Assessing goats fecal avoidance using image analysis based monitoring

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Abstract

Recent advances in sensor technologies and data analysis helped monitoring animal behavior over long time periods. This is particularly interesting to study the link between behavior and animal health. In this work, we studied the capacity of Creole goats to avoid feces on pasture. We developed an experimental framework, composed of a small pasture of 12x12=144m2 with two zones of 6x2=12m2 infested with feces, and a monitoring system, based on a time lapse camera, taking pictures every 20s from 6:30 to 18:00. A set of 3,800 images were manually labeled to (i) train a Yolo based CNN, ables to detect goats on the images and (ii) train a resNet50 based CNN, ables to identify the goats present on pasture. We used the framework to monitor the location of four Creole goats, selected for their various colors, to make automatic animal identification easier. We were able to determine when the animals were on the infested areas or not. Goats were allowed to graze for two weeks, separated from more than 2 months. Goats were worm free when grazing started and the level of infection was evaluated after grazing, using fecal egg count. Goats were detected in 88% of the cases and the precision for animal identification was estimated to 95%. Although goats exhibited various level of avoidance, it increased for all goats during the second grazing week, and the level of increase was proportional to the level of infection resulting from the first grazing week.

Keywords: Image Analysis, goats, fecal avoidance.

Introduction

Goats are an important resource mainly for meat and milk production, with approximately 94% of the animals located in Asia and Africa. Infection with gastro-intestinal nematodes (GIN) parasites is one of the main health constraints, responsible for reduced performances production and increased mortality, especially in young animals and adult females, during the periparturient period. In the past, GIN management successfully relied on systematic anthelmintic (AH) treatment. Unfortunately, resistant GIN populations to AH were gradually selected (Kaplan and Vidyashankar 2012). Thus, it is now widely admitted that relying only on AH is not a sustainable strategy (Charlier *et al.* 2018). To design alternative strategies adapted to farmers constraints, modeling could be an interesting tool. One of the main challenge to model GIN infection dynamic is to model ingestion, i.e. the timing and quantity of ingested larvae. The recent developments in precision livestock farming tools offer new opportunities, especially to characterize animal behavior, and to study the relationship with GIN infection.

In this article, we proposed an experimental framework to study the ability of the goats to avoid feces, based on automatic monitoring of the animals using image analysis (Li *et al.* 2021). Convolutional neural networks (CNN) are generally the most adapted image analysis tool and has been used successfully, mostly for pigs (Marsot *et al.* 2020; Zheng *et al.* 2020; Gan *et al.* 2021), but also for goats (Bonneau *et al.* 2020; Jiang *et al.* 2020; Su *et al.* 2021). Several methods for cattle monitoring also successfully identified animals using deep-learning technics (Qiao *et al.* 2019; Achour *et al.* 2020). The main advantage of using CNN is that powerful models, trained on millions of images and designed by research teams with relevant engineering skills, are available free of charge. Then, new users can almost directly use these CNN, just by retraining some parameters in order to be able to detect and classify their objects of interest. In this article, we proposed to use YOLO (Redmon and Farhadi 2017) associated with resNet-50 (He *et al.* 2016) to detect and identify the animals.

Material and methods

Experimental setup

The objective of the study was to monitor goats while grazing an experimental pasture, where the location of feces infested with GIN was known, in order to study their ability to avoid feces. The experiment was first conducted during *Week 1*, from April 12th 2021 to 19th, and repeated during *Week 2*, from June 28th 2021 to July 5th. The same pasture and animals were used for the two weeks.

We designed an experimental pasture of $12m \times 12m = 144m^2$, with two infested areas A and B, of $2m \times 6m = 12m^2$ each (see Figure 1). A total of 900g of infested feces with GIN were dropped homogeneously within each infested area. Feces were dropped manually 13 days before grazing on Week 1 and 10 days before grazing on Week 2, to maximize the number of infective larvae on pasture during grazing. The feces level of infection was measured using fecal egg count (FEC), in eggs per gram of feces (EPG, Aumont, Pouillot, and Mandonnet 1997). FEC was estimated from 10 different feces samples, for Week 1 mean FEC was *567 eggs/g* and was *4431 eggs/g* for Week 2.

To ensure that animals were not infested with GIN before grazing on Week 1 and 2, they were drenched using anthelmintic. Treatment efficacy was controlled by measuring the FEC one week before grazing. After grazing animals were maintained together in a stall and were fed with dry hay to avoid parasite ingestion outside of the grazing week. After grazing, the animals' level of infection was finally assessed using FEC, at least every week, starting 8 days after grazing.

