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SmartCow: an integrated infrastructure for increased research capability and innovation in the European cattle sector

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1. Author(s)

Organisation name lead contractor	WUR-DLO

Author	Organisation	e-mail
Rudi de Mol	WUR-DLO	rudi.demol@wur.nl
Joop van der Werf	WUR-DLO	joop.vanderwerf@wur.nl
Ingrid van Dixhoorn	WUR-DLO	Ingrid.vandixhoorn@wur.nl
Kees van Reenen	WUR-DLO	Kees.vanreenen@wur.nl
Isabelle Veissier	INRAE	Isabelle.veissier@inrae.fr
Romain Lardy	INRAE	Romain.lardy@inrae.fr
Marie Madeleine Mialon	INRAE	marie-madeleine.richard@inrae.fr

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EXECUTIVE SUMMARY

Background	*Various sensors are now available to record automatically behavioural data in cows. These raw data need to be processed to produce meaningful descriptors of that behaviour.*
Objectives	*One of the objectives of Task 7.2 is to propose quantitative metrics describing cow phenotypes from their behaviour recorded with the use of sensors. The present deliverable is focused on the processing of data on cow activity (time budget).*
Methods	*We investigated ways to visualise the data, basic mathematical operators (sum, average, weighted sum), statistical methods (variance, RMSSD, autocorrelation, multivariate analyses), modelling approaches (e.g. using Fast Fourier Transform) and ad-hoc operators. These calculations were applied to data from a system based on accelerometers (Nedap Smarttags on neck or leg) and a position system (GEA CowView).*
Results & implications	*Descriptors are proposed for the time budget of cows (i.e. the time spent in each activity per day), the activity level, the distribution of activities or their level within days and across days, and the synchronization of activities between cows from the same groups.* *These descriptors can then be used to predict more complex aspects such as health disorders or welfare. This will be investigated in the next deliverable (D7.4 - Relation between behavioural characteristics and health, welfare, efficiency).*

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1 Introduction

Several sensors can be used for the recording of cow activity. Most sensors are accelerometers positioned on the leg or the neck of the animal that detect movements; in general they detect if a cow is standing up or lying down, eating or ruminating or inactive (for reviews, see Rutten et al. (2013) or the survey from the Data Driven Dairy Decision For Farmers project available at https://4d4f.eu/content/technology-warehouse). Other sensors detect the position of animals (Real Time Locating Systems, RTLS); the activity is inferred from the animal position (e.g. the animal is declared resting if detected in a cubicle, and eating if near a trough). One can also imagine detecting the activity by other means like image analysis. Such devices allows knowing the main activities of the animals 24h/24.The basic information provided by sensors is to be processed in order to phenotype cows according to activity descriptors.

The present deliverable details such descriptors and provides explanations on how to calculate them. The calculations were applied on two types of sensors: an accelerometer and a RTLS. They can nevertheless be applied to data from other devices, on the condition that the monitoring of the animal activity is performed continuously (i.e. 24h/24, 7 days a week) and with sufficient details.

2 Acquisition of data

Two Precision livestock Systems were used to develop calculations of activity descriptors:

- A system based on accelerometers: The Smarttag Neck and the Smarttag Leg sensors manufactured by Nedap N.V. (Groenlo, The Netherlands) ,

- An RTLS: The CowView manufactured by GEA (Bönen, Germany).

2.1 Equipment

Smarttag Neck and Smarttag Leg sensors

The Smarttag Neck sensor is used for the monitoring of eating, rumination and inactive behaviour and the Smarttag Leg sensor is used for the monitoring of standing, lying and walking behaviour (See position of the tags on Figure 1). The hardware of the tag, the firmware in the tag, as well as the software for the processing of the raw data (data from the accelerometers or other sensors in the tag) are all part of the tag product as marketed by the manufacturing company, and these parts may change over time as technology progresses. In this study, tags were used of a version that was on the market in the years 2017-2019. The output given by these tags is described below.

