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Detection of changes in the circadian rhythm of cattle in relation to disease, stress, and reproductive events

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Highlights

- Our Fourier transform-based method detects changes in circadian rhythm
- Circadian changes in cows link to disease, stress, or calving/oestrus events
- The method detects 95% of the rhythm anomalies due to reproductive or disease events and 60–70% due to stress events, with less than 20% false-positives (non-event-related anomalies)
- It can help detect animals needing care.
- It can also assess overall animal welfare status or health/stress-sensitive phenotypes

Abstract

Disease and stress can disrupt the circadian rhythm of activity in animals. Sensor technologies can automatically detect variations in daily activity, but it remains difficult to detect exactly when the circadian rhythm disruption starts. Here we report a mathematical Fourier-Based Approximation with Thresholding (**FBAT**) method designed to detect changes in the circadian activity rhythm of cows whatever the cause of change (typically disease, stress, oestrus). We used data from an indoor positioning system that provides the time per hour spent by each cow resting, in alleys, or eating. We calculated the hourly activity level of each cow by attributing a weight to each activity. We considered 36-h time series and used Fourier transform to model the variations in activity during the first and last 24 h of these 36-h series. We then compared the Euclidian distance between the two models against a given threshold above which we considered that rhythm had changed. We tested the method on four datasets (giving a cumulative total of ~120000 cow*days) that included disease episodes (acidosis, lameness, mastitis or other infectious diseases), reproductive events (oestrus or calving) and external stimuli that can stress animals (e.g. relocation). The method obtained over 80% recall of normal days and detected 95% of abnormal rhythms due to health or reproductive events. FBAT could be implemented in precision livestock farming system monitoring tools to alert caretakers to individual animals needing specific care. The FBAT method also has the potential to detect anomalies in humans to guide healthcare intervention or in wild animals to detect disturbances. We anticipate that chronobiological studies could apply FBAT to help relate circadian rhythm anomalies to specific events.

Keywords

Fourier transform; chronobiology; disease; stress; oestrus; Precision Livestock Farming

1 Introduction

Circadian rhythms of activity are observed in most vertebrate and invertebrate animals and even in plants. Circadian rhythm is triggered by internal clocks that — in the absence of external cues — repeat a rhythm of about 24 h. In vertebrates, the main pacemaker is situated in the suprachiasmatic nucleus of the brain and coordinates peripheral clocks that are found in a majority of cells [1, 2].

Disruption of circadian rhythms can have far-reaching effects on physical and mental health, even leading to cancer and depression [2, 3]. In turn, stress or disease episodes in animals disrupt their circadian rhythm of activity. Circadian activity disruption is thus a proxy of these disorders. For instance, we observed that circadian variations in activity were less marked in diseased cows [4] but more marked when calves are regrouped with other calves, which is known to induce stress [5]. Such effects may involve glucocorticoids, which are significantly released during stress or disease and which help coordinate circadian rhythms by resetting cellular clocks downstream of the brain [6]. Identifying disruptions in circadian rhythm could serve to detect cases of stress or disease and, in turn, prompt animal caretakers to address such problems, determine their causes, and take remedial action.

Detecting disruption in activity rhythms requires continuous monitoring. There are sensor systems available that enable continuous monitoring and automatic detection of variations in daily activity in animals and in humans. For instance, Real-Time

Locating Systems (**RTLS**), accelerometers, automatic image analysis, and sound analysis all provide information on animal activity by distinguishing basic activities such as resting, standing, walking, and eating [7, 8]. However, interpreting the data from these tools remains difficult, as these basic activities depend on a cluster of factors including animal age and breed, design of the barn (e.g. number and location of resting and feeding areas), animal management variables (e.g. food distribution or milking time), diet, season, and more. Basic activities can also change in frequency from one day to another, which interferes with the way the rhythms are patterned, e.g. a low-frequency activity will also show only small variations during the day. Summarising the activity of an animal into an activity level can help identify the activity rhythm. Day–night cycle variations in activity level appear to be less dependent on factors that affect basic activities. In addition, the activity level is expressed in absolute terms, i.e. has no frequency. Calculating this circadian activity level could therefore serve to highlight differences between diseased or stressed animals and normal-status animals [4, 9]. However, it remains difficult to detect exactly when the rhythm starts to become disrupted.

There are numerous methods proposed to detect anomalies in time series. We first tested traditional machine learning methods (K Nearest Neighbours for Regression (**KNNR**), Decision Tree for Regression (**DTR**), MultiLayer Perceptron (**MLP**), Long Short-Term Memory (**LSTM**) [10] and then went on test the most promising methods available according to the latest literature reviews [11, 12], namely the Bag Of SFA Symbols **(BOSS),** Hierarchical Vote Collective Of Transformation-based Ensembles (**Hive-Cote**), Dynamic Time Warping (**DTW**), Fully Convolutional Network **(FCN**) and Residual Network (**ResNet**) algorithms [13]. As these methods require large datasets, data from several animals has to be processed together, making it difficult to identify the rhythm of each animal. Also, they do not always factor the cyclic aspects (here, circadian rhythm) into the time series.

