Variables of gait inconsistency outperform basic gait variables in detecting mildly lame cows

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ABSTRACT

To support herdsmen in finding the lame cows on their herds, several automated systems that measure lameness related cow features such as gait patterns, are being developed. Most of these systems are able to distinguish between non-lame and severely lame cows. Detecting mildly lame cows in an early stage of lameness however seems challenging. Inspired by the approach used in human gait research, new variables that measure the inconsistency in stride-to-stride variables were tested in Van Nuffel et al. (2013) and were able to show differences between a group of non-lame and a group of mildly lame cows. In order to investigate the added value of these inconsistency variables in detecting mildly lame cows, the data set of Van Nuffel et al. (2013) was used to build two new lameness detection models: one using solely basic gait variables and a second model using both basic and the new gait inconsistency variables. The second model using the gait inconsistency variables outperformed the model based on only basic gait variables by far in detecting the mildly lame cows with a sensitivity of 88 % and a specificity of 87 %. These results support the suggestion of incorporating such gait inconsistency variables into lameness detection models. Further validation of these gait inconsistency variables should be investigated using longitudinal studies where cows developing lameness and recovering from it are monitored daily.

KEYWORDS

Early lameness detection, Dairy cattle, Gaitwise, Gait inconsistency

INTRODUCTION

Due to the increasing numbers of cows per farm and hence per herdsman, the time to properly inspect every individual cow in their herd decreases. Therefore, sensors are being used to support the herdsmen to monitor their cows by automatically assessing cow specific features

such as somatic cell count for mastitis or activity for estrus detection). Besides mastitis and fertility problems, the high prevalence of lame cows on dairy herds is one of the main challenges the dairy industry is currently facing (Huxley et al., 2013). To apply effective treatment and ailment prevention, herdsmen must be able to detect the lame cows in their herd in an early stage in order to prevent the cause of the lameness from developing into a chronic situation (Clarkson et al., 1996; Zimmerman, 2001). When lame cows are treated within two weeks of becoming lame, recovery rates can be 60 to 75 % higher than when treated under conventional treatment protocol (Leach et al., 2012). As a result early lameness detection could reduce the costs of treatment and milk losses thanks to the more effective treatment (Gonzales et al., 2008). For several years, lameness research in cattle has been focused on quantitative and automatic methods to analyze gait as an alternative for the more subjective and time consuming visual locomotion scoring methods. One of these approaches is the development of Gaitwise, a walk-over device with an integrated pressure sensitive mat and specific software that calculates spatial (e.g. step length), temporal (e.g. stance time) and force related gait variables of claw-floor interactions of cows walking over the measurement zone (Maertens et al., 2011). Assuming that these gait variables change when a cow develops lameness, Gaitwise could serve as a lameness detection system that alerts the farmer of cows that show changes in these variables that are related to lameness. Measurements are fully automated and gait variables are available in real time. To describe the spatial (forward and sideward) and temporal relation between the different imprints of the four different legs of the cow during walking, twentybasic gait variables were analysed as described in Maertens et al. (2011). These basic gait variables (e.g. step width between imprint of the left front leg and the imprint of the right hind leg) are ideal to describe the general gait of the cows but less useable in practice as they are not easily seen by the human eye. Therefore, ten more specific gait variables were calculated in order to quantify different lameness attributes that are often used in visual locomotion scoring systems

which were calculated using the averaged value (of the two gait cycles measured during one measurement on the Gaitwise) of a combination of several basic gait variables. These ten specific gait variables are: Stride length (Y), stride time (T), stance time (ST), step overlap (SO), abduction (ABD), and asymmetry between left and right limbs in step width (AX), step length (AY), in step time (AT), in stance time (AST) and in force (AF) and the definitions are describes in Maertens et al. (2011). The detection algorithm of Maertens et al. (2011) was solely based on these 10 specific gait variables to correctly classify non-lame, mildly lame and severely lame cows with a sensitivity of 85 %, 76 %, 90 % and specificity of 86 %, 89 %, and 100 %, respectively. These results revealed that the combination of the specific gait variables used in this model ('stride length', 'stride time', 'step overlap', 'abduction' and asymmetry between left and right limbs in stepwidth', 'asymmetry in steplength', 'asymmetry in steptime', 'asymmetry in stance time' and 'asymmetry in relative force'), was efficient in distinguishing between non-lame and severely lame cows but detecting mildly lame cows was more challenging as the differences with non-lame cows are much smaller. These results were also found in Van Hertem et al. (2014):.