Animals

Four male Creole goats were selected to maximize color differences between individuals. The first goat, referred as *white*, had a black coat with white color patches on the belly, weighted 34.13kg and was 16 months old at the beginning of the

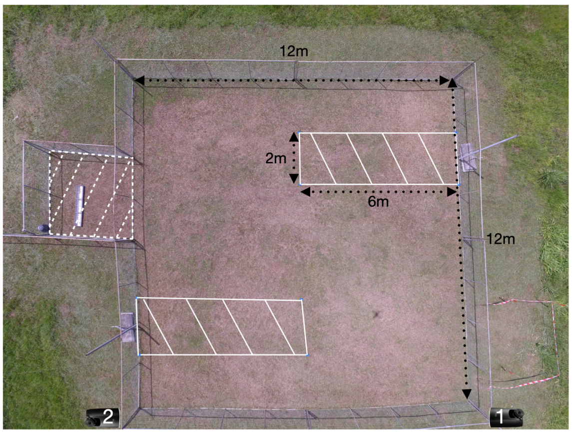

Figure 1: Pasture setup. The white dashed zones with solid lines are infested areas A and B. The white dashed square with dashed lines is the resting area. During experiment, we placed a sheet of metal inside this area to produce shade. On Week 1, we used the camera located on the bottom right corner of the pasture and on the bottom

experiment. The second goat, referred as *brown*, has a brown coat with a black strip on the back, weighted 33.93kg and was 12 months and 17 days old. The third goat, referred as *black*, had a homogeneous black coat, weighted 31.62kg and was 12 months and 17 days old. The last goat, referred as *red*, had a reddish brown coat with a black strip on the back, weighted 39.92kg and was 12 months and 11 days old. The animals from different sire origins, were raised at pasture and exposed to natural GIN infection, until the first stage of the experiment.

Recording behavior with time-lapse cameras

We used a construction time-lapse camera (Brinno TLC2000 pro 2018), setup to take one picture every 20s from 6:30 to 18:00. The analysis of the images acquired during Week 1, showed that the camera was facing the sun during sunrise, decreasing the quality of the images. The location of the camera was adapted accordingly for Week 2.

Animal detection

To detect animals, a common approach was used, based on the CNN YOLO v2 (Redmon and Farhadi 2017), known to run fast, with high accuracy and high learning capacities. For image feature extraction, we trained YOLO based on resNet-50 (He *et al.* 2016). In very few cases, YOLO returned more than 4 detections, mostly when multiple bounding boxes was associated to the same animal. When more than four bounding boxes was found, a non-max suppression method was used to remove the overlapping bounding boxes.

Animal identification

The results of the YOLO detection stage was a set of bounding boxes, $(x_a, y_a, w_a, h_a)_{a=1\ldots n}$, around the detected animals, where x_a and y_a were the column and row numbers of the top left corner of the bounding box number a. w_a and h_a were the width and height of the bounding box, and n was the number of bounding boxes/

detected animals. We then moved to the next step: identify the animals inside each bounding box.

This second step is an image classification problem, with 4 different classes, *white goat*, *brown goat*, *black goat* and *red goat*. There is several CNN that are available free of charge, and trained on more than one million of images to perform image classification with common objects such as dogs, stop signs or humans. However the network architecture and most of the layers can be directly used to recognize new classes, which is known as transfer learning. We also used resNet-50 with only the parameters of the last 10 layers being re-trained. When labelling the training images for (1) YOLO, the color of the animals was also labeled. Thus the 3,820 training images labeled for YOLO were used, to extract 12,236 images with color labels. In total, approximately 3,400 images were available for the white goat and 2,900 images for the other goats.

Compared to other image classification problem, an extra information was available: two detections cannot be in the same class. Instead of using the prediction of the CNN directly, we used it to compute the probability of each bounding box being from an animal of the four different colors. For each bounding box number a, (x_a, y_a, w_a, h_a), the CNN associated a set of probabilities $(p^a_{\text{white}}, p^a_{\text{brown}}, p^a_{\text{red}}, p^a_{\text{red}})$. A score was then calculated for each possible color configuration of the bounding boxes. If c^a is the color of the bounding box number a, the score of a configuration $\left(c^1, \ldots, c^n\right)$ is simply the sum of the probabilities of the bounding boxes to be in that colors:

$$V\left(c^1, \ldots, c^n\right) = \sum_{a=1}^{n} p^a_{c^a}.$$

Finally the color configuration with the highest score was chosen.

