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Application note: Validation of BovHEAT — An open-source analysis tool to process data from automated activity monitoring systems in dairy cattle for estrus detection

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ABSTRACT

This application note introduces the software called Bovine Heat Detection and Analysis Tool (**BovHEAT**), a validated and open-source analysis tool to process automated activity monitoring (**AAM**) data for estrus detection. We used activity data collected from a neck-attached accelerometer (Heatime, SCR Engineers Ltd., Netanya, Israel) that is widely adopted in the dairy industry. Developed with the Python programming language, **BovHEAT** offers fully automatic and scalable processing for estrus detection with additional functionality for handling missing values and a plausibility check for timing of events. Processed output is provided in an Excel file with result tables in the long and wide format. Additionally, a PDF file containing activity change line graphs is generated. For validation, we compared the accuracy and time of three different methods to process AAM data: 1) manual data evaluation (**MAN**), 2) Excel tool (**EXCEL**), and 3) **BovHEAT**. Two different datasets from 8 farms (1 farm in Canada; 7 farms in Germany) were used. Validation was performed independently by three investigators. In total, activity data from 60 cows representing a maximum number of 600 observations (50 days with 12 observations per day) per cow were used. Manual data evaluation was less accurate due to transcription errors, with 13 of 60 cows having at least one error. More specifically, 16 out of 110 estrus events were recorded incorrectly. The time to process AAM data and transfer the results into a standardized results table for 10 cows was 41.0 (range 28–53) minutes, 30.7 (18–48) minutes, and 11.7 (4–16) minutes for MAN, EXCEL and **BovHEAT**, respectively. Without the standardized results table, a fully automated run with **BovHEAT** processing the complete dataset of 5,477 cows, which consisted of 361 XLS and XLSX files, took 172 s. The results from this study indicate that **BovHEAT** speeds up processing, requires less user interaction and provides additional features. Our aim is to accelerate future research with AAM data and facilitate reproducibility via our validated analysis tool. Since **BovHEAT** is open-source and MIT-licensed, it allows customization to support different sensors and manufacturers. The **BovHEAT** tool can be evaluated, downloaded and contributed to on GitHub (https://github.com/bovheat/bovheat, https://doi.org/10.5281/zenodo.3890126).

1. Introduction

The dairy industry has undergone profound changes over recent decades. The number of farms has decreased considerably, whereas herd size has increased. The adoption of new technologies by dairy farmers is accelerating to improve efficiency and profitability (Barkema et al., 2015). Improvements in sensor technology, integration of data from multiple systems and, in particular, increased training of farmers, their personnel, and advisors to use sensor-derived data will enable precision dairy farming to be implemented. This implementation could lead to a more accurate identification of animals requiring attention and ultimately increased farm profitability. Precision technology (e.g., automated cow activity monitors and automated milking systems) helps to collect individual animal data and to provide farmers with real-time information that can be implemented in herd management (Rutten et al., 2013). These new technologies have been evolving rapidly, and it has become difficult for animal scientists to fully utilize the increasing number of massive and permanent data

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streams (Cabrera et al., 2020). Useful information needs to be extracted from the data to assist in the decision-making process (White et al., 2018). Automated activity monitoring (**AAM**) tools were one of the first adopted technologies of so-called precision livestock farming (**PLF**; Rutten et al., 2013).

Estrus detection for dairy cows in confined housing systems has become a greater challenge as milk production increases (López-Gatius et al., 2005), and cows are less likely to express estrous behavior on dry grooved concrete surfaces (Britt et al., 1986). The estrus detection rate in a recent survey of Canadian dairy herds (Denis-Robichaud et al., 2016) was below 50%. The proportion of cows truly bred upon estrus detection, however, is unclear, as these data were confounded by the use of timed artificial insemination (**AI**) protocols. The failure to submit cows for AI not only has a major impact on reproductive performance but also indicates an opportunity to improve profitability (Overton and Cabrera, 2017). Automated activity monitoring systems have been reported as a useful tool for accurate detection of estrus, which has the potential to increase reproductive performance in dairy farms with both cows and heifers (Michaelis et al., 2014). In addition to its implementation in reproductive management, continuously recorded data from AAM systems can offer additional information regarding health status (Stangaferro et al., 2016) and animal behavior (Pfeiffer et al., 2020). Furthermore, it has been shown that distinct characteristics of an estrus event such as estrus intensity provide useful predicting information on fertility in lactating dairy cows (Madureira et al., 2015).