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Figure 1. Position of a Smartag Neck (left) and a Smarttag Leg (right) on cow. Tags should be attached to cows according to the instructions of the supplying company. The Smarttag Neck sensor is attached to the lowest part of the neck collar of a cow. The Smarttag Leg sensor is attached to one of the front legs of a cow. We have had a few cases that a Smarttag Leg was lost from a cow. Never have we had cases that a Smarttag Neck lost.

The neck sensor gives per cow and per minute one out of four possible behaviours: eating, ruminating, inactive, other activity. Other activity is not further classified, hence consists of all activities other than eating and ruminating. Times are in local time-zone. We propose to aggregate the basic data into hourly data by summing up the minutes per clock hour. The neck sensor then gives per cow per hour the partition in:

- Time spent inactive (min)
- Time spent ruminating (min)
- Time spent eating (min)
- Time spent on other activities, that is neither inactive, ruminating nor eating (min/h)

The sum of these four times is 60 min.

The neck sensor also provides an overall activity level per 15 min. This data was not used so far because we don't know how it is calculated.

The leg sensor provides per cow per 15 min the time spent on three possible behaviours: lying, standing, walking. 'Standing' is to be interpreted as 'standing not walking, i.e. stand still'. Leg sensors are attached to front legs of cows and assumingly that position limits or prevents them from 'recognizing' behaviours other than the ones mentioned. Times are expressed in minutes (full or rounded off). For the same 15-min periods, the leg sensor provides a count of steps and a count of transitions from lying to standing or walking.

Each period of 15 min is time-labelled with the starting time of that period. Starting times are always at 14:00, 29:00, 44:00 and 59:00 min past the hour – which is slightly different from the quarters of a clock hour. Times are in local time-zone.

We propose to aggregate the basic data into hourly data by aggregating the four periods with starting times within one clock hour. The leg sensor then gives per cow per hour the partition or count of:

- Time spent lying (min)
- Time spent standing (min
- Time spent walking (min)
- Number of steps (-)
- Number of transitions from lying to standing (-)

The lying time, standing time and walking time add up to 60 min.

CowView

The CowView system consists of a locating sensor fixed on top of each cow collar that emits a signal in the ultra-wideband area. The signal is captured by antennas fixed in the barn ceiling (Figure 2). The position of the cow is determined by triangulation every second. If the cow is found in a cubicle, she is considered to be resting, if she is found near the feeder, she is considered to be eating, and if she is found in the alley, she is considered to be walking (if its position changes during successive sampling) or standing (if its position does not change). CowView provides two types of data:

- The position of the animal (every second)
- Its likely activity expressed as time spent resting, standing, walking, eating per hour (the same can be obtained per 15 min periods). For the purposes of the study, we merged walking with standing, as direct observations suggested that the device did not precisely distinguish these two activities in our facility.

