Automated recording of cow brush visits in a commercial dairy farm setting

G. Hofstra[1], F.G.J. Donkers[1], M. Houlebert[2], M.T.J. Terlien[3], J.B. Roelofs[4] and E. van Erp-van der Kooij[5]. ,
[1]*Applied Biology Department, HAS green academy - University of Applied Sciences, Onderwijsboulevard 221, 5223 DE 's-Hertogenbosch, The Netherlands*
[2]*UniLaSalle Institute Polytechnique, 3 Rue du Tronquet, 76130 Mont-Saint-Aignan, France*
[3]*Applied Geo Information Systems Department, HAS green academy - University of Applied Sciences, Onderwijsboulevard 221, 5223 DE 's-Hertogenbosch, The Netherlands*
[4]*Adaptation Physiology Group, Wageningen University and Research, PO Box 338 6700 AH Wageningen, The Netherlands*
[5]*Animal Husbandry Department, HAS green academy - University of Applied Sciences, Onderwijsboulevard 221, 5223 DE 's-Hertogenbosch, The Netherlands*
G.Hofstra@has.nl

Abstract

Farmers often install automatic cow brushes to promote grooming behaviour, potentially reducing stress. Health problems in cattle are typically accompanied by a suit of sickness behaviours and a reduction of low resilience behaviours such as grooming. Thus, decreased automatic brush use could be a potential indicator of disease. Our study aimed to develop and validate an algorithm for automatic monitoring of cow brush usage in a commercial dairy farm setting. The research took place on a commercial dairy farm in the Netherlands housing 130 Holstein Friesian dairy cows fitted with a Nedap SmartTag Neck that included cow location. Visual observations of cow brush usage were performed for 38 hours, distributed across 12 days by two observers, yielding 533 visits to the brush. Cows brushing (87.4% of visits) had a median brushing time of 1:22 minutes (range 00:10-20:03). An algorithm was developed and then validated to determine the time spent at the brush based on location data. Results show good precision (89.1%), recall (87.4%), and F1 score (88.3%) for the algorithm. Time spent at the brush for observations and algorithm was strongly correlated for the true-positives (Spearman's rank-order correlation: r=0.919; p<0.001; n=466), as were time observed at the brush and brushing time (Spearman's rank-order correlation: r=0.853; p<0.001; n=533). Our algorithm had a moderate predictive value for brushing time ($R^2 = 0.409$; $p<0.001$) indicating a need for further optimization. This study is the first step in validating an algorithm for automated recording of brushing time, enabling future studies relating brushing time to health and welfare.

Keywords: dairy cows, cow brush, monitoring, automation, PLF

Introduction

Health problems in cows are typically accompanied by a suit of sickness behaviours, which are an adaptive response to infection, injury, or metabolic disorders(Almeida et al., 2008; Johnson, 2002). Sickness behaviours may vary for different health problems (Dittrich et al., 2019). For example, with lameness lying duration increases and standing duration decreases (Blackie et al., 2011; Weigele et al., 2018; Yunta et al., 2012) whereas with mastitis the opposite is true (Fogsgaard et al., 2015; Siivonen et al., 2011). Many automated detection systems focus on measuring changes in core behaviours, such as activity and eating/ruminating. However, because core behaviours are essential for the short-term survival of the animal, they might decrease only at a relatively late stage of disease (Littin et al., 2008). Because of their instinctual behaviour as prey animals, cows may be hesitant to exhibit signs of pain and, for example, may not overtly show their lameness (Stasiak et al., 2003). Health problems may already reduce the expression of low-resilience behaviours, which are considered non-essential survival behaviours, at an earlier stage (Mandel et al., 2018; Weary et al., 2009). Grooming, as an important part of the natural behaviour of cattle (Bolinger et al., 1997), is one such low-resilience behaviour that can decrease when an animal is stressed or ill (Lecorps et al., 2021; Mandel et al., 2017). To promote and stimulate grooming behaviour, farmers often install automatic cow brushes. The automatic brush fulfills the cows' natural behaviour to groom and clean themselves (DeVries et al., 2007). The use of the cow brush has the potential to reduce stress, which might result in increased milk yield (Schukken & Douglas Young, 2009; Wilson et al., 2002), and it has been suggested as a possible positive welfare indicator in cows (Keeling et al., 2021). However, self-grooming time decreases with health problems such as mastitis (Fogsgaard et al., 2012), lameness (Mandel et al., 2018; Weigele et al., 2018), and metritis (Mandel et al., 2017). In the event of health problems in a dairy cow, the use of the automatic brush could be reduced by 50% (Mandel et al., 2017), making it a potentially useful indicator of disease. This study aimed to develop and validate an algorithm for the automatic monitoring of cow brush usage based on location data in a commercial dairy farm setting. The study involved visually observing the cow brush usage of 130 Holstein Friesian dairy cows fitted with a Nedap SmartTag Neck that included cow location.

