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A computer vision approach for the automatic detection of social interactions of dairy cows in automatic milking systems

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ABSTRACT
The integration of digital technologies and Artificial Intelligence (DT&AI) in veterinary practice is one of the key topics to improve Herd Health Management (HHM). The HHM includes the prevention of diseases, the assessment of the welfare, and the sustainability production of farm animals. In dairy cattle farming, particular attention is paid to automatic cow detection and tracking, as such information is closely related to animal welfare and thus to possible health issues. Cows are highly social animals; therefore, a better comprehension of social context can help improve their management and welfare. In the field of Precision Livestock Farming, computer vision represents a suitable and non-invasive method for automatic cow detection and tracking. In this study, we developed and tested the reliability of a deep learning-based computer vision system for the automatic recognition of dairy cows in a barn equipped with Automatic Milking System. We aimed to build the social network of 240 dairy cows (primiparous and multiparous) to understand how social interactions can influence their welfare and productivity.

Section: RESEARCH PAPER

Keywords: dairy cows; Computer Vision System; social interactions; Automatic Milking System; Animal Social Networks

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1. INTRODUCTION

The expert working group of the ECCTV (European Coordinating Committee on Veterinary Training) recommended the use of digital technologies and AI (DT&AI) in veterinary practice [1]. In particular, the ECCTV working group pointed out the importance of the integration of DT&AI in veterinary practice to improve Herd Health Management (HHM), including prevention, sustainability production, performance, and reproduction of farm animals. These recommendations are primarily applicable in the context of the cattle farming sector, which requires novel smart approaches, such as the use of novel technologies and new methodologies for data analysis. The emerging fields of Machine Learning (ML) and Artificial Intelligence (AI) in general are expected to be instrumental in addressing the new challenges facing the cattle farming sector [2].

In recent years increasing ethical issues and public concern pushed the dairy industry towards an intensification of the efforts to improve animal health and well-being. Animal welfare is influenced by the social environment and by the opportunity to interact with conspecifics despite the limitations due to bounded space and management practices [3]. Cows are known as highly social animals that evolved to live in large and structured groups. As it happens in other group-living species, individuals differ in the level of association they have with others, and these associations often result in lasting social bonds [4], [5]. Nevertheless, the social context of dairy cows is commonly unstable due to regrouping, a usual management practice on commercial dairy farms. It is well known that regrouping causes negative effects on welfare and productivity including the reduction of milk yield and feed intake [6]. Social interactions are important not only for animal welfare and productivity, but they are also related to the transmission of infectious diseases within a herd, health status and productivity [7], [8]. These links are more evident in free-stall barn equipped with Automatic Milking Systems (AMSs), where the milking is based on cows' voluntary visits, and the cows may have more freedom to control their own social interactions. A better comprehension of social context and space- usage of dairy cows in AMSs can improve animal welfare and enhance the health status of the herd, as well as provide useful information to develop good management strategies. Social network analysis (SNA) provides an opportunity to study complex social relationships between animals across a range of real-world social systems [9], [10]. The SNA has direct application to animal welfare because it allows to describe the patterns of individual interactions and investigate the factors that influence their social environment [11], [12].

In this context, within the Precision Livestock Farming (PLF) field, computer vision represents a suitable, promising, and non-invasive method for automatic cow detection of social interactions and tracking. Computer vision was successfully performed to identify individual cows [13], to detect behaviours [14], [15], and health issues such as lameness [16], [17]. In our study, we developed and tested the reliability level of a computer vision system, based on deep learning techniques, for the automatic recognition of 240 individual dairy cows within images representing their location in a barn equipped with AMSs. Although the computer vision approach has already been used for the detection of social interactions in dairy cows [18], to our knowledge this is the first study aimed to monitor such a large number of dairy cows simultaneously. The main aim of the study is to track the cows and build their social networks to understand how the social context can influence their welfare and production.

