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Development and evaluation of a fuzzy logic classifier for assessing beef cattle thermal stress using weather and physiological variables

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ABSTRACT

This research was carried out to develop a fuzzy logic classifier that integrates both weather and animal factors to assess individually the level of thermal stress in feedlot finishing cattle. An experiment was performed with two groups of Nellore feedlot finishing cattle for the acquisition of weather and physiological data including the average of surface temperature in different parts of the animal body using infrared thermography. A statistical analysis of the data was applied to seek the best correlation between the weather and physiological measurements and the infrared thermography (IRT) measurements in different parts of the animal body surface and to orient the construction of membership functions. A knowledge-based system was constructed from rules that associate the memberships of the input variables dry bulb temperature, wet bulb temperature and front surface infrared temperature which were found to be suitable for predicting the rectal temperature. Predicted rectal temperature was rated for the level of thermal stress and compared with the real rectal temperature and a traditional temperature–humidity index. The results indicated little correspondence between the fuzzy classifier and temperature–humidity index (29.3%), but the average rectal temperature value during the day showed great consistency (83.2%) between the fuzzy classifier and animal's response. In addition, the IRT measurements allowed an accurate assessment and classification of the individual thermal stress of animals in the same day. The proposed fuzzy classifier resulted in better estimates of the thermal stress level when compared to the traditional temperature–humidity index and fuzzy-based systems previously developed.

1. Introduction

One of the focuses of scientific and technological developments in animal production systems is currently related to improving the decision making process for increasing productivity and efficiency in resource utilization. It has long been known that climatic and environmental conditions especially have a significant impact on the performance of feedlot cattle because high ambient temperature, humidity and solar radiations reduce the performance, decrease animal comfort and, in extreme situations, can lead to the death of the animal (Collier et al., 2006; Scharf et al., 2011; Gaughan and Mader, 2013). The performance is adversely affected because conditions of increased temperature reduce the dry matter intake, increase the body temperature and decrease weight gain (Mader and Griffin, 2015).

Many indices of thermal stress considering environmental variables have been proposed (Dikmen and Hansen, 2009), and the one that is mostly used in research is the temperature–humidity index (THI) (Thom, 1959). Adjustment of the THI has been studied to better fit the prediction of thermal stress for animals, but the use of THI is limited and it does not consider the individual response of each animal and species (Brown-Brandl et al., 2005a; Eigenberg et al., 2005; Silva et al., 2007; Dikmen and Hansen, 2009). Furthermore, the thermal stress is a result of thermal energy exchange between the animals and the environment, and depends on both physiological and environmental factors (Taylor et al., 1969; Collier et al., 2006; Mader and Griffin, 2015).

Physiological responses such as respiration rate and body temperature are good indicators of animal welfare (Burfeind et al., 2012; Gaughan and Mader, 2013; Scharf et al., 2011). However, the approach to animal status assessment traditionally includes manual and visual scoring that is laborious, invasive and stressful for the animal (Wathes et al., 2008). Thus, the development of models for predicting the thermal stress that considers, in addition

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to environmental factors, the physiological response of the animal can contribute more adequately to infer the animal health and welfare (Mader, 2006; Silva et al., 2007; Dikmen and Hansen, 2009; Scharf et al., 2011).

Among the non-invasive tools, infrared thermography was studied for use in instrumentation systems, for continuous monitoring of the temperature of the body surface profiles and correlation with other animal welfare factors (Wathes et al., 2008). Montanholi et al. (2008) examined the relationship between the infrared thermography temperature of different body locations and heat and methane production in dairy cows. Schaefer et al. (2012) investigated the use of infrared thermography to non-invasively identify animals with bovine respiratory disease and examined the feasibility of automating the collection of infrared thermography data. Metzner et al. (2014) compared different algorithms for the evaluation of udder skin infrared thermography pictures for automated computer-supported processing and detection of acute mastitis and fever. Martello et al. (2015) evaluated the use of infrared thermography images as a tool for monitoring the body surface temperature of beef cattle, and its relationship with residual feed intake.

As a complement, it is important to investigate and develop a system based on non-invasive sensors integrated with soft computing techniques to allow continuous assessment of animal welfare for climate management in livestock production systems (Huang et al., 2010; Wathes et al., 2008). Brown-Brandl et al. (2005b) constructed and evaluated five different models to predict thermal stress for cattle: two statistical models, two fuzzy inference systems and one neural network. The weather data and the respiration rate collected during the experiments were applied to construct the models that use the weather data to estimate the respiration rate. The models based on soft computing tools, neural network and fuzzy logic, presented better results, but the authors noted the need for improvements to refine the prediction. Shao and Xin (2008) applied a real-time image processing system to detect movement and classify thermal stress state of group-housed pigs based on their resting behavioral patterns. Mirzaee-Ghaleh et al. (2015) observed the better performance of a fuzzy controller for monitoring and management indoor variables of a poultry house (temperature, relative humidity, and concentration of CO_2 and NH_3) when compared to a conventional on/off controller. The fuzzy system presented better performance for assessing and controlling the indoor variables with high accuracy and lower energy consumption.