We developed a mathematical Fourier transform-based method to detect changes in the circadian activity rhythm of animals, called 'Fourier-Based Approximation with Thresholding' (**FBAT** [13]). Fourier analysis is a powerful tool to analyse continuous cyclic functions. The assumption is that all cyclic signals $y(t)$ with a frequency f can be decomposed into a cosine function of frequency f and with an infinity of other cosine curves called harmonics h_n (n represents the rank of the harmonic), i.e.

$$y(t) = \sum_{n=-\infty}^{+\infty} |h_n| cos\big(2\pi nft + arg(h_n)\big)$$

where $h_n$is the harmonic of rank n represented by a complex number with $|h_n|$ its modulus and $arg(h_n)$ its argument.

The rationale for FBAT is as follows. Fourier transform is used to extract the cyclic component that reflects the circadian rhythm of two days. If the difference between the two days is higher than a certain threshold, then we consider that the rhythm has changed. The FBAT method proved to outperform the machine learning methods that we tested (see above) in terms of accuracy of the detection of deviations due to health or other disorders.

Here, we present the FBAT method and then test it on four datasets obtained on cattle farms. The datasets span various daily routines that include various disease episodes (acidosis, lameness, mastitis and other infectious diseases), reproductive events (oestrus, calving) or external stimuli that can stress animals. We assess the performance of the method by its capacity to detect activity-rhythm anomalies caused by such events, and we check whether performance varies between causes. FBAT is tested here on data from a commercial RTLS but it could easily be implemented on other animal (or human) behaviour recording devices to automatically detect individual disturbances.

2 Material and methods

2.1 Equipment used to detect cow activity and calculate activity level

We used data from the CowView system (GEA Farm Technology, Bönen, Germany), which is an RTLS that gives the position of each cow in a barn every second. Each cow is equipped with a tag on its neck collar. The position of the cow is determined by triangulation based on radio waves emitted by the tag and captured by fixed antennas in the barn. The cow's activity is inferred from its position: 'eating' if the cow is positioned at the feeding table, 'resting' if the cow is in a resting area (typically cubicles), else 'in alleys'. The time spent in each activity (expressed in seconds) is used to calculate the level of activity of the cow for each hour of the day by attributing a weight to each activity. The weights are derived from a factorial correspondence analysis (see [4] for details on the calculations). This analysis was performed on three farms with a total of more than 800 cows that were managed under different conditions (e.g. conventional *vs*. automatic milking, mixed diet *vs*. roughage and concentrate distributed separately). As the weights obtained on each farm showed good closeness, we elected to use averaged weights that can be applied on any dataset, i.e. -0.23 for resting, +0.16 for in alleys, and +0.42 for eating. All weights are expressed in s^{-1}, and hence activity level is unitless. Each cow is then represented by a time series of its level of activity for each hour.

2.2 Data processing to detect changes in circadian rhythm

The data are analyzed as sliding 36-h time series with a 1-h step between series: the data obtained from a cow over 30 days of monitoring produces 685 36-h time series (30 days × 24 h/day - 35 h). Each of these 36-h time series contains two 24-h sub-series A and B with a 12-h time lag (Fig 1).

**** Fig. 1 here ****

We use Fast Fourier Transform [14] to extract the harmonics and create a model $m(t)$ of each sub-series A and B according to the formula:

$$m(t) = \sum_{n=-z}^{z} |h_n| cos\left(2\pi n \frac{t}{24} + arg(h_n)\right),\ z \ \in [0,12]$$

where h_n is the harmonic of rank n ($|h_n|$ is its modulus and $arg(h_n)$ is its argument) and z is a parameter that corresponds to number of harmonics to keep in the model.

Working with a high z value, the resulting model is close to the original time series. Working with a low z value erases the time-series noise and the model is smooth. We limit our study to $z = 1$, which corresponds to a period of 24 h and thus reflects the circadian cycle. Higher values would reflect ultradian rhythms. Because of the 12-h time lag between the two sub-series A and B, their models need to be synchronized before we compare them. We therefore add $-\pi$ to each cosine component of the model for B. We then calculate the Euclidean distance between the two models:

$$distance(A, B) = \sqrt{\sum_{i=1}^{24} (B_i - A_i)^2}$$

where A_i and B_i are the values of models for A and B for each point in time.

A threshold τ is defined (see Section 2.5). If the distance between the two models is below τ, then the series is considered normal, else it is considered that the circadian rhythm has changed (Fig. 2).

***** Fig. 2 here ****

2.3 Datasets

We used four datasets to test our method. Two datasets are from the INRAE Herbipôle experimental unit (DOI: https://doi.org/10.15454/1.5572318050509348E12) and include data from experiments carried out for other purposes unrelated to this study. Two datasets are from commercial farms. All the data are from dairy cows.

- Dataset 1 includes 28 cows monitored for 6 months. The cows were administered lipopolysaccharide (**LPS**) in the mammary gland on one day to induce inflammation. They were milked at fixed times twice a day. The food was delivered in the morning then pushed back close to the feeding gates three times in the afternoon.
- Dataset 2 includes 28 cows monitored for 3 months. Half of the cows received a high-starch diet during 1 month to induce sub-acute ruminal acidosis. They were milked at fixed times twice a day, and fed twice a day.
- Dataset 3 comes from three commercial farms on which a total of 40 dairy cows were monitored for 1 month to detect oestrus from their milk progesterone profile (i.e. sudden drop in progesterone for at least 3

consecutive days). On two farms, the cows were milked at fixed times twice or three times a day, and food was delivered twice a day or only once in the morning then pushed back after each milking. The third farm was equipped with an automatic milking system, so the cows had no fixed milking times. Food was delivered in the morning and regularly pushed back by a robot.

