Automatic detection of deviations in activity levels in groups of broiler chickens – a pilot study.

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Automatic detection of deviations in activity levels in groups of broiler chickens – a pilot study.

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Abstract

Automatic monitoring of activity levels in broiler chicken flocks may allow early detection of irregular activity patterns, indicating potential problems in the flock. Leg disorders are the main welfare concern for modern broiler chickens. Dynamic control of broiler activity during the growing period may improve the muscular-skeletal development thereby reducing leg disorders and improving welfare of the animals. The undisturbed activity of groups of broiler chickens was investigated in three steps. The first step applied a model, which was able to filter out outliers in the data stream of automatically recorded activity from overhead video cameras. The second step described the undisturbed levels of activity in groups of broiler chickens over the course of a day in week 1, 2 and 3. The third step applied a method to detect deviations in activity level, thereby giving an indication of a level change in activity within the flock of broilers. The results indicate the potential for automatic detection of deviations in activity level in flocks of broiler chickens. One perspective for these methods is to develop automatic monitoring systems, which can notify the producer when the activity in the broiler flock deviates from an expected level at a given age. Such monitoring system may improve the welfare of commercial broiler chickens.

Keywords: Broiler chicken, Activity, Animal welfare, Monitoring, Dynamic linear modelling.
Nomenclature.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>~ $N$</td>
<td>normally distributed</td>
</tr>
<tr>
<td>$C_t$</td>
<td>variance associated with the filtered mean at time $t$</td>
</tr>
<tr>
<td>$C_{u_t}$</td>
<td>cumulative sum of the standardized forecast errors at time $t$</td>
</tr>
<tr>
<td>DLM</td>
<td>dynamic linear model</td>
</tr>
<tr>
<td>$D_t$</td>
<td>information available at time $t$</td>
</tr>
<tr>
<td>$e_t$</td>
<td>forecast error at time $t$</td>
</tr>
<tr>
<td>$M_N$</td>
<td>model describing a normal situation</td>
</tr>
<tr>
<td>$M_O$</td>
<td>model describing an outlier situation</td>
</tr>
<tr>
<td>$m_t$</td>
<td>filtered mean at time $t$</td>
</tr>
<tr>
<td>$Q_t$</td>
<td>forecast variance at time $t$</td>
</tr>
<tr>
<td>$u_t$</td>
<td>standardized forecast error at time $t$</td>
</tr>
<tr>
<td>$V_N$</td>
<td>observation variance of model $M_N$</td>
</tr>
<tr>
<td>$V_O$</td>
<td>observation variance of model $M_O$</td>
</tr>
<tr>
<td>$V_t$</td>
<td>observation variance at time $t$</td>
</tr>
<tr>
<td>$v_t$</td>
<td>error term of the observation equation at time $t$</td>
</tr>
<tr>
<td>$W_t$</td>
<td>evolution variance at time $t$</td>
</tr>
<tr>
<td>$w_t$</td>
<td>error term of the system equation at time $t$</td>
</tr>
<tr>
<td>$Y_t$</td>
<td>logarithmically transformed observation vector at time $t$</td>
</tr>
<tr>
<td>$\delta$</td>
<td>discount factor</td>
</tr>
<tr>
<td>$\theta_t$</td>
<td>underlying mean at time $t$</td>
</tr>
<tr>
<td>$\pi_N$</td>
<td>prior probability of model $M_N$</td>
</tr>
<tr>
<td>$\pi_O$</td>
<td>prior probability of model $M_O$</td>
</tr>
</tbody>
</table>
1. Introduction

