predefined threshold in motion detection process.

Image features selection usually depends on application natures. Shao et al. (1997) reported that several image features such as central moment, objects parameter, and occupied area percentage are helpful in describing animal postural behaviors. They used artificial neural network as classification tool to classify images into different thermal conditions. Geers et al. (1991) proposed a method that uses the occupation ratio and statistical analysis method. Tao et al. (1995) utilized fast Fourier transform analysis to identify potatoes shape in an image processing system. Miller and Delwilche (1991) reported their success to identifying peach surface defections by applying morphological filters. Tao et al. (1995b) classified potatoes quality by calculating the color properties in a machine vision system.

Since animal behavior-based temperature control is a dynamic process, which means pigs body weight changes in their growth process, a fixed system structure is not adequate. These studies focused on algorithm development and are based on still images rather than live animal images.
2.5 Areas Needing Further Investigation for Real-Time Application

The above representative studies had established good foundations for computer imaging and its application in animal environmental control. However more work is needed to meet the industrial operation needs. Among these requirements are the classification accuracy, the classification rate, and the most importantly, the automation. In commercial productions, animal caretakers cannot watch and record animal images around the clock, and it is not necessary to take images when animals are moving around. Another challenge is that the control system should be independent of animal body weight or size. Traditional static classification methods cannot be readily applied to this dynamic process.
CAHPTER 3. MATERIALS AND METHODS

3.1 Image Processing Algorithms

3.1.1 Image format

Animal postural behavior can be represented by color or gray-level images. Color images provide more visual information, but require more complex algorithms and more computation time to process. Another format that is often used in image processing systems is binary image that is simply composed of foreground objects and a background. Gray-level digital images are composed of pixels, and each pixel is assigned to a unique value based on the image intensity depth - 1 bit, 8 bits, or 16 bits, etc. In an 8-bit gray level digital image, a pixel can have any of 256 intensity values. Color images are composed of three independent image plans representing red, green and blue (RGB) colors. Binary image is the simplest image format that only contains two pixel intensity levels – the background that is usually assigned with intensity value “0”, and the foreground that is represented by intensity value “1”. Most images we see are either color images or gray level images. In order to get binary images, global thresholding must be applied to classify image pixels into objects and background. Digital image processing is the process that manipulates the matrix that represents each image according to a certain mathematical algorithm to represent, enhance and recognize original images.

3.1.2 Image segmentation

In order to represent or express animal thermal behavior, animals must be extracted from their background. This is accomplished by an image segmentation process. In our study, the objects are nearly white-colored pigs and the image background is a black color.
commercial plastic slat floor. A captured image has 256 gray level intensities. To reduce memory requirements and improve processing efficiency, an image is first converted into a binary image that maintains all the behavior information. Several image thresholding methods have been investigated in swine behavior image processing field such as optimal multilevel thresholding (Yin et al., 1997; Hu and Xin 2000). But in a real-time system, computation time is very critical requiring a balance between algorithm complexity and computation time. Because the average background intensity is much lower than the average intensity of the pigs in this research, we employed global thresholding. Namely, pixels with intensity level equal or higher than the threshold value (in this study, it is initialized to 128, users have the flexibility to change this value in the system configuration to adapt to different environments) are converted into foreground and reassigned an intensity value 1; whereas other pixels are converted into background-intensity value 0. Figure 3-1 depicts the original image and its binary image after global thresholding.

Another possible method to accomplish image segmentation is by comparing the original background with the current captured animals-laden image. A subtraction operation is used to distinguish the objects. This method has the following inherent drawbacks: 1). it needs to maintain the reference image, and 2). it can be corrupted by noise such as manure on the floor. Since the original image would be captured before any animals are introduced into the environment, the comparison result will not be valid if later the environment settings are changed. It is also vulnerable to large noises such as manure that is neither treated as part of the original reference image nor as the objects animals. One possible solution to this problem is to keep updating background image without any animals, which in most cases is not practical.
In our method, image background updating is not necessary because in each cycle of measurement the current image is compared with its previous one for motion detection purposes. Thus when a new image is captured into the buffer, the current image replaces its previous one for the next processing step.

3.1.3 Image noise reduction

Image noise is reduced by taking the average on three consecutively captured images, and the averaged image is saved as the original image to be analyzed by the processing algorithms. Large noise objects such as manure have to be removed from the image by filtration techniques.
We can consider the captured image as a mixture of the original image \( f(x, y) \) and a noise signal that is described as \( \eta(x, y) \), with \( \eta(x, y) \) having zero mean at each pixel. Thus, the captured image can be described as \( g(x, y) \)

\[
g(x, y) = f(x, y) + \eta(x, y) \tag{1}
\]

Let's define the averaged image \( g(x, y) \) calculated by the following equation

\[
\bar{g}(x, y) = \frac{1}{M} \sum_{i=1}^{M} g_i(x, y) \tag{2}
\]

then the expected value of \( \bar{g}(x, y) \) is

\[
E\{\bar{g}(x, y)\} = f(x, y) \tag{3}
\]

This is because of the zero mean property of the noise signal. The variance and the standard deviation at any pixel can be described as

\[
\text{variance at pixel } (x,y): \sigma^2_{g(x,y)} = \frac{1}{M} \sigma^2_{\eta(x,y)} \tag{4}
\]

\[
\text{standard deviation at pixel } (x,y): \sigma_{g(x,y)} = \frac{1}{\sqrt{M}} \sigma_{\eta(x,y)} \tag{5}
\]

The above equations indicate that as the number of images included in the averaging operations increases, the variation of the processed image at any pixel decreases, and the averaged image is closer to the original image.

