Proceedings of the World Congress on Genetics Applied to Livestock Production, 11.613

Individual cow identification in a commercial herd using 3D camera technology

Jørn Rind Thomasen[1], Jan Lassen[1], Glenn Gunnar Brink Nielsen[2], Claus Borggard[2], Peter René Bolvig Stentebjerg[2], Rikke Hjort Hansen[2], Niels Worsøe Hansen[2], Søren Borchersen[1]

[1]VikingGenetics, Ebeltoftvej 16, 8960 Randers, Denmark
jotho@vikinggenetics.com *(Corresponding Author)*
[2]Danish Meat Research Institute, Gregersensvej 9, 2630 Taastrup, Denmark

Introduction

Automatic cow identification becomes increasingly important for individual real time monitoring of production, health, behaviour etc., in modern dairy cattle production systems with large herd sizes. Examples of camera based classification of lameness (Viazzi et al., 2013) and conformation traits (Salau et al., 2017) have already been presented.
The aim of this study was to identify cows individually at the feeding table using a 3D camera system (Patent no: WO 2017/001538). The purpose of this identification was, with use of the same 3D camera system, to measure the feed intake for the identified cow (Lassen et al., 2017). However, the cow-id identification can also be used in combination with other features. A 3D geometric cow model with corresponding cow-id was used as reference. All cows in this study were labelled with unique cow-id, making it possible to calculate the success rate for 3D cow-id identification system.

Material and methods

Hardware Setup

The input hardware setup consists of two main units. The reference unit responsible for acquisition of the reference cow geometries with a corresponding cow-id. A prediction unit responsible for acquisition of the cow geometry in the area where the identification process takes place.
The reference unit consists of a single 3D camera using Time of Flight technology (Microsoft Xbox One Kinect v2) to create a 3D image and a RFID reader (Agrident Sensor ASR550). These were installed in a narrow corridor with a trigger system which ensured that one reference image was obtained from each cow when they pass through. The 3D camera was placed directly above the passing cows 3.4 m above floor level. The prediction unit consisted of 19 3D cameras (Microsoft Xbox One Kinect v2) placed in a line directly above the feeding area with a distance of 4.2 m to the floor. This setup ensured complete coverage of the entire 50 m long feeding table area in the test facility. The prediction unit records an image every 5 seconds.

Feature estimation

The first step in the identification process is to estimate features from the geometric information in the 3D images, which are useful for separating the individuals. This procedure is applied to both the images from the reference and the prediction units. The process starts by finding the outline and spine of the cow in the raw uncorrected 3D images as indicated in Figure 1A. A calibration procedure converts the region within the cow outline to a point cloud, so each pixel in this region of the 3D image is transformed into the corresponding spatial 3D coordinates. See Figure 1B for an example of the corrected point cloud. The calibration procedure is primarily done to remove distortions due to perspective. Furthermore, the calibration allows combination of the point clouds information from two neighbouring cameras if a cow is placed on the border between the cameras field of view. Upon this a corrected depth image of the cow region is created by interpolating the point cloud back into a 2D depth image. The corrected depth image is shown in Figure 1C.

The feature generation process starts by finding the points on the corrected depth image lying 3, 5, 10, and 15 cm below the spine level of the cow. The height is measured perpendicular to the spine of the cow to make the features invariant with respect to position and orientation. Cubic smooth splines are fitted to the points corresponding to each distance to reduce noise. An example of these contours are illustrated in Figure 1C. The raw spline features are generated by measuring distance between the intersection of the spine normal and the splines on each side of the cow. The raw spline features are normalized to correct for anatomically differences as seen in Figure 1D.

Classification algorithm

The classification algorithm is based on a linear discriminant analysis (Friedman, 1989) trained on the features from the reference unit. In this manner, each cow conforms a class in the linear discriminant model having the contours as numerous feature input.
To increase the accuracy and robustness of the classifier a post processing step is included in the classifier where the most probably cow-id is estimated based the time period where the cow stays in the same region of the feeding area. Both the feature estimation and classification algorithm were build using the NumPy (van der Walt, 2011).

Validation Experiment

The accuracy of the prediction algorithm was validated by labelling 97 Jersey cows with a semi-permanent marker in the feeding area of a commercial loose housing production system. The cows were marked on their backs so the marks were visible in the images from the above cameras. The algorithm to identify the cows at the feeding table, did however not use these marks as they not were visible in the 3D image. A minimum of 18 images and a maximum of 50 images of each cow was obtained with the reference unit and the classification algorithm was trained on these. Images were chosen with the prediction units every 15 minutes over an approximate 5 days long period. The cow-id of each cow present in the images was manually annotated for comparison with the identification algorithm. This resulted in 6357 manually labelled cow images distributed over 97 different cow-id.