However, the added value of lameness detection systems would increase considerably when also the mildly lame cows could be detected. To improve the detection of mildly lame cases, the potential of gait inconsistency variables for detecting lameness in such early stages was explored by Van Nuffel et al. (2013). This approach is based on the fact that in human gait research, increased stride-to-stride fluctuations (i.e. gait inconsistency) were found to be more closely related to early health problems compared to average gait variables. The potential of gait inconsistency variables for early lameness detection was elaborated in cows by investigating whether a cow that develops lameness first alters its gait by occasionally taking e.g. a shorter stride before altering its gait to shorter strides in general. Figure 1 illustrates the use of gait inconsistency variables for early lameness detection for the gait variable 'abduction'

(defined as the sideways distance between the front hoof imprint and a subsequent imprint of the hind hoof on the same side). In this figure, no abduction is seen in non-lame cows. In mildly lame and severely lame cows, small and large abduction can be seen in every gait cycle. It is hypothesized that before developing mild abduction in mildly lame cows, cows would occasionally start to show abduction, resulting in the inconsistent way of walking for this variable (inconsistent lame). Calculation of this type of variable however, requires a measuring system that is able to measure gait variables during more than one consecutive gait cycles in order to calculate the gait variables during these gait cycles and next, quantify the inconsistency in this variable between the different gait cycles. Most sensor system that measure gait variables in the literature however, calculate the mean value of a gait variables (cfr. how the specific gait variables are calculated using the Gaitwise system) or solely one variable during one gait cycle of a walking cow.

As two consecutive complete gait cycles of cows are measured during one measurement with the Gaitwise, gait inconsistency could be measured by calculating the Coefficient of Variation of the basic gait variables of these two gait cycles. In a previous study of Van Nuffel et al. (2013), both the basic gait variables and the gait inconsistency variables were compared between non-lame and severely lame cows and between non-lame and mildly lame cows -using two case-control studies,. The gait inconsistency variables were able to show significant differences between the group of mildly lame cows and its control group , where the more basic gait variables could not. In Van Nuffel (2014), all gait inconsistency variables of stance time, steplength and step time were significantly different between three groups of non-lame, mildly and severely lame cows. In addition, the inconsistency in gait increased significantly between non-lame and mildly lame cows but not between mildly lame and severely lame cows.

In order to further investigate the added value of these variables of gait inconsistency for the detection of mildly lame cows when incorporated into a detection model, the objective of this

study was to develop two new models (one based on solely the basic gait variables) and another based on the basic gait variables and the corresponding gait inconsistency variables. It is hypothesized that the detection results of latter model would perform better in detecting the mildly lame cows.

MATERIALS AND METHODS

Experimental set-up and data collection

Data were collected in 2011 at ILVO research farm (Melle, Belgium). Holstein Friesian cows were housed in a deep litter barn with straw bedding and had access to pasture from approximately the 15th April until 30th November. The cows were milked twice a day in a 2 x 3 auto-tandem milking parlour. The average milk yield is about 8500 liter per cow per year. In a return alley after the milking parlour, the Gaitwise system measured the gait of the individual cows after milking. Simultaneously, video recordings were taken and stored for locomotion scoring of the cows by a trained observer ($\kappa = 0.93$). A list of frequently used lameness attributes was used based on several locomotion scoring systems: non flexible joint movement (Flower and Weary, 2006), tender placement of the hoofs (Manson and Leaver, 1988), arched back (Sprecher et al., 1997), low speed (in general or difficulty in walking; Manson and Leaver, 1988), irregular footfall in time or place (Winckler and Willen, 2001), reduced tracking up (Flower and Weary, 2006), abduction (Manson and Leaver, 1988) and head bobs (Breuer et al., 2000). Finally, the gait was scored as ‘non-lame’ when the cow did not show any of these lameness attributes (locomotion score 1); ‘mildly lame’ if one lameness attribute was present (locomotion score 2) and as ‘severely lame’ if a single lameness attribute was very severe clearlyimpeding the locomotion or if multiple lameness attributes were present (locomotion score 3). Every time a cow walked over the Gaitwise, each hoof imprint was measured at least three times, which resulted in minimum two complete gait cycles. Basic gait variables were

registered as averaged values of these different hoof imprints within one measurement (Maertens et al., 2011). In addition to the averaged value, the coefficient of variation (CV) of each basic gait variable was calculated by dividing the standard deviation by the average value. These 20 CV's represent the stride-to-stride fluctuation of the 20 basic gait variables and are, therefore, referred to as gait inconsistency variables (e.g. incons_X-variables or incons_StanceTime) (Van Nuffel et al., 2013). As these variables were not normally distributed, a Ln transformation was used which resulted in normally distributed variables of inconsistency (Ln_(incons_StanceTime LH), etc.).