2. MATERIAL AND METHODS

2.1. Animals and housing

The research was carried out in a cubicle free-stall barn of a commercial dairy farm located in Candiolo, Torino, in the North-West of Italy, where Holstein Friesian cattle is reared. The barn consisted of two rectangular enclosed areas of 45 x 30 meters each. Each area hosted 120 dairy cows (primiparous and multiparous) served by two AMSs (Lely Astronaut A4). The cows were kept indoors in a loose housing system in a cubicle shed throughout their entire production cycle with no access to pasture. The animals were fed ad libitum (fresh feed twice daily at about 06:00 and 14:00 h) with a total mixed ration (TMR), and they obtained pellet concentrate from the AMS during milking as an incentive depending on the expected daily milk yield.

All the lactating cows had access to the AMS 24 h/d and were milked voluntarily. An electronic identification collar (Owes-H system, Lely, Maassluis, The Netherlands) was fitted to each cow for the purpose of registering all the individual measurements as soon as a cow enters the milking robot, such as the unique identification number, the entrance time and exit time, milk yield, milk temperature, protein, fat and lactose composition in a management software (T4C "Time-for-Cows" InHerd, Lely, Maassluis, The Netherlands).

2.2. Cameras' configuration

We placed a total of eight Super Wide Angle Fixed Bullet Network Cameras (Hikvision). Each camera was mounted to provide a total and clear view of the barn and of the milking robots (Figure 1).

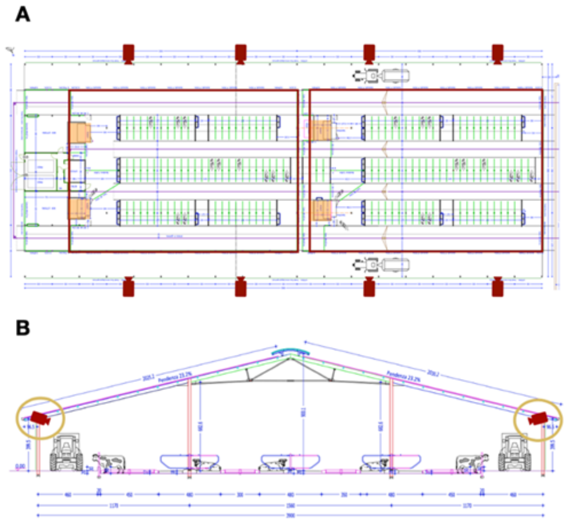

Figure 1. A: map of the barn and positions of the video cameras, orange squares indicate the milking robots; B: lateral vision of the barn. Cameras were mounted outside of the area occupied by the dairy cows.

The combined camera views ensured no blind spots, and each angle overlapped with the others to offer multiple viewing angles and optimize visualization of cows regardless of their position in the barn. Cameras were mounted outside the area occupied by the animals to avoid any disturbance during the check and cleaning operations.

2.3. Data and images analysis

The entire project was developed in Python (Python Software Foundation). The two major libraries used were OpenCV (Open-Source Computer Vision Library) [19] and PyTorch [20]. The open-source software library OpenCV offers a complete set of tools for creating real-time computer vision and machine learning applications. PyTorch is an open-source deep learning framework that is known for its flexibility and ease-of-use. In particular. it provides two high-level features as Tensor computation with strong GPU acceleration and deep neural networks built on a tape-based autograd system.

We aimed to locate the real-world coordinates of the cow via camera feed; our method consisted of three separate components: a camera model, a Convolutional Neural Network (CNN)-based detector, and a tracking model.