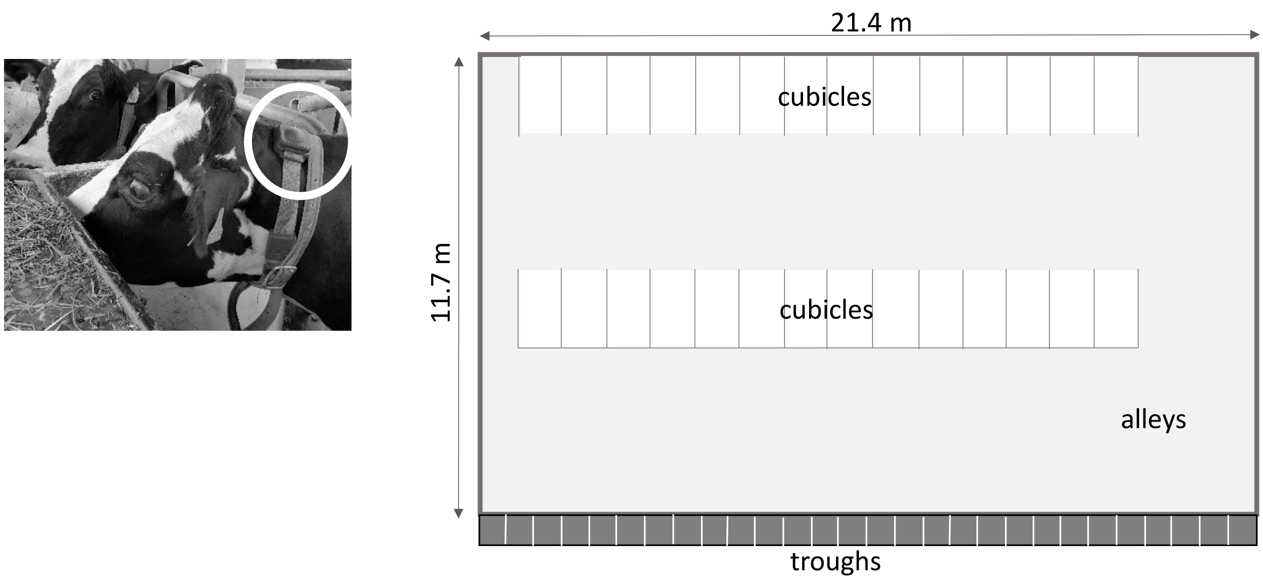

Figure 2. CowView tag on the cow collar (left) and virtual partitioning of the pens to distinguish activities (right)

For Smarttag Neck and Smarttag Leg as well as for CowView, raw or pre-processed data from the sensors are uploaded to the company servers, and processed into behavioural data. Behavioural data are presented to the user through a company's web interface. The interface allows the user to

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administratively connect and disconnect tags to cows. It shows alerts as an aid to cow management. Behaviours and changes in behavioural levels over time per cow or per group are typically presented to the user as graphs, without the possibility of getting the underlying figures. Therefore, for this study, special arrangement were made with the companies to receive the behavioural output data as export files in csv format (per hour or 15 min).

3 Calculation of activity descriptors

The sensor data acquired as described in Chapter 2 are transformed to metrics allowing to phenotype individual cows in terms of activity descriptors. These descriptors can subsequently be used for phenotyping more complex animal characteristics, especially in relation to health and welfare. These characteristics can be monitored - if the recording period and the target phenotype are concomitant, e.g. the detection of a health disorder by pre-clinical behavioural indices - or predicted if the recording period precedes the target phenotype, e.g. the prediction of a health risk postpartum from behavioural indices recorded prior to calving.

Several parameters have been investigated, some specifically based on research in the field of animal resilience (e.g. for the detection of animals that recover rapidly after a disturbance), others related to disease or stress detection. For instance, increased variance and increased autocorrelation are known as early-warning signals for critical transitions (Scheffer et al., 2009, 2012) while the change of a cow from healthy to diseased can be considered as a critical transition. Similarly, the circadian rhythm of activity is likely to be altered by disease and stress with in case of disease, alterations occurring 1-2 days before clinical signs (Veissier et al., 2017). Behavioural descriptors are to be calculated to be able to use such information. The algorithms used to calculate these descriptors are described in the following paragraphs.

3.1 Sum, average, variance, and RMSSD

The sensor data per cow per hour can be transformed into one measure per cow by applying basic statistics:

- Sum, the cumulative value of the sensor data. For instance, the time spent resting, eating, ruminating… per each hour or day of recording.
- Average, the average value of the sensor data over a defined interval, describing the central value. For instance, the average time spent resting, eating, ruminating… per hour of a given day or per day over several days.
- Variance, the variance of the sensor data over a defined interval, describing the spreading of the data around the average. The variance corresponds to the average squared deviation of values from average. It does not have the same units as the original data (e.g. h^2 instead of h). The Standard Deviation (SD), which is the square root of the variance, is more often used because it is expressed with the same units as the original values. The variance / SD between hours of a day can be used to describe the amplitude of variations within that day. The variance/SD between days reflects the amplitude of variations across days.
- The RMSSD can also describe the variations from one time interval to the next one. This calculation has been proposed to assess Heart Rate Variability (HRV) with RMSSD being the Root

Mean Square of Successive Differences between heartbeats. To assess HRV, RMSSD is obtained by calculating each successive time difference between successive heartbeats then each of the values is squared and the result is averaged before the square root of the total is obtained (Task Force on HRV 1996). The time difference between successive heartbeats can be replaced by the difference between the value of e.g. time spent in an activity. Like SD, RMSSD is expressed with the same units as the original values.

