Real-time individualized animal welfare monitoring using physiological data from wearables

A. Peña Fernández[1,4], F. Debruyne[2], G. Van Steenkiste[2], J. Bokma[2], S. Jourquin[2], T. Lowie[2], J. Clinquart[2], B. Pardon[2] and D. Berckmans[1,3,*]
[1]*KU Leuven, Belgium*
[2]*Ghent University, Belgium*
[3]*University of Tennessee, USA*
[4]*BioRICS NV, Belgium*
[*]Corresponding author: Daniel Berckmans, daniel.berckmans@kuleuven.be

Abstract

This work explores possibilities for monitoring animal welfare in an objective way by measuring physiological variables. Worldwide pneumonia is very common among calves. Sampling techniques have been developed to detect such pneumonia. The concern is to know whether these techniques impact animal welfare. The objective of this paper is to describe how we detect the effect of these sampling techniques of the respiratory tract on calf welfare. First experiments were conducted on three male Holstein-Friesian calves under thermal controlled experimental conditions. Following stressors were applied: deep nasopharyngeal swabbing (DNS), non-endoscopic bronchoalveolar lavage (nBAL), transtracheal wash (TTW), blood sampling and animal fixation. Each calf was wearing a sensor measuring heart rate (BPM, 3 Hz) and activity (x-, y-, z-accelerations; 26 Hz). A data-based mechanistic model adapts to each individual calve and next, the real-time model adapts to individual variations during possible stressful sampling techniques. The model decomposes the measured total heart rate into different components, namely heart rate components required for: the basal metabolism, the physical activity, and finally the mental component. The data-based mechanistic model for the dynamic response of the mental component during a sampling technique exhibits an R^2 = (95 ± 4) % and Young Identification Criterion YIC = (-7.4 ± 3.4). The individual model parameters for each calf vary from b_0 = 0.10 ± 0.03 bpm^{-1} to b_0 = 11.9 ± 0.6 bpm^{-1}, confirming individually different responses of each calf as expected.

Keywords: physiological data, stress monitoring, respiratory sampling techniques, PLF

Introduction

Bovine respiratory disease (BRD) is an important disease showing welfare implications due to high morbidity, mortality, production loss (Pardon et al., 2012b; Lowie et al., 2021). Therapeutic- and diagnostic costs cause significant economic losses to the feedlot industry due to decreased production and increased costs associated with treatment, estimated at $42/case (Dubrovsky et al., 2020). The most frequently used sampling techniques employed for respiratory disease diagnostics are the deep nasopharyngeal swab (DNS), the non-endoscopic broncho-alveolar lavage (nBAL) and the transtracheal wash (TTW) (Van Driessche et al., 2019). There are several studies evaluating the performance of these different techniques, showing, for instance that nBAL samples yielded more pure cultures compared to DNS ones, leading to a clinically interpretable culture result in 79.2% of the cases compared to only in 31.2% of the DNS samples (Van Driessche et al., 2017). Another study showed that the agreement among TTW, DNS and nBAL, was very good for identification of Pasteurella multocida, Mannheimia haemolytica, and Mycoplasma Bovis. These are bacteria that could be present in the lower airways of dairy calves with acute BRD (Doyle et al., 2017). However, there is a lack of studies focusing on assessing animal welfare by measuring the stress induced in the calves by performing such techniques.

Measuring stress in animals remains a difficult task (Chen et al., 2015). Animals try to cope with external stressors using behavioral and physiological stress responses and these can be measured via variables such as changes in form or frequency of behavioral patterns or changes in heart rate, body temperature and hormone levels in blood (Blokhuis et al., 1998). Many studies on stress and pain rely, solely or mainly, on plasma (Stilwell et al., 2008), saliva (Kovács et al., 2020) or hair (Heimbürge et al., 2019) cortisol assessment, but none of them lead to conclusive results. In this research, we aimed to monitor animal welfare in an objective way by measuring physiological variables, heart rate and activity data from the calves, and using them as inputs for the Mindstretch algorithm (Joosen et al., 2019) to estimate the heart rate mental component in real-time and relate its dynamics to the stress induced in the calves by each sampling technique.