To further evaluate the potential of the gait inconsistency variables, the dataset of the case-control studies of Van Nuffel et al. (2013) was further investigated for model building resulting in Gaitwise data. In Van Nuffel et al. (2013) cows were allocated to three groups: non lame, mildly lame and severely lame according to the following criteria: severely lame cows were noticed as lame by the herdsmen (based on farm records) and scored severely lame by the trained observer (n=10); mildly lame cows that were not noticed as lame by the herdsmen but scored mildly lame by the trained observer (n=10) and non-lame cows not noticed by the herdsmen and scored as non lame by the trained observer (n=16).. All the selected cows in this study that were mildly or severely lame, were lame at their left hind leg. For every cow, the corresponding 20 basic gait variables and the associated 20 gait inconsistency variables were calculated from the Gaitwise data of the morning measurements.

Statistical analysis

Two linear discriminant analyses were performed using the locomotion score assigned by the trained observer as a grouping variable. In the first linear discriminant analysis, the stepwise variable selection algorithm (using Wilks' lambda) selected basic gait variables that were capable of classifying a cow in a specific locomotion score group (1, 2 or 3) at $P < 0.05$ and eliminated basic gait variables that were not useful for grouping the cows at $P > 0.1$. In the

second linear discriminant analysis, both the basic gait variables and the gait inconsistency variables (Ln transformed to assess normality) were selected also using Wilks' Lambda. Variables selected for the models were checked for multicollinearity. No variables were excluded for that reason.

Model building was performed using the data set of 36 different cows (16 non-lame, 10 mildly lame, 10 severely lame) of Van Nuffel et al., (2013). Five cows were excluded in the last model because the mean of their basic variables was 0 and hence, no valid CV could be calculated. Cross validation was done for both models using 'leave-one-cow-out' where each cow, previously used in the analysis, was classified by the classification functions derived from all cows other than that cow. Classification functions, True Positive Rate and (1- False Negative Rate) of the two models were compared in order to determine if the new variables of inconsistency have added value for detection of the mildly lame cases. The True Positive Rate is the proportion of cows correctly classified by the model based on the locomotion scores of the trained observer (reference). The False Positive Rate is the proportion of cows incorrectly classified by the model based in the locomotion scores of the trained observer (reference).

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RESULTS

When only the basic gait variables were used for building the classification model on the data of the case-control study, only ‘stancetime left hind’ and ‘stridelength left hind’ were withheld in the model for classification of cows. This resulted in a correct classification rate of 72 % with nine out of ten misclassifications in the ‘mildly lame’ group. Cross validation of this model using leave-one-cow-out resulted in similar low results of sensitivity in detecting mildly lame cows (Table 1). Overall, only 58 % of the cases were correctly classified during cross validation.

Using both basic and gait inconsistency variables for building the second model, only two variables of gait inconsistency were withheld in the process: ‘inconsistency in stance time of left hind’ and ‘inconsistency in step length between left hind and right hind legs’. This resulted in a considerably better classification of the mildly lame cases for both the model itself and for the cross validation test (Table 2) with correct classification rates of 87 % and 77 %, respectively. Looking at Figure 3, the group centers of non-lame, mildly lame and severely lame cows are visually separated for the model based on basic and inconsistency variables. Using only basic variables (Figure 2), mildly and severely lame cows are much harder to separate.

DISCUSSION

Using this dataset of ‘severely lame cows noticed by the farmer’, ‘mildly lame cows not yet noticed by the farmer’ and ‘non-lame’ cows, two classification models were built: one using solely the basic gait variables and another using both basic and gait inconsistency variables. The classification performance of the model based on basic gait variables and cross-validation of the model was moderate (72 %) to low (58 %) (see Table 1 for the cross validation results). Especially, the True Positive Rate for classifying the mildly lame cows was very low (10 % and 0 % respectively). In the model based on basic gait variables, only ‘stance time on the left hind leg’ and ‘step length between two consecutive imprints of the left hind leg’ were withheld for classification. In the model using both the basic gait variables and the gait inconsistency variables, however, only two variables of inconsistency and none of the basic gait variables were withheld to separate between the three groups of cows; ‘inconsistency in stance time of the left hind leg’ and ‘inconsistency in step length between left and right hind legs’. Using this model and during cross validation of this model 87 % and 77 % of the cases were correctly classified respectively. More importantly, is that the True Positive Rate in classifying mildly

lame cows increased to 88 % compared to a 0 % in the model using only the basic gait variables.. Overall, the specificity of the model using gait inconsistency variables was good (> 85 %). As can be seen in figure 2 and 3, the model using only basic gait variables was indeed able to distinguish severely lame cows from other cows, but separation between non-lame and mildly lame cows appeared to be difficult. The model using both basic gait variables and gait inconsistency variables was able to clearly separate between all three groups of cows which can also be seen in Table 2.