Results

The results from the evaluation of the cow-id prediction algorithm can be seen in Table 1. The table is the result of a comparison process, which is pairing the manual labels with the predicted labels, based on the position of the cow. A cow is placed in the *"correctly predicted cow-id"* category if the cow is detected correctly and the predicted cow-id match the manual inspection. Cows detected correctly but with a wrongly predicted id at the feeding table are given by the "*wrongly predicted cow-id*" category. The "*wrongly detected cows*" contains cows where the detection of the cow in the image failed which makes the cow-id prediction processes impossible.

Table 1. Summary statistics for comparison of the contour based prediction algorithm with manual labels.

Sample	Count	Fraction [%]
Correctly predicted cow-id	5711	90
Wrongly predicted cow-id	335	5
Wrongly detected cows	311	5

The pairwise error is defined as the number of times one cow is misclassified as another cow normalized by number of observations of the first cow. It can be used to evaluate the uniformity of the errors between the different classes. The distribution of the pairwise errors lager than zero for all cows in the validation set is given in Figure 2A. The F1-score is used to evaluate the performance of the classifier for each cow. The F1-score measures both the ability of the model to predict the cow-id correctly and the ability not to give this id to a cow with another id. The distribution over the F1-scores for cows can be seen in Figure 2B. The F1-scores does not include the error rates described by the last category in Table 1 and should therefore only be regarded as a relative measure of the accuracy for the different individuals.

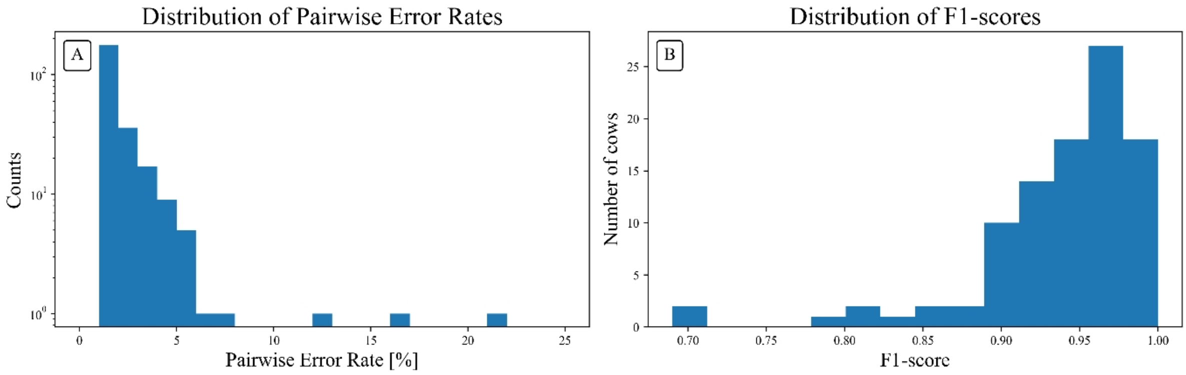

Figure 2. A, histogram of the non-zero pairwise error rates observed on the validation data. (Note the logarithmic y-axis.) B, histogram showing the distribution of F1-scores (one vs. all) for individual cow. The F1-scores does not include the error rates described by the last three categories in Table 1.

Discussion

With a fraction of 90% correctly predicted cow-id this study clearly demonstrates that the geometry of the cow back region is unique to each individual. A similar relation is well known for other species, for instance the human facial region (Bowyer et al., 2006). The distribution of the F1-scores for each of the 97 cows in the validation experiment can be partitioned into two as seen in Figure 2 B. A high accuracy group with F1-score above 0.87 and a tail group with cows where the prediction algorithm is less accurate and F1-score below 0.87. The latter group of cows are to some extent characterized by having much higher pair wise error rates than the rest of the cows. For instance, the 5 cows with a pair wise error above 10 % are all present in this region. These cows are in other words very similar to other cows in the validation set and as a result the classifier is less accurate for these. However, the

remaining pairwise errors are typically below 5% as seen by the distribution in the Figure 2A. The distribution indicates that cows with similar 3D features are not a general problem, and that the prediction errors are uniformly distributed over the entire herd of cows.
It is possible to further investigate the origin of the prediction errors from the 2 categories in Table 1. The 5% cows in the *"wrongly predicted cow-id"* category represent the fundamental limiting discriminative power of the given implementation of prediction algorithm. Whereas, the 5% *"wrongly detected cows"* in Table 1 are a result of the large image variations observed due to the behavioural patterns of the cows and the condition the images were acquired under. For instance, if two or more cows stand very close to each other they can be hard to separate. Decreased image quality from sunlight or dust in the air during the feeding period can also result in the *"wrongly detected cows"* category. Many of the events that leads to prediction errors have a relative short duration. A better utilisation of the cow-id prediction over time may therefor increase the accuracy of the system. In a commercial setup each cow will obtain daily 3D images from the prediction unit in order to update the prediction algorithm.