Material and methods

Research location

Our research took place on a commercial dairy farm in the Netherlands, housing, on average, 130 Holstein Friesian dairy cows in a freestall barn with concrete slatted floors and 130 deep-litter cubicles. All cows were milked with a three-stand GEA MIone AMS and had access to two DeLaval swinging cow brushes (SCB), of which only one was used in this research. The parity of the cows ranged from 1 to 8. The farm used the free-traffic system, in which all the cows had access to all areas in which they resided (e.g., cubicles, feeding fence, drinkers, AMS, and the grooming brush) at all times.

Cow location data

All cows were fitted with numbered collars with a SmartTag Neck sensor (Nedap livestock management, the Netherlands) that included location determining with an average accuracy of 30.5 cm (Ipema et al., 2013). Location data for every cow was registered every 5 seconds on a 20 cm grid unless the cow had not moved from her previous location, in which case no new data point was added.

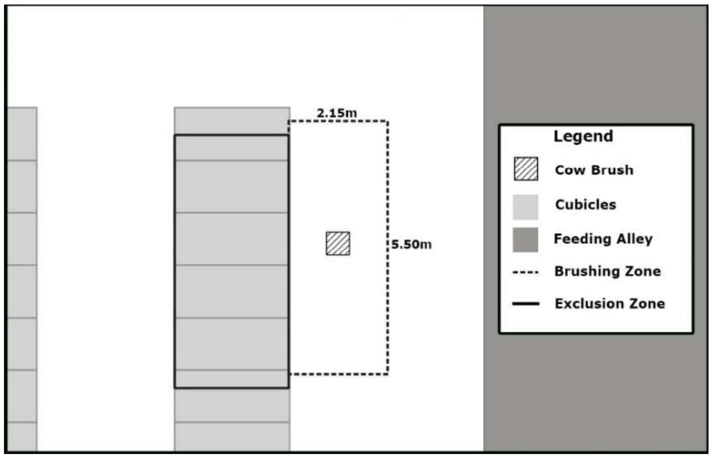

Figure 1: Overview of the barn with both virtual boundaries used by the algorithm: brushing zone and exclusion zone. The cubicles could only be entered from the left.

Brush usage observations

Brush usage observations were conducted for 38 hours and distributed across 12 days by two observers, positioned on a high umpire's chair in the feeding alley. The presence in the brushing zone and actual usage of the brush were recorded by the observers. In a pilot study, the brushing zone was defined as a virtual boundary around the cow brush based on the area in which the animals' SmartTag Neck was observed when using the cow brush. This brushing zone was used for both the brush usage observations and the algorithm to determine when a cow was present at the cow brush and was defined as a rectangle of 5.5 by 2.15 meters surrounding the brush (Figure 1). Additionally, a minimum time spent in the brushing zone was set at 20 seconds to distinguish between cows using the cow brush and cows passing through the area. When a cow approached the brush, the cow number, the time of entering the brushing zone, the start and stop time of a brushing session, and the time of leaving the brushing zone were recorded. A brushing session was defined as continuous brush usage of more than 10 seconds (Mandel et al., 2017).