From all three models using Gaitwise measurements (Maertens et al., 2011; model using solely basic gait variables; and the model using both basic gait variables and gait inconsistency variables), the model using specific variables (Maertens et al., 2011) and the model using basic gait variables were better in detecting the severely lame cows with a True Positive Rate of 90% and no false alarms (Maertens et al. 2011) and a True Positive Rate of 70% and 4 false alerts out of 100 alerts respectively.. The large differences between variables used in the model and the True Positive Rate and the False Negative Rate of the model of Maertens et al. (2011) and the model using only the basic gait variables might be caused by the large differences in measurement days and cows to build the model and the fact that the model of the basic gait variables was built using data of mildly and severely lame cows at only their left hind legs. The detection of the mildly lame cows of the model using the new variables of gait inconsistency however, outperforms the models using specific and basic gait variables with a True Positive Rate of 88 % and 13 false alerts out of 100 alerts . These results support the indication that variables of gait inconsistency within a measurement might be useful for early lameness detection. However – due to the fact that the models in this paper were based on only 36 cows and might only be useful for cows with lameness problems at their left hind legs -more research on time series of these variables for both healthy cows and cows that develop lameness is needed. In addition, the model of Maertens et al. (2011) seemed better suited for detecting

severely lame cows. Hence, lameness detection systems could use two types of models; one model for detection of the mildly lame cows incorporating variables of gait inconsistency and another model that focuses on the detection of the severely lame cows. As discussed by Rutten et al. (2013), only few other studies developed and validated their algorithm to detect lame cows, especially so if ‘using locomotion scoring by a trained observer as reference’ is an extra criterion. .

Comparing the performance of the detection algorithm of the new model using a combination of basic gait variables and gait inconsistency variables, with other studies however is not straight forward. Mainly due to the different criteria used for the cut-off value of the reference locomotion score for building the algorithm; Most studies score the gait of the cows using a 5-point locomotion scoring system, but combine locomotion score 1 and 2 in the group of non-lame cows. Locomotion scores 3 to 5 can be grouped as ‘lame’ cows or categorized as lame (locomotion score 3) and severely lame (locomotion score 4 and 5). Poursaberi et al. (2010) used the same scoring system as performed in this study, resulting in a group of non-lame cows where no sign of any of the lameness attributes was present and a group of mildly lame cows including cows that show the slightest form of attribute related to lameness. The severely lame cows are regarded as those that could be identified by the herdsmen if they are properly trained and interested in visual lameness detection. In the threshold setting of Pastell and Kujala (2007), Ito et al. (2010) and Viazzi et al. (2013; 2014), the group of non-lame cows included the mildly lame cows (locomotion score 2) which were considered in a separate group in our study. de Mol et al. (2013) disregarded the mildly lame cows (locomotion score 2) and tested his detection model for non-lame and severely lame cows (locomotion 3 or more). Poursaberi et al. (2010) developed an algorithm based on the arched back posture of cows using computer vision techniques with a 2D-camera (sideview). Using this approach of back posture measurements, more than 96 % of the cows were correctly classified, and all lameness cases were identified

(sensitivity of 100 %) with a specificity of 98 % (Poursaberi et al., 2010). Five out of six of the misclassified cows in this study were classified to a higher locomotion score by the model compared to the locomotion score reference, only one severely lame cow was classified as mildly lame (Poursaberi et al., 2010). Using a 5-point scale during locomotion scoring as reference, the correct classification rate using was 53 % in the study of Van Hertem et al. (2014) based on analyzing 'Back Posture Measurements' of cows walking under the camera with a 3D-camera.

Based on the available results and comparable approaches (i.e. using a trained observer as reference for performing the locomotion scoring and using similar threshold for defining mildly lame cows), only the 2D-image model of Poursaberi et al. (2010) - - seem better in detecting mildly lame cows compared to the model using a combination of basic gait variables and gait inconsistency variables measured by the Gaitwise system.