2.4. Image pre-processing

The first phase of the process consisted of the images pre-processing and was characterized by the following steps:

- Calibration of the intrinsic and extrinsic parameters of the cameras, this step consisted of selecting a parametric model that mapped each real-world point to the pixel where it is located within the image. To perform the calibration OpenCV has a function called calibrate-Camera(), based on Zhang's A Flexible New Technique for Camera Calibration [21] and Caltech's Camera Calibration Toolbox [22]. It takes as input the 3D object points with their corresponding 2D-pixel points and returns the calculated camera intrinsic matrix alongside the lens distortion coefficients.
- Rectification of wide-angle images in order to remove the lens distortion from an image captured by a camera and to recover the original proportions of the cow. To rectify an image the OpenCV function undistort() was used. This

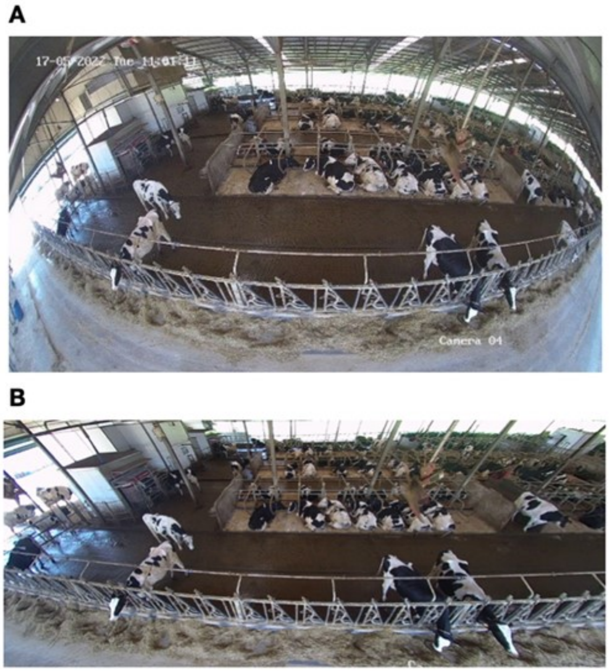

Figure 2. A: original image; B: undistorted image.

is used to remove the lens distortion from an image captured by a camera. It takes as input the image to undistort, the intrinsic matrix and the distortion coefficients calculated during the calibration process. The

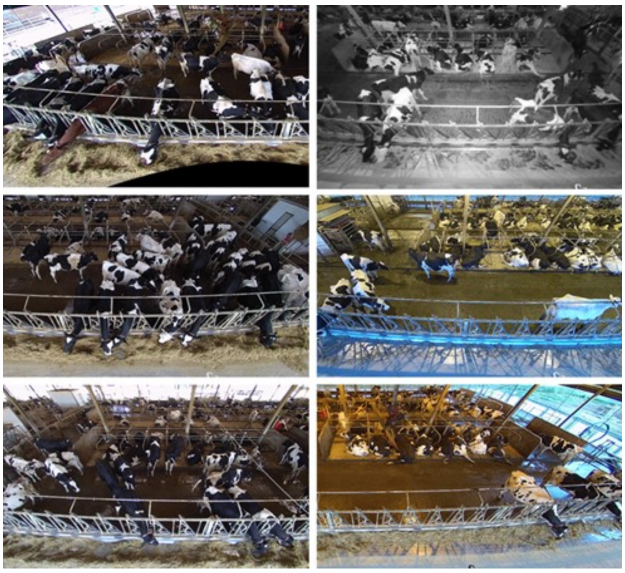

Figure 3. Example of selected training images.

Figure 4. Manual annotation of the cows with bounding boxes.

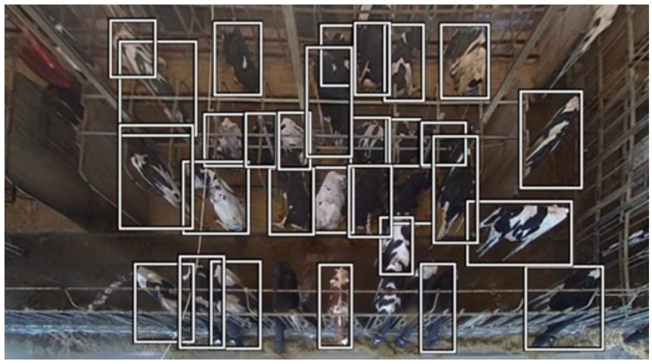

Figure 5. Manual annotation of the cows with bounding boxes using a similar top-down image.

result is an undistorted image that is free from lens distortion (Figure 2).