Algorithm

An algorithm was created in Python (v3.10) to determine the time cows spent in the brushing zone based on location data. The start time of a cow brush visit, according to the algorithm, was defined as the first data point inside the brushing zone, where the minimum time in the brushing zone was set at five data points, which was between 20 and 24 seconds. The end time was the first data point outside the brushing zone, minus 5 seconds. This was to prevent shorter presence in the brushing zone if a cow was located in the same spot within the boundary for a longer period, which caused no new data points to be registered. The iron bars of the cubicles next to the cow brush could cause a mild drift of the location data of the cows lying in a cubicle, occasionally misplacing a data point inside the brushing zone, causing false positives. Therefore, an exclusion zone was set parallel to the brushing zone, measuring 5.5 meters in length, and 2.5 meters in width (Figure 1). The algorithm would delete the cow brush visit if the cow had a data point in the exclusion zone directly before or after the cow brush visit. The exclusion zone was shifted slightly downward relative to the brushing zone to prevent cows walking past the cubicles to visit the brushing zone from being detected in the exclusion zone.

Algorithm validation

The brush visit observations were matched to the cow brush visits generated by the algorithm. The number of times a cow visited the cow brush and the duration of the visits were compared to the output of the algorithm where observations were set as reference standard. A true positive (TP) was defined as a cow brush visit found by both the visual observations and the algorithm. A false positive (FP) was defined as a cow brush visit detected by the algorithm but not found in the visual observations. A false negative (FN) was a visually observed cow brush visit that was not recorded by the algorithm. True negatives (TN) were not calculated as these were all other animals present in the barn. FNs with observations <24 seconds were removed from the dataset, and TPs with observations <20 seconds were changed to FP. When the algorithm generated multiple cow brush visits where the visual observations only detected one in the same period, caused by a cow crossing the virtual boundary, these split recordings were not viewed as false positives but recorded as one TP. To validate the duration, the durations of these split recordings were combined into one brushing time. The records of one cow had to be removed from the dataset due to faulty tag registration in the database. All FN and FP, and the TPs with an absolute difference in duration of the visit >1 minute between observation and algorithm, were visually inspected in QGIS (3.34 LTR) to identify the underlying detection errors for future improvements of the algorithm.

Statistical analyses

The algorithm performance indicators: precision as TP/(TP+FP), recall as TP/(TP+FN), and F1 as 2x((Precision*Recall)/(Precision+Recall)) were calculated. Spearman's rank-order correlation was calculated for the duration of observed and algorithm-recorded brush visits. An Ordinary Least Squares (OLS) regression analysis was conducted in Python to obtain a regression formula for determining the brushing time based on the cows' duration in the brushing zone according to the algorithm. The standard errors were corrected with the 'HC3' heteroscedasticity consistent covariance matrix (HCCM) to account for potential heteroscedasticity and residuals were checked for normal distribution and homoscedasticity. Based on the distribution of residuals, algorithm output data was trimmed to exclude the 5% largest data points before model fitting a second linear regression model.

Results and Discussion

A total of 533 visits to the cow brush were observed, with cows having a brushing session during 466 of these visits (87.4%). The median cow brush visit was 01:27 minutes (range 00:20-36:38). When cows used the cow brush, the median brushing session was 01:22 minutes (range 00:10-20:03). The algorithm yielded 554 recorded visits to the cow brush for the observation periods. For 24 observed cow brush visits, the algorithm recordings were split into two or more visits. After joining these split recordings, 523 visits remained. A total of 590 cow brush visits remained after the matching of observations with algorithm output (Table 1), resulting in good precision (89.1%), recall (87.4%), and F1 score (88.3%) for the algorithm in determining the presence of a cow in the brushing zone.

Table 1: Confusion matrix of observed visits and algorithm output. TP: true positives; FP: false positives; FN: false negatives; TN: true negatives. [1]TN was not calculated as these were all other animals present in the barn.