- Dataset 4 comes from a commercial farm with 300 cows monitored for 12 months. Like above, the farm was equipped with an automatic milking system, and food was delivered in the morning and regularly pushed back by a robot.

On each farm, the caretakers logged any event as soon as it was observed (oestrus, calving, lameness (scored visually as per Welfare Quality protocol [15]), clinical mastitis, clinical signs of other disease, accident-related health problems, disturbances such as handling for vaccination, change of pen, mixing of animals) in a logbook, together with the treatment applied to the animal. In addition, Datasets 1, 2 and 3 provide a labelling of days where inflammation (Dataset 1), acidosis (Dataset 2) or oestrus (Dataset 3) was checked or detected via additional measures. In Dataset 1, cow body temperature was monitored to check that they reacted to LPS. In Dataset 2, ruminal pH was monitored using a sensor (eCow bolus, Exeter, UK). According to the method proposed by Villot et al. [16], we normalized the ruminal pH values of each cow to take into account inter-individual variability, sensor drift and sensor noise, and then we considered that a cow was under subacute ruminal acidosis (**SARA**) when the normalized ruminal pH (**NpH**) decreased by at least 0.3 for more than 50 min/d and the daily standard deviation in NpH was above 0.2 or the daily NpH range was above 0.8. In Dataset 3, progesterone was assayed in the milk, and oestrus was detected when progesterone concentration dropped dramatically for several days (e.g. from 20 down to 5 ng/mL). Datasets 1 to 3 can thus be considered as reference datasets, as the labelling of abnormal days does not depend solely on visual observations. Dataset 4 from a large commercial farm served to test our method in real-world field conditions. Based on the available literature [17-19], we considered a certain number of days before and one day after each type of event where we suspected modified cow behaviour (Tab. 1). We excluded from analysis the subsequent days after the event (up to Day 7) because we did not have enough information to rule on whether or not the behaviour was likely modified and because our focus was on the early stages when caretakers need to take action.

**** Tab. 1 here ****

A 36-h time series was considered abnormal if it contained more than 12 h from a day labelled abnormal. We split each dataset into two blocks: 30% of all time series were taken at random and used as *training set*, from which threshold τ was calculated (see Section 2.5), and the remaining 70% was used as *test set*, to test whether threshold τ can accurately distinguish series labelled normal *vs*. abnormal.

2.4 Calculation

We assessed the performances of the FBAT method by calculating its recall of normal and abnormal time series. Abnormal series are those when an event was recorded, whatever the type of event. Let us consider that the normal series constitute the negative class and the abnormal series constitute the positive class. The recall of the normal series (rec_{-}, also known as ‘specificity’) represents the number of series labelled and detected as normal: true negative (**TN**) among all series labelled as normal, i.e. TN plus false positive (**FP**). The recall of the abnormal series (rec_+, also known as sensitivity) represents the number of series labelled abnormal and detected with a modified circadian rhythm: true positive (**TP**) among the number of all series labelled as abnormal, i.e. TP + false negative (**FN**):

$$rec_+ = \frac{TP}{TP + FN} \qquad and \qquad rec_- = \frac{TN}{TN + FP}$$

To estimate threshold τ, we calculate the Euclidian distance between all consecutive 24-h sub-series from the *training set*. The range between the minimum and maximum distance is sampled into 10000 values. The average between rec_+ and rec_- is calculated for each of these 10000 values, and τ is the value that obtains the highest rec_+ and rec_- average. An alternative would be to describe the variability in the Euclidian distance between 24-h sub-series when no event occurred and to set τ at e.g. twice the standard deviation. We tested this done in a first approach, but it resulted in a low rate of anomaly detection.

To assess the performance of our method, we calculated rec_+ and rec_- on *test sets*. We also calculated the proportion of events detected, i.e. events for which we detected at least one day with a modified circadian rhythm within the sequence of days surrounding them (as defined in Tab. 1). The performance of the method is also illustrated by its training time (i.e. time to compute threshold τ) and test time (i.e. time to detect all changes in circadian rhythm).

3 Results and Discussion

3.1 Overall performances of FBAT with thresholds adjusted to each dataset

Tab.2 gives the overall performances of FBAT on the four datasets. The results for threshold τ and rec_- were similar across all datasets, although rec_+ was slightly lower in Dataset 4 than in the other datasets. The method thus appears to perform equally well in various conditions. The calculation time — especially the time to calculate Threshold τ — depended on the farm and especially on the size of the dataset from the farm (see, for instance, Dataset 4, which is far larger than the others and required a much longer calculation time).

It can be argued that the value of threshold τ can change from one dataset to another depending on the number and type of events contained in the dataset. However, we did not observe this kind of effect: there were no marked variations in τ (between 1886 and 2216) between datasets despite their differences in number and type of events (e.g. Dataset 3 contains 29 oestrus and no other events). Moreover, FBAT can compute τ without requiring a huge amount of data. Dataset 3 comprised only 40 cows for 1 month and yet produced a similar τ to the other datasets, leading to high values of rec_+ and rec_- .

In all datasets, rec_- was above 75%, which means a farmer would receive less than 25% false alerts. By contrast, rec_+ was around 30%, which means that the method detects less than one third of the series labelled abnormal. At first glance, the method cannot reliably help farmers detect anomalies in cows. Note, however, that within the sequence of days surrounding an event — which we labelled abnormal as defined in Tab. 1 — the circadian activity rhythm of the cows may not be modified on all days, which could explain the apparent poor performance in terms of rec_+. We therefore questioned whether it was possible to detect at least one day with a modified circadian rhythm in a sequence surrounding a given event. Furthermore, days on which circadian activity rhythm changed may have been included in the *training set* and were thus excluded from the analyses on the *test sets*.