Broiler chickens in current production systems show very low levels of activity compared with their ancestors (Dawkins, 1989) and spend between 60-90% of their time inactive (e.g. Newberry, Hunt, Gardiner, 1988; Bessei, 1992; Bizeray, Estevez, Leterrier, Faure, 2002; Kristensen, Aerts, Leroy, Wathes, Berckmans, 2007). In recent years, there has been a focus on ways to increase the activity level of broiler chickens since this may improve their welfare. Increased activity may also improve the leg health of broilers (Reiter & Bessei, 1998; Bradshaw, Kirkden, Broom, 2002), allowing a more natural behavioural repertoire (Bizeray et al., 2002) and improving litter conditions thereby reducing the risk of ammonia burns on the hocks, feet and breasts of the birds (Ekstrand, Algors, Svendberg, 1997; Wang, Ekstrand and Svedberg, 1998). Just as too low activity levels can be detrimental, too high activity levels of broiler chickens, particularly later in the growing period, may also be detrimental for the welfare of the birds (Kristensen, 2010). Therefore, it is vital to ensure that broilers show the appropriate levels of activity at any given age.

Recent evidence suggests that it may be possible to control activity by using meal feeding (Nielsen, Litherland, Noddegaard, 2003) as well as temporal variations in light intensity (Kristensen et al., 2007). Results from these studies suggest that it may be possible to increase as well as decrease the activity level of broilers. This new potential for controlling activity in broiler chickens accentuates the need for a method which can detect the level of activity and notify the producer if the activity level deviates from the expected.

The main interest in monitoring and detecting activity levels automatically is firstly, to provide early detection of unexpected changes in activity levels (thus identification of potential problems in the flock) and secondly, as a basis for controlling activity of the broilers to some predefined level at a particular age, which may benefit the welfare of the animals. Dynamic modelling and monitoring of automatic recorded data can be performed using dynamic linear models (DLMs). The advantage of DLMs is that they can monitor changes in responses, which contain inherent variations, such as activity, over a period of time (Roush, Tomiyama, Garnaoui, D’Alfonso, Cravener, 1992).

Examples of applications of DLMs in animal husbandry are found in poultry (Roush et al.1992), swine production (Cornou 2007; Cornou and Lundbye-Christensen, 2010), and dairy cows (Norberg, Korsgaard, Sloth, and Løvendahl, 2008).

Here the undisturbed activity of groups of broiler chickens is investigated in three steps, in order to detect deviations from the normal activity level. The objective of the first step was to apply a model, which was able to filter out outliers in the data stream of automatically recorded activity from overhead video cameras, in order to reduce the number of erroneous deviations. The second step aimed to describe the undisturbed levels of activity in groups of broiler chickens over the course of a day in week 1, 2 and 3. The third step applied a method to detect deviations in activity level, thereby giving an indication of a level change in activity within the flock of broilers.
2. Methods

2.1 Experimental set-up
The activity recordings were part of a larger experiment on defining the optimal activity for broiler chickens, where male broiler chickens (ROSS308) were reared in 32 groups of six chicks from day-old until slaughter at 39 days of age. The pens were identical and measured 74 x 170 cm with wood-shavings as litter, a light intensity of approx. 40 lux and a photoperiodic regime of 16L:8D without dawn and dusk. Lights were on between 05:00-21:00 each day from day 2 of life. Each pen was equipped with a ceramic 60W heat bulb (giving out no visible light for the chickens) allowing the chickens to adjust their thermoregulation themselves. The broilers had ad libitum access to water and a commercial diet throughout the growing period. The groups of broilers were allocated different exercise treatments. A treadmill was constructed for the purpose of the experiment and consisted of a 1 m wide PVC belt moving over a stainless steel board via two cylinders by a variable engine, which could be adjusted in speed. The groups of broilers were moved from their home pens to the treadmill, where they walked 0, 50 or 100 m during a 20 minute period at a constant speed of 0.3 km h⁻¹, or stayed in pen as control. The chickens were trained in groups six days per week from two days of age.