The average method only applies when noise observes the zero mean assumption. Manure pieces are large spots in the captured images and they must be eliminated from the image background to generate a clean image. This is accomplished by applying the current image to an opening operation and a blob filling operation.
Opening operation acts as a morphological filter, which generally smooths object contours and eliminates small objects. The operation of opening $A$ by $B$ is expressed as

$$A \circ B = (A \Theta B) \oplus B$$  \hspace{1cm} (6)

where $A$ represents the opening set, $B$ represents the opening element structure. The above equation indicates that the opening operation is actually an erosion operation of $A$ by $B$, followed by a dilation operation of the result by $B$. The erosion and dilation operation are also morphological filters, which can be expressed as follows:

Erosion  \hspace{1cm} A \Theta B = \{ x | (B_x) \subseteq A \}  \hspace{1cm} (7)

Dilation  \hspace{1cm} A \oplus B = \{ x | (\hat{B})_x \cap A \neq \emptyset \}  \hspace{1cm} (8)

Where $\hat{B}$ is the reflection of set $B$,

$$\hat{B} = \{ x | x = -b, \text{ for } b \in B \}  \hspace{1cm} (9)$$

The property of dilation operation is to extend the boundary of image $A$, whereas the property of erosion operation is to contract the boundary of image $A$. After the opening operation with appropriate iterations (there are multiple places in the system software that need to apply this operation, in noise reduction process, we set the number of iteration to 3), small pieces of manure are eliminated from the image. Figure 3-2 illustrates the opening operation.

Please also note that in figure 3-2, the left-bottom pig lost its front leg after opening operation. This is expected due to the nature of opening operation. Any objects in the image that are narrower than the mask will be eliminated. Figure 3-3 illustrates the operations involved in opening operation – erosion and dilation. In this illustration, a 3 by 3 mask was used to perform erosion and dilation operations. Figure 3-3(a) represents the original image,
figure 3-3(b) is the erosion effect, figure 3-3(c) is the dilation effect of the original image, and figure 3-3(d) is the result of opening operation on the original image. It is clear that narrow connections in the image were eliminated. Erosion shrinks the shape of objects, while dilation expands the shape of the objects.

In some images the manure may be so large that it can not be eliminated by an opening operation, and in this case we adapt a blob filling method (a blob is defined as a
group of connected foreground pixels). The blob filling acts as a special filter that selects
blobs based on their area (pixel unit) and fills with background. Figure 3-4 shows the
opening and blob filling results. In these images the small objects represent manure. After 3
iterations of opening operations with a 3 x 3 mask, most small manure areas were eliminated,
but in image 3-3(c) one bigger piece of manure remained. To eliminate bigger manure pieces,
each blob area was calculated with a pixel unit and a 1.25% of the total image area was
selected as the threshold of blobs. Any objects with area equal to or smaller than the blob
threshold were then filled as the background.

Well designed image processing algorithms can significantly save computation time.
In our study the opening and blob filling operations are implemented by calling Software
Development Toolkit (SDK) functions MimOpen() and MblobFill() respectively in the
system software with the iteration number and filling area threshold discussed above.

3.1.4 Motion detection

The purpose of motion detection is to select images showing pigs at rest because
moving pigs do not reliably reflect their thermal comfort status. There are several motion
detection techniques in image processing field such as likelihood ratio method (Yakimovsky,
Y., 1976), Fourier transform (Gonzales et al., 1993) and shading model methods (Skifstad et
al., 1989; Hu and Xin, 2000) are two examples. Unlike image restoration problems, in our
study we are interested in detecting animal movement in the captured image, rather than
restoring blurred images. The basis for our motion detection is to identify if the animals are
Figure 3-4. Opening and blob filling operations of images containing manure pieces

at the same physical location or their movements/location changes are within the tolerance
between two consecutive capturing. A simple yet effective method is desired for the real-time
control requirements. In this study we employed a method of comparing the animals' previous shape with the current shape by taking a binary XOR operation, and then determining if the changes have exceeded a predefined threshold value (1% of the total area in this study). This simple method saves computation time while maintaining satisfactory motion detection accuracy.

The binary XOR operation on two images can be described as
\[ \text{XOR}(f, g)_{x,y} = \begin{cases} 0 & \text{if } f(x,y) = g(x,y) \\ 1 & \text{if } f(x,y) \neq g(x,y) \end{cases} \]

where

\[ f = f(x, y) \]
\[ g = g(x, y) \]

are two binary images, \( x \) and \( y \) represent the pixel coordinates. After the XOR operation, the overlapping parts of the two images were filled as background (intensity 0), and the moving parts are shown as the white area (intensity 1). Then a threshold (1\% of the image area in this study) was selected to judge if movement occurred during this time interval. Figure 3-5 illustrates an example of the motion detection process.

![Figure 3-5. Illustration of motion detection](image)

(a). original image  
(b). moved image  
(c). motion detection

Image capturing frequency is another factor that affects motion detection performance. If images are taken too frequently, algorithms cannot detect movement between two consecutive images because few pixels have changed. If the time interval is too long, the system can not capture the animal movement promptly. In order to overcome this difficulty, we carefully selected 2 seconds as the time interval between two image capturing cycles. This selection was a result of trial and error, whereas the test results showed that this time
interval is short enough to provide good system response while being able to detect animal movement effectively.

Table 3-1 listed some system settings. These are the default/initial settings because the system is designed to provide users flexibility to change system configurations. Most of these threshold values are selected to achieve desired system performance. Since the raw images captured in our system have 256 density levels, and considering the black background and the white animals, the global threshold of 128 can effectively distinguish animals from their background. In opening operations, too many iterations not only affect system performance (consume more CPU cycles), but also significantly change animals group shape. Manure elimination factor was chosen based on the average size of bigger manures compared to the single animal sizes. A higher limit value was selected that should be big enough to remove manure in an image but safely small as not to eliminate animals. Motion detection factor is selected so that it can distinguish animal movement but not sensitive to animal leg kicking and belly moving when breathing, again this also comes from the experiments. System timer is critical in real-time control systems, and will be discussed in detail in the system architecture section below. One hour system sleeping time is selected so that animals can adapt to a new thermal environment and thus show the corresponding behaviors.