**** Tab. 2 here ****

3.2 Performance of FBAT for detecting one day with a modified circadian rhythm within sequences surrounding events, using a fixed threshold

Given that threshold τ varied little between datasets (Tab. 2), we decided to set τ to a fixed 2000 for all datasets. This allowed us to skip the training phase and use the whole datasets to test our method. We then explored whether the method could detect at least one day with a modified circadian rhythm within a sequence surrounding a given event. We applied this procedure for each type of event.

We obtained a rec_{-} of 70.1%, 79.1%, 77.9%, and 81.7% for Datasets 1 to 4, respectively. On all datasets combined, rec_{-} was 81.1%, which further confirms that FBAT does not produce many false alerts (less than 20%). We cannot exclude that part of these alerts are actually not false alerts but correspond to events that caretakers did not record in the logbooks as they missed or considered unimportant. For instance, subclinical diseases like SARA are difficult to detect without close monitoring of the ruminal pH and so are often missed by direct observation. Likely events such as a power or a mechanical failure cutting the lighting in the barn or delaying food delivery or the milking may have gone unreported, whereas these stimuli act as synchronizers of circadian rhythm [2].

The proportion of abnormal sequences in which at least one day was detected with a modified circadian rhythm was 76%, 71.2%, 69.2% and 61.3% for Datasets 1 to 4, respectively. This proportion varied according to type of event to be detected (Tab. 3). In very few cases (1.3% of all abnormal cow*days in Dataset 4), there were two events that co-occurred, e.g. lameness and other disturbances. The corresponding cow*days were used to calculate the proportion of abnormal sequences detected for the two types of events.

**** Tab. 3 here ****

The rhythm anomalies that were best detected were those due to accidental events: only Dataset 4 contained accidental events (n=10), and all of them were detected. Under ‘accidental events’, we included accidental injuries, vaginal laceration, and retained placenta, all of which occur abruptly on a given day and are likely to cause cows substantial discomfort, which explains why they are easily detectable through disruption of the activity rhythm.

Nearly all calvings were detected: only one calving was missed out of the 180 present in the datasets. Next, 90% of oestruses were detected on average. Oestrus and calving are known to affect cow behaviour: overt oestrus causes hyperactivity, and cows about to calve lie down or change activity due to a change of pen, the pain induced by calving, and the presence of the calf [20]. On Dataset 3, where the exact time of oestrus was detected from milk progesterone on 40 cows, the proportion of detected oestrus was lower than in the other datasets (only 69.2%). It is likely that some cows had silent oestrus, i.e. with no overt behavioural signs. Unfortunately, this dataset does not include records of detection of oestrus by the caretakers (i.e. based on behavioural observations), so we cannot estimate whether our method detects more oestrus than a farmer would or only the overt cases of oestrus detectable by simple visual observation of the animals.

Diseases with inflammation or pain were also well detected, with an average of 97.8%, 84.1%, and 88.2% events detected for lameness, mastitis, and other diseases, respectively. However, only 81.5% of LPS-induced udder inflammation events were detected. This slightly lower detection rate may be due to the fact that the inflammation is less marked when induced by LPS than by pathogens, or that the sickness behaviour is less marked with a simple inflammation than when pathogens are present. Indeed, pain, hyperthermia, and decreased rumination last less than 24 h after LPS injection [21].

Overall, 69% of SARA events were detected (only in Dataset 2 where ruminal pH was monitored). Animals do not always suffer when their ruminal pH is low. Their gut flora can adapt to diet containing high amounts of starch and low pH, and animal behaviour can return to normal from one day to the next [22, 23]. For the moment, we cannot distinguish whether FBAT underperforms in SARA or whether it is simply a case of cows with SARA not always suffering. More measurements to identify SARA, such as milk urea nitrogen and blood bicarbonate [24], are needed in order to refine the detection of SARA and better calculate how FBAT performs.

The events on which the method underperformed were mixings (68.3% detection) and other disturbances (60.1% detection). Based on records noted in the farm logbooks, it was difficult to estimate whether the procedures undergone by the animals were liable to disturb them. The category ‘other disturbances’ includes various treatments, such as vaccination, administration of drugs, or relocations from a pen. These events may or may not disturb the animals depending on how they are handled and whether treatment induces some pain (an injection, for instance). Mixing very clearly disturbs the animals, triggering aggressive interactions, weakening group cohesion, and inducing chronic stress [25, 26]. However, in this study, we inferred the ‘mixing’ category from instances when one or more animals were moved from one pen to another, and so we thus cannot be sure that these animals were mixed with unfamiliar pen-mates. Therefore, the moderate proportion of mixings and other disturbances that FBAT detects likely reflects the fact that not all of them actually disturbed the cows.

Mixing and other disturbances represented 92% of all events recorded but were not accurately detected. When mixings and other disturbances are excluded from the analysis, the overall performance of our method—in terms of proportion of events detected—reached 94.6% in Dataset 4, which was used for field-validation. The performance of the method for detecting responses to accidents, LPS injection or mastitis still needs be estimated on larger datasets, as these events were underrepresented in our datasets (only 10, 27 and 44 cases, respectively).