- Selection of the training sample of images characterized by a variety of contexts (light conditions, time of the day, cow numbers, and body position) (Figure 3).
- Manual annotation of the cows in the training sample with a bounding box containing entirely the visible surface of the animal (Figure 4).

The final step in the image pre-processing phase was about the perspective transformation of the image to change the point of view and retrieve a similar top-down image. This transformation, which mathematically is simply a product between the intrinsic matrix and the transformation matrix, can help us with two problems: the pixel-world reprojection and the detections. With the top-down view the deepness problem is less effective and we are able to gain better real-point locations. Moreover, the bounding boxes are more homogeneous (with the original image, fore-ground boxes and back-ground boxes have great differences in size) leading to better detections (Figure 5).

To perform this step we implemented two OpenCV functions: getPerspectiveTransform(), to get the transformation matrix and warpPerspective() which simply apply the new matrix to the input image. The function getPerspectiveTransform() takes as input the coordinates of quadrangle vertices in the source image and the coordinates of the corresponding quadrangle vertices in the destination image while retrieving the perspective matrix. The function warpPerspective() instead, has as inputs the matrix computed by getPerspectiveTransform() and the source image and returns the new transformed image.

2.5. Object detection

After the conclusion of the image pre-processing phase, the annotated images were used to train a CNN-based detector EfficienDet [23] (Figure 6), this model allowed us to retrieve the location of the cow in the image for any previously unseen frame.

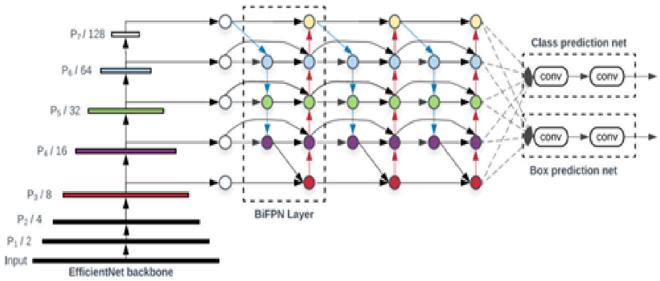

Figure 6. EfficienDet architecture [23].

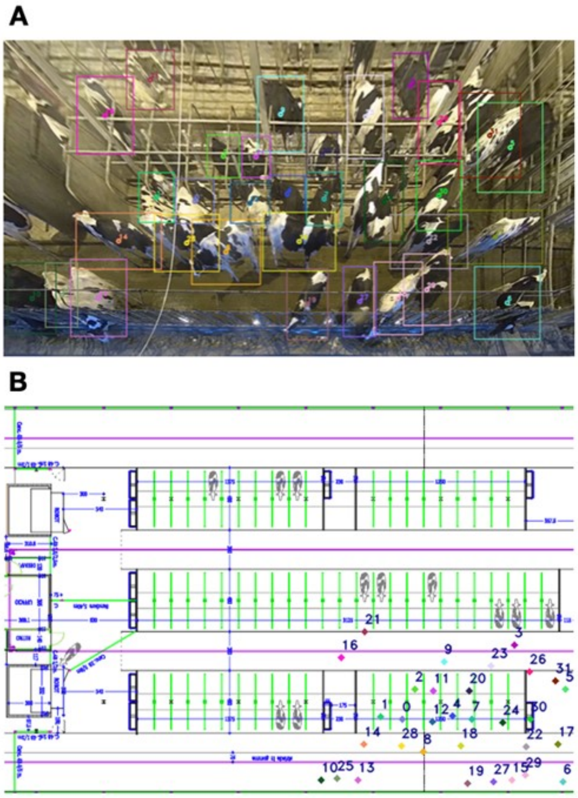

Figure 7. A: bounding boxes; B: projections on the floor of the centre of the cows. The projections of the cows concern images from a single camera

