ANIMAL BEHAVIOR AND WELL-BEING

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416 Implementation of virtual fencing in heifers for mountain summer grazing. Patricia Fuchs[1], Caren M. Pauler[2], Manuel K. Schneider[2], Christina Umstätter[3], Christina Rufener[4], Beat Wechsler[4], Rupert M. M. Bruckmaier[5], Massimiliano Probo[6], [1]*Graduate School for Cellular and Biomedical Sciences, University of Bern, Posieux, Switzerland*, [2]*Agroscope, Grazing Systems, Zurich, Switzerland*, [3]*Johann Heinrich von Thünen-Institute, Thünen-Institute of Agricultural Technology, Braunschweig, Germany*, [4]*Centre for Proper Housing of Ruminants and Pigs, Federal Food Safety and Veterinary Office FSVO, Ettenhausen, Switzerland*, [5]*Veterinary Physiology, Vetsuisse Faculty, University of Bern, Bern, Switzerland*, [6]*Agroscope, Grazing Systems, Posieux, Switzerland*

Abstract: A virtual fencing (VF) system is based on a smartphone application that defines an invisible grazing boundary based on global positioning. Animals are tracked via GPS collars. When reaching the virtual boundary, the collar emits an ascending audio tone, followed by a mild electric pulse (0.2 Joule) when crossing it. The technology is particularly promising in rough and extensive mountainous areas where physical fencing is difficult and more time-consuming. Environmental conditions may also affect the functionality of the VF system, with potential impacts on animal behavior. Therefore, the present study tested a VF system on 30 female heifers in a rotational grazing system on Swiss mountain pastures (approximately 1,300 to 1,500 m above sea level). Each heifer was equipped with a VF collar (Nofence AS, Batnfjordsør, Norway) for individual recording of audio tones and electric pulses. After two wk of VF training in the lowlands (approximately 700 m above sea level), during which the heifers learned to interpret the VF signals correctly, they were transported to the mountain pasture. For mountain grazing, the herd was divided into three groups of 10 heifers each, balanced for age (mean ± SD: 11.9 ± 1.6 mo) and breed (Holstein-Friesian, Montbeliarde, crossbreeds). The outer perimeter of the mountain pasture was surrounded by an electric fence. Its inner area was divided into 3 electrically fenced and 6 virtually fenced paddocks. For 83 d, all groups grazed simultaneously in separate paddocks and rotated sequentially through the 9 paddocks. Video cameras were placed along the virtual fences to record animal responses after receiving audio tones or electric pulses. Moreover, grass height was measured using a rising plate meter to estimate forage availability in the currently grazed paddocks. Throughout mountain grazing, each heifer received an average of 4.9 ± 6.9 audio tones and 0.3 ± 0.7 electric pulses per day. Generalized mixed-effects models revealed that the number of audio tones and electric pulses did not change over grazing periods or among days after paddock change. Behavioral responses of the animals were less pronounced once the heifers had learned the VF system. In addition, grazing interruptions after receiving an audio tone or electric pulse were shorter during mountain grazing compared with the training period ($P < 0.001$). Furthermore, lower grass heights ($P < 0.05$) as well as the occurrence of (common but) unpredictable events ($P < 0.001$), such as the presence of wildlife (e.g., lynx, deer) or neighboring cattle, increased the number of audio tones and electric pulses during mountain grazing. The VF system was still effective in keeping the heifers within their assigned paddocks under mountainous conditions. However, a well-considered handling when changing paddocks as well as a careful placement of the virtual fence is essential to avoid negative effects on the animals.

Keywords: animal behavior, cattle, pasture management

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419 Automated individual animal identification and feeding bunk scoring: a computer vision approach for beef cattle at Calan gate feeding system.

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Abstract: Recent developments in computer vision (CV) technology have significantly improved the management of beef cattle feeding systems by enabling precise monitoring and adjustment of feed intake based on individual needs. This study introduces an automated approach for identifying cattle at feeding bunks using CV and evaluates the effectiveness of a feeding bunk scoring system to optimize cattle feeding strategies. Utilizing a high-definition video capture setup, our research focused on the feeding behaviors of 6 heifers in one pen with the Calan Feeding System (American Calan, Northwood, NH). We deployed three Reolink PoE cameras (Model D400) strategically positioned above the feeding bunks, each overseeing two feeding bunks, to monitor feeding activity comprehensively. The cameras were set to record in Full HD (1920 x 1080 pixels) at 30 frames per second. We processed the frames using Python's OpenCV, resulting in 600 images that composed an array with dimensions 600 x 400x450 (pixels) x 3 (RGB). These images served as the basis for our analysis, which involved feature extraction via a ResNet-50 convolutional neural network, followed by dimensionality reduction through Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE). Our methodology included the use of k-means clustering to detect the presence of cattle at the bunk, achieving an Adjusted Rand Index (ARI) of 0.9933. We applied the DBSCAN clustering algorithm in the 'cattle present' images for individual animal identification, obtaining an ARI of 0.9174, indicating high model accuracy. To assess feeding efficiency, we analyzed 12,156 images of feeding bunks obtained using the same Python's OpenCV approach and then classified them into six categories based on Lundy et al., 2015: S00 (no feed), S05 (scattered feed), S10 (thin layer), S20 (25 to 50%), S30 (>50%), and S40 (untouched). Using a training, validation, and testing split of 70%, 15%, and 15%, respectively, our model demonstrated exceptional precision, recall, and F1 scores of 0.9989 and predictions in the Confusion Matrix testing accuracy of 99.89%, showcasing the model accuracy. However, when applied to a similar classification using the same Calan gate system, with 7,905 images, the performance of the model decreased, with less precision (0.5868), recall (0.3982), and F1 score (0.3653), most related to classes S10, S20, and S40, underscoring the need for further model refinement. Our findings highlight the potential of integrating CV into precision livestock farming, automating the identification of cattle at feeding bunks, and correlating it with feeding scores to estimate individual consumption accurately. This integration promises to enhance sustainable farming by enabling more precise resource utilization and optimizing individual animal performance. With CV technology, producers can significantly improve production efficiency, health management, and environmental sustainability within their operations. The technology also has a crucial role in reducing operational costs, making it a cost-effective and sustainable production method.

Keywords: animal identification, computer vision, precision livestock farming