Conclusion

This study presented a system for identification of cows based on the geometry of their back region in a commercial heard. The validation of the system achieved a precision of 90%. Future work will partly focus on improving the overall performance of the prediction system by improving the system's ability to detect cows in the 3D images under a wider range of conditions and to improve the classifier to reduce the number of wrongly predicted cow-id. Validation of the prediction algorithm in broader range of stable environments and on other breeds will also be needed before commercializing the system.

List of References

Bowyer, K.W., K. Chang, and P. Flynn. 2006. A survey of approaches and challenges in 3D and multi-modal 3D + 2D face recognition. Comput. Vis. Image Underst. 101:1–15.

Friedman, J.H. 1989. Regularized Discriminant Analysis. J. Am. Stat. Assoc. 84:165.

Lassen et al., 2017 Individual measure of feed intake on in-house commercial dairy cattle using 3D camera technology. *10th WCGALP*

Patent no: WO 2017/001538 "System and method for identification of individual animals based on images of the back"

Salau, J., J.H. Haas, W. Junge, and G. Thaller. 2017. A multi-Kinect cow scanning system: Calculating linear traits from manually marked recordings of Holstein-Friesian dairy cows. Biosyst. Eng. 157:92–98.

van der Walt, S., Colbert, S. C. and Varoquaux, G. The NumPy Array: A Structure for Efficient Numerical Computation, Computing in Sci. & Eng., 13, 22-30 (2011)

Viazzi, S., C. Bahr, a Schlageter-Tello, T. Van Hertem, C.E.B. Romanini, a Pluk, I. Halachmi, C. Lokhorst, and D. Berckmans. 2013. Analysis of individual classification of lameness using automatic measurement of back posture in dairy cattle.. J. Dairy Sci. 96:257–66.

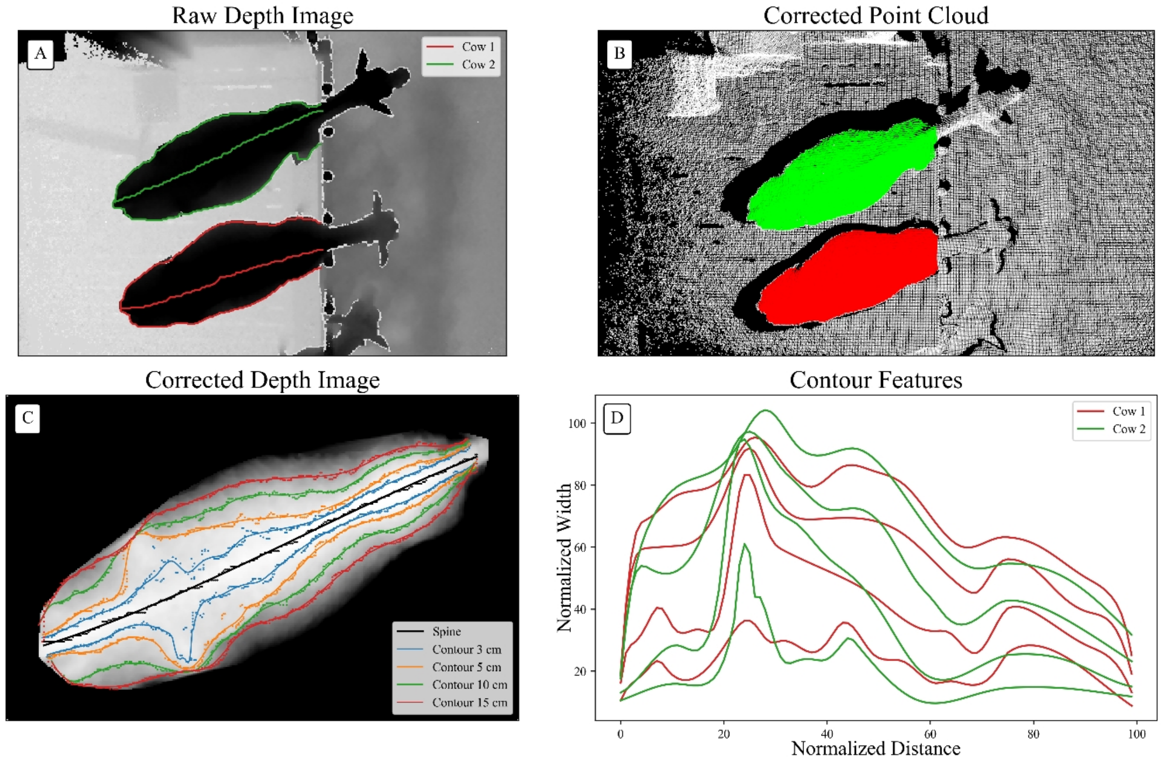

Figure 1. A, outline and spine of the cow in the raw uncorrected 3D images. B, corrected point cloud. C, corrected depth image and raw contours. D, spline features corrected for anatomically differences.