Table 3-1. Initial system settings

<table>
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<tr>
<th>Initial system settings</th>
<th>Values</th>
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<tr>
<td>Global threshold value</td>
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<tr>
<td>Number of iterations for opening operation</td>
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<tr>
<td>Blob factor for manure elimination</td>
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<td>Motion detection factor</td>
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<td>System waiting time after new setpoint</td>
<td>1 hour</td>
</tr>
<tr>
<td>System timer</td>
<td>2 seconds</td>
</tr>
</tbody>
</table>
3.1.5 Image features extraction

Image features represent image profiles. In our study, it is the animal resting behavior that reflects the thermal comfort levels. Feature extraction is important and in some cases are also difficult. Inadequate features cannot provide enough image information, too many features may require complex algorithm and extensive computation time, and they may even confuse the recognition system because of redundant features. Relevant features should minimize the feature dimension while providing enough image information. Shao et al. (1997) reported that several image features such as central moment, objects parameter, and occupied area percentage were helpful in describing postural behaviors of pigs. They employed artificial neural networks for classification of different thermal comfort states. Geers et al. (1991) proposed a method that used the occupation ratio only as classification criterion. Since animal behavior-based temperature control is a dynamic process, as body weight or size of the growing pigs changes with time, a fixed system structure would not be adequate. Continuous measurement of animal body weight is also not practical. Hence, features should be selected to minimize their dependence on animal age or body weight. A self-learning ability is also required to keep the recognition system adapting to changes in the observed animal behaviors.

In this study we examined several potential new features. They were:

- object compactness,
- average frequency of pixel changes from background to foreground,
- bounding box area occupation ratio,
- moment invariant, and
- various combinations of the above individual features.
The feature vector for each image can be described as:

\[ v = [c, a, f, \phi_1, \phi_2]^T \]  \hspace{1cm} (13)

where

- \( v \) is a feature point in a 5-dimensional feature space
- \( c \) is the compactness of pigs in an image
- \( a \) is the ratio of occupied area of pigs to its minimum bounding box
- \( f \) is the frequency of the pixel changing from background to foreground, also known as run-length frequency
- \( \phi_1 \) is the first moment invariant of pigs in an image
- \( \phi_2 \) is the second moment invariant of pigs in an image

Compactness \((c)\) value represents the shape of objects (pigs in this case) in an image. The more convoluted the shape is, the greater the value becomes. It has a minimum value of 1 for circles. The definition of compactness is

\[ c = \frac{p^2}{4\pi A} \]  \hspace{1cm} (14)

where \( p \) is the objects perimeter in pixel unit, and \( A \) is the closed area of the object in pixel unit. Generally pigs huddle together when feeling cold to minimize surface area exposure, which will result in a smaller compactness value. Pigs rest side by side when feeling comfortable, which will result in a larger compactness value.

Area occupation ratio \((a)\) reflects how closely objects touch one another, which is calculated as

\[ a = \frac{A}{\text{Feret} X \times \text{Feret} Y} \]  \hspace{1cm} (15)
where the $FeretX$ and $FeretY$ represent the dimension of the “minimum” bounding box (along the X and Y coordinates) of a blob in the horizontal and vertical directions. The minimum bounding box was defined by

$$FeretX = X_{\text{max}} - X_{\text{min}}$$

$$FeretY = Y_{\text{max}} - Y_{\text{min}}$$

$X_{\text{max}}$ and $X_{\text{min}}$ are, respectively, the maximum and minimum X coordinate in a blob. $Y_{\text{max}}$ and $Y_{\text{min}}$ are, respectively, the maximum and minimum Y coordinate in a blob.

Run-length frequency ($f$) represents the relative object distribution inside a blob. A higher $f$ value indicates more holes in a blob, which means the pigs are in either a comfortable or warm state. Since the blob shape or orientation can not be determined in advance, four directional calculations were chosen to generate an average value. The four directions are equally divided in the image with 45 degrees apart. These values represent the horizontal, vertical, and two diagonal direction frequencies, and the averaged value represents the overall frequency changes in the image. The four directional neighborhood configurations are represented as

for 0 degree

$$\begin{bmatrix} B & F \end{bmatrix}$$

(18)

for 45 degree

$$\begin{bmatrix} * & F \\ B & * \end{bmatrix}$$

(19)

for 90 degree

$$\begin{bmatrix} F \\ B \end{bmatrix}$$

(20)

for 135 degree

$$\begin{bmatrix} F & * \\ * & B \end{bmatrix}$$

(21)
where \( B \) stands for background pixels, \( F \) stands for foreground or object pixels, dot can be either background or object pixels. In other words, this process is to find the numbers of pixels with the specific neighborhood configurations described above. The following figure illustrates these configurations graphically.

![Pixel neighborhood configurations](image)

**Figure 3-6. Pixel neighborhood configurations**

Moments are important features in image processing. Moment invariants do not depend on body weight or rotation change of pigs in an image, and they reflect the shape of the pig groups which further reflects the pigs' thermal comfort levels. Hu (1962) discussed visual pattern recognition methods with moment invariants. Moments have specific physical and statistical meanings for images, but they are dependent on object positions. Central moments are not dependent on object positions but they are sensitive to object scales. In our case they would depend on pigs' body weight.

Seven moment invariants were developed and their potential uses had been discussed in Hu’s (1962) and Gonzalez’s (1992) research, considering their physical meanings and also concerned the time consuming calculations, we selected the first and second moment invariants in our study, the equations for moment invariants used in this study are as follows:
Central moment of order $p$ and $q$ 

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y) \quad (22)$$

Normalized central moment 

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{xx1}^{\frac{p+q+1}{2}}} \quad (23)$$

First moment invariant 

$$\phi_1 = \eta_{20} + \eta_{02} \quad (24)$$

Second moment invariant 

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad (25)$$

where $f(x,y)$ is the pixel intensity of either 0 or 1 in the binary images of this study. Hence, only the object parts ($f(x,y) = 1$) take part in the calculations. If $p=0$ and $q=0$, then $\mu_{pq} = \mu_{00} = A$, where $A$ is the projected area of the pigs.

### 3.1.6 Image features analysis

To classify animal behaviors into different thermal comfort states, image features should be sensitive to the shape of animal groups, at the same time, immune to influence by other factors such as change in body size.

Hot condition is quite easy to identify. To do so, we employed a series of morphological filters to process the image (opening and erosion operation). An appropriate order (erosion followed by opening) of applying these filters and iterations will distinguish pigs being apart from those nearly touching one another. Then a threshold value, which is the percentage of the separated blobs to the total number of pigs is used to check the blob or pig number and determine if the behavioral image belongs to warm or hot condition.

