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Predictive model based on artificial neural network for assessing beef cattle thermal stress using weather and physiological variables

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ABSTRACT

The performance of feedlot cattle is adversely affected by thermal stress but the approach to assess the status of animal stress can be laborious, invasive, and/or stressful. To overcome these constraints, the present study proposes a model based on an artificial neural network (neural model), for individual assessment of the level of thermal stress in feedlot finishing cattle considering both weather and animal factors. An experiment was performed using two different groups of Nellore cattle. Physiological and weather data were collected during both experiments including surface temperatures for four selected spots, using infrared thermography (IRT). The data were analyzed (in terms of Pearson's correlation) to determine the best correlation between the weather and physiological measurements and the IRT measurements for defining the best body location and physiological variable to support the neural model. The neural model had a feed-forward and multi-layered architecture, was trained by supervised learning, and accepted IRT, dry bulb temperature, and wet bulb temperature as inputs to estimate the rectal temperature (RT). A regression model was built for comparison, and the predicted and measured RTs were classified on levels of thermal stress for comparing with the classification based on the traditional temperature–humidity index (THI). The results suggested that the neural model has a good predictive ability, with an R^2 of 0.72, while the regression model yielded R^2 of 0.57. The thermal stress predicted by the neural model was strongly correlated with the measured RT (94.35%), and this performance was much better than that of the THI method. In addition, the neural model demonstrated good performance on previously unseen data (ability to generalize), and allowed the individual assessment of the animal thermal stress conditions during the same period of day.

1. Introduction

The performance of feedlot cattle is negatively affected by high ambient temperatures, humidity, and solar radiation, which reduce the dry matter intake, increase the body temperature, and decrease the weight gain (Mader and Griffin, 2015). Previous research demonstrated a strong correlation between weather variables and animal welfare, assessed in terms of physiological responses such as body temperature (Mader, 2006; Burfeind et al., 2012; Gaughan and Mader, 2013). However, the approach to assessing the animal status traditionally includes manual and visual scoring, which is laborious, invasive, and imposes stress on the tested animals (Wathes et al., 2008).

Some indices of thermal stress based on environmental variables have been proposed (Dikmen and Hansen, 2009). One of the most used in research is the temperature-humidity index (THI) (Thom, 1959). However, the THI does not consider the individual responses of animals and breed (Eigenberg et al., 2005; Da Silva et al., 2007; Dikmen and Hansen, 2009). Furthermore, the animal thermal stress is a result of thermal energy exchange between the animals and their environment, and depends on both physiological and environmental factors (Taylor et al., 1969; Collier et al., 2006; Mader and Griffin, 2015). Thus, development of models that use non-invasive input data for predicting the thermal stress that consider, in addition to environmental factors, the physiological response of the animal, can contribute more adequately to assessment of the animal health and welfare. Such methods are likely to contribute to novel decision making systems for increasing livestock productivity and efficiency of resource involved in livestock production (Scharf et al., 2011; Dikmen and Hansen, 2009; Martello et al., 2015).

The blood flow to the surface of the skin is an important regulator of heat exchange. Animal temperature in the superficial layers of skin can

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be used for diagnosing inflammatory processes that are accompanied by changes in the peripheral blood circulation, thus affecting local and general thermal equilibria (Metzner et al., 2014). Motivated by this notion, instrumentation systems that use infrared thermography (IRT) have been considered for monitoring body surface temperature profiles and their relationship to other animal welfare traits (Wathes et al., 2008). Montanholi et al. (2008) studied the correlation between the IRT-measured temperature of different body surface areas and heat and methane production in dairy cows. Montanholi et al. (2009) demonstrated the potential application of IRT in the assessment of feed efficiency in beef bulls. A non-invasive and automated method was suggested by Schaefer et al. (2012) for the identification of the bovine respiratory disease in receiver calves, using IRT. Metzner et al. (2014) compared different algorithms for the evaluation of udder skin thermography images for the detection of acute mastitis and fever, seeking to obtain objective and valid results for future automated computer-supported processing. Martello et al. (2015) evaluated the use of IRT images as a tool for monitoring the body surface temperature of beef cattle, and its relationship to residual feed intake.

Mathematical models are frequently generated to merge several input data and predicting some specific responses from a dynamic system. In a typical biological system, its component subsystems, such as the animal thermoregulation system, and the complex interactions between them, introduce a large number of variables, which results in rather complex mathematical modelling. Recently, some predictive modelling methods based on soft computing techniques have been used for assessment of animal welfare using non-invasive sensors integrated into predictive models (Huang et al., 2010; Sousa et al., 2016). Brown-Brandl et al. (2005) designed and evaluated five different models for predicting thermal stress in cattle: two statistical models, two fuzzy inference systems, and one artificial neural network (ANN). Among these, the ANN-based method yielded the best results. Shao and Xin (2008) considered a real-time image processing system for the detection of motion and classification of the thermal stress state of group-housed pigs, based on their resting behavioral patterns. Hernandez-Julio et al. (2014) evaluated techniques for modelling the physiological responses, rectal temperature (RT), and respiratory rate of black and white Holstein dairy cows. Again, the model based on the ANN demonstrated the best performance, followed by the models based on neuro-fuzzy networks and regression. Sousa et al. (2016) proposed a fuzzy classifier that yielded better estimates of the thermal stress level, compared with the traditional THI and previously considered fuzzy-based systems.

