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Master Thesis Proposal

Gait analysis for detecting lame cows using convolutional neural networks

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1. Introduction

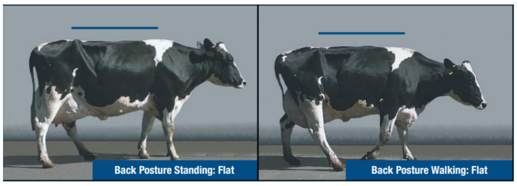
Lameness is a serious disorder in dairy farms that increases the risk of culling of cattle as well as economic losses, such as decrease in milk production and the cost of medication [1, 2]. This issue is addressed by lameness detection using locomotion scoring [1, 3], which assesses the gait patterns of cattle in order to monitor the lameness level of the animals. The scoring is typically estimated by veterinarians through visual inspection, which is not only time-consuming and laborious, but also subjective and may vary from time to time. Researchers have proposed different approaches to automatic lameness detection and scoring. Computer vision techniques are particularly suitable candidates for the task since such systems can operate remotely without changing the daily routine of the animals [4]. The detection is often based on the back posture of the cows [4, 5, 6, 7]. However, most work employs traditional computer vision techniques which requires feature engineering [4, 6, 7, 8]. Deep learning can tackle this issue because of its feature representation, allowing an end-to-end learning without the need to specify multiple stages for a task.

This study aims to develop an automatic locomotion scoring system using deep learning techniques, such as convolutional neural networks (CNNs), which are a type of deep learning architecture that has been used to solve many vision tasks with great success [9, 10], or recurrent neural networks (RNNs), which are effective for sequential data [11, 12]. The deep network takes a series of frames as input and outputs the predicted locomotion score. While there are many types of locomotion scoring systems, this study will adopt the 5-point scale established by Sprecher et al. [1]. The score ranges from 1 (normal) to 5 (severely lame), which is mainly based on the observation of the shape of a cow's spine. The locomotion score is assigned to each cow based on the archness of the back when the cow is standing and walking, as described in Table 1.1 and Fig.1.1.

To validate the efficacy of deep learning in lameness detection, a traditional machine learning technique, i.e. support vector machine (SVM), will be used as the baseline. Unlike deep learning, feature engineering is necessary for SVM, so several keypoints on the cow's body will be selected for pose estimation, in which spatial-temporal features can be extracted for lameness detection. These keypoints serve as the elements for gait and pose analysis of cows.

Table 1.1: Criteria used to assign a locomotion score and clinical description to cattle [1].

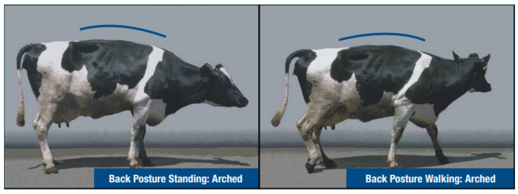
Locomotion Score	Clinical Description	Assessment Criteria
1	Normal	The cow stands and walks with a level-back posture. Her gait is normal.
2	Mildly lame	The cow stands with a level-back posture but develops an arched-back posture while walking. Her gait remains normal.
3	Moderately lame	An arched-back posture is evident both while standing and walking. Her gait is affected and is best described as short-striding with one or more limbs.
4	Lame	An arched-back posture is always evident and gait is best described as one deliberate step at a time. The cow favors one or more limbs/feet.
5	Severely lame	The cow additionally demonstrates an inability or extreme reluctance to bear weight on one or more of her limbs/feet.



(a) LS = 1

(b) LS = 2

(c) LS = 3



(d) LS = 4

(e) LS = 5

Figure 1.1: Locomotion scores (LS) of cows when standing and moving [13].

2. Related Work

2.1. Lameness detection

In order to deal with the lameness issues, a common method is to manually identify the variations in gaits or postures of the cows and assign locomotion scores. While it is quick to apply and easy to perform, it is time-consuming, subjective, and can lead to inconsistency [5]. Many researchers have proposed different approaches to automatic lameness detection by analyzing various measurements. One approach is to use load cells or pressure sensors to measure the ground reaction forces of the cows, such that the gait patterns of the cows, such as the stance time or asymmetry in weight bearing between the right and left limbs, can be observed [14, 15].

