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PROGRAM BOOK

Regular Sessions

[Regular Session I] Intelligent Computing & Artificial Intelligence I

October 20 Thursday 10:40~12:00 Tapo Chao A

Session Chair : Lee Chilwoo, Chonnam National University, Korea

1. (In-person) Classification of Lung Sounds using Machine Learning, Xiaoran Xu, In-Ho Ra, Ravi Sankar

2. (In-person) Synesthetic Information Collecting Method by Auditory Visualization & Multivariate linear regression, Gyumin Cho, Chang ook Ahn

3. (Virtual) Recent Research Trend in Efficient NLP of Transformer, Eunhui Kim¸ Myunggwon Hwang, Minho Lee

4. (In-person) Explore the Feasibility of Acoustic Model Augmented Transformer for Multi-Task Music Transcription, Taehyeon Kim, Chang Wook Ahn

5. (In-person) Attention Gated Recurrent U-Net for CT Image Segmentation of COVID-19 Lung Infection Region, Haoyu Chen, Kyungbaek Kim

6. (In-person) Stress analysis based on feature-level late fusion, Eun-Bin Choi, Hong-Hai Nguyen, Trong-Nghia Nguyen, Soo-Hyung Kim

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[Regular Session II] Smart Farms, Smart Agriculture & Image Processing

October 20 Thursday 10:40~12:00 Tapo Chao B

Session Chair : Seok won Jung, Mokpo National University, Korea

1. (In-person) Cattle Face Pose Estimation using Landmark Points for Smart Livestock Farming, Shujie Han, Alvaro Fuentes, Sook Yoon¸ Yongchae Jeong, Dong Sun Park

2. (In-person) Body Condition Score Classification of Dairy Cows Using Images with CNN Models, Sooram Kang, Youngsik Park, JaeBuhm Chun, Myung Hwan Na

3. (In-person) Annotation Consistency Analysis for Plant Disease Detection, Jiuqing Dong, Alvaro Fuentes, Sook Yoon, Taehyun Kim, Dong Sun Park

4. (In-person) 3D Brain Tumor Survival Days Prediction using Knowledge Distillation, Tien-Bach-Thanh Do, Soo-Hyung Kim, Huyng-Jeong Yang, Guee-Sang Lee

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Cattle Face Pose Estimation using Landmark Points for Smart Livestock Farming

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ABSTRACT

In precision livestock farms, real-time monitoring of cattle is an important field; especially cattle face recognition is an important method to automatically confirm cattle identity. Facial recognition algorithms require massive and diverse data support. In the current research on cattle face recognition, there are still limited types of data and insufficient types of labels. Especially for the upstream task of cattle face recognition, cattle face alignment is less concerned. In this paper, we present two contributions. First, we collect and annotate a new dataset of Hanwoo cattle faces from three cameras installed on an indoor farm, using bounding boxes and landmark points. Cattle in our dataset all have the same yellow fur with similar features. Second, we use landmark points to estimate cattle face pose to select suitable data for face alignment. Our experiments demonstrate that effective cattle face alignment methods can help distinguish the deep features of faces. We validate this result using an unsupervised clustering method.

KEYWORDS

Cattle face, pose estimation, dataset, face landmarks, precision livestock farm

1 INTRODUCTION

Modern agriculture has high requirements for the welfare of livestock, which greatly guarantees the quality and safety of livestock products[1]. In precision livestock farms, automatic and accurate monitoring of livestock is an essential requirement. To achieve it, many devices and algorithms are used, such as wearable RFID devices[2]–[5], GPS[6], surveillance cameras and surveillance camera-based cattle face recognition[7], cattle tracks[8], and cattle activity detection[9]. Specifically, wearable devices may affect the normal activities of cattle, and real-time long-term monitoring cannot be guaranteed. On the other hand, algorithms based on surveillance cameras can guarantee long-term and real-time monitoring but are less accurate than wearable devices, which are often prone to errors that confuse or lose cattle identity information, especially during long-term monitoring. Therefore, cattle identification is a key part of camera-based cattle surveillance algorithms, and the most commonly used method is cattle face recognition.