		Algorithm output		
		Yes	No	Total
Observed visits	Yes	TP 466	FN 67	533
	No	FP 57	TN[1] -	57
	Total	523	67	590

After plotting the data in QGIS, three different causes of FN could be identified, with the main cause being cows not having enough data points in the brushing zone to trigger the algorithm (Table 2). Unexpectedly, 6 FN visits had only 4 data points in the brushing zone, causing the algorithm not to trigger even though the cows were standing in the brushing zone for more than 30 seconds. This was very likely caused by the animals standing completely motionless in the brushing zone, causing no new data points to be recorded. This shortcoming could be fixed in a future version of the algorithm by including the time delta between data points or interpolating missing data points. For the FP, four causes were identified based on the QGIS plots. The main reason was that nine individuals were lying in a cubicle at the edge of the exclusion zone, with data points drifting into the brushing zone (Table 2). For both FN and FP, some cases were caused by an animal being on the edge of the brushing zone. This would make it either difficult to see for the observer whether the animal was in the brushing zone, or this would cause the data points to drift in and out of the brushing zone. A few cases were observed in which the algorithm yielded a visit, but the observed visit was <20 seconds, which should not have caused the algorithm to trigger (Table 2).

Table 2: Causes for False Negatives (FN) and False Positives (FP)

FN	Cause	number of cases	**FP**	Cause	number of cases
	Insufficient data points in brushing zone	31		Cow walking through brushing zone	13
	Datapoints in exclusion zone	23		Cow in cubicle	22
	Cow at edge brushing zone	13		Cow at edge brushing zone	13
				Observation < 20 seconds	9
	Total	**67**		**Total**	**57**

Time spent in the brushing zone for observations and algorithm was strongly correlated for the TPs (Spearman's rank-order correlation: $r=0.919$; $p<0.000$; $n=466$). In 32 cases

(6.8% of TP), the time difference between the time spent at the cow brush for observations and the algorithm was more than one minute. Time differences were mainly due to cows being at the edge of the brushing zone, causing either observational error or a data point drifting just outside the brushing zone (6.2%). This was also the reason for the split recordings, and this could possibly be resolved in future versions of the algorithm by checking the time difference between the different recorded cow brush visits. Time observed at the brush and duration of the brushing session were strongly correlated (Spearman's rank-order correlation: r=0.853; p<0.001; n=533). Considering only cows that used the brush during their visit, this correlation was slightly higher (Spearman's rank-order correlation: r=0.916; p<0.001; n=466). So, presence at the brush seems an informative proxy of brushing time, but not all cows will use the brush when visiting the brushing zone.

In our linear regression analysis, predicting the brushing time based on the cows' duration in the brushing zone according to the algorithm, the model demonstrated a moderate fit to the data, with 40.9% of the variance in brushing time being explained by the algorithm output ($R^2 = 0.409$; $F(1,588) = 28.7$; $p<0.001$; Figure 2)). The residuals of the regression model were found to be non-normally distributed due to kurtosis and appeared heteroscedastic where longer visits with no brushing caused the greatest variance. When the algorithm output data was trimmed to exclude the 5% largest data points prior to model fitting the linear regression model improved slightly ($R^2 = 0.522$; $F(1,558) = 238.6$; $p<0.001$; Figure 2) but some heteroscedasticity remained.

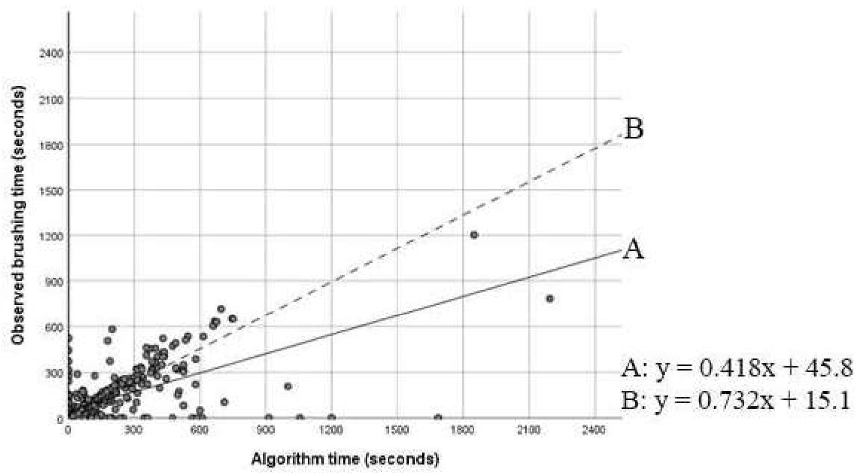

Figure 2: The relationship between the algorithm output and the observed brushing time for observed visits to the brushing zone including the linear regression models and their formulas. Model A is based on all algorithm output. For model B the largest 5% of the algorithm output was excluded before model fitting.

