115. Entropy of broiler activity: individual variation and consistency

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Abstract

Animal behaviour is complex and comparing average levels of behavioural activities is sometimes insufficient to pick up on behavioural differences between (groups of) animals. Entropy, a measure of the randomness or regularity of time series, might help us to describe aspects of behaviour better. In this study, we determined daily entropy in individual broiler activity levels over time, based on a time series of observed activity per 15 minutes across a day, to assess individual variation and consistency in entropy of activity. Activity data for calculation of entropy were available for 79 broilers for a maximum of 21 days. We observed individual variation in entropy between broilers, but the level of entropy was not very consistent across days. The individual variation in entropy indicates potential for future research to look into whether and how entropy differences relate to other traits in broilers.

Introduction

Animal behaviour is complex and multi-dimensional (Asher *et al.*, 2009) and studies have indicated that mean levels of behaviours are not always sensitive to differences between groups of animals. For example, Dawkins *et al.* (2012) studied broiler flocks using optical flow patterns and observed no correlation between the mean gait score (i.e. walking ability) of the flock and the mean optical flow, but did observe correlations between the mean gait score and the skew and kurtosis of optical flow. This indicates that descriptors of behaviours that capture more than mean behavioural activity levels have potential to provide more insight into (individual) differences in behaviour. One measure that has potential is entropy. Entropy is a measure of the randomness or regularity of time series based on the existence of patterns (Delgado-Bonal and Marshak, 2019) and it has been indicated that entropy can be informative for, or predictive of, human behaviour, health and well-being (e.g. Glenn *et al.* (2006)). Although to a smaller extent, entropy has also been studied, and found to be informative, in non-human animals (e.g. Stamps *et al.* (2013)). In this study, we aimed to describe individual broiler locomotor activity patterns over time and assess individual differences in these patterns, using entropy. Individual differences in entropy have potential to be linked to other traits in broilers and may in the future aid in individual broiler phenotyping.

Materials & methods

Animals and housing. Individual-level broiler activity data were collected for 24 hours per day, from 1 to 33 days old, in a group of 80 birds housed in a pen with a size of 1.8×2.6 m.

Activity tracking. To record the individual broilers' activity levels, we fitted the pen with an earlier-validated RFID activity tracking system (Van der Sluis *et al.*, 2020). This system consisted of tags, that could be fitted to the birds' legs, and a grid of antennas that was placed underneath the floor of the pen. These antennas could register the presence of tags and a log file was stored with information on the tag ID (i.e. bird ID), the time of registration and the antenna (i.e. location) at which the tag was registered. To calculate activity levels, we first determined for every minute whether an antenna switch (i.e. position change) was registered within this minute for this animal. We then calculated the number of minutes in which an antenna switch was registered per 15-minute bin. Subsequently, these values were categorized into four classes based on the quartiles observed in the data. Class one consisted of the observations up to

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and including the largest value observed in the lowest 25% of the data. Class two consisted of observations up to and including the largest value observed in the lowest 50% of the data, that were not already in class one. The upper limit for the third class was the 75% quartile, and the upper limit for the fourth class was the 100% quartile. In this process, we excluded values of zero (those were added as a fifth class), as a large part of the data consisted of zeroes due to low activity levels during the night. As activity is known to decrease with age in broilers (e.g. Weeks *et al.,* 2000), quartiles were determined within each day instead of across the full tracking period (Figure 1). Days on which there were overlapping numbers of antenna switches across the quartiles (e.g. one antenna switch was identified as both the first and second quartile limit) were excluded. This was the case for 28-days-old and older.

Entropy calculation. The resulting classes for the 15-minute bins of activity across each day were used as the underlying time series for the sample entropy (SampEn) calculation. The SampEn values can therefore be interpreted as a measure of regularity in activity within days, with lower values indicating more regularity and higher values indicating more randomness. However, SampEn can only be accurately calculated for days without missing data and therefore days on which the birds were weighed or their leg tags were checked, were excluded. This resulted in 21 days of data available for SampEn calculation, for which the pracma package (Borchers, 2021) was used in R (R Core Team, 2021). A total of 1455 entropy values were available, for a total of 79 individuals.

Statistics. All statistics were performed in R. Descriptive statistics were used to obtain a first overview of individual entropy values over time. To determine whether the individual entropy levels were consistent over time (i.e. the same individuals had relatively high or low entropy values on different days), we calculated Spearman rank correlations between the entropy values on different days, using the Hmisc package (Harrell Jr *et al.*, 2021). Visualisations were made using the ggplot2 (Wickham, 2016) and corrplot (Wei and Simko, 2021) packages. The level of statistical significance was set at 0.05.

Results

The overall mean entropy was 0.96 (SD 0.25), with a range from 0.07 to 1.65. Over time, the median entropy remained similar, but there did appear to be individual differences in entropy, as shown in Figure 2, where quite a large range of entropy values can be seen. The ranking of the entropy values of individual animals over days was not very consistent (Figure 3).