2.2 Data collection
One day per week, the broilers were left undisturbed in their home-pen and their undisturbed level of activity was recorded continuously via overhead video-cameras fitted above the floor in the centre of each pair of pens (Fig. 1). At 1, 2 and 3 weeks of age, the number of pixel-blocks changing between consecutive images was logged every minute via a digital motion detection system (MSH video). Pixel blocks were blocks of 8 x 8 pixels in the video image. These blocks of pixels represented changes in the image between consecutive images in a video-stream, and thus measured the changes occurring in the images over time. Each camera collected the sum of pixel blocks changing every minute, reflecting the amount of changes in the image or movement of the birds, every minute. Hence, the raw data series were number of pixel-blocks per frame per minute. In order to get normally distributed data, these series were logarithmically transformed. The activity pattern of a few selected pens was chosen for this paper to illustrate the modelling methods. Six pens of the 16 were chosen for the purpose of this paper, representing 2 control pens and 4 pens, which in the larger experiment showed a higher level of undisturbed activity than the control pens (Kristensen, 2010).
Fig. 1. Example of an image from the overhead video camera, recording the undisturbed activity of two home pens simultaneously as pixel-blocks changing between consecutive images in each pen.

3. Calculation

3.1 Filtering of outliers

Visual observation of the series showed evidence of outliers. To automatically detect and filter these outliers, a multi process dynamic linear model (DLM) of class II was implemented (West & Harrison, 1997). The multi process DLM (e.g. Thysen, 1993) is a recursive algorithm, which at each time point gives the posterior probability of a range of possible models describing the actual observation. In this case, we distinguished between two dynamic linear models (DLMs): a model describing a normal situation ($M_N$), and a model describing an outlier situation ($M_O$).

For each DLM, the observation equation (1) described the sampling distribution of the observation vector $Y_t$ (the logarithmically transformed series), and the system Eq. (2) described the evolution over time of the underlying mean $\theta_t$:

$$Y_t = \theta_t + v_t, \ \text{where} \ v_t \sim N(0,V)$$

$$\theta_t = \theta_{t-1} + w_t, \ \text{where} \ w_t \sim N(0,W)$$

where the errors sequences $v_t$ and $w_t$ are assumed mutually independent and normally distributed.

Given the information at time $t$ ($D_t$) the updating equations of the DLM (Table 1) provided estimates of the underlying level $\theta_t$, such as:

$$(\theta_t \mid D_t) \sim N(m_t, C_t)$$
where \( m_t \) is the filtered mean and \( C_t \) its associated variance.

Table 1. Updating equations of the DLM, example of a first order polynomial model (West and Harrison, 1997, pp.35)

<table>
<thead>
<tr>
<th></th>
<th>Model mean</th>
<th>Model variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Posterior, time t-1</td>
<td>( m_{t-1} )</td>
<td>( C_{t-1} )</td>
</tr>
<tr>
<td>Prior, time t-1</td>
<td>( m_{t-1} )</td>
<td>( C_{t-1} + W )</td>
</tr>
<tr>
<td>1-step forecast, time t-1</td>
<td>( m_{t-1} )</td>
<td>( C_{t-1} + W + V )</td>
</tr>
<tr>
<td>Posterior, time t</td>
<td>( m_t = m_{t-1} + A_t e_t )</td>
<td>( C_t = A_t V )</td>
</tr>
</tbody>
</table>

where \( e_t = Y_t - m_{t-1} \)

For both normal (\( M_N \)) and outlier (\( M_O \)) models, the evolution variance \( W \) (describing the evolution over time of the underlying mean) was determined by applying a discount factor \( \delta = 0.97 \) (West & Harrison, 1997, p 51). This discount factor represents a proportion of the uncertainty of the mean, or model variance \( C_t \), as:

\[
W = (1 - \delta) / \delta \times C_t
\]  

(4)

Differences between the two models \( M_N \) and \( M_O \) lie in the value of i) the observation variance \( V \) (describing short term variation of the model), set 20 times larger for \( M_O \) (\( V_O = 20 \)) as compared to \( M_N \) (\( V_N = 1 \); chosen on the basis of the visual plot (Fig. 3b) and ii) the prior probabilities: \( \pi_N = 0.98 \) and \( \pi_O = 0.02 \), indicating an arbitrarily chosen low probability of 2% for occurrence of outliers.