This work aims to propose a novel method for predicting the thermal stress of animals by taking into account previous research efforts (Brown-Brandl et al., 2005b; Hernandez-Julio et al., 2014) which were made to develop non-invasive techniques based on their physiological responses and soft computing modeling. More specifically, a classifier of thermal stress for beef cattle based on a fuzzy logic inference system is developed. This system determines the physiological factor which predicts the thermal stress level by means of collected weather data, physiological measurements and non-invasive infrared thermography pictures of different body parts.

2. Materials and methods

A method for designing the classifier of thermal stress based on fuzzy logic was developed and applied. It consists of three main steps as shown in the flowchart in Fig. 1.

The first step corresponds to feeding cattle for a specific period for the acquisition of weather data, invasive physiological data and the average of surface temperature in different parts of the animal body using thermography.

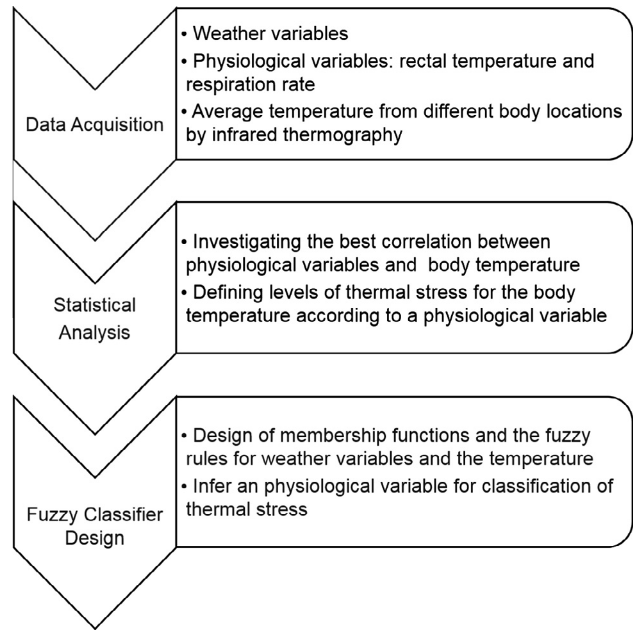

Fig. 1. Main steps proposed to design the heat stress classifier based on infrared thermography.

The second step corresponds to the statistical analysis of these data to determine which physiological variables, rectal temperature (RT) or respiration rate (RR) have the best correlation with the average infrared temperature of each body parts studied. In addition, it was sought to determine which parts of the body had a good correlation between their infrared temperature (IRT) and physiological variables (RR or RT). Thus, at this step it was possible to determine the physiological variable that would be applied while predicting output in the classifier, the part of the body whose temperature was used as a classifier input variable and the rating scale of heat stress from this input variable.

The third step corresponded to actual construction of classifier based on Fuzzy Logic (FC). A Fuzzy inference system is a soft computing tool of mapping from the given inputs to one or more outputs using Fuzzy Logic. The mapping created a basis on which decisions can be made, or patterns discerned. The process of fuzzy inference involves four main stages: (1) the membership functions associated to fuzzification; (2) the knowledge based on heuristic rules; (3) the fuzzy logic operators to aggregate the membership functions and the knowledge base; and (4) the defuzzification method (Zimmermann, 2001). The results of the second step were used for the construction of both membership functions of linguistic variables associated with the IRT as well as the linguistic output variable associated with the classifier's prediction.

2.1. Feedlot and data acquisition

The study was carried out at the facilities of Faculdade de Zootecnia e Engenharia de Alimentos (FZEA) of the Universidade 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 sea level. The average annual temperature is 22 °C, with approximately 1360 mm of rain per year. The study was conducted according to the Institutional Animal Care and Use Committee Guidelines of FZEA/USP (NRC, 2003).

The data acquisition consisted of two phases (two feedlots). The first phase was conducted to guide the development of the FC using weather and physiological measurements. The second phase was carried out to validate and enforce the FC developed. 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 between May (first phase) and July (second phase). The cattle were housed in individual pens (5 × 8 m) with soil-surface, automatic water fountains and sheltered feed bunks. The pens had additional shade for animals (20 m^2/head) which were fed a daily diet containing 85% of concentrate and 15% of roughage on an *ad libitum* basis (14.6% of crude protein, 9.9% of rumen degradable protein, and 74.5% of total digestible nutrients as estimated by Weiss et al. (1992)). The diet (dry matter basis) was composed by corn grain (41.2%), soybean meal (13.6%), citrus pulp (28.2%), crude sugarcane bagasse (15.0%), urea (0.8%), mineral mix (1.0%), ammonium sulfate (0.05%), potassium chloride (0.2%) and Rumensin® (0.03%).