- Less often, the deviation from average is expressed by calculating the absolute difference for a given instance and the average of all instances (e.g. the absolute difference between a given hour and the average across hours of the same day).

3.2 Factorial Correspondence Analysis and weighted sum to estimate the activity level

Intuitively lying corresponds to a lower level of activity than standing inactive, which in turn corresponds to a lower level of activity than standing active (walking, eating, interacting with other animals…). Veissier et al. (2001) proposed a method to calculate the level of activity in terms of a weighted sum of the time spent in the different activities. In absence of a gold standard to estimate the level of activity, Veissier et al. (2001) propose to attribute weights to activities that maximize variability between hours of the day. The weights are obtained from a factorial correspondence analysis (**FCA**) with the hours of the day as observations and the occurrence of the activities (that is the cumulated time spent in a given activity by all animals in the group) as variables. The method was first used on data from animal observations performed by scan sampling. It was then applied to data from CowView by Veissier et al. (2017). On the first axis of the FCA, the various activities are classified in the same order that we would classify them intuitively according to the level of activity they represent: resting obtains a lower weight than standing or walking that obtains a lower weight than eating. In Veissier et al. (2017), the first axis of the FCA summarized 93% of the variability between hours and the 3 activities obtained the following weights: resting, −0.15; in alleys (standing or walking), +0.12; eating, +0.34. The first axis of the FCA is then considered to express level of activity. For each cow and each day, the level of activity can be calculated, e.g. per hour, by multiplying the percentage of time spent in each activity by the weight attributed to the activity on the 1st axis of the FCA.

In order to estimate the weights of the activities, we recommend to remove outlier days, defined as data from a specific day and animal when the frequency of an activity is outside the 95% confidence interval [i.e., that animal spent more (or less) time on a given activity than its average $\pm$ 2 standard error calculated over the previous 14 days]. We assume that this animal encountered a disorder on that outlier day (e.g., it was diseased or some disturbance occurred in the barn).

The average described in the previous section can be applied to the level of activity per hour. This brings information on the average activity level of an animal, that is how much the animal is active.

3.3 Identification of periodic patterns

Actograms to visualise the distribution of activities

The distribution of an activity during the day can be represented by actograms (Refinetti et al., 2007). We propose to use a variant of the method of Strogatz (1987) to visualize the circadian pattern in sensor data (Rodríguez-Sánchez, 2020). An example is given in Figure 3 where a clear difference is visible in the time spent per hour on eating before and after calving.

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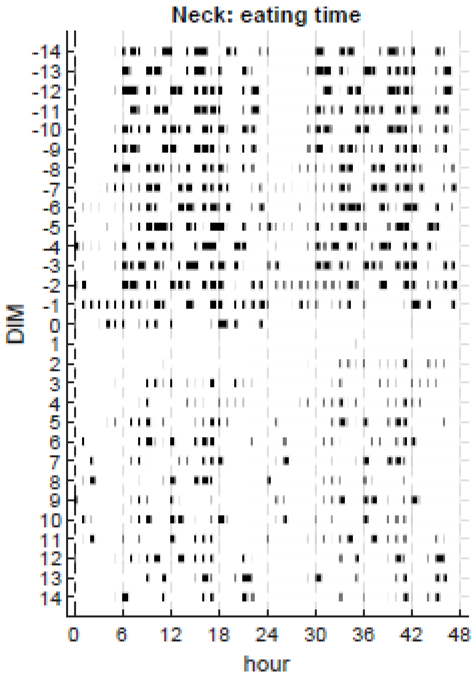

Figure 3. Actogram of the eating time per hour of Cow 7831 of Dairy Campus with hour within two successive days on the horizontal axis and days in milk (DIM) on the vertical axis. Each block represents the fraction of an hour spent on eating.