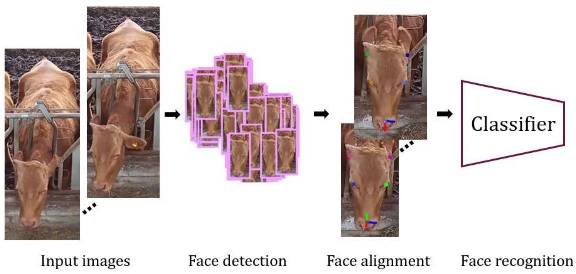

Figure 1: General overview of the face recognition system. First, faces are detected from the input images. Second, face alignment processes faces into the ideal format. Third, we perform face recognition by a classifier model.

Technically, a face recognition system consists of three steps as the Fig. 1 shows: face detection, face alignment, and face recognition. In detail, face detection belongs to the field of object detection, which requires the location of the face to be detected in the original image, and it does not require identification information. Face alignment is to obtain facial landmarks on the detected faces and use them to correct face poses and remove poor samples, which usually include samples after occlusion or deformation. Finally, face recognition extracts the identity information of the fixed face and assigns an ID to the face.

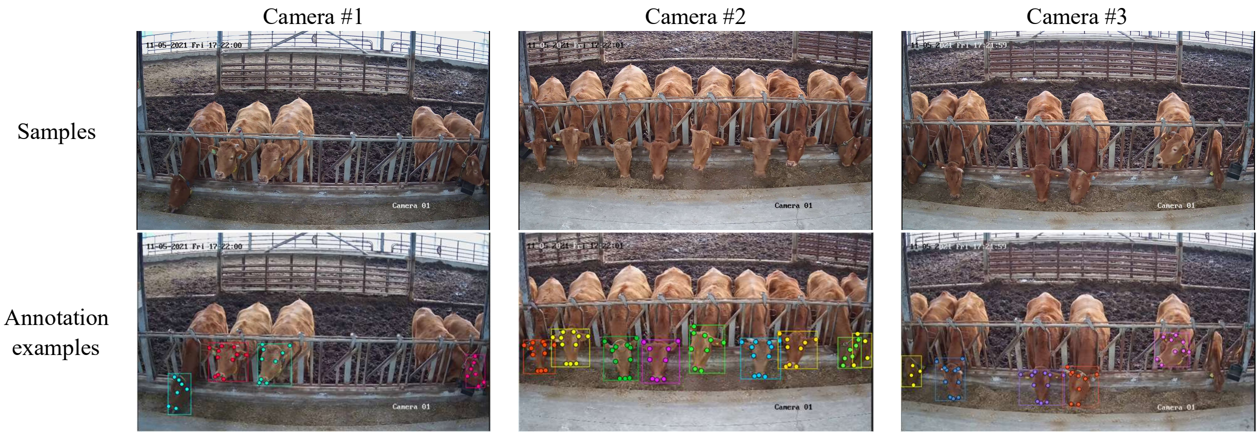

Figure 2: The first row shows samples of our datasets from different camera but at same time. The second row shows the annotation examples in same images.

In recent years, many face recognition algorithms have been applied to cattle face recognition[7], [10], [11]. But cattle face recognition still has many challenges. First, cattle face recognition requires enough cattle face data that are usually collected by researchers. Most of them are samples of cows[12]. Milking cows have unique black and white patterns, which makes cow face recognition easy. Conversely, beef cattle lack distinct characteristics and relevant datasets. Second, many studies focus on cattle face recognition and pay less attention to cattle face alignment. It leads to many cattle face datasets only annotating the cattle face location and ignoring the cattle face landmarks. Third, good cattle face alignment will effectively improve the accuracy of cattle face recognition. Therefore, analyzing the cattle face alignment method has many benefits for cattle face recognition.