Another popular approach makes use of computer vision techniques to visually observe the gait characteristics or poses of the cows. Song et al. associated the scale of lameness with the step overlap of the cows from side-view images; the results show a positive linear relationship between cows' trackways overlap and locomotion scores by human observation [8]. Poursaberi et al. developed a vision system to assess the lameness of cows by fitting two ellipses on the back posture of the cows [6]. However, the analysis of side-view images from 2D cameras can be affected by the changing lighting conditions, and the installation of side-view cameras in a farm is often difficult [5, 16]. To overcome the drawbacks of 2D camers, some researchers proposed methods of back arch estimation of cows by using 3D cameras [4, 17].

2.2. Deep learning

Deep learning is a branch of machine learning that has been applied to solve various tasks efficiently, such as computer vision and natural language processing. Unlike traditional machine learning techniques, deep learning can learn representations of data without feature engineering, which is achieved through the architecture of deep neural networks. With multiple layers, a deep network can learn features in a hierarchical fashion; the farther a layer is from the input layer, the more abstract the feature it can extract [11].

One of the most popular forms of deep learning are convolutional neural network (CNNs), which contain a series of convolutional and pooling layers whose primary goals are feature extraction and dimensionality reduction, respectively. Rectified linear unit (ReLU) is usually used between layers to introduce nonlinearity. At the end of the network are fully connected layers that predict a class score or other forms of output. CNNs are largely used for vision tasks, and have many variations for addressing different issues [18, 19].

Recurrent neural network (RNNs), designed to process sequence data, are another popular form of deep learning. They have feedback loops and maintain in the hidden layers a state vector that capturing the history of the past elements of the sequence [11]. Long short-term memory (LSTM) networks [20] are a variation of RNNs with special hidden units that determine the amount of the past and new information to remember. They circumvent the vanishing and exploding gradients problem of conventional RNNs, so that are more effective to learn long sequences [11].

2.3. Motion analysis

Motion analysis is a popular topic of computer vision because of its wide applications [21], including surveillance, human-machine interaction, athletic movement analysis, clinical diagnosis, among others. Generally, there are three major tasks: detection, tracking, and recognition or behavior understanding [22, 23]. Detection involves motion segmentation to differentiate the objects from the background as well as object classification to determine the type of the objects; tracking is a temporal process concerned with objects matching in consecutive frames using visual features; recognition aims to interpret the behaviors of the objects through the sequence of frames [22, 23]. Since this thesis is concerned with pose estimation along with gait and pose analysis, this section focuses on these two topics; the former can be considered as the next step or part of object tracking [24], while the latter belongs to behavior understanding.

2.3.1. Pose estimation

Pose estimation is the process of detecting the configuration, either joints or keypoints, of an object of interest [24]. Both spatial and temporal features can be extracted from the estimated poses over time, and can be further used for behavior understanding. The approaches can be divided into traditional and deep learning-based, as discussed below.

Traditional approaches

Traditional pose estimation approaches can be divided into two classes: top-down [25] and bottom-up [26]. Top-down estimation tries to match the projection of body with the image observation; it has the drawbacks of manual initialization of estimate in the first frame, and occlusion issue. Bottom-up estimate assemblies the body parts into a whole body, requiring detectors for body parts [27]. The two classes can be combined for better estimate [28, 29].

Deep learning-based approaches

DeepPose [10] is a human pose estimation algorithm by applying a cascade of convolutional neural networks, each of which being a regressor. The prediction is refined at each stage in which the processed image is cropped around the predicted joints location from the preceding stage. Another CNN-based system, called DensePose [30], is based on the mask-RCNN architecture that contains a cascade of proposing regions-of-interest (ROI); it was designed to map all human pixels of an image to the 3D surface of the human body. While most studies focus on human pose estimation, Pereira et al. developed a CNN-based animal pose estimation system called LEAP (LEAP Estimates Animal Pose) [31]. The authors adopted a fully convolutional network architecture that maps from raw images to a set of confidence maps for each body part. The locations of body parts are obtained by minimizing the errors between ground truth and predicted confidence maps. Another study [32] implemented transfer learning to track body parts of the animals in the laboratory with minimal training data. The model, called DeepLabCut, is a deep residual neural network (ResNet) based on the architecture of a human pose estimation model called DeeperCut [33].