Basic descriptors of circadian variations

To describe the intensity of variations within days, the SD, RMSSD, or absolute difference (see Section 3.1) can be applied to the basic activities (e.g. the time spent eating per hour) or the level of activity per hour (Section 3.2). The higher the SD, RMDD or the absolute difference, the more marked the variations between hours of the day.

SD and RMSSD were used in Veissier et al. (2017) to highlight that the within day variations are less marked one or two days before a mastitis or a lameness was detected by farmers. The absolute difference was used by WUR to analyse changes from before to after calving.

Autocorrelation

Autocorrelation (at lag 1) is the correlation between successive values of a sensor variable, describing the similarity between successive values. The methodology for calculating autocorrelation in the context of so-called 'critical transitions' is described in Dakos et al. (2012).

Non-periodicity is defined as the mean squared difference of a correlogram with a sinusoid with a 24-h cycle and an amplitude of 0.25, where the correlogram is a plot of the correlation of the variable for different time lags (see Van Dixhoorn et al., 2018 for an example). This measure is an extension of the autocorrelation at lag 1. Here all lags are taken into consideration and included in the correlogram. The lags are usually based on hourly intervals, but for both the active time and the number of bouts, a 6-h period can be used instead of the hourly values. An example is given in Figure 4 where the correlogram of eating time per hour is presented.

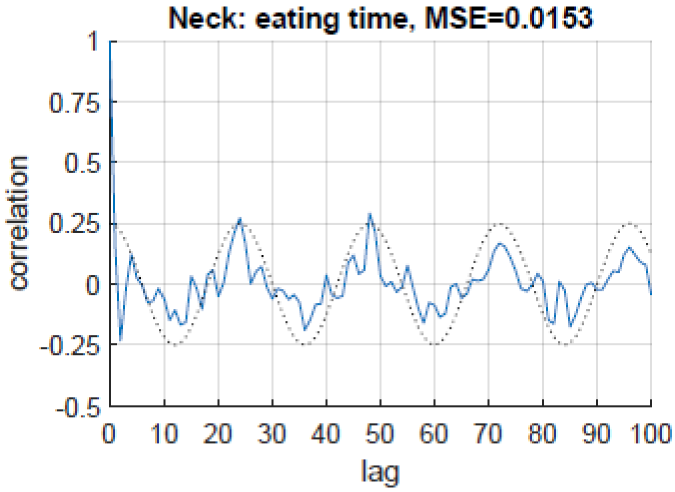

Figure 4. Correlogram, that is a plot of the sample autocorrelations versus the time lags in hours, of eating time per hour (blue line); the non-periodicity is the mean squared error of the correlogram with a sinusoid function with a cycle of 24 h and an amplitude of 0.25 (dotted line).

Fast Fourier Transform

So far we described calculations in the time-domain. That is, the focus was on the duration of activities. In this section we use the Fourier analysis which belong to frequency-domain where the activities are not described by their duration but their frequency (the question is "how often they occur?). The conversion from time to fequency domain can be done rapidly by using the Fast Fourier Transform (FFT) algorithm (Chatfield and Xing, 2019).

Patterns in the sensor data become visible as frequencies with high peaks. For our application, Fast Fourier Transform is defined as the sum of the peaks at 1, 2, 3 and 4 in the amplitude spectrum of the variable determined with a Fast Fourier Transformation. This is a measure of the regularity of behaviour occurring once, twice, three times or four times a day. An example is given in Figure 5. Hence, the outcome of FFT indicates the extent to which cows display circadian (i.e. about 24 h) to ultradian rhythms (several cycles within a day).

In the time domain usually, an hourly interval is used, but for both the active time and the number of bouts the aggregate values per 6-hour (or more) periods are used instead of the hourly values. These two characteristics are treated differently because their lower values, e.g. the number of bouts per hour is mostly a zero/one variable, where the number of bouts per 6 hours can be treated as an ordinary numeric variable.