The predictive ability of the algorithm for brushing time might be improved by resolving the FN/FP causes. However, cows standing close to the brush without brushing will occur, making it difficult to predict brushing time based on proximity to the brush only. Installing a sensor in the cow brush recording active brushing (Mandel et al., 2018) might be useful in combination with our data. However, it has also been observed on several occasions that multiple cows were standing close to the brush but only one was actively brushing. It could be argued that the duration of brushing is of lesser importance than the frequency of visits for detecting a disease. For example, in lame cows the frequency of brush visits and feeding bouts decrease (Frondelius et al., 2022; Weigele et al., 2018).

Conclusions

This study is the first step in validating an algorithm for automated recording of brushing time in a commercial dairy farm setting, enabling future studies relating brushing time to health and welfare. Work can still be done to improve algorithm performance on predicting the duration of brushing sessions, but high recall and precision were reached for the presence at the cow brush.

Acknowledgments

This project was funded by the Dutch Research Council (NWO 023.017.003)

References

Almeida, P. E., Weber, P. S. D., Burton, J. L., & Zanella, A. J. (2008). Depressed DHEA and increased sickness response behaviors in lame dairy cows with inflammatory foot lesions. *Domestic Animal Endocrinology*, *34*(1), 89–99. https://doi.org/10.1016/j.domaniend.2006.11.006

Blackie, N., Amory, J., Bleach, E., & Scaife, J. (2011). The effect of lameness on lying behaviour of zero grazed Holstein dairy cattle. *Applied Animal Behaviour Science*, *134*(3–4), 85–91. https://doi.org/10.1016/j.applanim.2011.08.004

Bolinger, D. J., Albright, J. L., Morrow-Tesch, J., Kenyon, S. J., & Cunningham, M. D. (1997). The Effects of Restraint Using Self-Locking Stanchions on Dairy Cows in Relation to Behavior, Feed Intake, Physiological Parameters, Health, and Milk Yield. *Journal of Dairy Science*, *80*(10), 2411–2417. https://doi.org/10.3168/jds.S0022-0302(97)76193-9

DeVries, T. J., Vankova, M., Veira, D. M., & Von Keyserlingk, M. A. G. (2007). Short communication: Usage of mechanical brushes by lactating dairy cows. *Journal of Dairy Science*, *90*(5), 2241–2245. https://doi.org/10.3168/jds.2006-648

Dittrich, I., Gertz, M., & Krieter, J. (2019). Alterations in sick dairy cows' daily behavioural patterns. *Heliyon*, *5*(11). https://doi.org/10.1016/j.heliyon.2019.e02902

Fogsgaard, K. K., Bennedsgaard, T. W., & Herskin, M. S. (2015). Behavioral changes in freestall-housed dairy cows with naturally occurring clinical mastitis. *Journal of Dairy Science*, *98*(3), 1730–1738. https://doi.org/10.3168/jds.2014-8347

Fogsgaard, K. K., Røntved, C. M., Sørensen, P., & Herskin, M. S. (2012). Sickness behavior in dairy cows during Escherichia coli mastitis. *Journal of Dairy Science*, *95*(2), 630–638. https://doi.org/10.3168/jds.2011-4350

Frondelius, L., Lindeberg, H., & Pastell, M. (2022). Lameness changes the behavior of dairy cows: daily rank order of lying and feeding behavior decreases with increasing number of lameness indicators present in cow locomotion. *Journal of Veterinary Behavior*, *54*, 1–11. https://doi.org/10.1016/j.jveb.2022.06.004