Materials and methods

Study Design, Animals and Housing

Ten male Holstein-Friesian calves, coming from the same dairy farm when aging thirty-four to forty-three days old, followed a two-week habituation period. They were individually housed in a research stable at Ghent University. The pens are straw bedded, and visual contact with other calves is possible. The calves had ad libitum access to hay, water and concentrates, being fed 3 L of commercially available milk replacer twice a day from individual drinking buckets. The calves' health status was daily assessed visually, and rectal temperature was taken twice a day, during milk feeding. The trial protocol was approved by the Ethical committee of the Faculty of Veterinary Medicine and Bioengineering from Ghent University under license EC2020-087.

Sensor system

The Movesense active sensor system (Movesense Ltd, Finland, Vantaa) is attached to a shaved area at the left side of the thorax just behind the shoulder with the Movesense strap (Movesense Ltd, Finland, Vantaa). It collects heart rate, electrocardiogram (128 Hz), nine degrees of freedom inertial measurement unit (26 Hz) and temperature data. Besides, an in-house developed gateway, with a build-in camera module based on the ESP-32 CAM board placed above each pen, records a top view of each individual calf allowing posterior labelling of the calf behaviour and experimental procedures.

Sampling techniques

This work focuses on three sampling techniques: DNS, nBAL and TTW. To take a DNS, a researcher restraint the calf and inserts a nasal swab into the ventral meatus of the nasal cavity up to the level of the ventro-medial corner of the eye, rotating it a couple of times before removal. For the nBAL, the procedure was the same as the one described in Van Driessche et al. (2016). For the TTW sampling, the tracheal region at the level of the neck was shaved, rubbed (with hibitane solution 5%), scrubbed (with ispropanol 99%), and locally anesthetized with 3 mL procaine hydrochloride (4%) per subcutaneous injection with a 21G needle. The trachea was secured with one hand and with the other hand a central venous catheter (Centracath, Vygon, Ecouen, France) for human use was inserted through the skin into the tracheal lumen. The catheter was advanced until the wedge position was reached, and 30 mL of physiological 0.9% NaCl solution was injected and instantly aspirated. After aspiration, the catheter was removed, and the calf released. For blood sampling all the calves received a permanent intrajugular vein catheter before the experiment (MILA international, Kentucky, Florence, US). Blood samples were collected at -1h, 0h, +1h, +5h and +24h relative to the respiratory tract sampling.

As the duration needed to perform the sampling techniques are different, we decided to consider a sampling event as the combination of the sampling technique together with the subsequent blood sampling.

Total heart rate decomposition

By monitoring in a synchronized way, animal's movement and heart rate, the dynamic responses of total heart rate and movement to stressor can be measured. Using these two variables as inputs, the Mindstretch algorithm (BioRICS n.v. Leuven, Belgium) decomposes the total heart rate into three different components: the basal, physical (Phys) and mental (Ment) components as described by Eq. (1):

$$HR_{total} = HR_{basal} + HR_{phys} + HR_{ment} \tag{1}$$

Mindstretch is an adaptive real-time individualized model, as the model's parameters are estimating through time solely with data from that specific animal. For a detailed description of this method, we refer to the dynamic analyses used for mental monitoring for humans (Berckmans et al., 2007) and animals (Norton et al., 2017). In this work, the days in which there is a suspicion of a calf undergoing an infection (rectal temperature > 39 °C) are not used to evolve the internal parameters of the Mindstretch algorithm.