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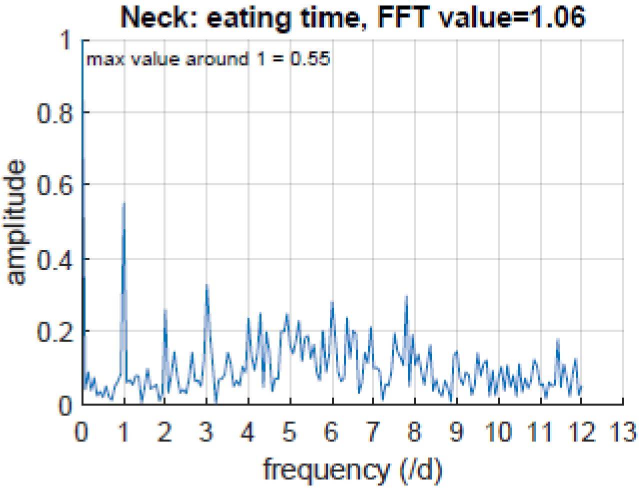

Figure 5. FFT plot the eating time per hour of Cow 7831 of Dairy Campus with peaks at 1, 2 and 3; Peak 1 correspond to the fact that the eating behaviour is essentially depending on a circadian rhythm (24 h) and Peak 2 and 3 correspond to ultradian cycles, probably due to the fact that the food is delivered several times a day.

3.4 Regularity of activity organisation from one day to the next

Traditional approach

Our measure of regularity is based on a previous behavioural study in dairy cows (Schrader, 2002), and indicates to what extent an individual cow performs the same behaviour at the same times on two consecutive days. The method presented here can be used for any state behaviour as long as states have reasonable durations. In our study, regularity is computed for (1) eating (and non-eating) behaviour, and for (2) lying (and non-lying) behaviour. The latter is taken as an example here.

Minutes of lying behaviour need to be available per cow per 15 min period for multiple (n) days. One day consists of 96 such periods. Data of a chosen day 0 is used as reference data for day 1, day 1 is reference data for day 2, and so further on.

Each 15 min period for each cow during n days is labelled as either “yes” or “no” for lying behaviour. 15 min periods with 8 or more minutes of lying are labelled as “yes”; periods with 7 or less minutes of lying are labelled as “no”. Each 15 min period of a day is then compared with the same 15 min period of the previous day. Equal labels on both days (either both “yes” or both “no”) result in code “1” for regularity; different labels result in code “0”. The count of codes “1” during a day of 96 periods - expressed as ratio or percentage - is our measure of regularity for this cow during this day.

Missing lying data on the current or on the previous day will result in a missing value for regularity for that 15 min period. We have only used data of complete days (96 records), but one could set an acceptable threshold for the minimum number of 15 min periods required.

As a starting point, regularity can be calculated per cow per day. Thereafter, regularity can easily be grouped over cows and/or over days. The average of the cow-day regularity values is then calculated. This will either result in a measure of regularity for one particular cow during a longer period of time, or a regularity for a group of cows (herd) on one particular day. A combination of the two groupings will result in a regularity for a particular herd during a particular period of time.

We realize that management times of feeding and milking might affect our measure of regularity; however, the underlying assumption is that management times do not alter dramatically on a daily basis.

Fourier-Based Approximation with Thresholding (FBAT) method to detect changes in the circadian rhythm

Wagner et al. (2020) developed a method to detect changes in the circadian rhythm. The method called Fourier-Based Approximation with Thresholding (**FBAT**) uses Fast Fourier transform to model the variations of activity during 24 h periods into sinusoids. The models obtained on consecutive periods are then compared to detect if the rhythm has changed. To this aim, the Euclidian distance between the models is calculated. For the detection of diseases or stress, the authors propose to compare the model obtained on a given 24 h period and that obtained on another 24 h period starting 12 h after the first one (figure 6). The details of the calculations are given in Wagner et al. (2020). 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). FBAT code is available at https://github.com/nicolas-wagner/FBAT.

Compared to the traditional approach, FBAT allows removing noise in the data. Indeed, animals never do exactly the same activity at the time of the day between consecutive days. Despite such slight variations, their general pattern of activity may (or may not) remain the same and this is what FBAT captures.