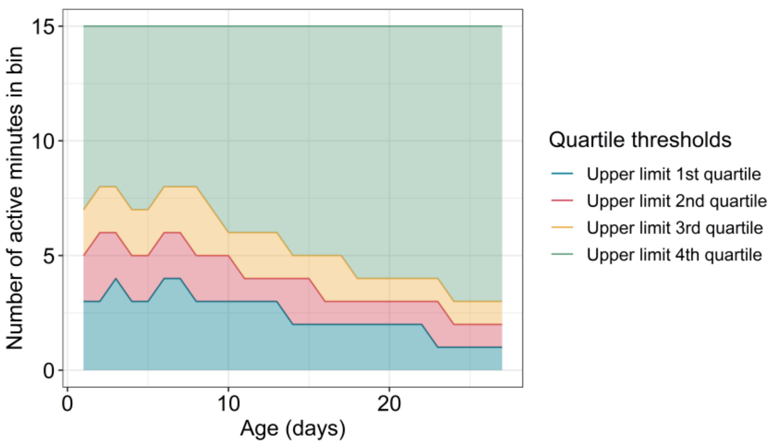

Figure 1. Quartile thresholds over time for number of active minutes per 15-minute bin.

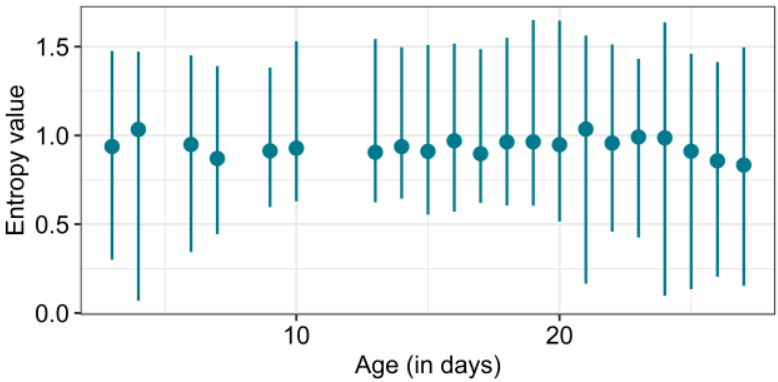

Figure 2. Median entropy values (circles) over time. Bars show the range from the minimum to the maximum observed entropy value for that specific day.

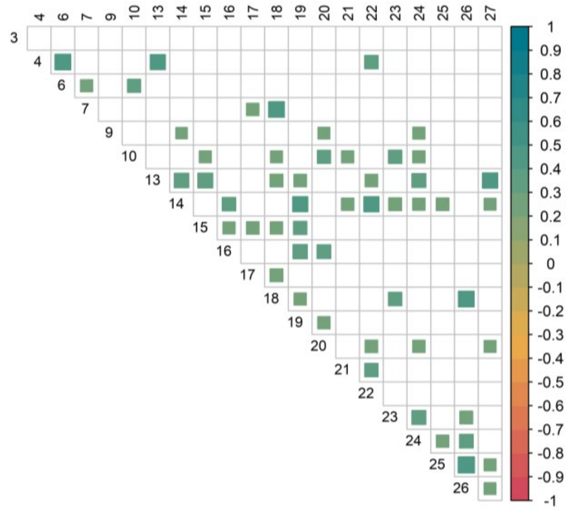

Figure 3. Spearman rank correlations between entropy values of individual animals on different days. On the axes, the day number is shown. Colours and sizes of squares indicate the strength of the correlation. Only correlations with *P*<0.05 are shown, squares associated with non-significant correlations are left empty.

Discussion

In this study, we examined entropy of activity of individual broilers over time and assessed whether there are consistent individual differences in entropy. We observed that the median entropy in activity from 3 to 27 days old was similar, but that there was quite a large range of observed entropy values within a day, suggesting that there are individual differences in entropy. This indicates potential for future research to look into whether and how such entropy differences are related to other traits. Other studies have indicated that differences in entropy can be linked to, for example, animal health. Fasmer and Johansen (2016) observed that spontaneously hypertensive rats displayed a higher complexity of movement time series (that is, a higher entropy) than control rats. However, the lack of strong correlations in entropy values over time observed here suggests that these differences are not consistent. Studies in laying hens have observed quite some consistency in movement patterns for some individuals, when looking at transitions between five zones in a commercial aviary (Rufener *et al.*, 2018). In this study, however, the activity patterns were simplified considerably by looking at 15-minute bins and five activity categories, and no locations or directions of movement were taken into account. Possibly, if a more detailed overview of activity would have been used as the underlying time series, more consistency in activity or movement patterns would have been observed. On the other hand, the lack of consistency in entropy might be interesting too: perhaps changes in entropy are related to specific traits or environmental conditions of the broilers, but this requires further investigation. Overall, it would be worth exploring different ways of applying entropy to animal behaviour data in the future, to understand how to best capture the behaviour feature of interest and to examine possible relationships with other traits.

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