3.3 Timing of the detection of abnormal rhythm

Fig. 3 shows the timing of detection of an abnormal rhythm — when detected — in relation to the logging of events by caretakers in Dataset 4. On these figures, the day when an event was logged starts at 00:00 because we have no indication as to the exact moment when the caretaker noticed the event.

Rhythm anomalies due to ’other disturbances‘ started to be detected from 12 h on the day the event was logged — probably at the time that the event actually occurred — and continued to be detected up to 2 days after. Likewise, anomalies due to accidents were detected from 10 h on the day the event was logged, and more than 90% of them were detected within the next 4 h. Therefore, events that occur abruptly in time likely translate very rapidly into activity rhythm modifications, which means the method can promptly detect these problems.

In the case of calving, 80% of rhythm anomalies were detected 30 h before logging, i.e. two days before actually calving. In the case of oestrus, rhythm anomalies were detected on the day the oestrus was logged, which implies that some cases were detected during the night, probably before the caretaker detected the oestrus. Such early detection of calving and oestrus through rhythm anomaly could prove vitally important for managing reproduction on a farm, since cows may need assistance with calving and the time-window for insemination is short.

Anomalies due to lameness started to be detected 1.5 days before the lameness was logged (60% of cases) and more than 80% of these cases were detected no later than 12 h before the day they were logged. In the case of mastitis, 60% of rhythm anomalies were detected 24 h before the day they were logged and 90% were detected no later than the day they were logged. In the case of other diseases, 60% of anomalies were detected 32 h before the day they were logged and more than 95% of anomalies were detected no later than the day they were logged. The FBAT method is thus likely to detect anomalies due to diseases one or two days before clinical signs manifest. This could prompt caretakers to pay closer attention to animals displaying such anomalies and possibly call in a vet for a diagnosis and rapid treatment.

4 Conclusion and perspectives

Our new Fourier-Based Approximation with Thresholding (FBAT) method can detect changes in the circadian rhythm of activity. These changes are closely related to many events experienced by animals, including disease, accident or stressful disturbance in the barn. The method produces less than 20% false alerts (i.e. changes unrelated to a problem logged by caretakers) and detects about 95% of rhythm anomalies caused by reproductive or health problems. The method can detect problems at a very early stage of disease, before clinical signs manifest. Alerts can thus be sent to the animal caretaker to flag animals showing a modified rhythm. When an alert is sent, the caretaker can take quickly a management decision, e.g. to check calving progress, inseminate a cow in oestrus, separate the cow from the rest of the group, or look for clinical signs to identify a disease and engage treatment.

For the moment, FBAT is unable to distinguish between events experienced by animals. This can be seen as a limitation of the method, as it does not provide a diagnosis. FBAT uses only the rank-1 harmonic provided by the Fourier transform corresponding to the circadian rhythm. We did not handle variations that may occur within a day, which might be relevant to identify a given disorder (e.g. cows under SARA with a low activity between the two daily meals [27]). To overcome this limitation, the method could be further developed to take into account harmonics of rank above 1. An alternative solution could be to use other methods to model the rhythm, such as wavelet transforms [28][29],.

From another angle, being able to detect any problem whatever the cause may be seen as an asset. First, the same tool can issuing warning that something is wrong and that animals need to be checked in case remedial action is needed. Second, this tool can also serve for assessing animal welfare. Indeed, oestrus and calving frequency should be about the same across farms, and so any variations between farms are likely to be due essentially to health disorders and stress experienced by the animals. FBAT could thus be used as an overall measure of animal health and stress status, based on the occurrence of disturbing events. Applying FBAT on a sample of farms along with a reference method for animal welfare assessment such as the Welfare Quality method [15] would help to check whether it can be used for such a purpose. FBAT could also be used to phenotype animals according to their sensitivity to potentially stressful events.

FBAT is easy to implement. The Fourier transform is a well-known technique that can be readily computed in several programming languages. It is quicker to compute than machine learning methods: the computation time is 6 to 280 times shorter than the more advanced machine learning algorithms DTW, Hive-Cote or BOSS, and 13 to 22 times shorter than the neural network methods FCN and Resnet [13].

The farms from which data were used in our study had different routines that may have affected the rhythm of their cows. The cows were milked at fixed intervals on some farms *vs*. with an automatic milking system allowing cows to choose when to be milked on other farms. Food was delivered two or three times a day on some farms *vs*. more evenly distributed across the day by a robot pusher in other farms. Furthermore, the type of events detected differed between datasets. Despite such variations, the threshold that optimized the distinction between a normal *vs*. modified rhythm was stable, enabling us to apply the same threshold to all datasets, which resulted in similar performances across all farms except the farms from Dataset 3, as discussed above. The fact that the threshold does not vary much between farms should be checked on a larger population of farms. If the stability is confirmed, then a pre-defined threshold could be used without having to go through training to define the threshold for a given farm, thus making FBAT very easy to apply. It remains possible to adjust the threshold to a given farm or even to each cow of that farm, in which case data will need to be recorded for a few weeks to estimate the threshold before it can be applied to detect anomalies on that farm or cow.

FBAT is to be applied on data produced by close animal monitoring, which cannot feasibly be done without activity sensors. We applied FBAT on data from a RTLS tool. Extending the method to data from other sensors only requires eliciting the weights attributed to each activity to calculate the activity level and compute the threshold used to compare daily variations between days. This can be done on a few datasets, as achieved here.

FBAT was designed to be integrated in precision livestock farming tools to help farmers manage their animals. However, it has also the potential to detect anomalies in humans to guide healthcare or in wild animals to detect disturbances (e.g. by humans or predators). We anticipate that chronobiological studies could apply FBAT to help relate circadian rhythm anomalies to specific events.

