

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

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1 Detection of changes in the circadian rhythm of cattle in relation to disease,

2 stress, and reproductive events

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14 Highlights

- 15 Our Fourier transform-based method detects changes in circadian rhythm
- 16 Circadian changes in cows link to disease, stress, or calving/oestrus events
- 17 The method detects 95% of the rhythm anomalies due to reproductive or
- 18 disease events and 60–70% due to stress events, with less than 20% false-
- 19 positives (non-event-related anomalies)
- 20 It can help detect animals needing care.
- It can also assess overall animal welfare status or health/stress-sensitive
 phenotypes
- 23

24 Abstract

25 Disease and stress can disrupt the circadian rhythm of activity in animals. Sensor 26 technologies can automatically detect variations in daily activity, but it remains 27 difficult to detect exactly when the circadian rhythm disruption starts. Here we report 28 a mathematical Fourier-Based Approximation with Thresholding (FBAT) method 29 designed to detect changes in the circadian activity rhythm of cows whatever the 30 cause of change (typically disease, stress, oestrus). We used data from an indoor 31 positioning system that provides the time per hour spent by each cow resting, in 32 alleys, or eating. We calculated the hourly activity level of each cow by attributing a 33 weight to each activity. We considered 36-h time series and used Fourier transform 34 to model the variations in activity during the first and last 24 h of these 36-h series. 35 We then compared the Euclidian distance between the two models against a given 36 threshold above which we considered that rhythm had changed. We tested the 37 method on four datasets (giving a cumulative total of ~120000 cow*days) that 38 included disease episodes (acidosis, lameness, mastitis or other infectious diseases), 39 reproductive events (oestrus or calving) and external stimuli that can stress animals 40 (e.g. relocation). The method obtained over 80% recall of normal days and detected 41 95% of abnormal rhythms due to health or reproductive events. FBAT could be 42 implemented in precision livestock farming system monitoring tools to alert 43 caretakers to individual animals needing specific care. The FBAT method also has 44 the potential to detect anomalies in humans to guide healthcare intervention or in wild 45 animals to detect disturbances. We anticipate that chronobiological studies could 46 apply FBAT to help relate circadian rhythm anomalies to specific events.

47

49 Keywords

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

52

53 **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].

59 Disruption of circadian rhythms can have far-reaching effects on physical and mental 60 health, even leading to cancer and depression [2, 3]. In turn, stress or disease 61 episodes in animals disrupt their circadian rhythm of activity. Circadian activity 62 disruption is thus a proxy of these disorders. For instance, we observed that circadian 63 variations in activity were less marked in diseased cows [4] but more marked when 64 calves are regrouped with other calves, which is known to induce stress [5]. Such 65 effects may involve glucocorticoids, which are significantly released during stress or 66 disease and which help coordinate circadian rhythms by resetting cellular clocks 67 downstream of the brain [6]. Identifying disruptions in circadian rhythm could serve to 68 detect cases of stress or disease and, in turn, prompt animal caretakers to address 69 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

73 Locating Systems (RTLS), accelerometers, automatic image analysis, and sound 74 analysis all provide information on animal activity by distinguishing basic activities 75 such as resting, standing, walking, and eating [7, 8]. However, interpreting the data 76 from these tools remains difficult, as these basic activities depend on a cluster of 77 factors including animal age and breed, design of the barn (e.g. number and location 78 of resting and feeding areas), animal management variables (e.g. food distribution or 79 milking time), diet, season, and more. Basic activities can also change in frequency 80 from one day to another, which interferes with the way the rhythms are patterned, 81 e.g. a low-frequency activity will also show only small variations during the day. 82 Summarising the activity of an animal into an activity level can help identify the 83 activity rhythm. Day-night cycle variations in activity level appear to be less 84 dependent on factors that affect basic activities. In addition, the activity level is 85 expressed in absolute terms, i.e. has no frequency. Calculating this circadian activity 86 level could therefore serve to highlight differences between diseased or stressed 87 animals and normal-status animals [4, 9]. However, it remains difficult to detect 88 exactly when the rhythm starts to become disrupted.