Managing and processing data from AAM systems for research and practice purposes have become complex and challenging tasks due to the increased volume, variety and sampling frequency of the data. One prevailing processing solution is a spreadsheet tool called HeatCalc, which has been used in recent publications (Madureira et al., 2015). HeatCalc is built in Excel (Office 2019, Microsoft Corporation, Redmond, WA, US) and utilizes a sequence of functions, filters, user copy and paste tasks and pivot tables. However, the HeatCalc Excel tool lacks: 1) ease of use, as a multitude of manual steps have to be performed, 2) flexibility, as the solution is limited by Excel's functionality, and therefore 3) scalability. The use of such Excel-based solutions leads to time-consuming and error-prone analysis of AAM data, especially when analyzing large datasets. Furthermore, the mentioned processing sequence of the HeatCalc Excel tool has not been validated nor has the tool been published in a scientific journal. Therefore, the objective of this study was to develop and validate an open-source analysis tool for the automated processing of dairy cow activity data from AAM systems.

2. Development of BovHEAT

We developed an analysis tool, called the Bovine Heat Detection and Analysis Tool (**BovHEAT**), with the open-source Python programming language (van Rossum and Drake Jr, 1995) to batch-process multiple AAM files with minimal user interaction and provide additional features, including missing data interpolation and PDF visualization of activity data.

2.1. Internals and delivery

The analysis tool utilizes the following Python packages: 1) *xlrd* (https://github.com/python-excel/xlrd) and *xlsxwriter* (https://pypi.org/project/XlsxWriter/) to read and write both XLS and XLSX files, 2) *pandas — data analysis and statistics library* (McKinney, 2011) for data manipulation including filtering, merging and split-apply combine operations (Wickham, 2011) and 3) *matplotlib* (https://github.com/matplotlib/matplotlib) for visualization and PDF creation.

During the development of **BovHEAT**, we implemented fully automated unit and integration tests, which are performed on every code revision. These tests ensure correct results for all current and future **BovHEAT** versions by testing them against the validated dataset. Installation is not required, as the entire **BovHEAT** tool is packaged and delivered as one single standalone executable file for three commonly used operating systems (Windows, macOS and Linux). The executables are built and tested through GitHub Actions (https://github.com/features/actions).

2.2. Automated activity monitoring (AAM) data

To develop and validate a software tool to process AAM data, we used data from a neck-attached accelerometer (Heatime, SCR Engineers Ltd., Netanya, Israel), referred to as the AAM system in this paper, to conduct a proof-of-concept study. The AAM system was chosen because it is popular in the dairy industry (Michaelis et al., 2013) and has been used extensively in different research settings, including reproductive performance (Fricke et al., 2014) and health disorders (Stangaferro et al., 2016). Activity and rumination characteristics were monitored by the AAM system using tags that record the cow's movement and intensity, as well as rumination. The data were received by a stationary radio frequency base unit, which was connected to the on-farm computer. The on-farm computer was equipped with the accelerometer software DataFlow II (SCR Engineers Ltd., Netanya, Israel), which stored the activity data as aggregated average activity blocks of 2-h time periods (12 blocks of 2 h per day) per cow. We acquired the data during on-site farm visits via exports from accelerometer software DataFlow II on the on-farm computer. The raw activity data from each cow were converted by accelerometer software into an activity change index using a proprietary algorithm. The algorithm uses the difference between the cow's momentary mean activity and its mean activity of the past seven days, weighted by its standard deviation (Bar, 2010). LeRoy et al., 2018 were previously able to explain the algorithm's calculation steps in detail. Index values for activity change range from −100 to 100 index points (decreased activity −100 to 0; increased activity 0 to 100).