2.3.2. Gait and pose analysis

Gait and pose analysis is the study of animals' motion with an aim to detect biomedical information, which can be utilized to identify individuals, biomechanical abnormalities or diagnose diseases [34]. Gait, the pattern of walking, provides particularly important biomedical information for analysis because of its repeatability, robustness, and remote accessibility [35]; moreover, gait is a reliable indicator of health condition [36, 37]. Although most studies used gait for biometric recognition [34, 35, 38], there is a growing interest in medical applications [37, 36]. Many gait analysis methods have been proposed, and vision-based is preferred over marker-based since it is nonintrusive and easier to set up. Vision-based gait analysis consists of three main steps: image acquisition, data processing, and gait analysis [36]. While pose also provides important information about an individual's health condition or behaviors [6, 39], pose analysis in the literature is mostly concerned with pose estimation rather than recognition.

The author in [40] tried to recognize walking patterns by applying principal component analysis (PCA) to the frame-to-frame optical flows. Another study used linear discriminant analysis (LDA) to extract gait features from binary silhouette to detect walking patterns of Parkinson's disease [41]. Due to the automatic feature learning ability, deep learning has been applied to gait analysis for feature extraction. One study [34] combined a gait energy image (GEI) based Siamese neural network and a three-dimensional CNN (C3D) to extract spatial-temporal gait features. The authors in [12] proposed a feature learning method for gait recognition: a CNN is used to extract joint heatmaps, which are fed into an LSTM network that models high-level motion features.

Despite the research of vision-based lameness detection and the popularity of deep learning in various fields, to the extent of our knowledge there are currently no published works on the combination of both. Besides, the majority of relevant deep learning-based studies focus on biometric recognition rather than medical gait or pose analysis. This thesis aims to applied deep learning techniques to lameness detection of cows. To further understand the detection of lameness, cow pose analysis is another important issue and will be addressed in the study as well.

3. Methodology

3.1. Data acquisition and preprocessing

The data are side-view videos collected using Samsung FULL HD Camcorder at the Teaching and Research Station Frankenforst of Bonn University on nine different days. Each video ranges from around three to ten minutes long and contains several walking cows, each of which was recorded separately on a walkway around eleven meters from the camera. There are 65 cows in total, each cow has her own ID number for recognition, and was examined and assigned a locomotion score by a veterinarian on three different days. The scores are considered as the ground truth.

Each video is first trimmed into shorter video clips, each of which contains only one cow walking from left to right of the frame. However, in some of the videos there is a person guiding the cow. Furthermore, these video clips are cropped in such a way that the cow is at the center of each frame, which also reduces the size of the data. This cropping step is achieved by applying the TensorFlow Object Detection API [42] to the original videos and using OpenCV toolbox to extract the region of interest.

3.2. Pose estimation

In order to automatically predict the locomotion score for a cow, it is necessary to first estimate the pose of the cow by extracting a few keypoints from her body. As described in Section 2.1, the lameness is closely related to the back posture and step overlap, so the keypoints on a cow's back and hooves can be selected as shown in Fig. 3.1. To optimize the performance of lameness detection, different choice of keypoints will be explored. The deep learning-based pose estimation framework for animals, called DeepLabCut [32], is used in this project. The framework provides a graphical user interface (GUI) using wxPython for keypoints labeling. One advantage of DeepLabCut is that it supports both manual and automatic frame extraction for data labeling. To evaluate the performance of the estimation, the percentage of correct keypoints (PCK) will be used.

Figure 3.1: Ten keypoints (colored crosses) on a cow for pose estimation: head, neck, withers, three points on the back, and one on each hoof.

3.3. Gait and pose analysis for locomotion score prediction

The estimated keypoints from the last step are used as the features for gait analysis. Two approaches will be employed in the thesis: the first approach uses support vector regression (SVR) as the baseline; the second approach applied deep learning techniques. It should be noted that the locomotion score prediction can be considered as a regression problem even though the original scoring system [1] has five distinct scores.

Support vector regression (SVR), a variation of support vector machine (SVM), requires hand-crafted features for data discrimination. Different spatial-temporal features, such as the curvature of cow's back, the stride of cow's gait, and the motion of cow's head, will be explored for lameness detection. In the deep learning-based approach, different architectures will be tested. As the amount of data in this work is much less than most open-source datasets, transfer learning will be applied using CNNs, RNNs, or a combination of both for automatic locomotion scoring. The models take as input a sequence of images, each of which contains a cow with or without partial occlusion. A video clip of one cow along with the locomotion score and the location of the keypoints are considered as a training sample. The output is a predicted locomotion score in the range of one and five. The data will be separated into training and test sets, and the mean squared errors will be used for scoring regression evaluation. Fig.3.2 shows the general framework of the locomotion scoring system.