89 There are numerous methods proposed to detect anomalies in time series. We first 90 tested traditional machine learning methods (K Nearest Neighbours for Regression 91 (KNNR), Decision Tree for Regression (DTR), MultiLayer Perceptron (MLP), Long 92 Short-Term Memory (LSTM) [10] and then went on test the most promising methods 93 available according to the latest literature reviews [11, 12], namely the Bag Of SFA 94 Symbols (BOSS), Hierarchical Vote Collective Of Transformation-based Ensembles 95 (**Hive-Cote**), Dynamic Time Warping (**DTW**), Fully Convolutional Network (**FCN**) and 96 Residual Network (**ResNet**) algorithms [13]. As these methods require large 97 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 cyclicaspects (here, circadian rhythm) into the time series.

100 We developed a mathematical Fourier transform-based method to detect changes in 101 the circadian activity rhythm of animals, called 'Fourier-Based Approximation with 102 Thresholding' (**FBAT** [13]). Fourier analysis is a powerful tool to analyse continuous 103 cyclic functions. The assumption is that all cyclic signals y(t) with a frequency f can 104 be decomposed into a cosine function of frequency f and with an infinity of other 105 cosine curves called harmonics h_n (n represents the rank of the harmonic), i.e.

106
$$y(t) = \sum_{n=-\infty}^{+\infty} |h_n| \cos(2\pi n f t + arg(h_n))$$

107 where h_n is the harmonic of rank *n* represented by a complex number with $|h_n|$ its 108 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.

124 2 Material and methods

125 2.1 Equipment used to detect cow activity and calculate activity level

126 We used data from the CowView system (GEA Farm Technology, Bönen, Germany), 127 which is an RTLS that gives the position of each cow in a barn every second. Each 128 cow is equipped with a tag on its neck collar. The position of the cow is determined 129 by triangulation based on radio waves emitted by the tag and captured by fixed 130 antennas in the barn. The cow's activity is inferred from its position: 'eating' if the cow 131 is positioned at the feeding table, 'resting' if the cow is in a resting area (typically 132 cubicles), else 'in alleys'. The time spent in each activity (expressed in seconds) is 133 used to calculate the level of activity of the cow for each hour of the day by attributing 134 a weight to each activity. The weights are derived from a factorial correspondence 135 analysis (see [4] for details on the calculations). This analysis was performed on 136 three farms with a total of more than 800 cows that were managed under different 137 conditions (e.g. conventional vs. automatic milking, mixed diet vs. roughage and 138 concentrate distributed separately). As the weights obtained on each farm showed 139 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 140 141 expressed in s⁻¹, and hence activity level is unitless. Each cow is then represented by 142 a time series of its level of activity for each hour.

143 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 subseries A and B with a 12-h time lag (Fig 1).

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

150

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:

153
$$m(t) = \sum_{n=-z}^{z} |h_n| \cos\left(2\pi n \frac{t}{24} + \arg(h_n)\right), \ z \in [0, 12]$$

154 where h_n is the harmonic of rank n ($|h_n|$ is its modulus and $arg(h_n)$ is its argument) 155 and z is a parameter that corresponds to number of harmonics to keep in the model. 156 Working with a high z value, the resulting model is close to the original time series. 157 Working with a low z value erases the time-series noise and the model is smooth. We 158 limit our study to z = 1, which corresponds to a period of 24 h and thus reflects the 159 circadian cycle. Higher values would reflect ultradian rhythms. Because of the 12-h 160 time lag between the two sub-series A and B, their models need to be synchronized 161 before we compare them. We therefore add – π to each cosine component of the model for B. We then calculate the Euclidean distance between the two models: 162