Two datasets were used, which represented two possible data export schemes. Files from the AAM system were exported with the corresponding herd accelerometer software DataFlow II. The first dataset contained activity data of 260 Holstein cows from May 2018 until April 2019 from the University of British Columbia's Dairy Education and Research Centre in Agassiz, Canada. Activity data for all cows were exported on a weekly basis, which resulted in multiple files, each containing activity data from 7 days. Therefore, in this export scheme, the observations of a single cow are spread across multiple XLSX files. The second dataset contained activity data from 7 commercial dairy farms in Northeast Germany representing 5,217 Holstein cows from July 2018 until April 2020. The activity data were exported for all cows that calved within the last 7 d on each farm. The files contained the complete activity data from calving until 50 days in milk (DIM). In this export scheme, all observations of a single cow were stored in one XLSX file.

Sample activity data files with both export schemes from both datasets are provided and can be inspected in the **BovHEAT** GitHub and Zenodo repositories.

2.3. Estrus parameter definition

Each estrus event can be defined by three different behavioral events in the time sequence: onset of estrus (**ONSET**), peak of estrus activity (**PEAK**), and the end of estrus (**END**). The onset of estrus is defined as a cow passing a certain level for the activity change index. This level is a farm-specific threshold that is defined by the herd manager. An animal eligible for breeding is considered to be in heat as soon as it passes this threshold. The end of estrus is defined by the first instance at which the index value falls below this threshold again. The intensity of an estrus event can be defined by the peak of the activity change index during an estrus event. The duration (**DUR**) of an estrus event can be defined as the interval from ONSET to END. An example of an estrus event is depicted in Fig. 1.

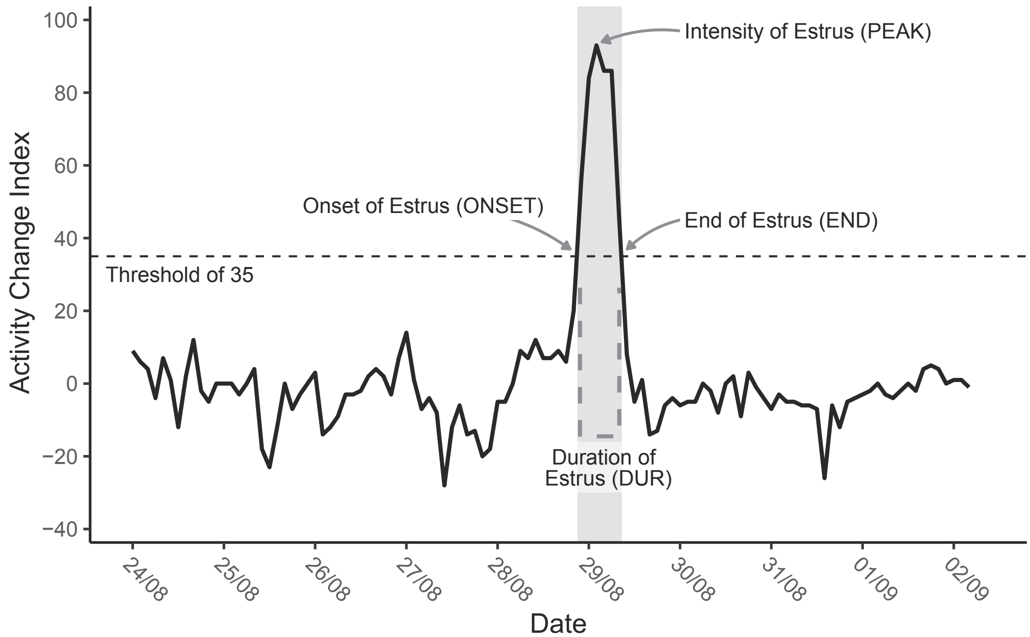

Fig. 1. A schematic representation of a cow's activity change index at an alert and estrus event characteristics used in the study. The raw activity of each cow is continuously recorded in 2-h periods (dates are recorded as months/day) and converted into an activity change index value using a proprietary algorithm by the AAM system (Heatime, SCR Engineers Ltd., Netanya, Israel). Onset of estrus (ONSET) is defined as a cow exceeding an activity change index value of 35. End of estrus (END) is defined by the first instance at which the index value falls below 35 again. The intensity of an estrus event (PEAK) is represented by the peak of the activity change index value during an estrus event. The duration of an estrus event (DUR) is defined as the interval from ONSET to END of an estrus event.