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Author contributions

Nicolas Wagner: Methodology, Software, Validation, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing, Visualization. **Marie-Madeleine Mialon:** Formal analysis, Investigation, Data curation, Writing - Review & Editing, Project administration. **Karen Helle Sloth**: Investigation, Data curation, Writing - Review & Editing**. Romain Lardy:** Methodology, Writing - Review & Editing, Project administration. **Dorothée Ledoux**: Data curation, Writing - Review & Editing. **Mathieu Silberberg:** Data curation, Writing - Review & Editing. **Alice De Boyer Des Roches**: Data curation, Writing - Review & Editing. **Isabelle Veissier:** Conceptualization, Formal analysis, Data curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Supervision, Project administration, Funding acquisition.

Appendix A. Data, equipment, and software

Data: Part of the data are private, and so the datasets cannot be made public.

Equipment: The indoor tracking system is commercialized by GEA Farm technologies (Bönen, Germany). The manufacturer claims a precision of 50 cm for the detection of a cow's position. In the INRAE experimental farm that provided two of the datasets used here, we observed a precision of 16 cm [30].

Server and software: FBAT was developed in the Python programming language with the fast Fourier transform function available in the NumPy library (https://numpy.org/devdocs/reference/generated/numpy.fft.fft.html#numpy.fft.fft). The code is available at https://github.com/nicolas-wagner/FBAT. We used a server composed of an Intel Xeon E7-8890 v3 CPU (2.5 GHz with 46 Mb of cache) and 3 Tb of RAM, of which we used less than 8 Gb. For field use of FBAT, the detection of changes in the circadian rhythm will need less than 1 Gb, depending on the size of the on-farm dataset produced.

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Illustrations

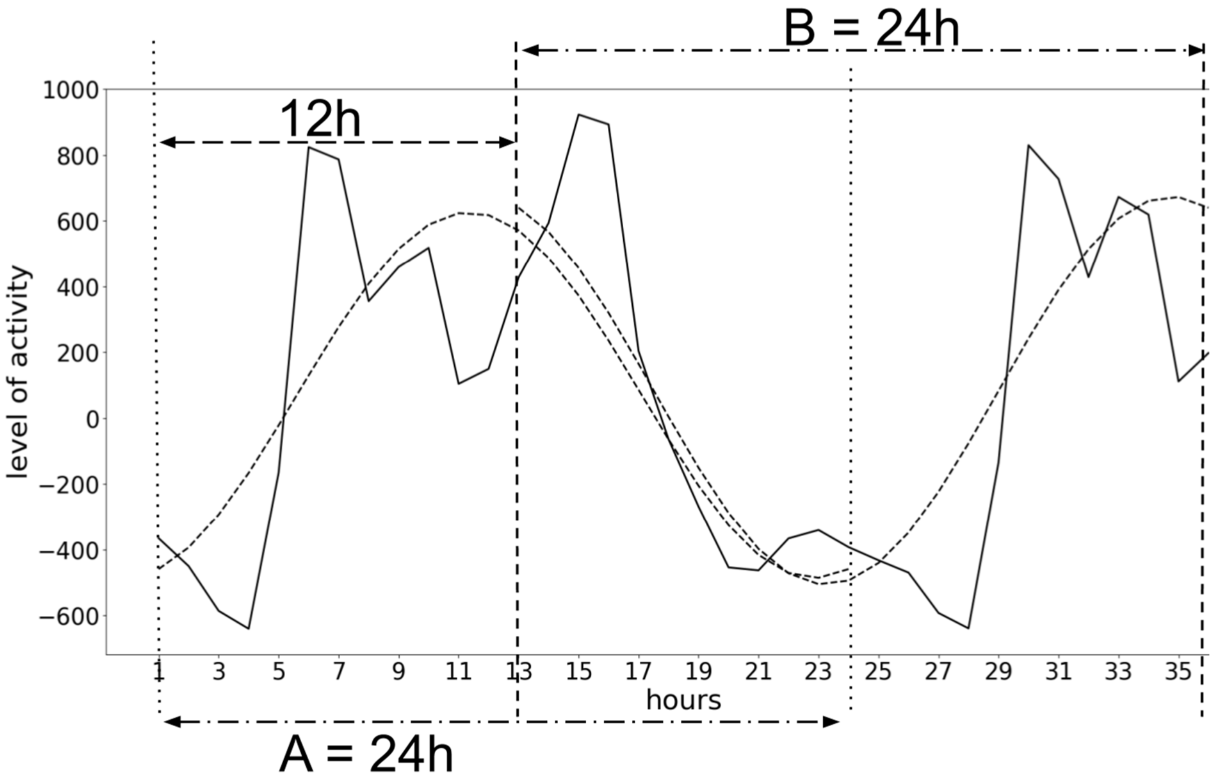


Fig. 1. Example of a 36-h time series of cow activity modelled with a Fourier transform. Solid line: activity level calculated from basic activities (weighted sum of the time spent ‘resting’, ‘in alleys’ or ‘eating’, unitless). Dotted lines: Fourier transform of the first and last 24-h segments of this 36-h time series.