As for human research, where multiple gait cycles are analysed, measuring more than two or three gait cycles within one measurement would provide added value to these results. However, the added value of such experimental set-ups with Gaitwise-systems might not correspond to the huge extra costs. The current Gaitwise system is 6 m long and 1 m wide and additional space is needed right before and after the measurement zone to ensure fluent cow traffic. Therefore, when installing the Gaitwise system into an existing housing system, it will occupy a fair amount of space and will probably even block a part of the feeding fence or cubicles. Ideally, the system would be placed at the exit of a milking robot or milking parlour such that the cow gaits are measured after milking and the ID of the cow is already known. Also, cows will be motivated to walk over the measurement device on their way to the feeding area, which decreases the risk that they stop in the measurement zone. Similar to the Gaitwise system, both the StepMetrix™[®] (Boumatic, Madison, WI, USA) and the measurement set-ups for any

vision techniques also need additional space like an alley set-up where measurements can be performed or video footage can be taken. This might create a drawback for this kind of measurement systems compared to the measurement of weight differences in the milking robot or measurements with accelerometers. Such space could be incorporated in the plans of new barns. However, creating sufficient space in any existing barn is challenging, especially as cows should preferably pass this measurement zone daily - if possible after milking - and should be identified simultaneously. This requires a free zone inside the barn after the milking parlour, rotary or robot or even at the exit to the pasture for measurements during the grazing season. In addition, possible ways for downscaling the Gaitwise resulting in lower production costs are being considered. One approach would be to decrease the number of sensors needed by shortening the measurement zone which means that all legs will be measured only once or twice. However, this would omit the possibility to calculate the stride-to-stride fluctuations which were found to be promising for the detection of the mildly lame cows.

CONCLUSION

As in human gait research increased stride-to-stride fluctuations were found to be more closely related to health problems than average gait variables, the added value of incorporating gait inconsistency variables for the detection of early lameness in cows was investigated by comparing the results of two models: one based on basic gait variables and a second one based on basic gait variables and gait inconsistency variables. Looking at the models used to classify between non-lame, mildly lame and severely lame cows, the model based on basic and inconsistency variables could detect mildly lame cows better compared to the model based on basic or specific variables only. Moreover, the only variables selected by the stepwise Linear Discriminant Analysis procedure were gait inconsistency variables. These results support the suggestion that gait inconsistency variables have higher potential for the detection of mildly

lame cows. Whether these gait inconsistency variables are more promising in detecting lameness at an early stage should be investigated in future research on practical farms.

Conflict of interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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FIGURES

Figure 1. Visualization of the gait inconsistency hypothesis for early lameness detection: before non-lame cows show mildly or severe abduction during the development of lameness, they first show stride-to-stride fluctuations or ‘inconsistency’ in showing the mild abduction.

Figure 2. Combined group plots of the linear discriminant analysis of the canonical variables for all cows in the data set and for the group centre of the groups with locomotion score 0, 1 and 2 (based on basic gait variables only).

Figure 3. Combined group plots of the linear discriminant analysis of the canonical variables for all cows in the data set and for the group centre of the groups with locomotion score 0, 1 and 2 (based on both basic gait variables and and gait inconsistency variables).

TABLES

Table 1. Summary of cross-validation classification of cows with locomotion score 1, 2 or 3 using basic gait variables obtained from the Gaitwise system in relation to the locomotion score given by the trained observer as reference.

<i>Group based on the locomotion scores of trained expert</i>	<i>Predicted group by the model based on basic gait variables</i>			<i>True Positive Rate (%)</i>
	Locomotion score 1	Locomotion score 2	Locomotion score 3	
Locomotion score 1	14	2	0	88
Locomotion score 2	9	0	1	0
Locomotion score 3	1	2	7	70
<i>1 – False Positive Rate</i>	<i>50</i>	<i>85</i>	<i>96</i>	

Table 2. Summary of cross-validation classification of cows with locomotion score 1, 2 or 3 using basic gait variables and gait inconsistency variables obtained from the Gaitwise system in relation to the locomotion score given by the trained observer as reference.

<i>Group based in the locomotion scores of trained expert</i>	<i>Predicted group by the model based on the basic gait variables and gait inconsistency variables</i>			<i>Sensitivity (%)</i>
	Locomotion score 1	Locomotion score 2	Locomotion score 3	
Locomotion score 1	10	2	2	71
Locomotion score 2	0	7	1	88
Locomotion score 3	1	1	7	78
<i>Specificity (%)</i>	<i>94</i>	<i>87</i>	<i>86</i>	