163
$$distance(A, B) = \sqrt{\sum_{i=1}^{24} (B_i - A_i)^2}$$

164	where A_i and B_i are the values of models for A and B for each point in time.
165	A threshold τ is defined (see Section 2.5). If the distance between the two models is
166	below $\boldsymbol{\tau},$ then the series is considered normal, else it is considered that the circadian
167	rhythm has changed (Fig. 2).
168	
169	***** Fig. 2 here ****
170	
171	2.3 Datasets
172	We used four datasets to test our method. Two datasets are from the INRAE
173	Herbipôle experimental unit (DOI: https://doi.org/10.15454/1.5572318050509348E12)
174	and include data from experiments carried out for other purposes unrelated to this
175	study. Two datasets are from commercial farms. All the data are from dairy cows.
176	- Dataset 1 includes 28 cows monitored for 6 months. The cows were
177	administered lipopolysaccharide (LPS) in the mammary gland on one day to
178	induce inflammation. They were milked at fixed times twice a day. The food
179	was delivered in the morning then pushed back close to the feeding gates
180	three times in the afternoon.
181	- Dataset 2 includes 28 cows monitored for 3 months. Half of the cows received
182	a high-starch diet during 1 month to induce sub-acute ruminal acidosis. They
183	were milked at fixed times twice a day, and fed twice a day.
184	- Dataset 3 comes from three commercial farms on which a total of 40 dairy
185	cows were monitored for 1 month to detect oestrus from their milk
186	progesterone profile (i.e. sudden drop in progesterone for at least 3

187 consecutive days). On two farms, the cows were milked at fixed times twice or 188 three times a day, and food was delivered twice a day or only once in the 189 morning then pushed back after each milking. The third farm was equipped 190 with an automatic milking system, so the cows had no fixed milking times. 191 Food was delivered in the morning and regularly pushed back by a robot. 192 Dataset 4 comes from a commercial farm with 300 cows monitored for 12 -193 months. Like above, the farm was equipped with an automatic milking system, 194 and food was delivered in the morning and regularly pushed back by a robot. 195 On each farm, the caretakers logged any event as soon as it was observed (oestrus, 196 calving, lameness (scored visually as per Welfare Quality protocol [15]), clinical 197 mastitis, clinical signs of other disease, accident-related health problems, 198 disturbances such as handling for vaccination, change of pen, mixing of animals) in a 199 logbook, together with the treatment applied to the animal. In addition, Datasets 1, 2 200 and 3 provide a labelling of days where inflammation (Dataset 1), acidosis (Dataset 201 2) or oestrus (Dataset 3) was checked or detected via additional measures. In 202 Dataset 1, cow body temperature was monitored to check that they reacted to LPS. 203 In Dataset 2, ruminal pH was monitored using a sensor (eCow bolus, Exeter, UK). 204 According to the method proposed by Villot et al. [16], we normalized the ruminal pH 205 values of each cow to take into account inter-individual variability, sensor drift and 206 sensor noise, and then we considered that a cow was under subacute ruminal 207 acidosis (SARA) when the normalized ruminal pH (NpH) decreased by at least 0.3 208 for more than 50 min/d and the daily standard deviation in NpH was above 0.2 or the 209 daily NpH range was above 0.8. In Dataset 3, progesterone was assayed in the milk, 210 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

212 as reference datasets, as the labelling of abnormal days does not depend solely on 213 visual observations. Dataset 4 from a large commercial farm served to test our 214 method in real-world field conditions. Based on the available literature [17-19], we 215 considered a certain number of days before and one day after each type of event 216 where we suspected modified cow behaviour (Tab. 1). We excluded from analysis 217 the subsequent days after the event (up to Day 7) because we did not have enough 218 information to rule on whether or not the behaviour was likely modified and because 219 our focus was on the early stages when caretakers need to take action.

220

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

222

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.

228 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**):

239
$$rec_{+} = \frac{TP}{TP + FN}$$
 and $rec_{-} = \frac{TN}{TN + FP}$

240 To estimate threshold τ , we calculate the Euclidian distance between all consecutive 241 24-h sub-series from the *training set*. The range between the minimum and maximum 242 distance is sampled into 10000 values. The average between rec_+ and rec_- is 243 calculated for each of these 10000 values, and τ is the value that obtains the highest 244 rec_{+} and rec_{-} average. An alternative would be to describe the variability in the 245 Euclidian distance between 24-h sub-series when no event occurred and to set τ at 246 e.g. twice the standard deviation. We tested this done in a first approach, but it 247 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).