3.2. Modelling the normal levels of activity

After filtering out the outliers in the data series, each ‘cleaned’ series was modelled with a dynamic linear model (DLM). The chosen DLM had unknown and constant observation variance \( V \), which was estimated in the updating equations (West & Harrison, 1997, pp. 111-112). The evolution variance \( W \) was also unknown, and two values of discount factor were used, as in the models suggested in section 3.1. Initial values \( (m_0, C_0) \) are based on the mean and standard deviation of the first 10 min observations of the given series.

3.3 Detecting level deviations in activity

To reduce the number of observations and partly smooth fluctuations observed at the minute level, the suggested monitoring method was based on series previously averaged over 15 min. The chosen DLM had unknown and constant observation variance \( V \), and the evolution variance \( W \) was set to zero; this specific DLM referred to a static model with constant parameters defined by unit discount factor, as in Cornou (2007).

At each time \( t \), the forecast errors \( (e_t) \), corresponding to the differences between the observations and the model forecasts, are standardised with the respective forecast variance \( Q_t \) as \( u_t = e_t / \sqrt{Q_t} \). The cumulative sum \( (Cu_t) \) is thereafter calculated as:
The model deviations were thereafter monitored by applying a V-mask at each time \( t \) of the cumulative sum of the standardised errors. The V-mask method has previously been applied to detect changes in the circadian pattern of water consumption in pigs (Madsen & Kristensen 2005), amongst other applications. Figure 2 (left) shows a typical V-mask. The V-mask is directly applied on the cumulative sum of the standardized errors with the point O on the last value of \( C_{t} \) and the line OP parallel to the horizontal axis. The V-mask is applied to each new point on the cumulative sum and the arms extend backward to the origin. If any of the cumulative sums lies outside the arms of the mask, an alarm is given and the value of the cumulative sum is reset to zero. Parameters used for the V-mask were \( A=1 \), \( \delta\alpha=1.5 \), \( \alpha\alpha=0.01 \) and \( \beta\beta=0.01 \) (Montgomery, 1997). This set up indicated that the magnitude of the level shift detected was of a minimum of 1.5 units of standard deviation and that the probability of incorrectly concluding that a shift occurred and of failing to detect a shift was 1%. Figure 2 (right) illustrates a V-mask in application.

![V-mask diagram](image)

**Fig. 2.** V-mask used to monitor the cumulative sum of the standardised errors. Left panel: V-mask and parameters; right panel: Illustration of the V-mask applied on a cumulative sum.

4. Results

4.1 Filtering of outliers

Figure 3 illustrates the application of the multi process DLM for camera 4 in the day of activity recording in week 1. It can be seen that outliers that appear in (b) are well detected by the outlier model \( M_{O} \); probabilities for \( M_{O} \) are indicated in (d): the further away outliers are from the series, the highest is the probability for model \( M_{O} \).

Observations recognized by the multi process DLM as outliers, with a probability above \( p=0.2 \), are deleted from the series and replaced by missing values; in that case, the filtered mean is set equal to the previous one and only its associated variance is updated, becoming larger as more observations are missing.
The outliers were primarily due to brief camera faults. It appears that most outliers were observed during the first week. The total number of detected outliers (measured from 05:30 to 20:30, due to few differences in time for turning on-off the light) for the 6 cameras was 62 in week 1, 23 in week 2 and 6 in week 3.

![Diagram of camera data analysis](image)

**Fig. 3.** Application of the multi process DLM on series from camera 4 for week 1, during the light period (05:00 to 21:00). (a) raw series; (b) log transformed series (dots) and filtered mean (plain); (c) model probabilities for the normal model \((M_N)\); (d) models probabilities for the outlier model \((M_O)\).