Ipema, A. H., Van De Ven, T., & Hogewerf, P. H. (2013). Validation and application of an indoor localization system for animals. *Precision Livestock Farming 2013*, 135–144.
Johnson, R. W. (2002). The concept of sickness behavior: a brief chronological account of four key discoveries. *Veterinary Immunology and Immunopathology*, *87*(3–4), 443–450. https://doi.org/https://doi.org/10.1016/s0165-2427(02)00069-7
Keeling, L. J., Winckler, C., Hintze, S., & Forkman, B. (2021). Towards a Positive Welfare Protocol for Cattle: A Critical Review of Indicators and Suggestion of How We Might Proceed. *Frontiers in Animal Science*, *2*. https://doi.org/10.3389/fanim.2021.753080
Lecorps, B., Welk, A., Weary, D. M., & von Keyserlingk, M. A. G. (2021). Postpartum stressors cause a reduction in mechanical brush use in dairy cows. *Animals*, *11*(11). https://doi.org/10.3390/ani11113031
Littin, K., Acevedo, A., Browne, W., Edgar, J., Mendl, M., Owen, D., Sherwin, C., Würbel, H., & Nicol, C. (2008). Towards humane end points: Behavioural changes precede clinical signs of disease in a Huntington's disease model. *Proceedings of the Royal Society B: Biological Sciences*, *275*(1645), 1865–1874. https://doi.org/10.1098/rspb.2008.0388
Mandel, R., Harazy, H., Gygax, L., Nicol, C. J., Ben-David, A., Whay, H. R., & Klement, E. (2018). Short communication: Detection of lameness in dairy cows using a grooming device. *Journal of Dairy Science*, *101*(2), 1511–1517. https://doi.org/10.3168/jds.2017-13207
Mandel, R., Nicol, C. J., Whay, H. R., & Klement, E. (2017). Short communication: Detection and monitoring of metritis in dairy cows using an automated grooming device. *Journal of Dairy Science*, *100*(7), 5724–5728. https://doi.org/10.3168/jds.2016-12201
Schukken, Y. H., & Douglas Young, G. (2009). *Field Study on milk production and mastitis effect of the DeLaval Swinging Cow Brush*. https://api.semanticscholar.org/CorpusID:110596886
Siivonen, J., Taponen, S., Hovinen, M., Pastell, M., Lensink, B. J., Pyörälä, S., & Hänninen, L. (2011). Impact of acute clinical mastitis on cow behaviour. *Applied Animal Behaviour Science*, *132*(3–4), 101–106. https://doi.org/10.1016/j.applanim.2011.04.005
Stasiak, K. L., Maul, D., French, E., Hellyer, P. W., & Vandewoude, S. (2003). Species-specific assessment of pain in laboratory animals. *Contemporary Topics in Laboratory Animal Science*, *42*(4), 3–20. https://www.researchgate.net/publication/10624240
Weary, D. M., Huzzey, J. M., & Von Keyserlingk, M. A. G. (2009). Board-invited Review: Using behavior to predict and identify ill health in animals. *Journal of Animal Science*, *87*(2), 770–777. https://doi.org/10.2527/jas.2008-1297
Weigele, H. C., Gygax, L., Steiner, A., Wechsler, B., & Burla, J. B. (2018). Moderate lameness leads to marked behavioral changes in dairy cows. *Journal of Dairy Science*, *101*(3), 2370–2382. https://doi.org/10.3168/jds.2017-13120
Wilson, S. C., Mitlo Èhner, F. M., Morrow-Tesch, J., Dailey, J. W., & Mcglone, J. J. (2002). An assessment of several potential enrichment devices for feedlot cattle. *Applied Animal Behaviour Science*, *76*, 259–265. https://doi.org/https://doi.org/10.1016/S0168-1591(02)00019-9

Yunta, C., Guasch, I., & Bach, A. (2012). Short communication: Lying behavior of lactating dairy cows is influenced by lameness especially around feeding time. *Journal of Dairy Science*, *95*(11), 6546–6549. https://doi.org/10.3168/jds.2012-5670