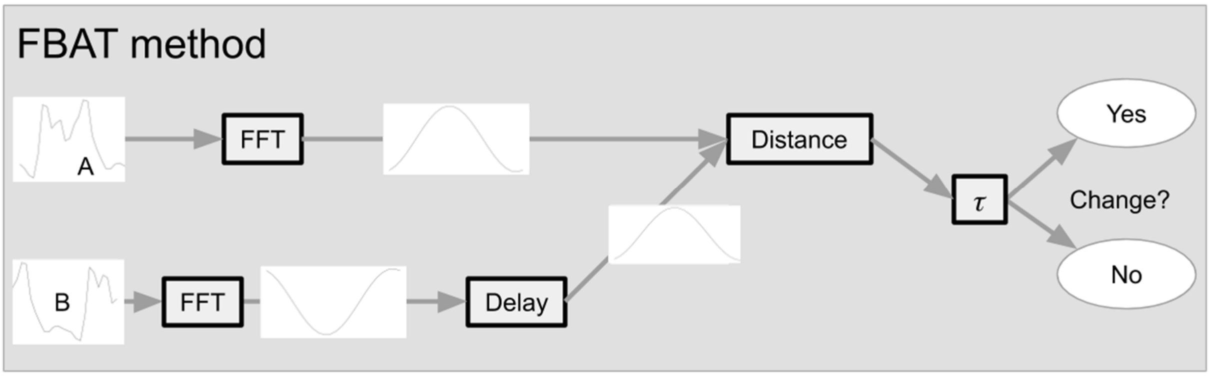


Fig. 2. Framework of the FBAT method to detect changes in circadian activity rhythm. Within a 36-h time series, we used Fast Fourier Transform (**FFT**) to model the variations in activity during the first and last 24-h segments of this 36-h series. After aligning the two models in time, we calculate the Euclidian distance between them and then compare that distance to a given threshold, above which we consider that the rhythm has changed.

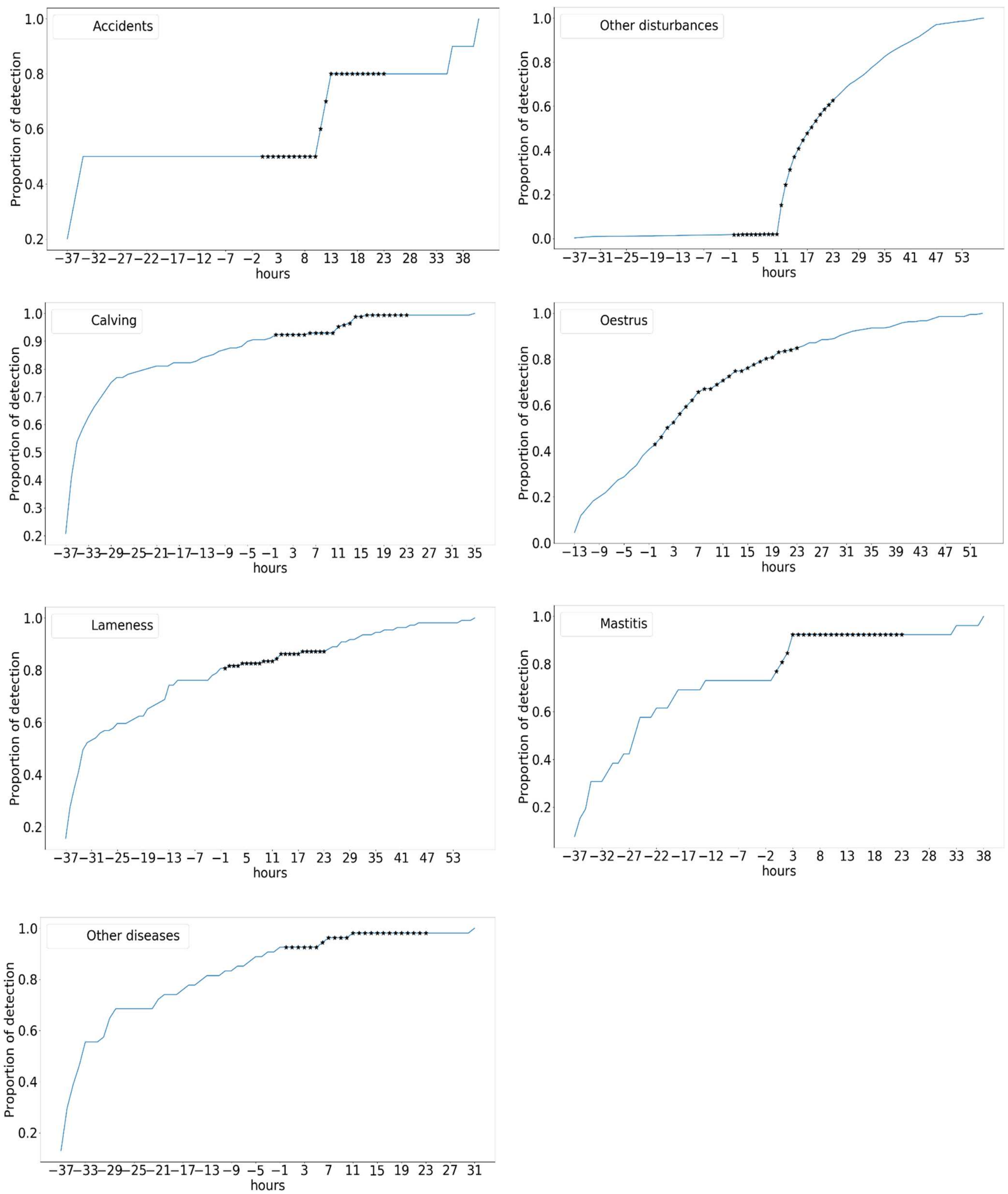


Fig. 3. Detection of rhythm anomalies in relation to events logged by caretakers in Dataset 4 (taken for field validation). Stars represent the hours of the day when an event was logged, arbitrarily starting from 00:00.