2.4. Source data

The **BovHEAT** tool automatically detects and imports all folders containing XLS and XLSX files exported in the English or German language via DataFlow II. Additional languages can be added to the analysis tool by creating a translation table for the required column headings. The files must contain the following columns with their corresponding headings, which are set correctly by default by DataFlow II: "Cow Number", "Date", "Time", "Activity Change", "Lactation number" and "Days in Lactation". Damaged files or files with incorrect column headings will be skipped. The user can define the desired threshold for estrus detection and specify an observation period by selecting DIM values for start and end. To include days before calving, the start value can be negative. The calving date is determined by DIM = 0. In the case that no observation with DIM = 0 is available (i.e., missing or corrupted), the earliest DIM value is used to retroactively calculate the calving date. If multiple lactations of one cow are detected in the read data, each lactation will be analyzed individually. Overlapping and duplicate observations are detected, and invalid observations are discarded. This scenario occurred in our first dataset, when several consecutive files, each containing 7 days of AAM data, had to be merged. The **BovHEAT** tool additionally supports unsupervised execution through command-line options (e.g., folder path, start and stop DIM value, threshold, language, core count, output file and interpolation limit).

2.5. Missing values and short interestrus intervals

The **BovHEAT** tool addresses missing values through a two-step method. First, missing values are interpolated if the number of missing consecutive observations is less than 3 (i.e., <6 h). The imputation of missing data, however, should be used with caution, as it may lead to incorrect conclusions (White et al., 2018). The interpolation can be disabled, and the limit of missing consecutive observations can be changed. As a second step, information regarding the percentage of usable activity data in the selected observation period is reported in the XLSX results, granting the ability to filter for the desired amount of minimum usable data. Future studies need to address whether the introduction of cows with missing data leads to a bias when evaluating AAM profiles of cows and their association with biological outcomes. Depending on the amount of missing data, this introduction of cows with missing data might represent a serious bias to animal scientists, as changes in activity cannot be detected, although they occur (i.e., false negative events). A plausibility check for short estrus intervals was added. A flag is set if two estrus events occur within less than 10 h. Short interestrus intervals have been associated with reduced pregnancy per AI (Tippenhauer et al., 2021), although the physiological reason is unclear.

2.6. Output and visualization

After processing, the results are saved in a single XLSX file that contains two result table formats. In the wide-formatted table, each cow is contained in a single row. For each estrus event the cow had, several columns of estrus parameters were added. In the long-formatted table, each cow can occupy multiple rows, one for each estrus event. This format reduces the number of estrus parameters columns. All processed cows are listed and subdivided by their ID and lactation number. The tables contain the following information: folder name (i.e., farm name), cow ID, lactation number, calving date, warning flag for estrus events with an abnormal pattern (i.e., 2 estrus events within 8 h), usable activity data within the selected observation period (%), maximum activity change index value, and number of estrus events within the observation period. For each estrus event, the following values are calculated: the date and time for ONSET and END, activity change index value at PEAK, DIM value at PEAK, date and time for PEAK and DUR of the estrus event.

Additionally, a PDF file is generated containing line graphs showing the activity change index for the selected observation period for each lactation of each cow. Estrus events are highlighted, and the calving dates are marked within the graph. The searchable PDF file contains farm name, cow ID, lactation number, and the percentage of usable data for each cow and lactation (Fig. 2).

Sample files for the PDF line graphs and the XLSX results with both wide- and long-formatted tables are provided and can be inspected in the **BovHEAT** GitHub and Zenodo repositories.

3. Validation and processing method

To evaluate the accuracy and functionality of the **BovHEAT** tool, we compared three different methods to process AAM data: 1) manual data evaluation (**MAN**), 2) the aforementioned HeatCalc Excel tool (**EXCEL**),