Classification of cold and comfortable conditions is more challenging, especially considering body size changes due to pig growth and different group shapes. A fixed occupation area ratio would not adapt to this dynamic process. Image features must be able to
distinguish the shape differences between comfortable and cold conditions for variable body sizes. Run-length frequency has the property of object area independence because it is determined by the frequency that pixels change from background to foreground in an image. Feeling cold, pigs will huddle, which results in a lower run-length frequency. Figure 3-7 shows large and small animal's thermal postures under different thermal conditions and table 3-2 lists the corresponding feature vectors. From the table it is clear that in both cases (larger and smaller pigs) the comfortable images have higher frequency values than the cold images.

Moment invariants are widely used in pattern recognition problems, emphasizing shape matches. Pigs display different postural patterns under different thermal conditions. Moment invariant maps each group shape into a unique value, which only depends on the shape of the group rather than the scale. This property eliminates the influence of body size. There is significant difference of the moment invariants between cold and comfortable conditions as shown in table 3-2.

Compactness is another body size independent parameter. It does not give a precise shape description but rather a degree of spatial distribution. A lower compactness value represents a more compact shape, as is the case with cold conditions. A higher value represents a more scattered distribution, corresponding to comfortable conditions. The compactness value is not sensitive to the exact group size or animal body size. It remains relatively constant for each thermal condition but distinguishable between the different conditions.

The area occupation ratio ($a$) in the minimum bounding box is less body size insensitive than the other features discussed above. But still it provides useful information
about distribution of the pigs. Lower values generally correspond to cold conditions and higher values to comfortable conditions (table 3-2).

3.2 Image Classification Algorithms

3.2.1 Classification of animal thermal behaviors

A number of image processing and pattern recognition techniques have been investigated to classify images. Among these studies, neural networks provided encouraging results. Since most of these methods focused on theoretical foundations, more improvements are needed to develop commercially applicable products. One of the drawbacks among these methods is their static structure. For example, neural networks need to be trained before it can be used to classify images. In our study, we provided a simple yet adaptive classification method, which was designed to meet the real-time system requirements.

Specifically, we employed a minimum distance method to classify cold or comfort conditions. Sliding windows were used to keep recent animal behavior information for each thermal condition category up to date. Ambient temperature sensor reading is used as the check of upper/lower limits to ensure the environment or setpoint to be in the predefined temperature zone. An alarm signal will be issued if the ambient temperature is beyond the predefined acceptable zone (e.g., TNZ). Within the acceptable zone, the image blob number is selected for identifying hot condition, and the other features focus on separating comfort conditions from cold conditions.

The complex nature of the pigs' behavior makes it impossible to express the spatial distribution of the pigs with a single feature. In our research we employed a minimum distance classification method. In this method, the distance between an unknown feature
point (which is the feature vector representing an image) and different known classes is calculated. The image under consideration is classified into the known class that has the minimum distance to it. This classification operation is expressed as

\[ I \in C_j, \text{ if } D(I, C_j) = \min \{D(I, C_i)\}, \text{ for } j = 0,1 \]

(26)

\[ D(I, C_i) = \sqrt{(I_a - C_{ia})^2 + (I_c - C_{ic})^2 + (I_f - C_{if})^2 + (I_{\theta_1} - C_{i\theta_1})^2 + (I_{\theta_2} - C_{i\theta_2})^2} \]

(27)

where \( I \) is the new image, and \( j \) represents comfortable (0) and cold class (1), \( C_i \) represents the condition that the image is classified to.

The minimum distance method can be implemented using the minimum distance between the point in the image of consideration and any point in the database of each class, or the minimum distance between the point/image of consideration and the central point of each class. Considering the irregularity of pigs' behavior, we adopted the latter method in calculating the minimum distances.

A sliding window was used in our research to learn pigs' behaviors as they grow, and to update the system database. The procedure is to keep a certain number of recent pig behaviors in a window. When a new image is classified, the new feature vector enters into the corresponding feature window as the newest data, and the oldest feature vector is discarded. The class center is updated based on the new data. The classification process is always based on the latest information. In this way, the system learns and updates the behavior changes as pigs grow.
Figure 3-7 (a). Postural behaviors of larger pigs under cold and comfortable conditions.
Figure 3-7 (b). Postural behaviors of smaller pigs under cold and comfortable conditions
Table 3-2. Feature vectors vs. cold and comfortable conditions of 10 images

<table>
<thead>
<tr>
<th>Image Number</th>
<th>Occupation Ratio ($a$)</th>
<th>Run-length Frequency ($f$)</th>
<th>Compactness ($c$)</th>
<th>Moment Invariant 1 ($\phi_1$ *10)</th>
<th>Moment Invariant 2 ($\phi_2$ *100)</th>
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<td>Avg/STD</td>
<td></td>
<td></td>
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<td>Cold Condition, Larger Pigs</td>
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<th>Occupation Ratio (a)</th>
<th>Run-length Frequency (f)</th>
<th>Compactness (c)</th>
<th>Moment Invariant 1 ((\phi_1 \times 10))</th>
<th>Moment Invariant 2 ((\phi_2 \times 100))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comfortable Condition, Smaller Pigs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>1</td>
<td>0.527</td>
<td>1.935</td>
<td>5.411</td>
<td>1.990</td>
<td>0.900</td>
</tr>
<tr>
<td>2</td>
<td>0.551</td>
<td>1.746</td>
<td>4.886</td>
<td>2.080</td>
<td>1.100</td>
</tr>
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<td>3</td>
<td>0.460</td>
<td>1.944</td>
<td>5.194</td>
<td>2.220</td>
<td>1.500</td>
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<tr>
<td>4</td>
<td>0.491</td>
<td>1.835</td>
<td>5.956</td>
<td>2.030</td>
<td>1.700</td>
</tr>
<tr>
<td>5</td>
<td>0.408</td>
<td>1.957</td>
<td>5.169</td>
<td>2.240</td>
<td>1.100</td>
</tr>
<tr>
<td>6</td>
<td>0.588</td>
<td>2.012</td>
<td>4.999</td>
<td>1.994</td>
<td>1.190</td>
</tr>
<tr>
<td>7</td>
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<td>2.012</td>
<td>5.006</td>
<td>1.995</td>
<td>1.190</td>
</tr>
<tr>
<td>8</td>
<td>0.491</td>
<td>2.220</td>
<td>6.672</td>
<td>2.002</td>
<td>1.646</td>
</tr>
<tr>
<td>9</td>
<td>0.594</td>
<td>2.075</td>
<td>5.249</td>
<td>1.992</td>
<td>1.188</td>
</tr>
<tr>
<td>10</td>
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<td>2.032</td>
<td>5.756</td>
<td>2.030</td>
<td>0.860</td>
</tr>
<tr>
<td>Avg</td>
<td>0.513</td>
<td>1.977</td>
<td>5.430</td>
<td>2.057</td>
<td>1.237</td>
</tr>
<tr>
<td>SD</td>
<td>0.067</td>
<td>0.130</td>
<td>0.552</td>
<td>0.095</td>
<td>0.289</td>
</tr>
</tbody>
</table>