At least three daily measurements were defined in order to obtain the variation of physiological variables (RT and RR) throughout the day. The schedule for measurements was adjusted according to the animal handling labor work during their placement into the squeeze chute. In the first phase, the small number of animals ($n = 8$) allowed four daily measurements. However, in the second phase, three daily measurements were defined due to the increased labor work of handling 18 animals. The measurements of RT, RR and IRT of all animals in the first phase were collected daily at 07h00, 11h00, 14h00 and 16h00. The same variables in the second phase were collected daily at 07h00, 12h00 and 16h00.

The RR was measured by counting the flank movements within a time period of 15 s. The procedure was repeated three times for obtaining an average for the 15 s period. This average was used to calculate movements per minute. The RR was measured with the animals in their barn, just before the IRT and RT measurements which were collected with the bulls restrained in the squeeze chute. RT was manually collected with a digital thermometer (Viomed® – VMDT01), simultaneously with IRT.

Infrared images were collected using a camera (TI 20-9 Hz – Fluke, Fluke Corporation, Everett, WA, USA) and the emissivity value used was 0.98. Four body locations were of interest for this study: front, ocular area, flank, and front feet (Fig. 2). The animals were brought individually from their pens and placed in the shade for taking thermography images. The IRT were taken at a distance of approximately 1 m from each of the body locations studied. The images were interpreted using the software FLUKE InsideIRTM 4.0 (FLUKE Corporation, EUA). The IRT traits defined in this study were the average temperature of a specific shape of each body location photographed (Fig. 2a, b and d), except the ocular area, therefore defining a sub-area of each image. For the ocular area (Fig. 2c), the IRT trait was the maximum temperature within it. The total number of measurements in the first phase was 256 of which 33 thermographic images were dropped from analysis due to the low quality of the images and therefore low reliability of the temperature values. In second phase, were obtained 540 measurements and all of them were used to validate the classifier.

A data logger (HOBO® U12) was installed at the center of the pens at 2 m above the floor, approximately at the same level of the animals head. Among other weather data, dry bulb temperature (DBT, °C) and wet bulb temperature (WBT, °C) were considered for this study based on the several research results that show the high correlation between these variables and the thermal stress (Mader, 2006; Dikmen and Hansen, 2009). These variables were automatically recorded 24 h a day at hourly intervals. In the first phase, the average DBT and relative humidity (RH) were 23.8 ± 0.37 °C (range 8.8–31.6 °C) and 70 ± 1.31%, respectively. In the second phase, the average DBT and RH were 26.4 ± 0.15 °C (range 18.6–29.6 °C) and 40 ± 0.47%, respectively.

2.2. Statistical analysis and definition of thermal stress levels

Pearson's correlations were computed to evaluate the association between IRT of different body locations (front, ocular area, flank and front feet) and physiological variables (RT and RR) and to determine the IRT most related to them. With similar purpose, correlations between IRT and DBT as well as WBT were computed and used to determine the lags between these inputs. All analyses were performed using the SAS System software 9.3 (SAS Institute Inc., Cary, NC, USA). Therefore, at this step, the following factors were determined: the physiological variable to be predicted as the output of the fuzzy inference system and the part of the body and its temperature to be used as its input.

The levels of surface temperature corresponding to low, medium or high heat stress are not well established in the literature. Therefore, the rating scale of heat stress from the input variable IRT was determined from its amplitude within the data set, based on a two-step process: (1) definition of the thermal stress levels (or classes) of IRT according to the ranges of the physiological parameter (RT, RR) reported in the literature (Kolb, 1987; Hahn, 1999; Kadzere et al., 2002; Mader, 2006); (2) creation of the corresponding IRT classes according to the received correlations between the IRT and physiological parameters from the statistical analysis performed. The intervals of temperatures obtained by the IRT were ranked into three levels with regard to the fuzzy terms: Low, Medium and High; and into four levels of thermal stress: normal, alert, danger and emergency. The concept of fuzzy terms is presented in Section 2.3.

2.3. Design of the classifier

The FC designed was composed of two modules: an inference system based on fuzzy logic for predicting a physiological variable, and a sub routine that classifies the output of the inference module into the already defined four levels of thermal stress.

The inference module was implemented through the Fuzzy Logic Toolbox from Matlab software version R2010b (Mathworks Inc., USA) according the Mamdani method. Mamdani's fuzzy inference is the most common model that can be applied to guide the construction of the membership functions and the fuzzy rules. It is supported by a formal methodology to transfer human experiences or knowledge to the inference system. Linguistic variables are used to compose fuzzy sets, and simple and intuitive conditional statements (fuzzy rules or knowledge-based) that, after the aggregation process, generate a fuzzy set for each output variable that needs defuzzification (Zimmermann, 2001).