This paper continues the approach presented by Sousa et al. (2016) for developing a non-invasive method for prediction of physiological variables related to the thermal stress state of cattle. The objective of this study was to develop and test an ANN-model to provide a prediction of animal thermal stress state using surface temperature and weather data.

2. Materials and methods

The proposed model based on ANN (neural model) for predicting physiological variables was developed and tested on two different groups of Nellore finishing cattle confined in two phases (two feedlots) for data collection. The data collected should broadly cover the problem domain including exceptions and conditions within the boundaries of the problem domain. In this sense, different numbers of animals (first phase n = 8, second phase n = 18) and data collection schemes were used applied for each group, for increasing the data heterogeneity for the ANN training. In both phases, the acquired physiological data included rectal temperature (RT), respiration rate (RR), and body surface temperature (IRT) from four body locations detailed in Sousa et al. (2016): front, ocular area, flank, and front feet. In addition, the weather data of the dry bulb temperature (DBT) and wet bulb temperature (WBT) were stored and used in modelling.

Before constructing the neural model, a statistical analysis based on Pearson's correlation was performed on the IRT data from different body locations (front, ocular area, flank and front feet) and physiological variables (RT and RR), to determine the best body location and physiological variable to use in the predictive model. The results of this statistical analysis are detailed in Sousa et al. (2016), who used the same groups of animals to develop a fuzzy logic-based predictive model.

After the data were collected and analyzed, the neural model was designed, trained, and modified as needed, for yielding accurate results. A regression model was built for comparison. The final models that were built were then run against the selected test data to generate predictions, calculate linear correlations between the measured and estimated animal responses, and evaluate the models' predictive abilities. In addition, the predicted RT (PRT) was rated for the level of thermal stress (thermal stress classification) and compared with the classification of thermal stress based on the measured RT and on the traditional THI.

2.1. Data acquisition and statistical analysis

The experiments were conducted between May (first phase) and July (second phase), 2010, at the facilities of the Faculty of Animal Science and Food Engineering (FZEA) of the University of São Paulo (USP) in Pirassununga, SP, Brazil, located at 21°57′02″S, 47°27′50″W, at a mean elevation of 630 m above the sea level. The average annual temperature in that region is 22.00 °C, with approximately 1360 mm of rain per year. In the first phase, the average temperature and relative humidity were 23.80 ± 0.37 °C (range 8.80–31.60 °C) and 70.00 ± 1.31% (range 40.00–96.10%), respectively. In the second phase, these parameters were 26.40 ± 0.15 °C (range 18.60–29.60 °C) and 39.70 ± 0.47% (range 23.90–74.90%), respectively.

The experiments were regulated according to the Institutional Animal Care and Use Committee Guidelines of FZEA/USP. The physiological data in both phases were collected daily with the cattle restrained in the squeeze chute over the shade (around 10 min), using the same tools. In the first phase, eight Nellore steers (18 month-old, 380 ± 15 kg initial body weight, and castrated) were evaluated over a period of eight days. In the second phase, eighteen Nellore steers (16–21 month-old, 334 ± 19 kg initial body weight, and castrated) were evaluated over a period of ten days. For both phases the cattle were allotted in individual pens and were exposed to natural environmental conditions. The cattle were housed in individual pens (5 × 8 m) with soil-surface, automatic water fountains and sheltered feed bunks, fed ad libitum diet.

In the first phase the measurements of RT, RR, and IRT were collected for all cattle at 7 a.m., 11 a.m., 2 p.m., and 4 p.m. In the second phase (n = 18) the same variables were measured at 7 a.m., 12 a.m., and 4 p.m. The RT was collected manually, using a digital thermometer (VMDT01, Viomed, China). The RR was measured by counting the flank movements within a period of 15 s, and the measurements were repeated three times for obtaining an average RR for the period. The IRT images were acquired using a thermographic camera (TI 20-9 Hz, Fluke Corporation, Everett, USA) with the emissivity of 0.98, at a distance of approximately 1 m from each of the four body locations (front, ocular area, flank, and front feet). The WBT and DBT data were stored using a data logger (HOBO U12, Onset Computer Corporation, USA) that was fixed at the center of the pens at 2 m above the floor, approximately at the level of the cattle head. These weather variables were automatically recorded 24 h a day, with hourly intervals. Additional details about the animals, the feeding, the facilities and the physiological data collected are described in Sousa et al. (2016).

Before performing the statistical analysis, the data (IRT, RR, TR, DBT, WBT) from measurements associated to low quality images were manually eliminated. The images were interpreted using the software FLUKE InsideIRTM 4.0 (FLUKE Corporation, EUA) and it was obtained the average temperatures for the front, flank, and front feet areas, and