3.2.2 Feature sensitivity analysis

Further analysis of image features and classification methods indicated that feature elements contribute differently to image classification performances. To normalize the contribution of each selected feature element to \(D(I,C)\), we introduced an averaged distance which is derived from equation (27) and described as:

\[
\bar{D}(I_1, I_2) = \sqrt{\frac{\sum_{j=1}^{N} (I_{1,j} - I_{2,j})^2}{N}}
\]  

(28)

where \(\bar{D}(I_1, I_2)\) is the average distance between two distinct images (cold vs. comfortable) \(I_1\) and \(I_2\), \(I_{1,j}\) and \(I_{2,j}\) are the \(j\)th feature element of image \(I_1\) and \(I_2\). \(N\) is the number of feature elements.

Figure 3-8 shows the average feature values of larger pigs and smaller pigs under cold and comfortable conditions as shown in table 3-2, and figure 3-9 presents the calculated...
distance for each feature element. From figure 3-9 we observe that the compactness element is important in distance calculation. It is quite reasonable because the compactness feature represents how close a group of pigs huddle together.

Based on the analysis of feature performances, we selected several feature combinations listed in table 3-3 for further feature sensitivity analysis, and their average distances are listed in table 3-4. Figure 3-10 provides visual comparisons.

From above analyses we conclude that different features and feature combinations perform differently in distinguishing cold and comfortable conditions. The compactness feature is the most important in distance calculation. Feature set 3, 4, and 7 are more important than other feature combinations in calculating feature distance. A fewer number of features can reduce the computation time, but may sacrifice system stability. In this research, we decided to maintain all features in our feature space.

Figure 3-8. Feature values of cold and comfortable conditions of different sizes of paper-cut pigs in postural behaviors as show in figures 3-7.
Figure 3-9. Absolute distance between cold and comfortable conditions of the feature elements for postural patterns shown in figures 3-7.

Table 3-3. Combinations of feature elements for sensitivity analysis

<table>
<thead>
<tr>
<th>Feature Set 1</th>
<th>Feature Set 2</th>
<th>Feature Set 3</th>
<th>Feature Set 4</th>
<th>Feature Set 5</th>
<th>Feature Set 6</th>
<th>Feature Set 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupation Ratio (a)</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency (f)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Compactness (c)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Moment Invariant 1 ((\phi_1))</td>
<td>✓</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Moment Invariant 2 ((\phi_2))</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
</tbody>
</table>

Table 3-4. Average absolute distance (AAD) between cold and comfortable conditions for the different feature combinations listed in table 3-3.

<table>
<thead>
<tr>
<th>Feature Set</th>
<th>Larger Pigs AAD</th>
<th>Smaller Pigs AAD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set 1</td>
<td>1.607</td>
<td>1.361</td>
</tr>
<tr>
<td>Set 2</td>
<td>1.984</td>
<td>1.620</td>
</tr>
<tr>
<td>Set 3</td>
<td>2.430</td>
<td>1.982</td>
</tr>
<tr>
<td>Set 4</td>
<td>3.362</td>
<td>2.774</td>
</tr>
<tr>
<td>Set 5</td>
<td>1.796</td>
<td>1.520</td>
</tr>
<tr>
<td>Set 6</td>
<td>2.033</td>
<td>1.740</td>
</tr>
<tr>
<td>Set 7</td>
<td>2.482</td>
<td>2.118</td>
</tr>
</tbody>
</table>
3.3 System Architecture

This real-time image processing system is composed of image capturing and digitizing component, image processing component, and peripheral device control component. They are connected to the host computer and are controlled by the system software. Several third party I/O products including device drivers and hardware board are integrated into the system to enhance its performance.

Up to four CCD cameras or three cameras plus one VCR signal channels can be interfaced with the system. Signal channels can be switched by system software while the program is running, which is very helpful when monitoring multiple object areas. Live animal images were digitized into gray level digital image format by a frame grabber (Matrox Meteor II, Matrox Electronic Systems Ltd. Canada). These digital images then serve as the raw data for the image processing algorithms and classification. Figure 3-11 shows the diagram of the system architecture.
3.3.1 System requirements

In order to monitor animal behaviors and classify images into certain thermal categories on a real-time basis, the system should meet the following requirements:

- System shall have a live image display on the computer monitor (or both computer monitor and TV monitor as needed).
- System shall be incorporated with motion detection features that distinguish pigs moving from resting conditions.
- System shall be able to access multiple channels.
- System shall be able to switch between camera input and VCR input.
- Operation and control can be switched between online and offline status.
- User should be able to configure system settings on real-time basis.
• System shall have self-learning ability, which is the key factor that makes the system independent of animal ages or body weights

• Adjustable control timer to adapt to different environmental conditions. The time interval should be consistent after it has been set. This feature is required because animals need time to adapt to temperature changes and thus adjust their behaviors.

• Live image display shall not be interrupted by image capturing, image processing, or device control processes.

Among the requirements listed above, the features that distinguish this system from other existing systems are body weight independence and self-learning ability. In most systems, the system setting/configuration is fixed until changed next time. This static system structure is not suitable for dynamic processes such as pig growth, where not only desired environmental temperature changes, but also the pig body size. Thus, the system shall be embedded with abilities to train itself to adapt to new patterns, and the training process shall not be too long to affect system processing performance.