Evaluate detection

To evaluate the capacity of the method to detect and identify animals, a MATLAB application was designed to select randomly an image on the data bank and displayed the detected animals with their estimated color. For each color (i.e. white, brown, black and red), the user first selected if the animal was detected, non-detected or absent (i.e. inside the resting area). When the animal was detected, the user also had to record its true and estimated color. A second script was designed to manually record the location (2) of the missed detection.

We ran the application to control more than 600 images for each Week. In order to assess the capacity of the method to detect the animals, we computed the percentage of detected animals. In order to assess the capacity of the method to identify the animals, we compared the estimated and true color of each detection. Then we evaluated the sensitivity and precision for each color class.

Fecal avoidance capacity

To characterize the capacity of the animals to avoid infested areas, the number of times each animal was detected on the infested and non infested areas was computed. In order to compare the two quantities, the number of detections was normalized by the surface area of each zone, which provided a number of detections per m^2. Finally, the avoidance index was defined as the ratio of the number of detections per m^2 inside the non-infested and the infested areas:

$$\text{Avoidance Index} = \frac{d^{nia}/120}{d^{ia}/24}. \quad (3)$$

Where d^{nia} is the number of detection inside the Non-Infested Area and d^{ia} is the number of detection inside the two Infested Areas A and B.
An avoidance index > 1 means that the number of detections per m^2 was strictly higher for the non-infested area. The greater was the avoidance index, the greater was the feces avoidance.

Statistical analysis

In order to quantify the animals' level of infection after grazing, FEC was determined on a regular basis. To summarize this information, we used the logarithm of the area under the FEC curve (LAF). The LAF allowed the characterization of the infection dynamic over the entire measurement period. The LAF increased with the animal level of infection.
The correlation between the individual LAF obtained on Week 1, denoted LAF_i for animals $i = 1,\ldots,4$, and the increase in the weekly avoidance on Week 2, denoted AV_i, was studied using the Pearson's correlation coefficient. It is equal to:

$$\frac{1}{3}\sum_{i=1}^{4}\left(\frac{\text{LAF}_i - \mu_{LAF}}{\sigma_{LAF}}\right)\left(\frac{\text{AV}_i - \mu_{AV}}{\sigma_{AV}}\right),$$

Where μ and σ are the mean and standard deviation.

Results and Discussion

Animal detection and identification

The percentage of animal detected is available in Table 1. The white goat had the highest detection rate (95%). The white coat patches on the belly of this goat was highly discriminant and certainly helped the detection and identification by the algorithms. The red and black goats had similar detection rates (89.45% and 87.9% respectively), whereas the brown goat was the one with the lowest detection rate (79.4%). Most of the missed detections were located on the part of the pasture farthest from the camera. It has also been noted that missed detection was highest between 6:00 to 8:00 during Week 1, due to sunrise.
The sensitivity and precision of the animal identification method are available Table 1. The average sensitivity was close to 95% for each week. We observed confusion between the brown and red goats, which had similar shade. There was also some confusion between black and white goats, which had most of the coat of black color. When the white coat patches on the belly was not visible, the identification method recognized the white goat as the black one. As for the detection method, a better sensitivity and precision during Week 2 was observed, due to camera position.

Tableau 1: Percentage of detected animals using Yolo, as well as sensitivity and precision of the animal identification method.

	Animal detection		Animal Identification			
			Week 1		Week 2	
	Week 1	**Week 2**	Sensitivity	Precision	Sensitivity	Precision
White	95%	95%	98.9%	95.7%	99%	97.6%
Brown	78%	80.8%	95.9%	85.9%	94.4%	94.1%
Black	84.3%	91.5%	89.4%	95.7%	94.2%	96.7%
Red	86.8%	92.1%	92%	97.6%	95.7%	95.1%
Average	**86%**	**89.9%**	**94%**	**93.7%**	**95.8%**	**95.9%**

Post-grazing level of infection

The FEC remained relatively low ($< 4{,}000$ EPG) after Week 1 (see Figure 2. a and b). The brown goat had the highest FEC value (mean FEC = *2653 eggs/g*). On the last FEC measurement, the black and white goats had relatively similar FEC values, close to 2,000, although the white goat had lower FEC at the beginning (mean FEC = *934 eggs/g* for the white and *1,467 eggs/g* for the black). The FEC of the red goat did not exceed *700 eggs/g*, which could be considered as a low level of infection.
After Week 2, the level of infection of the black goat was high with FEC value close to *17,000 eggs/g* (mean FEC = *11,415 eggs/g*). The FEC of white and brown goats were similar, with a maximal value close to 3,000 eggs/g (mean FEC = *1,679 eggs/g* for white and *1,342 eggs/g* for brown). A peak of FEC (*4,290 eggs/g*) for the red goat was observed 21 days after the grazing period. Thereafter, the FEC decreased to reach levels similar to the white and brown goats (mean FEC = *1,473 eggs/g*).