Triangular and trapezoidal shapes were used to compose the membership functions for the inputs and outputs. The 'fuzzy shape initially set per variable, their domains and the degree of overlap between neighboring sets as well as the fuzzy knowledge-based sets were achieved through the results of statistical analysis, literature review and an intuitive understanding of the output prediction. Following that, the model based on the fuzzy system was run (simulated) a few times to fine-tune the knowledge base and membership functions.

All knowledge bases used the operator AND for proposition rules with three inputs and one predicted physiological output:

$$\text{if } A_{\text{DBT}} \text{ is } B_1 \text{ and } A_{\text{WBT}} \text{ is } B_2 \text{ and } A_{\text{IRT}} \text{ is } B_3 \text{ then } A_{\text{predicted}} \text{ is } B_4,$$

where A_{DBT}, A_{WBT}, A_{IRT} and $A_{\text{predicted}}$ are linguistic variables related to DBT, WBT, IRT, and the predicted physiological output, respectively, and B_1, B_2, B_3, B_4 are fuzzy terms.

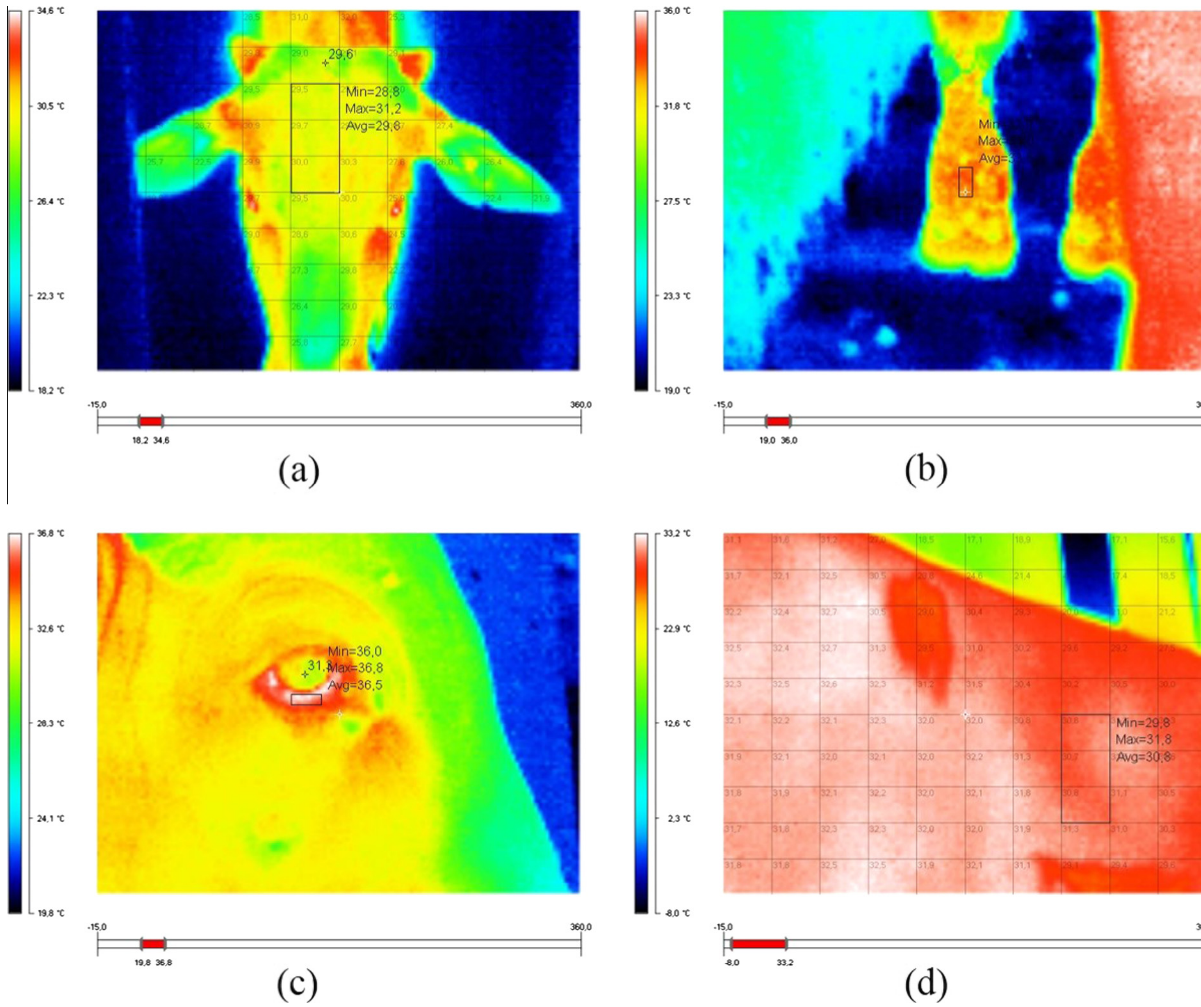

Fig. 2. Illustrative infrared images of the (a) front, (b) feet, (c) ocular area and (d) flank. The specific shapes of each body location used for deriving the infrared temperatures are also shown.