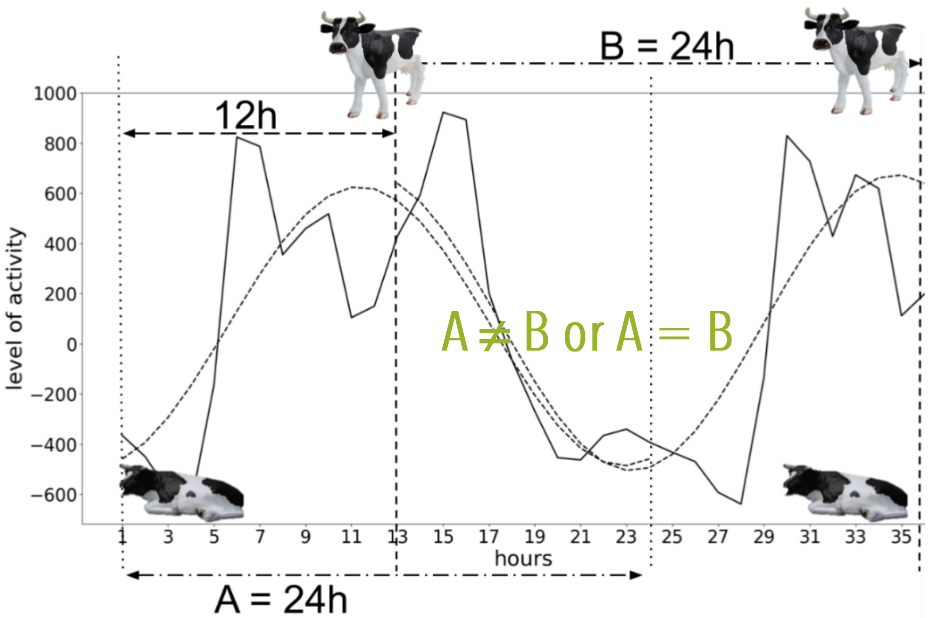

Figure 6: FBAT method applied to data on activity level (processed from CowView). Models A and B, for two 24 h periods separated by 12 h, are obtained by a FFT. Their distance is compared to a threshold defined in a way to optimise the distinction between normal and abnormal time series, here days when no specific event occurs vs days when a cow was found sick or when a disturbance occurred (e.g. mixing animals).

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3.5 Synchrony

Cows are generally member of groups, sharing the same space of living. Animals from the same group tend to express the same activity, in other words they are synchronised with each other. We propose to assess the synchrony at herd as well as at individual level:

- Synchrony of a herd indicates to which proportion of a day the herd performs equal behaviour, meaning that the majority of cows do the same thing at the same time.

- Synchrony of an individual cow indicates to what extent the individual cow performs the same behaviour as the majority of the herd.

There are several methods to assess the synchrony of a herd or of an individual. They can be used for any state behaviour as long as this state has reasonable durations. For instance, synchrony can be computed for eating or lying, but not for social interactions which are generally brief. It can be computed for specific activities or whatever the activity (overall synchrony). Whenever possible, synchrony should be assessed from scan sampling, that is at a given time, the activity of all animals is determined instantaneously (as at first glance from direct observations). CowView allows knowing the instantaneous activity of an animal, as in scan sampling. However, sensors often provide the time spent in a given activity on a given period. For instance, with the Smarttag leg sensor, the time spent in each activity is given per 15-min intervals. For instance, if an animal has been lying for 8 or more minutes, then its activity will be considered “lying” for the whole 15 min. In that case, the synchrony will be approximated from the most likely activity of the animals during that interval.

Synchrony at group level

Each point in time - in case of scan sampling - or each time-interval can be labelled “yes” or “no” for a given activity. Then one can consider that the herd is synchronous for this activity if the majority (at least 60% or 80%) of cows show that activity (majority of “yes”). Ne can attribute a score 1 when such synchrony is observed, then the count of codes “1” during a day of 96 15 min intervals - expressed as ratio or percentage – provides a measure of synchrony for this herd and this activity during this day. The same can be done for each activity. The results largely depend on the threshold chosen for determining if the group is synchronised.