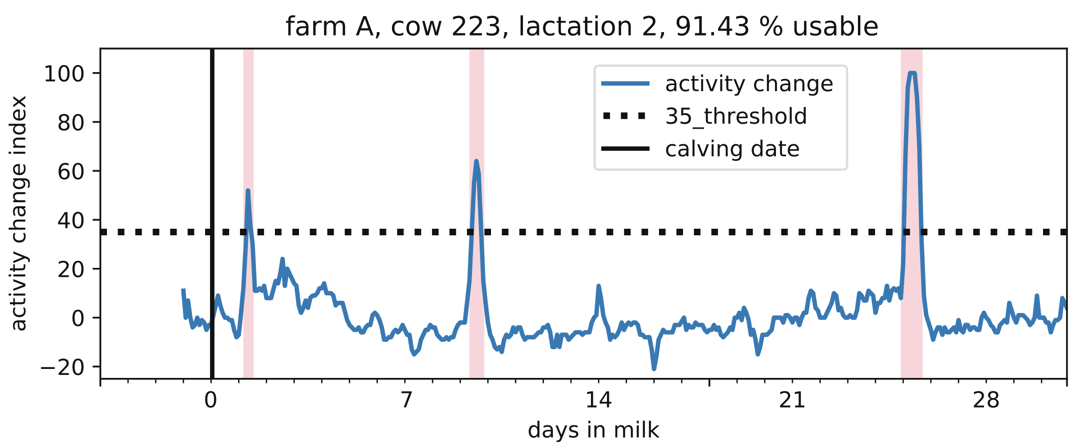

Fig. 2. A sample activity change index line graph with highlighted estrus events and descriptive title generated by **BovHEAT**. The calving date and the user-selected threshold for heat detection are marked. These graphs are generated for each lactation of each cow in the processed dataset and are saved in a PDF file, allowing the user to check and visualize the activity patterns and calculations performed by **BovHEAT**.

and 3) the developed analysis tool (**BovHEAT**). An estrus event was reported accurately if all five characteristics were identified correctly: timing of ONSET, END and PEAK, PEAK activity change index value and DUR. The validation was performed independently by three investigators (JL Plenio, A Bartel, S Borchardt). For this independent validation, activity data from a total of 60 cows were used. Sixty cows were selected by randomly choosing 30 cows from each of the two datasets. They were subsequently subdivided into six groups containing 10 cows each. The maximum number of observations regarding activity change data was 600 (50 days with 12 observations per day) per cow. Twenty out of 60 cows had complete datasets. Among the 40 cows with incomplete datasets, on average, 101 observations regarding activity change data were missing, ranging from 6 to 360 observations per cow (Table 1).

To compare the time to process the data and the accuracy of the results among the three methods, each 10-cow group was analyzed by the three investigators, each using one of the three methods. Each investigator performed the methods in a different order. Organizing and reporting the results into a standardized table was included in the time for analyses. The column order and format of the standardized results table was designed not to favor any of the three methods. If there was a disagreement among the three methods, the truth was determined by revisiting the raw data and reaching a consensus between the three investigators.

Statistical analyses to compare the time to process the data of the three methods were performed using R version 4.0.0 (R Foundation, Vienna). The time was log transformed to achieve a normal distribution. Statistical testing was performed using a repeated-measures ANOVA accounting for the triple analysis of the six datasets by each of the three investigators, followed by a post hoc multiple comparison *t*-test with Tukey correction (R packages emmeans version 1.4.6).

Table 1
Basic descriptive statistics for two datasets representing automated activity monitor (**AAM**) data[1] from 60 lactating Holstein cows that were used to validate three different methods to process AAM data.

Parameter	Dataset 1[2]	Dataset 2[3]
Number of cows	30	30
Number of farms	1	7
Estrus events per cow		
0	0	3
1	11	11
2	17	4
3	1	5
≥ 4	1	7
% usable activity data within the observation period[4]		
100%	3	17
80–99%	19	10
40–79%	8	3

[1] Heatime, SCR Engineers, Netanya, Israel.
[2] Files from the AAM system were exported using DataFlow II on a weekly basis for all cows.
[3] Files from the AAM system were exported using DataFlow II on a weekly basis for all cows that calved within the last 7 d on each farm, including information from calving until 50 DIM.
[4] Individual activity data were captured in 2 h blocks with 12 observations per day. The observation period was 50 days. Therefore, the maximum number of usable activity data observations was 600.

4. Results

Results are summarized in Table 1.