The aggregation stage that was implemented for those statements is the Max–Min technique that sets the inputs via the "max imum" function and creates outputs via the "minimum". The final stage of the fuzzy inference system is the determination of the expected crisp value by a process known as defuzzification. The Centroid defuzzification is the most commonly used technique and it was chosen as the defuzzified values have a tendency to change smoothly around the output fuzzy value, that is, changes in the fuzzy set topology from one model frame to the next, commonly result in smooth changes in the predicted value (Zimmermann, 2001).

2.4. Evaluation and validation of the classifier

The FC performance was evaluated in two ways: (1) by comparison between the predicted value of the physiological variable with its measured value using the linear correlation; (2) by comparison between the thermal stress classification obtained by the FC with the classification obtained according to the traditional temperature–humidity index (THI) proposed by Thom (1959). Values of the THI were determined for every time interval by using

$$\mathrm{THI} = 0.72 \times (\mathrm{DBT} + \mathrm{WBT}) + 47 \tag{1}$$

THI thresholds that were used in the present study to classify into heat stress levels were the same adopted by Livestock Weather Safety Index (Thom, 1959; Eigenberg et al., 2005), that categorized THI as normal ($\mathrm{THI} \leqslant 74$), alert ($74 < \mathrm{THI} \leqslant 79$), danger ($79 < \mathrm{THI} \leqslant 84$) and emergency ($\mathrm{THI} > 84$).

The values of the measured and predicted physiological variables were classified into four categories: normal, alert, danger and emergency (Section 2.2). Thereby, the frequency distribution and coincidence (%) were used to summarize the distribution of values in the categories and to allow a comparative analysis between the levels of thermal stress which correspond to the THI, FC and the measured physiological variables. This methodology (comparative analysis) was applied to both phases of the experimental procedure. On one hand, the data obtained from the first phase ($n = 8$) was used to evaluate the performance of the FC regarding the detection of thermal stress. On the other hand, the measurements from the second group of animals ($n = 18$) were used for the validation of the FC.

3. Results and discussion

3.1. Data analysis

The correlations between physiological and weather variables from the first group of animals are presented in Table 1. Overall, physiological traits were positively correlated with DBT and WBT. The IRT traits were better correlated (0.97–0.80) to the

Table 1
Correlations (r) between infrared temperature traits of different body parts (IRT), physiological variables (RT and RR) and weather variables (DBT and WBT).

Traits	r_{DBT} (p value)	r_{WBT} (p value)
IRT – Front	0.97 (0.0001)	0.86 (0.0001)
IRT – Eyes	0.92 (0.0001)	0.80 (0.0001)
IRT – Feet	0.95 (0.0001)	0.83 (0.0001)
IRT – Flank	0.93 (0.0001)	0.85 (0.0001)
RT	0.78 (0.0001)	0.66 (0.0001)
RR	0.58 (0.0001)	0.60 (0.0001)

weather traits (DBT and WBT) than the physiological traits (RT and RR) (0.78–0.58). Considering all IRT traits, front temperature had the highest correlation with DBT (0.97) and WBT (0.86).

The relations between the RT and RR with IRT traits were also studied by Pearson's correlations (r) as shown in Table 2. For all parts of the body, the surface temperatures observed were positively associated with RR and RT.

The data in Table 2 indicate that an increase in these temperatures is linked to an increase of RR and RT. Similar to these results, Collier et al. (2006) and Martello et al. (2010) found a positive correlation between RR and IRT ($r = 0.73$ and $r = 0.64$, respectively) and between RT and IRT ($r = 0.73$ and $r = 0.55$, respectively). Considering all IRT traits, the IRT front had the highest correlation with RT ($r = 0.79$). Previous studies (Kessel et al., 2010; Mccafferty, 2007) considered regions of the head (i.e., brain) as an indicator of core temperature because of its proximity to the brain, which houses the central nervous system and is responsible for body temperature regulation (Weschenfelder et al., 2013).

From the statistical results (Tables 1 and 2), RT, which presented the best correlation with IRT and weather variables, was chosen to be applied as the predicting output by the fuzzy inference system and IRT of the front was chosen as an input physiological variable in the FC. The predicted output from fuzzy inference system in this study is called PRT (Predicted Rectal Temperature).

The next step was defining intervals of heat stress for the IRT front. Body temperatures taken closer to external surface are subject to the influence of environmental temperatures and are less stable than deeper body temperatures such as RT. As mentioned earlier, the surface temperature limit values indicating presence of stress for the cattle are not well established in literature. In previous studies, Berry et al. (2003) and Montanholi et al. (2008) found IRT temperatures of different body sites and observed different patterns of temperature depending on the body region available. In this study, the interval of heat stress for IRT front was obtained by considering the ranges of RT values corresponding to the levels of heat stress for cattle which are best established in the literature (Table 3).