Modelling mental heart rate component

The mental heart rate component is further modelled by using the CAPTAIN Toolbox (Taylot et al., 2017) in MATLAB 2016b software (Mathworks Inc., USA). Throughout the system model identification, SISO TF models with time-invariant parameters are tested. This model has the following general structure described in Eq. (2) (Young, 1984),

$$y(t) = \frac{B(z^{-1})}{A(z^{-1})} u(t-\delta) + \xi(t) \tag{2}$$

where $y(t)$ and $u(t)$ are the output (HR_{Ment} in bpm) and the input (binary input, 0 before the start of the sampling technique and 1 until the end) of the model, respectively; $\xi(t)$ is additive noise assumed to be zero mean, serially uncorrelated sequence of random variables with variance σ^2, accounting for measurement noise, modelling errors and effects of unmeasured inputs to the process; t is the measurement sample; δ is the input's time delay, expressed in number of time intervals; $A(z^{-1})$ and $B(z^{-1})$ are two series given by Eq's (3) and (4):

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_{n_a} z^{-n_a} \tag{3}$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_{n_b} z^{-n_b} \tag{4}$$

where a_i and b_i are the model parameters to be estimated; z^{-1} is the backward shift operator, i.e. $z^{-1}y(t) = y(t-1)$, with y and t defined as in equation (1); n_a and n_b are the orders of the A and B polynomials, respectively. The model parameters are estimated using a Refined Instrumental Variable (RIV) approach (Young, 1984). Normally, the model is referred to as the triad [n_a n_b δ], being n_a referred to as the model order.

The goodness of the fit is quantified using the coefficient of determination, R_T^2 which general expression is given by Eq. (5) (Young, 1984),

$$R_T^2 = 1 - \frac{\sigma_\xi^2}{\sigma_y^2} \tag{5}$$

where σ_o^* is the variance of the residuals, when comparing the model estimations with the output measured values, and $\sigma_{\ddot{A}}^*$ is the variance in the output. In addition, the Young Information criterion (YIC) is estimated. It is given by Eq. (6),

$$\mathrm{YIC} = \log_o » \frac{Ü ...}{Ü} + \log_o »^{\&} \sum_{1@\&}^{T} \frac{Ü ...}{lâ} ... \qquad (6)$$

where σ^*_o is the variance of the residuals, $\sigma^*_{\ddot{A}}$ is the variance of the output, h is the number of estimated parameters, p_{11} are the diagonal elements of the covariance matrix from the parameter's estimations and a^*_1 is the square value of the i-th parameter.

Model features

When the preferred SISO TF model is a first order model ($n_a = 1$), the time constant (TC) and steady state gain (SSG) can be estimated as model features as (Young, 1984):

$$\mathrm{TC} = -\frac{\ddot{a}p}{\mathrm{sm}\,(Rl()} \qquad (7)$$

$$\mathrm{SSG} = \frac{\Delta\ddot{A}}{\Delta\mathring{a}} = \frac{h.}{\&5l(} \qquad (8)$$

If the preferred SISO TF model is of second order ($n_a = 2$), then the model is further studied to check whether this second order model allows a split in a serial, parallel or feedback first order models configuration as shown in Figure 1 (Boonen et al., 2000).

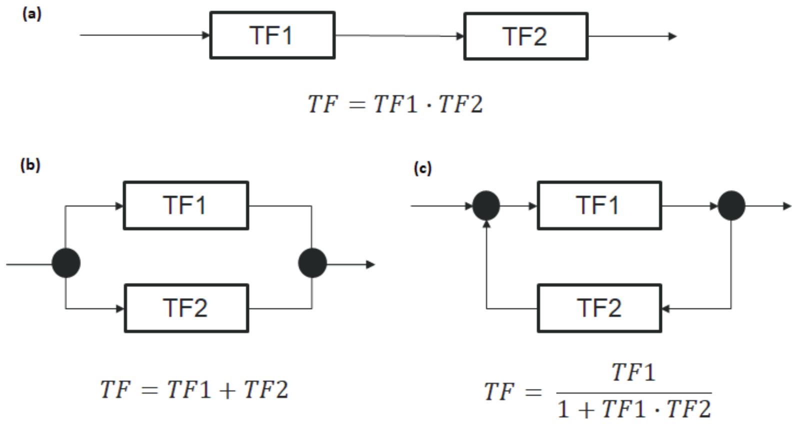

Figure 1: Possible model split configurations of a second order model into a combination of first order models. These configurations are series (a), parallel (b) and feedback (c) configurations in which each equation shows the relation between the second order model (TF) with each first order model (TF1 and TF2), respectively.