Avoidance capacity

The weekly avoidance index increased between Week 1 and 2 for all the animals (see Figure 2. b and c). The weekly avoidance index increased by 76%, 207%, 142% and 60% for the white, the brown, black and red goat respectively. Interestingly, the greater LAF value was observed during Week 1 and the greater weekly avoidance index was

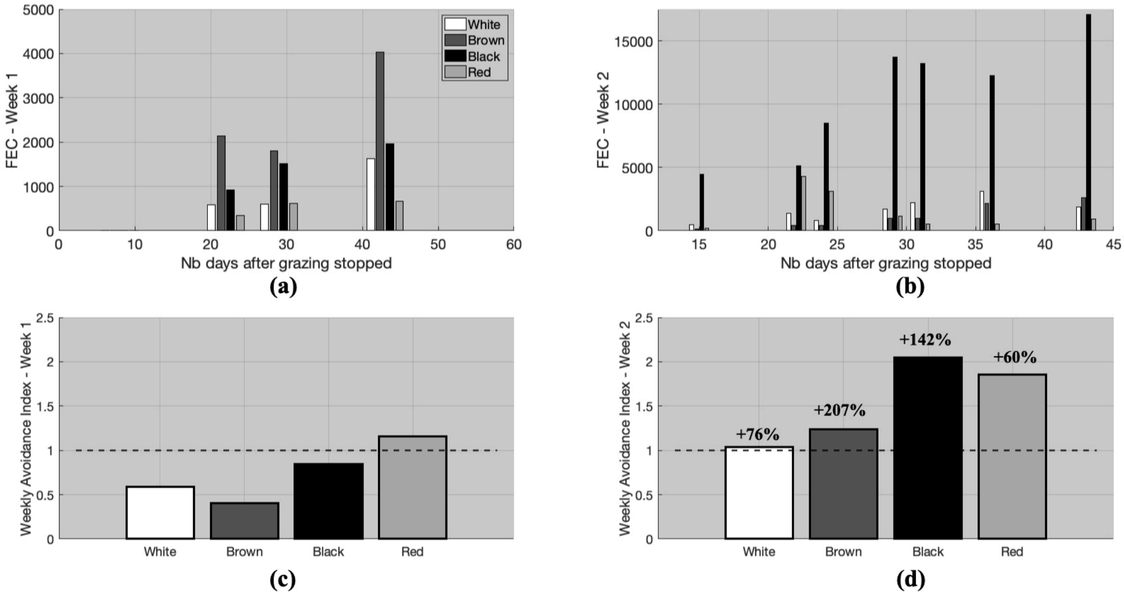

Figure 2: Individual fecal egg count (FEC), in eggs/g of feces, for Week 1 (a) and Week 2 (b), as a function of the number (Nb) of days after grazing stopped. Individual avoidance index during Week 1 (c) and Week 2 (d).

observed during Week 2. The Pearson's correlation coefficient between the LAF on Week 1 and the increase in the weekly avoidance index on Week 2 was *0.93*. In line with this result, for sheep, it has been shown that the avoidance capacity increased with the level of infection (Hutchings *et al.* 1999; Cooper, Gordon, and Pike 2000).

Conclusions

In this study, we provided a conceptual framework to study goats behavior at pasture and tested it to study the interaction between grazing behavior and parasitism. This framework is based on automatic animal monitoring using image analysis, to detect and identify the animals on the images, allowing to record the spatial coordinates of the animals over time and derive interesting indicator, such as the avoidance index. Overall, image analysis could be a useful tool to monitor animal behavior on pasture. The main advantages being the low cost of the cameras and no handling of the animals. With more developments, it could be expected that a variety of variables, such as locations, activities or animal interactions, could be computed from only one sensor, the camera. However, using image analysis remains technical, as it needs to train specific deep neural network, which could be complicated for non-specialist. In this work, we showed that animal identification was possible, thanks to the various colors of the individuals. This might not be possible for generic studies and automatic identification remains a major constraint for grazing goats. By now, GPS combined with accelerometers probably remains the easiest solution to get continuous individual data. However, ou study demonstrated that image analysis is a potential alternative, and future improvements could open new perspectives for monitoring animal behavior.