- 254
- 255 3 Results and Discussion

256 3.1 Overall performances of FBAT with thresholds adjusted to each dataset

257 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).

264 It can be argued that the value of threshold τ can change from one dataset to another 265 depending on the number and type of events contained in the dataset. However, we 266 did not observe this kind of effect: there were no marked variations in τ (between 267 1886 and 2216) between datasets despite their differences in number and type of 268 events (e.g. Dataset 3 contains 29 oestrus and no other events). Moreover, FBAT 269 can compute τ without requiring a huge amount of data. Dataset 3 comprised only 40 270 cows for 1 month and yet produced a similar τ to the other datasets, leading to high 271 values of rec_+ and rec_- .

272 In all datasets, *rec*₋ was above 75%, which means a farmer would receive less than 273 25% false alerts. By contrast, rec_+ was around 30%, which means that the method 274 detects less than one third of the series labelled abnormal. At first glance, the method 275 cannot reliably help farmers detect anomalies in cows. Note, however, that within the 276 sequence of days surrounding an event — which we labelled abnormal as defined in 277 Tab. 1 — the circadian activity rhythm of the cows may not be modified on all days, 278 which could explain the apparent poor performance in terms of rec_{+} . We therefore 279 questioned whether it was possible to detect at least one day with a modified 280 circadian rhythm in a sequence surrounding a given event. Furthermore, days on 281 which circadian activity rhythm changed may have been included in the training set 282 and were thus excluded from the analyses on the test sets.

283

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

285

286 3.2 Performance of FBAT for detecting one day with a modified circadian rhythm
287 within sequences surrounding events, using a fixed threshold

288 Given that threshold τ varied little between datasets (Tab. 2), we decided to set τ to a 289 fixed 2000 for all datasets. This allowed us to skip the training phase and use the 290 whole datasets to test our method. We then explored whether the method could 291 detect at least one day with a modified circadian rhythm within a sequence 292 surrounding a given event. We applied this procedure for each type of event. 293 We obtained a *rec*₋ of 70.1%, 79.1%, 77.9%, and 81.7% for Datasets 1 to 4, 294 respectively. On all datasets combined, rec_ was 81.1%, which further confirms that 295 FBAT does not produce many false alerts (less than 20%). We cannot exclude that 296 part of these alerts are actually not false alerts but correspond to events that 297 caretakers did not record in the logbooks as they missed or considered unimportant. 298 For instance, subclinical diseases like SARA are difficult to detect without close 299 monitoring of the ruminal pH and so are often missed by direct observation. Likely 300 events such as a power or a mechanical failure cutting the lighting in the barn or 301 delaying food delivery or the milking may have gone unreported, whereas these 302 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.

310

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

312

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.

319 Nearly all calvings were detected: only one calving was missed out of the 180 320 present in the datasets. Next, 90% of oestruses were detected on average. Oestrus 321 and calving are known to affect cow behaviour: overt oestrus causes hyperactivity, 322 and cows about to calve lie down or change activity due to a change of pen, the pain 323 induced by calving, and the presence of the calf [20]. On Dataset 3, where the exact 324 time of oestrus was detected from milk progesterone on 40 cows, the proportion of 325 detected oestrus was lower than in the other datasets (only 69.2%). It is likely that 326 some cows had silent oestrus, i.e. with no overt behavioural signs. Unfortunately, this 327 dataset does not include records of detection of oestrus by the caretakers (i.e. based 328 on behavioural observations), so we cannot estimate whether our method detects 329 more oestrus than a farmer would or only the overt cases of oestrus detectable by 330 simple visual observation of the animals.

