A Deep Learning Framework for Improving Lameness Identification in Dairy Cattle

Yasmine Karoui,[1,2] Amanda A. Boatswain Jacques, [2] Abdoulaye Baniré Diallo, [2] Elise Shepley [3] and Elsa Vasseur [3]

[1] Laboratoire de Combinatoire Informatique Mathématique, Université du Québec à Montréal, PO BOX 8888 Downtown Station, H3C 3P8
[2] Institute for Signal Processing and System Theory, University of Stuttgart, Stuttgart, Germany
[3]McGill University, Department of Animal Science, Québec, Canada
diallo.abdoulaye@uqam.ca,

Abstract

Lameness, characterized by an anomalous gait in cows due to a dysfunction in their locomotive system, is a serious welfare issue for cows and farmers. Prompt lameness detection methods can prevent the development of acute lameness in cattle. In this study, we propose a deep learning framework to help identify lameness based on motion curves of different leg joints on the cow. The framework combines data augmentation and a convolutional neural network using an *LeNet* architecture. Performance assessed using cross validation showed promising prediction accuracies above 99% and 91% for validation and test sets, respectively. This also demonstrates the usefulness of data generation in cases where the data set is originally small in size and difficult to generate.

Introduction

Lameness in dairy cows poses a huge concern for farmers, and early lameness detection is important for providing effective, inexpensive treatment and preventing future ailments (Jabbar et al. 2017). Traditional lameness detection methods using visual observation have been considered as time-consuming, labor-intensive and subjective tasks (Song et al. 2008). In order to improve a cow's health and well-being and lower the financial losses associated with lameness, automatic lameness detection systems using sensor-based methods are currently being investigated. For example, (Jabbar et al. 2017) categorized visual cow locomotion data with a linear support vector machine (SVM) achieving a classification accuracy of 95.7%. More recent work (Wu et al. 2020) investigates applications of deep learning (DL) methods to detect lame cows in videos, such as Long-Term Short-Term Memory (LSTM) cells, to extract chronological patterns in the data with high success rates (98.5%). Nevertheless, this kind of approach requires a large amount of data to drive a powerful prediction model. It is important to develop an automatic lameness detection system that is both accurate and trainable on reduced data sets. In this study, we developed a method combining data augmentation and a convolutional neural network (CNN) classifier using leg joint motion curves as features to detect lameness.

Materials and Applied Methods

Creating Kinematic Gait Data from Cows A set of cows (with or without lameness issues) was selected for kinematic gait analysis. Reflective markers were placed on eight points on each side of the cow's body (front leg: fore coffin, fore fetlock, carpal, and elbow; hind leg: hind coffin, hind fetlock, dorsal calcanie, and stifle), and on three locations on the cow's back (tail head, arch of back and withers). Videos of these cows walking along a passageway wearing markers were recorded and scored by a trained visual observer. A 3D biomechanical analysis program (Vicon Motus 10.0; CONTEMPLAS GmbH, Kempton, Germany) is used to create a motion template for each cow. Automatic tracking of the reflective markers in the X, Y and Z planes, as well as the rotational matrix R, was then carried out. This process can be repeated on the same set of cows several times across a span of times, given a set of videos.

Materials and Methods

The methodology is divided into three main steps identified in Figure 1. These include *Data Preprocessing and Visualization*, *Data Augmentation* and *Classification*.

Data Preprocessing and Visualization First, the data retrieved from the *Vicon Motus* software can be cleaned by removing outliers and performing smoothing. Here we consider a point as an outlier if its value exceeds a threshold

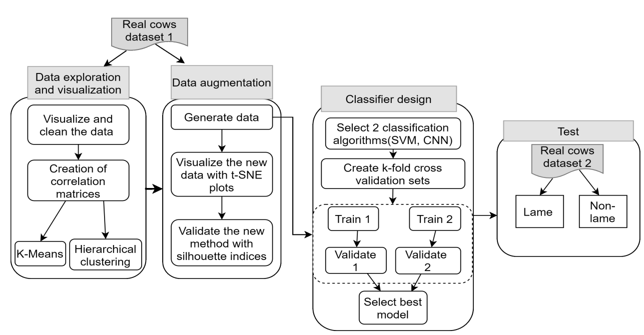

Figure 1: Flowchart showing the technical route.