Results and discussion

Heart rate components dynamics

Applying the Mindstretch algorithm to the real-time heart rate and movement data collected for each calf, the total heart rate is split into the basal, physical and mental components. From Figure 2, it is clear that each sampling technique induces different dynamics in both physical and mental heart rate components. Similar dynamics are observed for TTW and nBAL techniques regarding the physical heart rate component, showing only some variability at the end of the test, meanwhile the DNS technique induces peaks in each step of the test. Regarding the mental component, all three sampling techniques induce completely different dynamics, although the maximal variation for each sampling technique is reached at the end of the blodsampling.

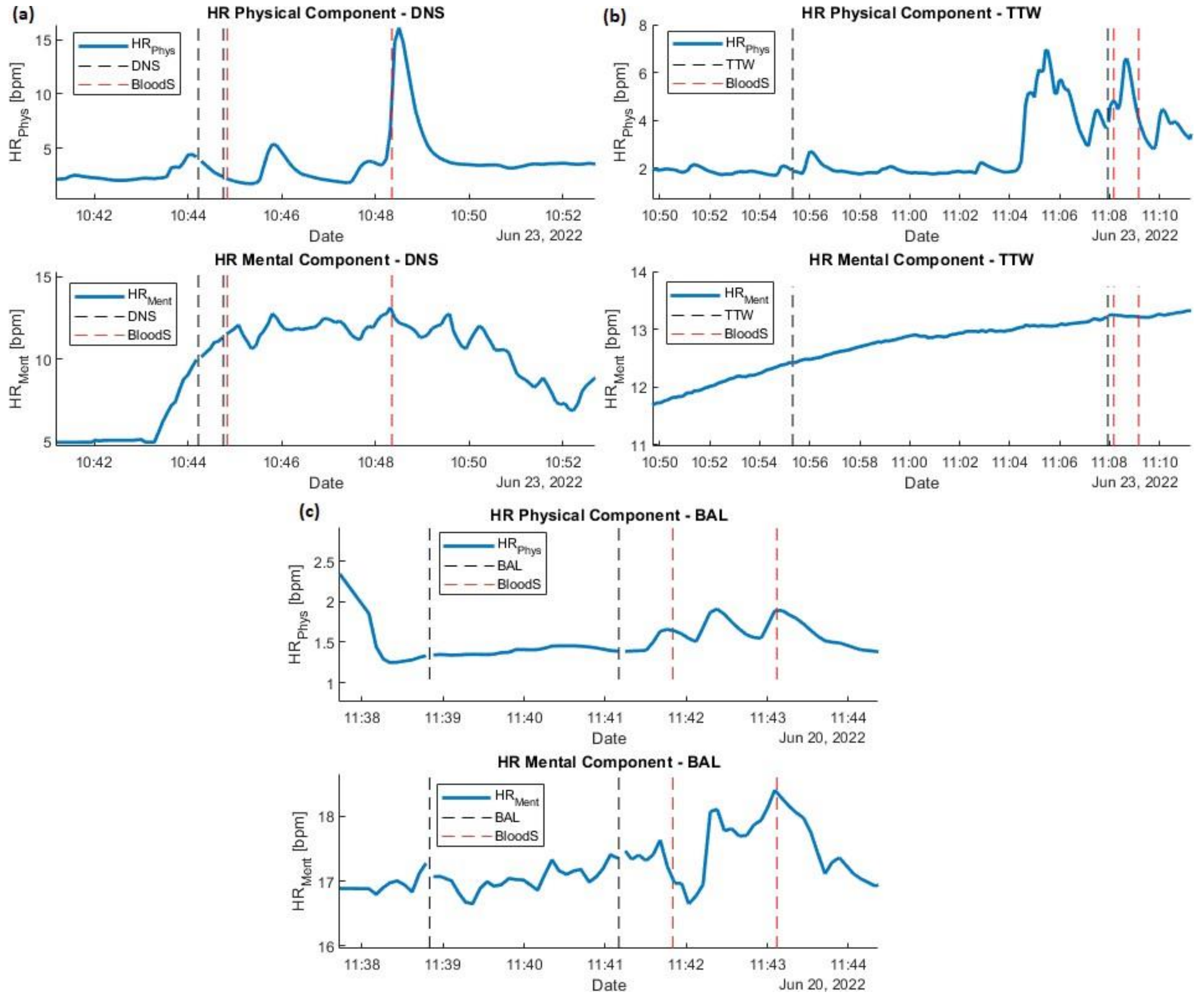

Figure 2: Examples from 3 different calves of the physical ($HR_{Phys,}$ upper graphs) and mental (HR_{Ment}, lower graphs) heart rate components evolution from right before starting the sampling technique until right after it, of the DNS (a), TTW (b) and nBAL (c) sampling techniques. The vertical black and red dashed lines indicate the start and end of the test and the blood sampling respectively.

Modelling the dynamics of the heart rate mental component