3.3.2 Image acquisition component

The image acquisition component is composed of CCD cameras and an image grabbing board - the digitizer.

The CCD cameras monitor animal behaviors and transmit images to the image processing component. The cameras are mounted above the center of pigpens, and are connected via a multi-channel cable to the image grabbing board in the hosting PC. The resolution of the captured image is calculated by the project area divided by the image pixels.
In this study, the pigpen is 8 feet by 10 feet, and the image size is 640*480 pixels, so the calculated resolution is 0.0375 (8*12*10*12/(640*480)) inch^2/pixel.

The image grabbing board is the interface between the cameras and the image processing component - the system software. Inserted in the hosting PC, it serves as a digitizer for the input images from the cameras. There are various commercial digitizers for different purposes. In our system we adopted Matrox Meteor image grabbing board (Matrox Meteor II, Matrox Electronic Systems Ltd. Canada\(^1\)). The Matrox Meteor board is a monochrome and color PCI frame grabber. It doesn’t have on-board memory or display, but grabs images directly into the host memory or VGA frame buffer according to the system’s configuration. Meteor board supports standard CCD cameras and works with a software library (SDK) provided by Matrox Ltd.

The grabbed images can be digitized into pixels with depth of 8-bit (monochrome), 15-bit or 32-bit, and transferred directly to display memory when working with a VGA card that supports fast linear-memory accesses to its frame buffer, or transferred into a temporary buffer in the system RAM if the VGA card doesn’t support the fast linear-memory accesses. The first working mode provides fast image display; the second mode is called pseudo-live transfer, which can be viewed as real-time if the speed of transferring images from system RAM to VGA board is fast enough. Figure 3-12 and figure 3-13 illustrate the direct and pseudo-live data transmission modes. In our system we allocated 8 MB system memories for display, and adopted the 8-bit pixel depth images (256 intensity levels). This configuration provides image resolutions up to 1800 x 1440, which is adequate for our purpose.

\(^1\) Mention of product or vendor names is for presentation clarity, and does not imply endorsement by the author or Iowa State University nor exclusion of other suitable products.
Matrox Meteor PCI Bus

VGA Card

Features
• Image data transferred directly to display memory
• Doesn’t involve the host CPU

Figure 3-12. Matrox Meteor direct data transmission mode

Matrox Meteor PCI Bus

System Memory

VGA Card

Features
• Image data transferred by an intermediate host buffer
• No specific display card required
• Involves Host CPU

Figure 3-13. Matrox Meteor pseudo-live data transmission mode
3.3.3 Signal control component

The signal control component is a TD3001-PGL data acquisition board (Data Translation Co. Marlboro, MA) with device drivers. The TD3001-PGL board is connected between the host PC and a DT300-T screw terminal panel serving as the signal connector.

Figure 3-14. General flow chart of the single value operations for DT3000-PGL
This data acquisition board communicates with the system via a software interface—DataAcq Software Development Kits (SDK) provided by the vendor (Data Translation, Inc). This SDK is incorporated in the system software to control the data I/O. In our system the TD3001-PGL board functions as D/A and A/D converter.

The data acquisition board can be configured to work under different operation modes, including digital and analog data format, continuous or single value operations. We adopted the single value operation mode, because all the system operations are controlled by a system timer and during one time cycle the output signal maintains its value. Figure 3-14 illustrates the general flow chart of the single value operations.

![System software flowchart](Figure 3-15. System software flowchart)
3.4 System Software Design

The system software is developed in Microsoft Visual C++/MFC environment on Windows NT platform. Device drivers are provided by MIL32 library (Matrox Electronic Systems Ltd., Canada). System software provides real-time image display and classification with user friendly interface. Figure 3-15 depicts the system software architecture.

The system starts with initialization. Upon powering up, the system checks the communication channels, camera working status, and digitizer conditions, and initializes image feature database. The system sets default input channel to channel 0 and sends commands to the camera to start displaying animal images on the computer monitor or TV monitor. A timer is then issued at this point, which controls the processing steps.

3.4.1 System timer

As previously described, for real-time systems computation time is as critical as algorithm complexity. Adjustable computation cycle is desired so that the program can adapt to different environmental configurations.

There are generally two methods for loop control processes. The first method uses a software loop. In this method certain control conditions are checked either at the beginning of a loop or at the end of a loop. If the control conditions are \textit{FALSE}, then the program exits from the loop, otherwise it executes the commands enclosed in the loop. The other method is the system timer, where whenever a predefined time interval is exhausted, the system timer will issue a time-out signal, informing the main program to call service functions. This method is very similar to a hardware interrupt. The advantage of a system timer is that it is independent of the CPU speed, and provides precise step control. This feature makes the
system perform consistently, easy to use and flexible to adapt to different animals. Figure 3-16 illustrates the process of the system timer.

In our study, the system control is implemented by employing a system timer, which controls all the processing steps including image capturing, feature vector generating, image classification, sliding window (animal behavior database) update and system control. Appropriate selection of the time interval is a trial and error process. Too short time interval

Figure 3-16. System timer process
will interrupt the calculation process or make system oscillate; on the other hand, too long
time interval cannot respond animal behavior changes promptly and thus may not provide
accurate information. In our research we selected 2 seconds as the control cycle.

To allow animals to adapt to new temperature settings, another timer is used to count
the eclipsed time since last setpoint changes, system only outputs signals to external devices
if this waiting time is expired, in our case it is initialized to one hour.

3.4.2 Flow control of image acquisition process

Image acquisition starts immediately after system initialization, or when a new
system time cycle starts. Raw images are digitized into 256 gray levels, followed by global
thresholding to generate binary images. When a new cycle starts, 3 images were captured and

![Image Flowchart](image.png)

Figure 3-17. Image acquisition process
averaged to minimize noise. The noise-reduced image then replaces the previous image in the image buffer for the next time cycle, and is fed into the image processing algorithms. Figure 3-17 depicts this process.

3.4.3 Flow control of image segmentation process

As discussed before, the purpose of image segmentation is to extract animals from their background with a simple and fast algorithm. In our study, we adopted global thresholding method to segment the animals from their background. Opening operation is followed to remove bigger noise spots. In this process, manures are eliminated by blanking.