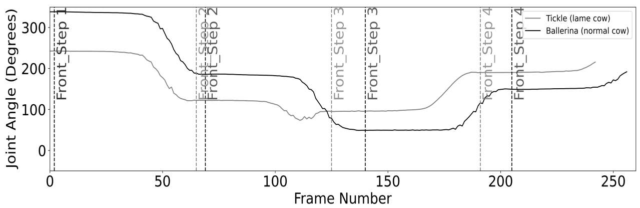

Figure 2: Example of fore fetlock motion curves for the angular matrix R for a normal and a lame cow.

of 2 standard deviations (σ) of the mean value of the corresponding monotonic segment of the data. Following this, a representation of the 32 joint-axis motion sequences, corresponding to the 8 joint markers in each of the X, Y, Z and R axes, is embedded into a matrix for each motion (see Figure 2 for examples of motion curves).

Data Augmentation and Simulation of Synthetic Motion Extending the number of motion curves by collecting additional cow samples is a complex, expensive and time-consuming task requiring the manipulation of many animals. Moreover, even larger herds are composed of no more than a few hundred cows, which corresponds to a small sample to do advanced ML with. Therefore, to design a potent classifier, one could extend the existing data by adding synthetic motion samples mimicking the probable space of gait kinematics. This space would represent all possibilities of variation in the movement. Our preliminary approach consists of adding random noise with magnitudes of 1, 2, 5, 10, 15 and 20% to the motion curves and then smoothing them with a median filter. To assess whether this approach would preserve the homogeneity of samples issued from the same seed cow, we performed a K-means clustering of the generated synthetic data followed by silhouette index computation. If the silhouette index was above a threshold t then the generation is retained. Finally, we provide an external validation with real clusters derived from the ones defined by gait scoring by an expert. Clusters obtained an average silhouette index above 0.70 (result not shown). Therefore, we can conclude that the generated samples preserved the same lameness characteristics (i.e: label) as the cows they were derived from.

Classification A CNN based on the *LeNet* model by (LeCunn et al. 1998) with the addition of 4 batch normalization layers in the framework was chosen as the model architecture. The batch size was set to 16 and the number of epochs was equal to 50. The CNN was trained using 24 000 cow samples which were converted to vectors of identical size for training. The input data was structured as a 3D vector including 32 time-series corresponding to the movement of 8 different markers in the cow's front and back leg, each tracked in 4 different axes. This gave an input vector of size 8 x 4 x 192 for each cow. Each time sequence vector represented an interval equal to 3 front and back steps. The data was normalized to maintain values between -1 and 1. The data set was also balanced for it contained 12000 (50%) lame and non-lame cows.

Variation	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
1%	76.74	78.60	77.60	76.40
2%	83.80	83.80	83.60	83.20
5%	90.76	92.20	91.40	90.60
10%	81.54	84.60	82.40	81.40
15%	79.99	80.06	80.04	80.02
20%	76.92	77.80	77.40	77.00

Table 1: Prediction results of testing instances.

Results

Multiple CNN models were built based on the configuration mentioned in the previous subsection. During training, the models were evaluated following a 5-fold cross-validation framework using a *Monte Carlo* optimization approach. The prediction performances on the test set were then recorded by each trained model. Results are presented in Table 1.

The best prediction performance was achieved by the model built from the data including 5% variation from the original data, with scores above 90% for the different performance metrics (Accuracy, Precision, Recall and & F1-score). When the percentage of variation deviates from the 5%, we can observe a progressive drop of performance. In this context, the obtained results indicate that the data generated with a threshold of variation around 5% provides a model with potentially better generalization.

Conclusion

In this study, we proposed a DL framework to detect lameness in dairy cows. Synthetic kinematics data were generated to provide enough samples to train a DL classifier. This method allowed us to train a CNN based on the *LeNet* architecture. The overall results show an average F1-score and accuracy both above 80%. In addition, we highlight the possibility of training models with synthetic kinematic data generated from a reduced original data set, and the success achieved on classifying real cows that were unseen by the model during training. However, it will be important to extend such methods by adding data from more diverse cows in the future.

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