Tab. 1. Days labelled normal *vs*. abnormal according to type of event recorded on the farm. Black cells are for the day when the event was logged by caretakers, dark grey cells are for days when behaviour is likely to be modified (black and dark grey cells are for days considered abnormal), light grey cells are for days when there is insufficient literature data to expect or not a change in behaviour (days excluded from the analysis), and white cells are for days when we expect no change in animal behaviour (normal days).

Days Type of event	D-3	D-2	D-1	D0	D1	D2	D3	D4	D5	D6	D7	D8	D8
Accidental event[1]													
Calving													
Oestrus[2]													
Lameness													
Mastitis													
Other disease													
LPS injection[3]													
Ruminal acidosis[4]													
Mixing													
Other disturbances[5]													

[1] Injuries, retained placenta, vaginal laceration

[2] Detected visually by caretakers or from milk progesterone profile

[3] LPS injected in the mammary gland

[4] Detected from ruminal pH

[5] Interventions, e.g. vaccination, oestrus synchronization, anthelmintic treatment, claw trimming, relocation

Tab. 2. Overall performance of FBAT on four datasets. The threshold τ used to differentiate normal *vs*. abnormal time series was computed on *training sets* (30% of each dataset). rec_- and rec_+ are for the percentage of normal series detected as normal and the percentage of abnormal series detected as abnormal (i.e. with a modified circadian rhythm) on *test sets* (70% of each dataset). Training time is the time to compute threshold τ. Test time is the time to detect any changes in activity rhythm.

Dataset	**No. cow*days**	**Training time (s)**	**Test time (s)**	**τ**	rec_-	rec_+
1	5124	2810	25.8	2216	75.8	29.3
2	2562	1220	10.9	1947	76.4	32.6
3	1220	781	7.3	1894	75.7	32.4
4	109800	69300	526	1886	78.6	24.9

Tab. 3. Performance of FBAT expressed in terms of detection of at least one day with a modified circadian rhythm within a sequence surrounding an event, stratified by type of events (with a fixed threshold $\tau = 2000$).

Events		Datasets			
		1	**2**	**3**	**4**
Accidental event[1]	no. events	0	0	0	10
	% detected	na	na	na	100
Calving	no. events	9	0	0	171
	% detected	100	na	na	99.4
Oestrus[2]	no. events	41	7	29	257
	% detected	95.1	85.7	69.2	91.4
Lameness	no. events	4	16	0	114
	% detected	100	93.8	na	98.2
Mastitis	no. events	9	3	0	32
	% detected	100	0	na	87.5
Other disease	no. events	10	8	0	66
	% detected	80	75	na	90.9
LPS injection[3]	no. events	27	0	0	0
	% detected	81.5	na	na	na
Ruminal acidosis[4]	no. events	0	271	0	0
	% detected	na	69	na	na
Mixing	no. events	63	0	0	0
	% detected	68.3	na	na	na
Other disturbance[5]	no. events	145	667	0	12079
	% detected	69	71.7	na	59.3

[1] Injuries, retained placenta, vaginal laceration

[2] Detected visually by caretakers or from milk progesterone profile

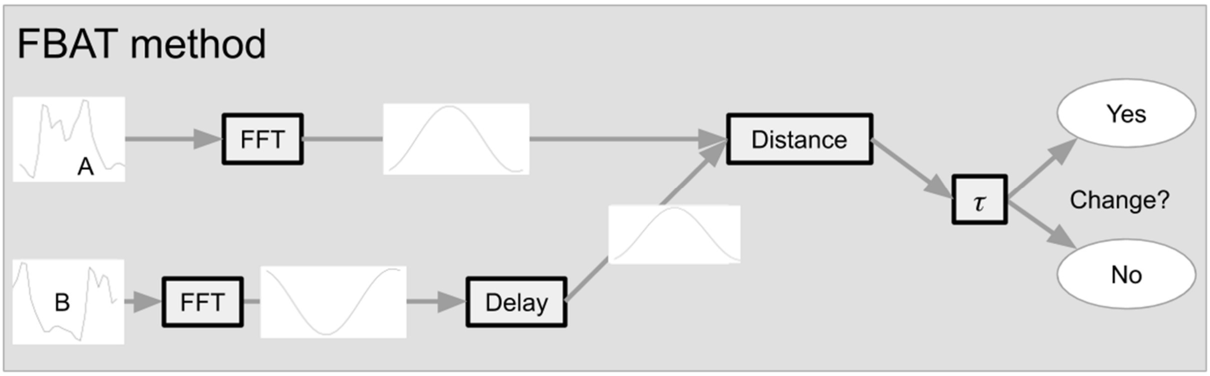
[3] LPS injected in the mammary gland

[4] Detected from ruminal pH

[5] Interventions, e.g. vaccination, oestrus synchronization, anthelmintic treatment, claw trimming, relocation

na: not applicable

Graphical abstract



Within a 36-h time series, we use Fast Fourier transform (FFT) to model the circadian rhythm of activity during the first and last 24-h segments. After aligning the two models in time, we calculate the Euclidian distance between them and compare it to a given threshold, above which we conclude that the rhythm has changed.