Overall, the three investigators agreed that 110 valid estrus events were to be identified. The mean ($\pm$standard deviation) duration of an estrus event was 11.4 $\pm$ 4.8 h. The minimum and maximum estrus event duration was 2 h and 22 h, respectively. The number of estrus events per cow ranged from zero to six events. Four cows had an estrus event with a short estrus interval within the observation period and were flagged by **BovHEAT**. Three cows had no estrus events within the observation period (Table 1). For each estrus event a cow reported, we evaluated the date and time for ONSET, PEAK and END, activity change index value at PEAK, and DUR of an estrus event. Both EXCEL and **BovHEAT** correctly identified all estrus events and their parameters. Manual data extraction was less accurate due to various human errors, including calculation, transfer and reporting mistakes, with 13 out of 60 cows having at least one error (3, 4 and 6 errors per investigator). More specifically, 16 out of 110 estrus events were recorded incorrectly. The time to process AAM data and copying the results into a standardized results table from 10 cows was 41.0 (range 28–53) minutes, 30.7 (18–48) minutes, and 11.7 (4–16) minutes for MAN, EXCEL, and **BovHEAT**, respectively, showing that **BovHEAT** considerably shortens the analysis time of the 10-cow group, being 3.51 times faster than MAN ($P < 0.001$) and 2.63 times faster than EXCEL ($P < 0.001$). A minor improvement by a factor of 1.34 was present for EXCEL when compared to MAN ($P = 0.196$). A greater advantage can be expected for larger datasets due to scalability using **BovHEAT**.

5. Discussion and outlook

The objective of this study was to develop and validate an open-source analysis tool for the automated processing of dairy cow activity data collected from an AAM system. Our results indicate that the **BovHEAT** tool has several advantages compared to manual data processing and data processing using the HeatCalc Excel tool that was previously used by several research groups. We were able to show that processing AAM data using **BovHEAT** required less time, provided more accurate results than manual data processing and eliminated potential human errors. We expect that the actual time-saving benefits for larger datasets will increase as our analysis also included the time consumed to copy the output of **BovHEAT** into a standardized table. However, since **BovHEAT** generates an Excel file with result tables in the long and wide format, this step may be skipped, as the data are usable directly after analysis without the need for further data transformation. For example, a complete run of the second dataset of 5,477 cows, which consisted of 361 XLS and XLSX files, took 172 s utilizing a computer equipped with an 8-core CPU. While incorporating the capabilities of the aforementioned HeatCalc Excel approach, our analysis tool offers additional features such as batch-processing of large amounts of AAM data, handling of missing values and short interestrus detection. As shown in our validation of the two datasets, missing values seem to be a common issue when processing AAM data. Only 20 out of 60 cows had complete activity data from an entire observation period of 50 d per cow. The reasons for missing activity data remain speculative. Possible causes are sensor malfunctions, data transmission errors or insufficient calibration time after a cow was fitted with an AMM system sensor. Contrary to the HeatCalc Excel approach, **BovHEAT** does not require an additional calving date column, as it utilizes the DIM column for calving date calculation. As a positive side effect, this allows for the inclusion of cows that received a neck collar after calving (i.e., without a calving date or an observation for DIM = 0). The additional PDF output, which contains activity change line graphs, helps to visualize and understand the activity patterns of the dairy cows. With the provided sample dataset and executables for Windows, Linux and macOS, our **BovHEAT** tool can be tested and evaluated immediately.

The presented advantages of our analysis tool could benefit future research using AAM data of thousands of animals while facilitating reproducibility. These advantages, in turn, support dairy scientists to gain a better understanding of the physiology and behavior of dairy cows and to develop new decision support tools to optimize reproductive management. The **BovHEAT** tool is released under the permissive and open-source MIT license and can be evaluated, downloaded and contributed to on GitHub (https://github.com/bovheat/bovheat, https://doi.org/10.5281/zenodo.3890126).

CRediT authorship contribution statement

J.-L. Plenio: Conceptualization, Software, Validation, Investigation, Visualization, Writing – original draft. **A. Bartel:** Conceptualization, Software, Validation, Visualization, Writing – original draft. **A.M.L. Madureira:** Data curation, Writing - review & editing. **R.L.A. Cerri:** Data curation, Writing - review & editing. **W. Heuwieser:** Resources, Writing - review & editing. **S. Borchardt:** Conceptualization, Validation, Supervision, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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