Four different calves per sampling technique, for which data are available to assess the mental heart rate components dynamics, were selected. Tables 1 to 4 summarize the results from the system identification modelling and Figure 3 show an example for each sampling technique modelling response. The modelling of the mental heart rate component dynamics induced by the DNS sampling techniques leads consistently to a first order SISO TF model, to a second order model, split in a feedback configuration of first order models for the TTW sampling technique and a miscellaneous of model structures for the nBAL sampling technique.

Table 1: Features of the first order SISO TF models found as best to model the dynamic response of the heart rate mental component of a calf during the DNS sampling technique (DNS + blood sampling).

	Calf 1	Calf 2	Calf 3	Calf 4
a_1	-0.76	-0.87	-0.98	-0.83
b_0	0.6	0.87	0.16	0.37
TC	18	37	247	153
SSG	2.5	6.7	8.0	2.2
R^*_c	94	97	99	85
YIC	-2.5	-9.6	-13.2	-6.4

Table 2: Features of the second order SISO TF models found as best to model the dynamic response of the heart rate mental component of a calf during the DNS sampling technique (TTW + blood sampling)

	Calf 1	Calf 2	Calf 3	Calf 4
a_1	-1.68	-1.85	-1.97	-1.96
b_0	0.77	0.85	0.98	0.96
a2	0.34	1.58	0.28	0.01
b_1	0.19	-1.58	-0.28	-0.01
R^*_c	97	96	95	99
YIC	-3.3	-6.8	-6.5	-10.6