Synchrony calculations can be biased by the number of animals in the group or the frequency of an activity. To overcome these biases it is possible to calculate what would be the synchrony within a group obtained by chance and to compare it to what is observed. This can be done by calculating a kappa coefficient to assess the concordance of activity between animals (Tuomisto et al., 2019) or an overdispersion index (Raussi et al 2011). It is also possible to assess the synchrony of a group of animals by the average of the synchrony of each individual with the group (see below).

Synchrony at cow level

In line with calculating group synchrony by considering whether the majority of the animals in the group perform the same behaviour (see above), it is possible to calculate synchrony at individual level by considering whether a focal animal performs the majority behaviour of the group. To this aim, selection is to be made of the periods of the day during which the herd showed synchronous behaviour. For instance, if the activity is described per intervals of 15 min, this means selecting the 15-min intervals where more than 60% (or 80%) of the cows are lying, or on the contrary non lying (if lying behaviour is the focus).

The synchrony of an individual cow can also be assessed by comparing the activity of that cow with that of the other cows in the group. The synchrony of a focal animal with the other members of its group is then expressed as the percentage of the group members performing the same activity as that of the focal animal (e.g. Veissier et al. 1990). In that case, no threshold need to be defined.

Note that when calculating synchrony, missing data for one or more cows for one or more periods result in a missing value for synchrony at herd or individual levels, unless corrective factors are applied (for instance, calculating percentage on the animals from which data are obtained).

Synchrony is calculated per herd per day and per cow per day. Thereafter, synchrony can easily be averaged over days. In case synchonicity is assessed taking into account the majority activity in the group, it t is not advisable to average cow synchrony values into a group value, because the chosen threshold for 'majority' will have a disproportional impact on such a figure.

4 Conclusion

Basic data on cows' activity provided by sensors can be processed in different ways to describe the time budget of cows (i.e. the time spent in each activity per day), the activity level, the distribution of activities or their level within days and across days, and the synchronization of activities between cows from the same groups. There is evidence that these descriptors can then be used to predict more complex aspects such as health disorders or welfare. For instance, autocorrelation seem to be a good predictor for critical transitions (Rennen et al., in prep) whereas disease and stress induce variations in the circadian rhythm (Veissier et al 2017). This will be investigated in the next deliverable (D7.4 - Relation between behavioural characteristics and health, welfare, efficiency). A summary of the various descriptors that an be calculated is provided in Table 1.

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Table 1 : Summary of calculations from activity data provided by sensors

Domain	Method	Purpose
Visualisation of data	Actogram	A graphical representation of the activity of a cow to the time of day over a period of time. Behavioral patterns over the day can be visualised as well as occurrence of fragmented rest in contrast to rest blocks, or activity blocks.
Time domain	Sum (or average)	Average of specific activity per day gives a rough indication of the level of this behaviour or the average level of activity
Time domain	Weighted sum	Weigthed sum of time spent in each activity is used to calculate a level of activity
Time domain	Variance / SD/RMSSD/absolute difference	Within individuals : Variations during the day (of a given activity or the activity level)
Time domain	RMSSD	RMSSD of the daily patterns and a fixed sinusoid gives insight into how fixed the daily patterns of specific activity are during a specific period of time.
Time domain	Non periodicity	Gives insight in fixed patterns over the day
Time domain	Autocorrelation	Detection of periodic patterns (e.g. circdian cycle)
Frequency domain	Fourier transform	Identification of periodic patterns (circadian, ultradian cycles); detection of changes in rhythm
Concordance	Overdispersion index and Cronbach alpha	Homogeneity of activity across animals from the same group (herd synchrony)
Concordance	Ad hoc calculation of herd synchrony (sum of instance where a majority of animals perform the same activity)	Homogeneity of activity across animals from the same group (herd synchrony)
Concordance	Ad hoc calculation of animal synchrony with its herd (sum of instance where it performs the major activity of the group; proportion of animals performing the same activity as the focal one)	Similarity of homogeneity of activity across animals from the same group (animal synchrony)

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