3.2. Fuzzy logic classifier

The membership functions μ_{DBT} and μ_{WBT} shown in Fig. 3a and b are, respectively related to the weather inputs DBT and WBT. They are composed of three fuzzy terms Low, Medium and High. The ranges of IRT shown in Table 3 were applied to elaborate the membership function μ_{IRT} presented in Fig. 3c.

Table 2
Correlations (r) between infrared temperature traits of different body parts (IRT) and physiological variables (RT and RR).

Traits	r_{RT} (p value)	r_{RR} (p value)
IRT – Front	0.79 (0.0001)	0.63 (0.0001)
IRT – Eyes	0.77 (0.0001)	0.55 (0.0001)
IRT – Feet	0.72 (0.0001)	0.60 (0.0001)
IRT – Flank	0.76 (0.0001)	0.63 (0.0001)

Table 3
Classification of levels of heat stress of beef cattle due to the rectal temperature ranges (RT) and the infrared temperature of front of animals (IRT front).

Levels of thermal stress	RT[a], °C	IRT, °C
Normal	RT < 39.1	IRT < 35.0
Alert	39.1 ⩽ RT < 39.5	35.1 ⩽ IRT < 35.4
Danger	39.5 ⩽ RT < 40.5	35.4 ⩽ IRT < 36.5
Emergency	RT ⩾ 40.5	IRT ⩾ 36.5

[a] Kolb (1987).

The central value of the range of IRT between 35.10 °C and 35.40 °C (Table 3) was selected as the central point of the term Medium, associated with 1.0° of membership and with a range of uncertainty of ±1.25 °C around this center point (total range is 34.00–36.50 °C). Thus, the term Medium has some complementary values for degree of membership with the term Low (left width) in the range of 34.00–35.25 °C and with the term High (right width) in the range of 35.25–36.50 °C.

The limit points 39.10 °C, 39.40 °C and 40.50 °C for the RT showed in Table 3 were applied to construct the membership functions μ_{PRT} related to the physiological variable output PRT. As shown in Fig. 4, it is composed of five fuzzy terms: Low, Medium-Low, Medium, Medium-High and High.

For constructing the membership function μ_{PRT}, the central value of the range between 39.10 °C and 39.40 °C (Table 3) was chosen as center point of the term Medium and associated with 1.0° of membership with a range of uncertainty of ±1.25 °C around this center point (total range is 38.00–40.50 °C). This range was not just associated with the Medium term but also the terms Medium-Low and Medium-High as seen in Fig. 4. Thus, the Medium term has some complementary values of degree of membership with the Medium-Low (left width) and Medium-High (right width). Similarly, the term Medium-Low has some complementary values of degree of membership with the term Low and the term Medium-High has some complementary values of degree of membership with the term High.

The fuzzy inference system consists of 28 linguistic rules (knowledge base) related to the fuzzy sets (membership functions) to define the relation between the inputs WBT, DBT and IRT to the PRT output. The set of rules is shown in Table 4.

3.3. Evaluation of the classifier

The linear correlation between the RT and PRT, as shown in Fig. 5, was used to evaluate the performance of the model in predicting the rectal temperature.

The simulation allowed the fine-tuning of the modeling and made it possible to obtain 0.71 as the value for correlation coefficient (Fig. 5). The robust correlation shows the feasibility of the application of the Mamdani method associated with the Max–Min technique, the AND aggregation operator and the centroid defuzzification process. Furthermore, the result of this correlation (0.71) is considerably better than the result obtained in the work of Brown-Brandl et al. (2005b) ($r = 0.52$) that evaluated, among other methods, a fuzzy inference model based on Mamdani method for prediction of RR. In addition, the present study employed three inputs for the inference process while Brown-Brandl et al. (2005b) used five inputs that made the model construction more complex by the increment of membership functions with a continuous increment in the number of knowledge-based rules.

To verify the potential of the FC as thermal stress classifier for cattle, the PRT related to each set of measurements from the first confinement ($n = 8$) was classified in levels of thermal stress according to Table 3 and compared with the THI classification.