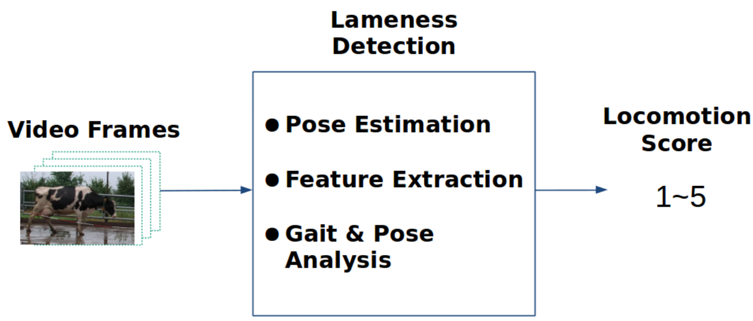


Figure 3.2: Framework of locomotion score prediction.

4. Project Plan

4.1. Work Packages

Starting date: 01 February, 2019
Completion date: 31 July, 2019

4.1.1. Task Description

Work package 0: Problem formulation

- **0.1** Identify tasks and problems
- **0.2** Work plan
- **Milestone 0:** Proposal

Work package 1: Literature survey

- **1.1** Automatic lameness detection
- **1.2** Pose estimation
- **1.3** Gait analysis
- **1.4** Deep learning based motion analysis
- **Milestone 1:** Comprehensive state of the art

Work package 2: Data preprocessing

- **2.1** Data acquisition
- **2.2** Data annotation
- **Milestone 2:** Labeled training data

Work package 3: Gait and Pose analysis

- **3.1** Keypoints selection
- **3.2** Pose analysis using different features

- **3.3** Baseline model program
- **Milestone 3:** Trained baseline model with results

Work package 4: Model design and training

- **4.1** Design of the architecture of deep neural network
- **4.2** Data training and validation
- **4.3** Error analysis
- **4.4** Model adjustment
- **Milestone 4:** Trained model with results

Work package 5: Evaluation

- **5.1** Model testing
- **5.2** Comparison of different approaches
- **Milestone 5:** Evaluation results

Work package 6: Result analysis

- **6.1** Quantitative analysis
- **6.2** Plots and tables
- **Milestone 6:** Data analysis

Wrok package 7: Report

- **7.1** Report draft
- **7.2** Report revision
- **Milestone 7:** Final report

4.2. Project Schedule

The project schedule is shown in Fig. 4.1.

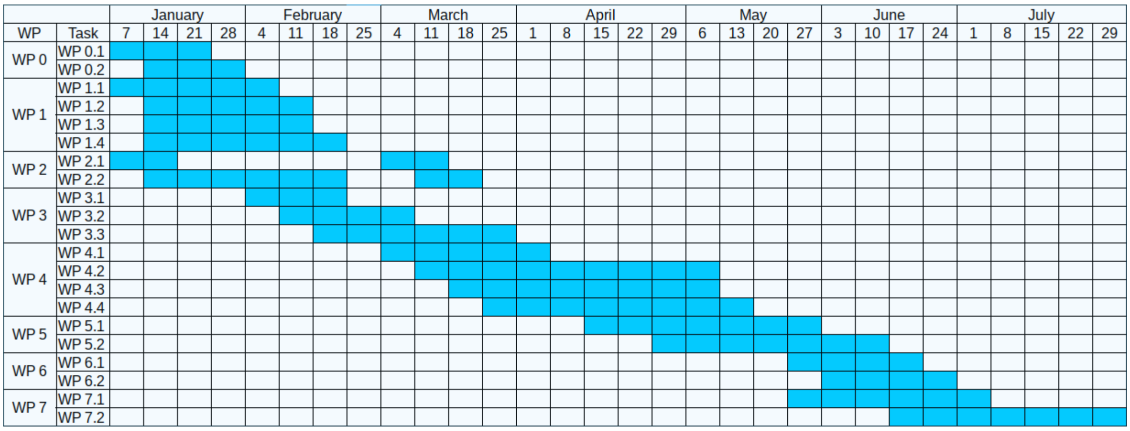


Figure 4.1: Work packages of the project.

4.3. Deliverables

4.3.1. Minimums

- Annotated bibliography of current research in lameness detection, gait and pose analysis
- Evaluation of pose features for gait and pose analysis

4.3.2. Expected

- A running automated locomotion-scoring algorithm
- Comparison between traditional and deep learning-based approaches

4.3.3. Maximum

- Convincing experimental evidence, that the approach can be adopted to real agricultural businesses

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