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References

Achour, Brahim, Malika Belkadi, Idir Filali, Mourad Laghrouche, and Mourad Lahdir. 2020. "Image Analysis for Individual Identification and Feeding Behaviour Monitoring of Dairy Cows Based on Convolutional Neural Networks (Cnn)." *Biosystems Engineering* 198: 31–49.

Aumont, G, R Pouillot, and N Mandonnet. 1997. "Le dénombrement Des éléments Parasitaires: Un Outil Pour L'étude de La Résistance Génétique Aux Endo-Parasites Chez Les Petits Ruminants." In *Workshop Final de L'AT Cirad-Mipa*, 72:94.

Bonneau, Mathieu, Jehan-Antoine Vayssade, Willy Troupe, and Rémy Arquet. 2020. "Outdoor Animal Tracking Combining Neural Network and Time-Lapse Cameras." *Computers and Electronics in Agriculture* 168: 105150. https://www.sciencedirect.com/science/article/pii/S0168169919322562.

Charlier, Johannes, Stig M Thamsborg, David J Bartley, Philip J Skuce, Fiona Kenyon, Thomas Geurden, Herve Hoste, *et al.* 2018. "Mind the Gaps in Research on the Control of Gastrointestinal Nematodes of Farmed Ruminants and Pigs." *Transboundary and Emerging Diseases* 65: 217–34.

Cooper, Jane, Iain J Gordon, and Alan W Pike. 2000. "Strategies for the Avoidance of Faeces by Grazing Sheep." *Applied Animal Behaviour Science* 69 (1): 15–33.

Gan, Haiming, Mingqiang Ou, Fengyi Zhao, Chengguo Xu, Shimei Li, Changxin Chen, and Yueju Xue. 2021. "Automated Piglet Tracking Using a Single Convolutional Neural Network." *Biosystems Engineering* 205: 48–63.

He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. "Deep Residual Learning for Image Recognition." In *Proceedings of the Ieee Conference on Computer Vision and Pattern Recognition (Cvpr)*.

Hutchings, MR, I Kyriazakis, IJ Gordon, and F Jackson. 1999. "Trade-Offs Between Nutrient Intake and Faecal Avoidance in Herbivore Foraging Decisions: The Effect of Animal Parasitic Status, Level of Feeding Motivation and Sward Nitrogen Content." *Journal of Animal Ecology* 68 (2): 310–23.

Jiang, Min, Yuan Rao, Jingyao Zhang, and Yiming Shen. 2020. "Automatic Behavior Recognition of Group-Housed Goats Using Deep Learning." *Computers and Electronics in Agriculture* 177: 105706.

Kaplan, Ray M, and Anand N Vidyashankar. 2012. "An Inconvenient Truth: Global Worming and Anthelmintic Resistance." *Veterinary Parasitology* 186 (1-2): 70–78.

Li, Guoming, Yanbo Huang, Zhiqian Chen, Gary D Chesser, Joseph L Purswell, John Linhoss, and Yang Zhao. 2021. "Practices and Applications of Convolutional Neural Network-Based Computer Vision Systems in Animal Farming: A Review." *Sensors* 21 (4): 1492.

Marsot, Mathieu, Jiangqiang Mei, Xiaocai Shan, Liyong Ye, Peng Feng, Xuejun Yan, Chenfan Li, and Yifan Zhao. 2020. "An Adaptive Pig Face Recognition Approach Using Convolutional Neural Networks." *Computers and Electronics in Agriculture* 173: 105386.

Qiao, Yongliang, Daobilige Su, He Kong, Salah Sukkarieh, Sabrina Lomax, and Cameron Clark. 2019. "Individual Cattle Identification Using a Deep Learning Based Framework." *IFAC-PapersOnLine* 52 (30): 318–23.

Redmon, Joseph, and Ali Farhadi. 2017. "YOLO9000: Better, Faster, Stronger." In *Proceedings of the Ieee Conference on Computer Vision and Pattern Recognition*, 7263–71.

Su, Qingguo, Jinglei Tang, Jinhui Zhai, Yurou Sun, and Dongjian He. 2021. "Automatic Tracking of the Dairy Goat in the Surveillance Video." *Computers and Electronics in Agriculture* 187: 106254.

Zheng, Chan, Xiaofan Yang, Xunmu Zhu, Changxin Chen, Lina Wang, Shuqin Tu, Aqing Yang, and Yueju Xue. 2020. “Automatic Posture Change Analysis of Lactating Sows by Action Localisation and Tube Optimisation from Untrimmed Depth Videos.” *Biosystems Engineering* 194: 227–50.