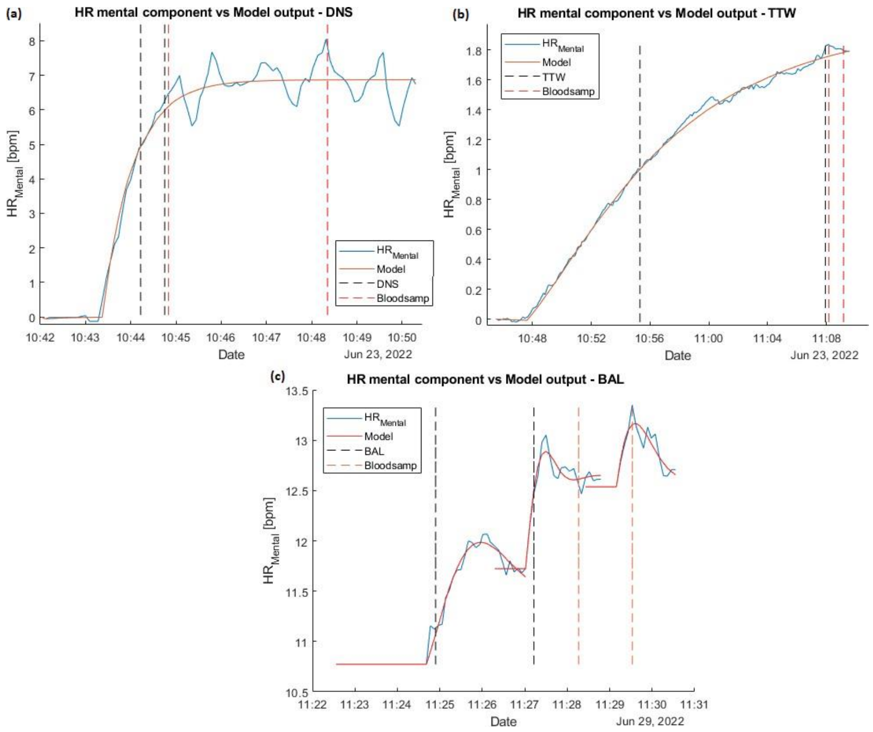

Figure 3: Example of the dynamic response of the heart rate mental component (HR_{Ment}, blue solid line) in beats per minute (bpm) and SISO TF models (red solid line) for the DNS test from Calf 2 (a), the for the TTW test from Calf 4 (b) and the nBAL test from Calf 1 right before, during and right after the combination of sampling technique and blood sampling. The vertical black and red dashed lines indicate the start and end of the test and the blood sampling respectively.

Besides, the modelling results match the sampling techniques descriptions. The DNS is the simplest in terms of procedure and it also exhibits the simplest model structure. TTW and nBAL consist of two steps, but meanwhile for TTW happens simultaneously and the sampling technique can be modelled by a second order model, the nBAL steps are more independent leading to the need of using different individual SISO TF models to characterize the impact in the heart rate mental component dynamics. Also, the parameter values vary for each calf and for different tests, which is expected. Since each calf is a complex, dynamic, time variant and dynamic CITD entity (Berckmans, 2006), the physiological state of each calf is individually different, as the response to the sampling technique. This is pointed out in the differences in parameters and metrics, such as the TC and the SSG, values in the model for each calf.

Table 3: Model parameters (a_{11}, a_{21} unitless and b_{10}, b_{20}, in bpm·s^2·m^{-1} for TF_1 and TF_2, respectively) and features, such as the time constant ($TC_{1,2}$, in s) and the steady state gain ($SSG_{1,2}$, in bpm·s^2·m^{-1}) for the two different first order SISO TF model (TF_1 and TF_2).

	Calf 1	Calf 2	Calf 3	Calf 4
a_{11}	-0.93	-0.86	-0.97	-0.98
a_{21}	-0.96	-0.99	-0.98	-0.93
b_{10}	0.17	1.54	0.28	0.01
b_{20}	11.93	0.04	0.04	0.20
TC_1	5	32	379	389
TC_2	39	1593	382	149
SSG_1	0.46	1.80	0.29	0.01
SSG_2	5.27	0.04	0.03	0.98

Table 4: Summary of the different SISO TF models needed to characterize the dynamic response of the heart rate mental component of the calf to the nBAL sampling technique.

	Calf 1	Calf 2	Calf 3	Calf 4
Model 1	2nd order - Feedback	1st order	1st order	1st order
Model 2	2nd order - Feedback	1st order	2nd order - Serial	2nd order - Feedback
Model 3	2nd order - Feedback		2nd order - Parallel	

Conclusions

By modelling the dynamics of the heart rate components during different sampling techniques, it is possible to evaluate the mental impact of the sampling technique. These results show that the DNS sampling technique induces the simpler response in the heart rate mental component dynamics. It can be described by a first order SISO TF model, $R_c^* = (94 \pm 5)\%$ and $\mathrm{YIC} = (-8 \pm 3)$. The TTW shows an increased complexity in the dynamics induced in the heart rate mental component, but it is still possible to use a single SISO TF second order model, $R_c^* = (97 \pm 2)\%$ and $\mathrm{YIC} = (-7 \pm 3)$. From this we hypothesize the TTW test has a higher mental impact on the calf than the DNS and blood sampling. Finally, the BAL exhibits the more erratic impact in the heart rate mental component dynamics. This research will be extended to a larger number of calves to verify these preliminary results from a limited sample.

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