Figure 3-18. Image segmentation process
small blobs in the binary image, which provides a clean picture of animal postural behaviors. Figure 3-18 depicts the image segmentation process.

### 3.4.4 Flow control of image motion detection process

Image motion detection is critical and challenging, as only the images showing animals at rest can be used as classification images. There are several motion detection algorithms, including global thresholding method and multi-threshold method (Hu and Xin, 2000). In our system motion detection is accomplished by comparing current image to the previous one. This method provides fast system response and precise comparison result. Figure 3-19 depicts this process.

![Image motion detection diagram](image)

Figure 3-19. Image motion detection
3.4.5 Feature extraction and image classification

After the system has selected the appropriate image – those that show animals at rest, the next step is to conduct image pattern classification. The program extracts appropriate image features and then classifies the images into distinct categories representing different thermal conditions. The temperature set point is adjusted accordingly, and the behavior databases are updated. Since animals need time to react to the new ambient temperature setting, the system will “sleep” for 1 hour to allow animals to adjust their behaviors to the new environment. But live images will continue to be displayed that show the current animal comfort level and the system conditions.

The input channels can be switched at any time. When the program detects a channel selection message, it will automatically call the `MdigChannel()` function to switch to the selected channel.

The software implementation can be described by the pseudo code in figure 3-20.

3.4.6 Self-learning ability

In order to adapt to animal behavior changes or body weight changes, the system program is embedded with a self-learning ability, which is implemented based on a pre-built behavior database and updated using a sliding window technique.

Initially an appropriate database is used as the basis to classify animal behaviors. The initial database was established by collecting the feature profiles at different animal ages. It provided with the system and serves as the starting reference for user system. When a new classification result is produced, the system program adds the new result into the appropriate behavior database, and then deletes the oldest behavior features. The process, also known as
BEGIN
Calculate blob number in the binary image after segmentation
IF (blob number is greater than hot condition threshold)
Classify animal thermal condition as warmer/hot
Display thermal conditions
Modify set point
Turn on cooling devices (fan, etc)
ELSE
Select the largest blob
Calculate compactness
Calculate occupation ratio
Calculate the overall run-length frequency
Calculate the first moment invariant
Calculate the second moment invariant
Calculate minimum distance between feature vector of current image and those of the cold and comfortable conditions
IF (the difference between the two distances is less than 1%)
Image is classified as condition unknown
Algorithms return
ELSE
IF (the distance to the cold is less than the distance to the comfortable)
Image is classified as cold condition
Update cold condition database
Update display
Modify setting point
Turn on heater
ELSE
Image is classified as comfortable condition
Update display
Function return
ENDIF
ENDIF
ENDIF
ENDIF
END

Figure 3-20. Feature extraction and classification process

sliding window, allows the program updates the behavior database so that the classification is always based on the recent information. Figure 3-21 shows the diagram of sliding window database updating.

3.4.7 Device control logic

Adjustment of animal environmental temperatures is achieved by operation of external devices (e.g. fans, heaters). The system software outputs signals based on the image classification results to adjust the temperature set point. Current temperature is also measured and used to ensure that the temperature is within the proper range, i.e. as a sage guard. Air temperature and the hi-low limits are also displayed. If the temperature reading is too high or
Figure 3-21. Updating of animal behavior database using sliding windows

too low, the system software will issue a temperature out of range alarm regardless of the image classification results. This helps protect the system from excessively heating or cooling the environment and thus the animals.

3.4.8 Multi-channel feature

As a real-time system, it is desirable to display the animal behaviors and process images continuously. Since there may be more than one targeting pigpens, the system program should be able to monitor and display multiple images from different channels. In system software design, multi-channel display and shifting were achieved by the combination of channel selection function $MdigChannel()$ and digitizer allocation function $MdigAlloc()$ with appropriate parameters.

The $MdigAlloc()$ function sets up the data format from the input device-digitizer. In the system program we specify the data format as the default setting: RS-170, 640x480, 8 bits, 12.5MHz and analog input. Considering the possibility that we may input images from
VCR, the data format is modified as $DEFAULT+M\_VCR$. After setting up the data format, all channel images come from the same digitizer, and they are switched by specifying channel numbers. $MdigChannel()$ specifies the active channel number as input. The standard Matrox Meteor board has four input channels $M\_CH0$ through $M\_CH3$, where $M\_CH0$ can also work as a VCR input channel. A system menu is provided to allow users to select input channels. Figure 3-22 shows the channel selection pull-down menu. Using this technique, the system program can switch images between different channels, or retrieve stored images from the storage media.

3.4.9 On-line configuration

Another feature of the system is its flexibility to change the system settings and configurations at real time. The system software achieves this goal by providing on-line options and system parameter reconfigurations. All the configuration processes can be

![Figure 3-22. Channel selection operation in pull-down menu.](image)
implemented while the program is running. It is not needed to reload the system after its parameters have been changed. Figure 3-23 illustrates the system configuration process.

In the system configuration box, users can define set point values or adjustment increment for the cooling and heating processes, input number of animals in a pigpen, adjust global threshold values to convert to binary image for advanced users to manually maximize the system performance. The user also can adjust the default temperature setpoint. Besides this, the system provides the flexibility that the user can choose either camera channels when monitoring live animals or select VCR channel when analyzing animal behaviors that are recorded on a video tape. All these configuration changes become effective once the user confirms the action by pressing the OK button.

Figure 3-23. System configuration dialog box
CHAPTER 4. RESULTS AND DISCUSSION

The system was developed and evaluated in two phases. In the first phase we simulated real animals with paper-cut pigs, where we focused on the prototype establishment and assessment. In the second phase, we tested the system performance with live animal images recorded on video tape.

4.1 System Simulation with Paper Pigs

The system was first evaluated with paper pigs. Two groups of paper pigs were constructed based on real pig images. Paper pigs were arranged to simulate different thermoregulatory behaviors, and even some extreme postural patterns.

Figure 4-1 shows a typical thermal behavior when the pigs feel comfortable. Four pigs rest nearly touching one another and one pig rests apart from the group. In this situation, the image classification algorithm detected two blobs and selected the bigger blob to present the group of the pigs, and correctly classified the thermal condition as comfortable.