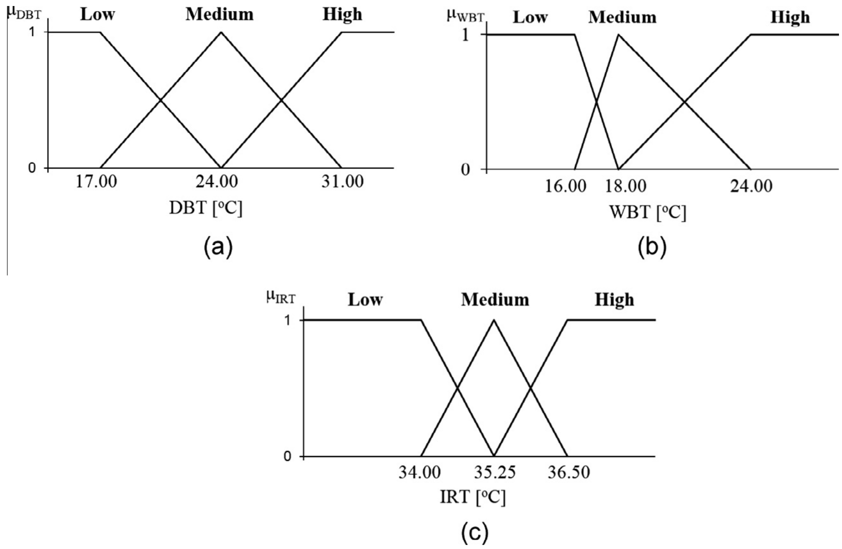

Fig. 3. Membership input functions for: (a) dry bulb temperature (DBT); (b) wet bulb temperature (WBT); (c) infrared temperature of the animal front surface (IRT).

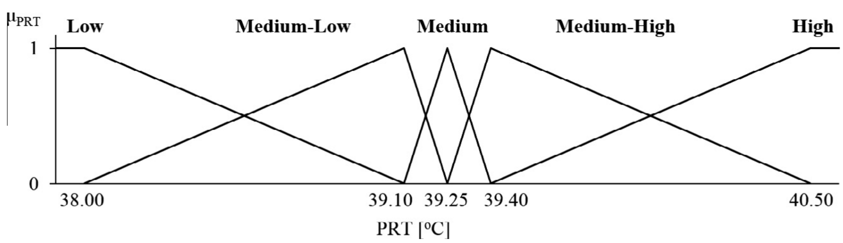

Fig. 4. Membership output function for the predicted rectal temperature (PRT).

Table 4
Set of rules for the fuzzy inference system. If the set of conditions are used as inputs (first three columns), then the model predicts the rectal temperature (last column).

if Dry bulb temperature	and Wet bulb temperature	and Infrared temperature	then Predicted rectal temperature
Low	Low	Low	Low
Low	Low	Medium	Medium-Low
Low	Low	High	Medium-Low
Low	Medium	Low	Low
Low	Medium	Medium	Low
Low	Medium	High	Medium-Low
Low	High	Low	Low
Low	High	Medium	Medium-Low
Low	High	High	Medium-Low
Medium	Low	Low	Medium-Low
Medium	Low	Medium	Medium
Medium	Low	High	Medium
Medium	Medium	Low	Low
Medium	Medium	Medium	Medium-Low
Medium	Medium	High	Medium
Medium	High	Low	Medium-Low
Medium	High	Medium	Medium-Low
Medium	High	High	Medium
High	Low	Low	Medium-Low
High	Low	Medium	Medium
High	Low	High	Medium
High	Medium	Low	Medium-Low
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High	Medium	High	Medium
High	High	Low	Medium-Low
High	High	Medium	Medium-High
High	High	High	High

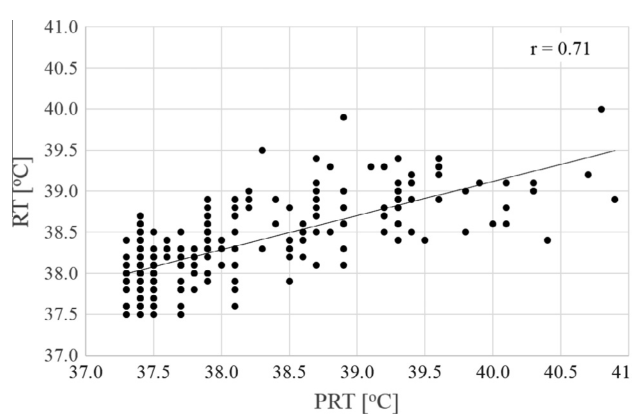

Fig. 5. The linear relationship between measured rectal temperature (RT) and predicted rectal temperature (PRT). The points represent individual measurements, the line represents the linear regression, and r represents the correlation coefficient.

Additionally, a comparison was made between the FC and THI assessments. The RT measurements were also considered as a reference classifier, for which the values of limits were the same as shown in Table 3.

The comparison between the assessments of THI and FC agreed in only 29.3% (Table 5). It is observed that the FC classified 83.2% of the data as normal while the THI showed 28.1% in this condition. It is noted that the FC presents only 1.2% as emergency while THI 28.1%.

Table 5
Frequency distribution and coincidence (%) of the classification of the data by fuzzy classifier (FC), rectal temperature (RT) and temperature humidity index (THI), using data from eight animals.