In this paper, we collected a face dataset of Hanwoo cattle in our experimental site located in South Korea. Hanwoo is a beef cattle with pure yellow fur from Korea. Compared with other breed, Hanwoo's facial features are more similar and not easy to identify. We not only annotate face locations but also up to 11 facial landmarks per cattle as references for face alignment. Further, we analyze the influence of cattle face pose changes on cattle face feature clustering through facial landmarks. According to our analysis results, cattle face pose estimation and screening of frontal cattle faces can more effectively distinguish cattle with different identities.

2 EXPERIMENTAL AND COMPUTATIONAL DETAILS

2.1 Datasets

To collect the Hanwoo face dataset, we used three cameras to monitor the cattle faces during feeding time, i.e., 5:22 pm, as shown in the top row of Fig. 2. Our dataset contains videos captured by three non-overlapping cameras within 5 minutes starting at 5:22. We use 15 fps video in which 17 cattle are unevenly distributed across the three cameras. Finally, we get the 13,500 images to consist of our datasets.

For the cattle face data, we use the coordinates of the upper left and lower right to label the position of the face as shown in the bottom row of Fig. 2. Further, we annotate up to 11 landmarks of the face that including the nose, sides of the mouth, eyes, bottom points of the ears, top points of the ears, and the bottom points of the horns. In our dataset, some cattle do not grow horns, so they are not labeled. In addition, we do not label the landmarks of occluded areas.

2.2 Template of 3D Face Landmarks

To facilitate the estimation of the pose of the cattle face, we estimate the template coordinates of the 3D landmarks of the cattle face. 3D landmarks coordinates are a set of 3-dimension scalars containing the 2D position and the distance from the point to the camera. We take the cattle nose as the origin and set it to (0,0,0). The template coordinates of other landmarks are their relative distances from the origin. The template coordinates as shown in Table 1. Notice that the top points of the ears change frequently relative to the coordinates of the origin and some cattle do not have horns so we did not estimate their templates.

Table 1: **Template coordinates**

Landmarks	Coordinates(mm)
Nose	(0, 0, 0)
Left of mouth	(25, -35.4, -14.1)
Right of mouth	(-25, -35.4, -14.1)
Left eye	(45, 96.8, -96.8)
Right eye	(-45, 96.8, -96.8)
Bottom of left ear	(50, 106.1, -109.4)
Bottom of right ear	(-50, 106.1, -109.4)

We use the DLT algorithm[13] to solve the Perspective-n-Points problem that can estimate the pose of the face which is made up of the rotation (roll, pitch, and yaw) and 3D translation of the camera with respect to the world. According to the rotation of the face, we select the suitable pose as the aligned faces to improve the recognition performance.

3 RESULTS

3.1 Face Pose Estimation

First, we tested the influence of different landmarks on cattle face pose estimation. We design two different groups of landmarks. Specifically, a group contains 5 landmarks, namely the nose, eyes, and the bottom of the left and right ears. The other group contains 7 landmarks, namely the nose, eyes, the bottom of the left and right ears, and the sides of the mouth. The experimental results are shown in Fig. 3. We use blue for roll, green for pitch, and red for yaw. We found that the first group of landmarks can better describe the cattle face pose. The more critical landmark is that the pose description is inaccurate. Therefore, we use the first group of landmarks as a reference for face alignment.

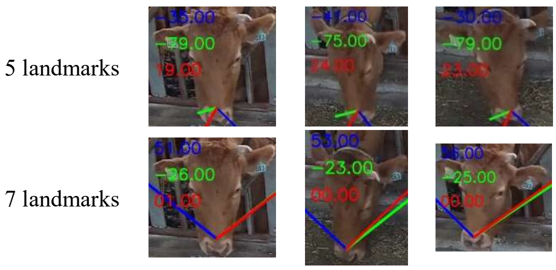

Figure 3: Example results of face pose estimation by different landmarks. We show quantitative and qualitative results on the picture by using the blue for roll, green for pitch, and red for yaw.