Figure 4-2 is another condition where one larger pig and a smaller pig stay away from a group of smaller pigs under a comfortable condition. Even though this postural pattern is more complex than the ideal pattern of resting side by side, the algorithm is still able to select the correct blob - the group of the animals and identifies the thermal behaviors as comfortable. Thus no temperature adjustment is needed.

The snapshots as shown in figure 4-3 further represent the analysis results of various animal thermal behaviors under comfortable conditions. These results confirmed the effectiveness of feature analysis and image classification algorithms described in Chapter 3.
Figure 4-1. Paper pigs simulation of thermal behavior under comfort condition

By comparing the number of blobs inside an image with the number of pigs in the pen, hot condition is relatively easy to identify. Figure 4-4 shows an example of the animal postural behavior and the classification result under hot condition.

Generally when pigs feel cold, they huddle in a single group to reduce the exposure surface area. However some images may contain exceptional postural behaviors such as those shown in figure 4-5, where a single pig is separated from the huddling group. In these situations, the image feature extraction algorithm and classification algorithm were based on the largest blob, and the results were with our expectation. Figure 4-6 shows the classification results under cold condition.
Figure 4-2. Paper pigs simulation of thermal behavior under comfort condition

Figure 4-3. Some exceptional postural behaviors under comfortable
Figure 4-4. Classification of animal thermal image under hot condition

Figure 4-5. An exceptional postural behavior of pigs under cold condition
4.2 System Evaluation with Live Animals

The system is designed for real-time thermal comfort assessment and temperature control of live animals. To evaluate and validate the system performance, three groups of young pigs weighing 3.5 kg, 7 kg, and 12 kg respectively, were used in our study. Each group of pigs were exposed to temperature changes from cold to warm conditions in the same pigpen. A video camera in conjunction with a VCR was used to capture behaviors of pigs under different environmental conditions. The recorded images were then fed into our classification system for testing.

The environmental temperature changed from 15°C to 32°C, covering the TNZ and the lower and upper critical limits. In order to get the best system performance, lighting
condition remained unchanged and a dark wire mesh metal floor was used for the pigpen. The relatively white colored pigs and the dark-colored floor provided a good contrast between the pigs and the background.

4.2.1 Motion detection performance

The system performance was evaluated by two important factors: motion detection sensitivity and classification accuracy.

As discussed above, animal movement was determined by the difference between previous image and the current image. The smaller the sensitivity value (the percentage of moving area to the whole image area), the more sensitive system responds to animal movement. The selection of the sensitivity value is a trial-and-error process. System would fluctuate if too small sensitivity values are chosen. Likewise, too larger values could not detect animal movement effectively. In our system, a MOTION_FACTOR of 0.01 results in adequate motion detection sensitivity and keeps the system functioning stably. Pig movements in our recorded video images were effectively detected and reported. At the same time, animals’ small movements such as breathing and legs kicking were ignored. Figure 4-7 shows some randomly selected motion detection images.

4.2.2 Image classification performance

Another important factor in evaluating the system performance is the image classification rate. For each group of animals, the video image contains cold, hot, or comfortable temperature conditions. Classification of these raw images showed that the system can precisely classify animal behaviors into the corresponding comfort-state categories. Figure 4-8 shows several examples of the classification results.
The database serves as the starting point. Since the image features were carefully selected to be animal body size independent, the initial database is used for all three groups of animals with different body size/weight. As the classification proceeds, new image features replace the old database points, which make the classification more accurate. To make this system ready to use in an industrial environment, the initial database should contain sufficient images features that covers various pigs' body sizes at different thermal conditions. The users don’t need to train the system or provide any custom data.

Figure 4-7. Animal motion detection results- all movements were positively identified
Figure 4-9 to 4-11 showed the internal steps and images during the image processing and classification process. From the internal images, we can see that the algorithm can clearly convert the original complex images into simple format and provide correct classification results.

Figure 4-8. Sample image classification results
Figure 4-9. System performance under comfortable condition
a). Original gray level image of live pigs

b). Binary image after global thresholding

c). Binary image after opening and blob filling

Figure 4-10. Processing of behavioral images for cold condition
a). Original gray level image of live pigs

b). Binary image after global thresholding

c). Binary image after opening and blob filling

Figure 4-11. Processing of behavioral images for hot condition
4.3 Discussion

Feature selection is the challenging and critical part in image processing and classification processes. More features might not necessarily improve system performance because redundant feature elements increase calculation time. Different feature elements have different impacts on animal behavior classification. The compactness and run-length frequency are most important in distinguishing cold and comfortable conditions based on animal postural behavior patterns. Combination of five features used in this study makes the system function stably. Minimum distance classification method works well for both small and large animals.

Each of the features used in this study can distinguish cold and comfortable conditions for a given pig body size, but a combination of these features yields more accurate and robust classification when dealing with dynamic or changing body size. Learning process makes the system keep updating its database, which overcomes the weakness of fixed structure in a dynamic process. In our real-time system we found that too short time interval (< 0.5 second) results in unstable system when dealing with pig's movement. A time cycle of 2 seconds provides good system stability and responsiveness.
CHAPTER 5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Real-time assessment and control of swine thermal comfort levels by analyzing its thermoregulatory behavior is feasible. Such a behavior-based system prototype was developed and tested in this study. The feature set investigated in this study provides adequate animal behavioral information, and can adapt to different pig body sizes. Specifically,

1. The image features employed effectively represent animal thermal behaviors under different environmental conditions.
2. The image features are proven to be animal body weight independent.
3. The image classification algorithms are effective and accurate.
4. Animal thermal behavior based real-time environment control is proven to be practical.

5.2 Recommendations for Future Work

Future work should focus on improving the system performances by investigating advanced image processing algorithms and classification methods. Some suggestions are as follows:

- Validation of the system performance on commercial swine farms.
- Dealing with a mixture of pigs with different colors.
- Implement simultaneous multiple channels control.
- Classify overall thermal condition based on the average of each channel condition for multi-channel applications.
• Evaluate tree classification method.

• Investigate more efficient features and feature combinations.

• Seeking industrial partnership to transfer the technology to the swine industry.
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