331 Diseases with inflammation or pain were also well detected, with an average of 332 97.8%, 84.1%, and 88.2% events detected for lameness, mastitis, and other 333 diseases, respectively. However, only 81.5% of LPS-induced udder inflammation 334 events were detected. This slightly lower detection rate may be due to the fact that 335 the inflammation is less marked when induced by LPS than by pathogens, or that the 336 sickness behaviour is less marked with a simple inflammation than when pathogens 337 are present. Indeed, pain, hyperthermia, and decreased rumination last less than 24 338 h after LPS injection [21].

339 Overall, 69% of SARA events were detected (only in Dataset 2 where ruminal pH 340 was monitored). Animals do not always suffer when their ruminal pH is low. Their gut 341 flora can adapt to diet containing high amounts of starch and low pH, and animal 342 behaviour can return to normal from one day to the next [22, 23]. For the moment, we 343 cannot distinguish whether FBAT underperforms in SARA or whether it is simply a 344 case of cows with SARA not always suffering. More measurements to identify SARA, 345 such as milk urea nitrogen and blood bicarbonate [24], are needed in order to refine 346 the detection of SARA and better calculate how FBAT performs.

347 The events on which the method underperformed were mixings (68.3% detection) 348 and other disturbances (60.1% detection). Based on records noted in the farm 349 logbooks, it was difficult to estimate whether the procedures undergone by the 350 animals were liable to disturb them. The category 'other disturbances' includes 351 various treatments, such as vaccination, administration of drugs, or relocations from 352 a pen. These events may or may not disturb the animals depending on how they are 353 handled and whether treatment induces some pain (an injection, for instance). Mixing 354 very clearly disturbs the animals, triggering aggressive interactions, weakening group 355 cohesion, and inducing chronic stress [25, 26]. However, in this study, we inferred the 356 'mixing' category from instances when one or more animals were moved from one 357 pen to another, and so we thus cannot be sure that these animals were mixed with 358 unfamiliar pen-mates. Therefore, the moderate proportion of mixings and other 359 disturbances that FBAT detects likely reflects the fact that not all of them actually 360 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).

368 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.

387 Anomalies due to lameness started to be detected 1.5 days before the lameness was 388 logged (60% of cases) and more than 80% of these cases were detected no later 389 than 12 h before the day they were logged. In the case of mastitis, 60% of rhythm 390 anomalies were detected 24 h before the day they were logged and 90% were 391 detected no later than the day they were logged. In the case of other diseases, 60% 392 of anomalies were detected 32 h before the day they were logged and more than 393 95% of anomalies were detected no later than the day they were logged. The FBAT 394 method is thus likely to detect anomalies due to diseases one or two days before 395 clinical signs manifest. This could prompt caretakers to pay closer attention to 396 animals displaying such anomalies and possibly call in a vet for a diagnosis and rapid 397 treatment.

398

399

400 4 Conclusion and perspectives

401 Our new Fourier-Based Approximation with Thresholding (FBAT) method can detect
402 changes in the circadian rhythm of activity. These changes are closely related to
403 many events experienced by animals, including disease, accident or stressful

404 disturbance in the barn. The method produces less than 20% false alerts (i.e. 405 changes unrelated to a problem logged by caretakers) and detects about 95% of 406 rhythm anomalies caused by reproductive or health problems. The method can 407 detect problems at a very early stage of disease, before clinical signs manifest. Alerts 408 can thus be sent to the animal caretaker to flag animals showing a modified rhythm. 409 When an alert is sent, the caretaker can take quickly a management decision, e.g. to 410 check calving progress, inseminate a cow in oestrus, separate the cow from the rest 411 of the group, or look for clinical signs to identify a disease and engage treatment.

412 For the moment, FBAT is unable to distinguish between events experienced by 413 animals. This can be seen as a limitation of the method, as it does not provide a 414 diagnosis. FBAT uses only the rank-1 harmonic provided by the Fourier transform 415 corresponding to the circadian rhythm. We did not handle variations that may occur 416 within a day, which might be relevant to identify a given disorder (e.g. cows under 417 SARA with a low activity between the two daily meals [27]). To overcome this 418 limitation, the method could be further developed to take into account harmonics of 419 rank above 1. An alternative solution could be to use other methods to model the 420 rhythm, such as wavelet transforms [28][29],.