### 4.2 Modelling the normal levels of activity

Optimization of the discount factor was performed for week 1, for 2 cameras, corresponding to the control group; value for the discount factor \(\delta\) was ranged from 0.1 to 1, by 0.01 intervals. The best fit, indicated by the minimum squared errors, was found for a value of 0.41. This low value of \(\delta\) indicated that the level of activity was fluctuating rather much over time. However, the purpose of the method was to study potential level deviations (and not to fit the best model); here it was used at much higher discount factors.

Figure 4 shows the results of the filtered means for camera 5 (left panel) and camera 7 (right panel), for week 1, 2 and 3, using discount factors with values \(\delta=0.97\) (grey lines) and \(\delta=1\) (black lines). It can be seen that the activity pattern over the course of a day was similar for the three weeks, but that the level of activity, measured in this way, increased with the age (and thus the size) of the chickens. Figure 4 also illustrates that the activity level increases towards the end of the day.
Fig. 4. Filtered mean series of number of blocks per frame, for camera 5 (left panel) and camera 7 (right panel): for week 1 (plain line), week 2 (plain wide line) and week 3 (dotted line). In grey: using a discount factor $\delta = 0.97$, in black: $\delta = 1$. Horizontal axis: time, in hours (from 05:00 to 21:00).

4.3. Detecting level deviations in activity
To assess significant deviations in the level of the underlying value, each series was modelled assuming a constant underlying value $\theta_t$, i.e. a discount factor of 1. Figure 5 illustrates the implementation of the V-mask for camera 5 in week 1 and camera 7 in week 3. Vertical lines indicate the alarms given by the V-mask. For both cameras, the cumulative sums ($Cu_t$) of standardized errors (a1 and a2) show that the activity level tended to decrease from the onset of light until approximately 15:00. For camera 5, the V-mask gave an alarm 14:00 (b1); by observing the cusum (a1), it can be seen that it was due to a sharp decrease of activity at this time. For camera 7, the alarm observed at 14:45 corresponds to an increase of activity due to a stockperson entering the pen. The alarms observed at approximately 20:00 in both cases correspond to a significant increase of activity prior to the onset of the dark period. It should be noticed that when an alarm occurs (b1 and b2), cumulative sums was re-initialised, by setting the value to 0 and monitoring was done from this new starting point.

Overall, there were 26 alarms given in the 6 pens in week 1, 2 and 3. A closer examination of the alarm times revealed that the alarms were given during three distinct periods of the day: Between 05:00 and 09:00 in the morning (2 alarms), between 14:00 and 16:00 in the afternoon (6 alarms) and between 18:00-21:00 in the evening (18 alarms). No alarms were given outside these time-periods. A similar number of alarms were given irrespective of the exercise treatment and age, (average 4.5 vs 4 alarms per pen for the unexercised vs. exercised pens respectively, and 9, 7 and 10 alarms during week 1, 2 and 3, respectively), indicating that the model may adapt to the activity level of the pen. There were 23 alarms when activity rose and 3 alarms when activity decreased.
5. Discussion and conclusion

The methods suggested in this study aimed at filtering outliers on the observation (minute) level, and model and monitor series on 15 min basis, by use of a V-mask applied on the standardised errors. Plotting of the cumulative sum of the standardised errors indicated that activity progressively decreased from 05:00 (where the light was turned on) and increased few hours before the light was turned off (at 21:00). Application of the V-mask indicated significant level changes i) when disturbances occurred during the day, ii) when activity level increased a few hours before the light was turned off, and iii) when activity level decreased.