Table 2: Average rotation information

NO. of cattle	Rotation (roll, pitch, yaw)
#1	(-36, 49.5, 49.5)
#2	(-34.5, 42.3, 42.1)
#3	(-32.8, 42.5, 32.5)
#4	(-35.4, 37.9, 19.4)
#5	(-25.3, 25.8, 13.7)
#6	(-7.5, -4.4, -9.3)
#7	(-12.6, 19.0, 5.5)

3.2 Analysis of the tSNE Distribution

To verify the role of cattle face pose estimation, we perform an unsupervised clustering analysis on part of the data. We use the tSNE algorithm to analyze the data of 7 cattle that per face have 100 images. The clustering results are shown in Fig. 4. Most cattle faces can be separated, but the features on the left and right sides of the cattle face are very different and easily confused with other cattle faces, such as No. 1, No. 6, and No. 7 cattle. After 5 landmarks of cattle face pose estimation, the cluster analysis result of the image is shown in Fig. 5. We filter the frontal faces, which makes the cluster analysis results of cattle faces better, only some of No. 6 cattle samples are confused. The average rotation information of each cattle is shown in Table 2. Most of the cattle have similar poses, except for the No. 6 and No. 7 cattle.

4 CONCLUSIONS

In summary, we self-collected our Hanwoo cattle dataset, which contains 13,500 images of 17 cattle with the same coat color. We marked the location of the cattle face and also the landmarks of the cattle face. These landmarks can be used for cattle face pose estimation and face alignment. As the upstream task of cattle face recognition, cattle face alignment can provide downstream images with better quality to simplify the difficulty of downstream tasks. Nonetheless, the cattle face recognition task is still limited by the insufficient number and diversity of datasets. Therefore, cattle face pose estimation task also requires accurate 3D landmarks data to improve performance.

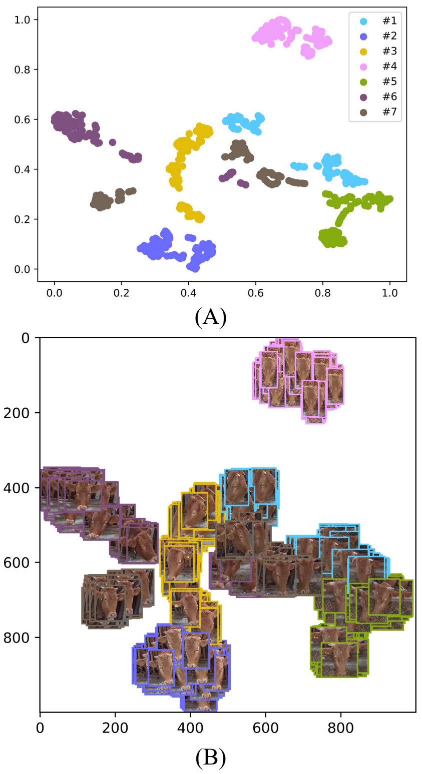

Figure 4: Example results without pose examination. (A) tSNE distribution of cattle faces. (B) Corresponding images of the distribution.

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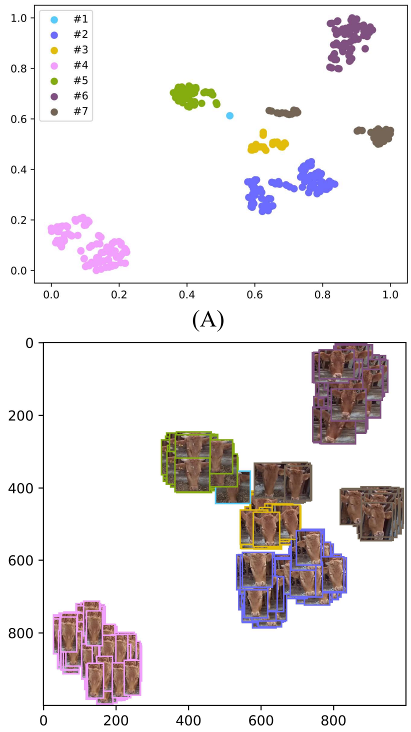

(A)

(B)

Figure 5: Example results after pose examination. (A) tSNE distribution of cattle faces. (B) Corresponding images of the distribution.

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