421 From another angle, being able to detect any problem whatever the cause may be 422 seen as an asset. First, the same tool can issuing warning that something is wrong 423 and that animals need to be checked in case remedial action is needed. Second, this 424 tool can also serve for assessing animal welfare. Indeed, oestrus and calving 425 frequency should be about the same across farms, and so any variations between 426 farms are likely to be due essentially to health disorders and stress experienced by 427 the animals. FBAT could thus be used as an overall measure of animal health and 428 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].

438 The farms from which data were used in our study had different routines that may 439 have affected the rhythm of their cows. The cows were milked at fixed intervals on 440 some farms vs. with an automatic milking system allowing cows to choose when to 441 be milked on other farms. Food was delivered two or three times a day on some 442 farms vs. more evenly distributed across the day by a robot pusher in other farms. 443 Furthermore, the type of events detected differed between datasets. Despite such 444 variations, the threshold that optimized the distinction between a normal vs. modified 445 rhythm was stable, enabling us to apply the same threshold to all datasets, which 446 resulted in similar performances across all farms except the farms from Dataset 3, as 447 discussed above. The fact that the threshold does not vary much between farms 448 should be checked on a larger population of farms. If the stability is confirmed, then a 449 pre-defined threshold could be used without having to go through training to define 450 the threshold for a given farm, thus making FBAT very easy to apply. It remains 451 possible to adjust the threshold to a given farm or even to each cow of that farm, in 452 which case data will need to be recorded for a few weeks to estimate the threshold 453 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.

465

466

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482

483 Author contributions

484 **Nicolas Wagner:** Methodology, Software, Validation, Formal analysis, Investigation,

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486 Mialon: Formal analysis, Investigation, Data curation, Writing - Review & Editing,

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492 Conceptualization, Formal analysis, Data curation, Writing - Original Draft, Writing -

493 Review & Editing, Visualization, Supervision, Project administration, Funding494 acquisition.

495

496 Appendix A. Data, equipment, and software

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

498 Equipment: The indoor tracking system is commercialized by GEA Farm technologies

499 (Bönen, Germany). The manufacturer claims a precision of 50 cm for the detection of

500 a cow's position. In the INRAE experimental farm that provided two of the datasets

501 used here, we observed a precision of 16 cm [30].

- 502 Server and software: FBAT was developed in the Python programming language with
- 503 the fast Fourier transform function available in the NumPy library
- 504 (https://numpy.org/devdocs/reference/generated/numpy.fft.fft.html#numpy.fft.fft). The
- 505 code is available at https://github.com/nicolas-wagner/FBAT. We used a server
- 506 composed of an Intel Xeon E7-8890 v3 CPU (2.5 GHz with 46 Mb of cache) and 3 Tb
- 507 of RAM, of which we used less than 8 Gb. For field use of FBAT, the detection of
- 508 changes in the circadian rhythm will need less than 1 Gb, depending on the size of
- 509 the on-farm dataset produced.
- 510

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- 588





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).

Type of event	Days	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 disturbance	es 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.	Training time	Test time	τ	rec_	rec_+
	cow*days	(s)	(s)			
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

629

- 631 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
- 633 type of events (with a fixed threshold $\tau = 2000$).

Evente		Datasets					
Events		1	2	3	4		
Accidental event ¹	no. events	0	0	0	10		
Accidental event	% detected	na	na	na	100		
Calving	no. events	9	0	0	171		
Carving	% detected	100	na	na	99.4		
Oostrus ²	no. events	41	7	29	257		
Oestrus	% detected	95.1	85.7	69.2	91.4		
Lamonoss	no. events	4	16	0	114		
Lameness	% detected	100	93.8	na	98.2		
Maetitie	no. events	9	3	0	32		
พลรแนร	% detected	100	0	na	87.5		
Other disease	no. events	10	8	0	66		
Other disease	% detected	80	75	na	90.9		
I PS 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		
winning	% 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.