The activity was modelled during the first three weeks of life, since this has recently been shown to be a critical period for the activity of broiler chickens for the development of the muscles and bones (Kristensen, 2010). The activity level increased with the age of the broilers from 1-3 weeks of age, in accordance with previous studies (Nielsen et al., 2003). However, the magnitude of this increase is mainly an artefact of the recording method of activity, since the broilers took up more and more pixels in the image as they grew, and as such moved more and more pixels as they moved.
The method suggested for filtering of outliers is based on a multi process DLM which includes a normal and an outlier model. It could be argued that a threshold value could be used for outliers filtering; this however require optimisation of this value for each week, as the activity level increases. The benefit of this dynamic filtering method is that it automatically adapts to the changing level of activity during the course of the growing period in a particular flock.

The models suggested in this paper could be used at any stage of the production period and required no variance estimation: i) for outliers filtering, the observation variance $V$ was set to the arbitrary value of 1 for $M_N$, and 20 times higher for $M_O$; ii) for monitoring the series level, the DLM used assumed unknown constant observation variance; iii) factor discounting was used for dealing with unknown evolution variance $W$ in all models.

The high level of activity shown as the lights turn on in the morning is initially mainly due to the cameras being overexposed in the first minute after light is switched on, and partly due to a rise in activity of the chickens when light is switched on. The cumulative sum of standardised errors showed that after the initial high level at the beginning of the photoperiod, the activity level decreased progressively until mid-day, and increased few hours before light was turned off. It can be discussed whether modelling this high-low-high level would be relevant, if such a V shape is to be expected. A multi process dynamic linear model that includes a i) negative trend, ii) positive trend and iii) outliers models could be used for this purpose. This V shape was observed in the data from the original minute-observations, 5 min averaged as well as 15 min averaged. However, if the aim is to keep a constant activity level during given periods, the suggested monitoring method seems adequate. A V-mask, or alternatively a Tabular Cusum (Montgomery, 1997) or control charts (De Vries & Reneau, 2010), can serve as an alarm system when the activity level reaches significant lower or higher values, and as such allow intervention by activating or deactivating the animals. The advantage of the suggested monitoring system, based on standardised errors, is that no reference value for the expected level is needed. In that sense, they can be applied at any stadium in any flock.

The V-mask was able to detect a significant increase in activity towards the end of the light period in most groups. This is a well-known phenomenon, with the birds filling their crop and finding a suitable place to rest for the night (Kristensen, 2008). This has been found in other studies (e.g. Nielsen et al., 2003; Kristensen et al., 2007) and confirms that the birds were able to anticipate the onset of darkness (Kristensen, 2008). The V-mask could also detect increases in activity levels, due to the stockperson entering the pen. In this small experimental set-up with only 6 young broilers per group, it is expected that the system detects the relatively large change in pixels in the image, as a stockperson enters, whereas at a commercial scale, the system may be less sensitive to changes such as these. However, as shown in Fig. 5 (a2), the entry of the stockperson at a time where activity was on a gentle downwards slope, may actually stimulate activity in the birds, which may last longer than the visit of the stockperson. The decrease in activity levels during mid-day in some groups, which was detected by the V-mask may reflect the diurnal variations in behaviour, as well as some level of synchronisation in the pen, where social facilitation may determine the pattern of active or passive behaviours within the group.

Whether different treatments affect the reduction of activity in the middle of the day should be tested, or the trend observed by the end of the day, which here resulted in alarms. Whether a V
shape activity level or a stable constant activity level throughout the light period is expected, the suggested models and methods appear relevant to fit the given time series and provide alarms when the activity level deviate from what is either expected (in the experimental phase) or desired (once applied in a herd as a monitoring method).

In conclusion, the results of the modelling methods applied here indicate the potential for automatic detection of deviations in activity level in flocks of broiler chickens. A straightforward application for these modelling and monitoring methods is the development of an alarm system that could notify the producer, in real time, when the activity level in a particular flock deviates from its normal daily rhythm or its desired level of activity. This would allow a faster re-adjustment of the activity level which would be most beneficial for the welfare of the animals.

6. Acknowledgements

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7. References