	THI				
	Normal	Alert	Danger	Emergency	Total
FC					
Normal	28.1	25.0	18.7	11.33	83.2
Alert	0.0	0.0	0.0	9.4	9.4
Danger	0.0	0.0	0.0	6.2	6.2
Emergency	0.0	0.0	0.0	1.2	1.2
Total	28.1	25.0	18.7	28.1	100.0
RT					
Normal	28.1	25.0	17.6	21.1	91.8
Alert	0.0	0.0	1.2	5.9	7.0
Danger	0.0	0.0	0.0	1.2	1.2
Emergency	0.0	0.0	0.0	0.0	0.0
Total	28.1	25.0	18.7	28.1	100.0

Table 7
Frequency distribution and coincidence (%) of the classification of the data by fuzzy classifier (FC), temperature humidity index (THI) and rectal temperature (RT), using data from eighteen animals.

	RT				
	Normal	Alert	Danger	Emergency	Total
FC					
Normal	84.5	9.7	0.7	0.0	94.9
Alert	3.2	0.9	0.2	0.0	4.4
Danger	0.7	0.1	0.0	0.0	0.8
Emergency	0.0	0.0	0.0	0.0	0.0
Total	88.4	10.7	0.9	0.0	100.0
THI					
Normal	20.1	0.0	0.0	0.0	20.1
Alert	37.3	2.2	0.1	0.0	39.6
Danger	28.5	7.2	0.7	0.0	36.4
Emergency	2.4	1.2	0.1	0.0	3.7
Total	88.4	10.7	0.9	0.0	100.0

Similar to the comparison between THI and FC, the comparison between the classifications obtained by THI and RT presented low coincidence (Table 5). The assessments performed by THI and RT show only 28.1% of coincidence during the days of the experiment. The THI classifies 28.1% of measures as emergency while RT is 0%. Indeed, RT values above 40 °C were not observed indicating that animals were not in a situation of emergency.

The positive performance of the FC can be ascertained by its comparison with RT (Table 6). As opposed to that observed between THI and RT (Table 5), FC and RT classified 83.2% of the measures at the same level of stress (80.9% as normal and 2.3% as alert). Moreover, the assessments carried out by the FC approached better those carried out by RT (Table 6) than those carried out by THI (Table 5).

3.4. Validation of the classifier

The next step was to validate the FC measured from the second group of animals ($n = 18$). As was done previously, the measured RT of these animals was used as a reference to classify and compare the stress levels (Table 7).

Clearly, the comparison between FC and RT assessments showed correspondence in 85.4% of the measurements (Table 7) as well as a slight improvement in FC efficiency (83.2% coincidence, Table 6). Just as observed for RT classification, FC did not classify any measure as emergency, showing a slightly better response for eighteen animals than for eight animals. Additionally, FC appears to have underestimated the condition of alert, classifying some of these measures as a normal condition. Thereby, the desired generalization capability for a soft computing model related to its ability to have a persistent performance on unseen data, was observed in this FC. This means that FC developed using a relatively small dataset can accurately represent the thermal stress process and can be used to predict this trait in different and larger datasets. Moreover, this generalization capability reinforces that the adopted methodology for FC design, that guided the construction of the knowledge base and membership functions, was adequate to estimate the animals' thermal stress.

Table 6
Frequency distribution and coincidence (%) of the classification of the data by rectal temperature (RT) and by fuzzy classifier (FC), using data from eight animals.

	FC				
	Normal	Alert	Danger	Emergency	Total
RT					
Normal	80.9	7.0	3.5	0.4	91.8
Alert	1.6	2.3	2.7	0.4	7.0
Danger	0.8	0.0	0.0	0.4	1.2
Emergency	0.0	0.0	0.0	0.0	0.0
Total	83.3	9.3	6.2	1.2	100.0

To verify the performance of THI in the data set of eighteen animals, the assessments were compared with RT (Table 7). The assessments performed by THI and RT presented a very low correspondence of 23% (20.1% as normal, 2.2% as alert, 0.7% as danger and 0% as emergency), thus having a slightly worse classification than the previous set of eight animals (28.1% coincidence, Table 5).

4. Conclusion

A methodology was presented for the development of a classifier of thermal stress for beef cattle based on fuzzy logic inference system that predicted the rectal temperature by means of weather (dry bulb temperature and wet bulb temperature) data and the non-invasive physiological measurement of body surface temperature using infrared thermography. The assessments of the fuzzy classifier presented a strong coincidence with the cattle's thermal stress assessed according the rectal temperature measured. Moreover, the fact that the same fuzzy classifier maintained a satisfactory assessment for animals from different feedlots (different data sets in different seasons) strengthens the potential of this model for application as a thermal stress classifier. Thus, the application of the non-invasive technique based on infrared thermography showed great potential when associated to the fuzzy inference system for predicting the rectal temperature.

The performance in assessment of the fuzzy classifier was markedly superior compared to the temperature–humid index. Furthermore, unlike what occurs with the temperature–humidity index, it was observed that the fuzzy classifier allowed an individual assessment, i.e. in the same period of the day, different animals of the same group were classified into different levels of thermal stress. The reason is that the model uses the surface of body infrared temperature as an input and consequently consider an inherent characteristic of each animal.

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