EfficienDet is an object detector developed by the Google Brain Team in July 2020, and it is composed of three distinct but related parts:

- Backbone model: feature maps will be produced via base convolutions taken from an existing image classification architecture.
- Feature Pyramid Network: a feature extractor that generates numerous sets of proper-sized feature maps.
- Predictive layers: objects in these feature maps will be located and identified using prediction convolutions.

Then, we associated to each bounding box a further point representing an estimate of the projection on the floor of the centre of the cow, this point was used to revert from the image coordinates to the real-world coordinates (Figure 7).

2.6. Object tracking

Object tracking is the process of identifying and tracking the location of an object over time in a sequence of images or video frames. We used Euclidean-based tracking as tracking model [24].

In Euclidean-based tracking, object detections in consecutive video frames are first extracted using an object detector. The detections are then assigned to object tracks based on their spatial proximity. The spatial proximity is typically measured using the Euclidean distance between the centres of two detections. The detection with the closest Euclidean distance (i.e., a measure of the distance between two points in an Euclidean space) to the current object track is then associated with that track. Object tracks are updated as new detections are added in subsequent frames. If a detection cannot be associated with any existing track, a new track is created. If multiple detections are found to be close to a single track, the detection with the closest Euclidean distance is associated with the track, and the other detections are used to create new tracks.

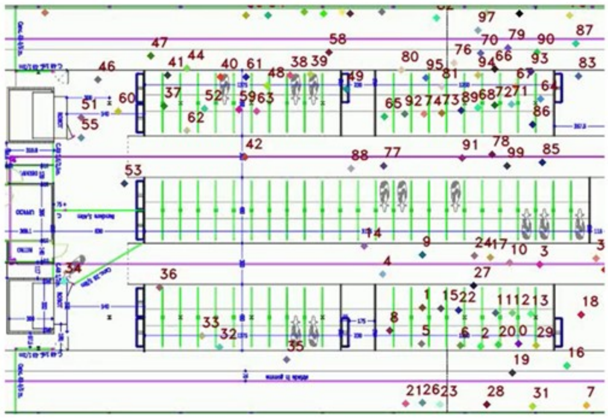

Figure 8. Screenshot of the primiparous dairy cows tracking video.

We implemented a simple 2D object tracking by using the coordinates of a previous frame and comparing it with the current frame and we found the distance between the current frame and the referenced frame using Euclidean distance for each object. We considered it as the same object when the Euclidean distance was less than 40 cm. If the distance of two objects was greater than 40 cm it meant that was not the same cow, so it needed to be registered as a new point. Registering a point simply means that a new point will be added to the tracking objects list.

As for the cow that was no longer identified, its corresponding point is not completely removed from memory but only “hidden”. A point was “hidden” in memory for a period of time defined in input to the algorithm: this was needed in case a cow was not identified only for a short period of time, and then returned to be identified again.

3. RESULTS AND DISCUSSION

When a cow was detected for the first time a temporary unique ID was assigned, and its identity was propagated through time by the tracking module. For each time, a frame with tracked points on the floor plan image was saved. Each point was identified by its own colour (Figure 7, panel B). All the saved frames were then merged together through the use of OpenCV’s class VideoWriter to create a video where the user can see the cows movement (Figure 8). As input, it needs the frames list, the frame resolution values, and the frame per second value. The created system turned out to be very accurate.

In addition to creating the final video with the tracked points (corresponding to the cows) moving within the barn, a .csv file containing the following information was also created: time, cow’s temporary ID, and position. The position (i.e., the real-world coordinates) is the corresponding point on the barn floor map, expressed in centimetres. By using the real-world coordinates, we computed the spatial proximity between each couple of cows to identify the social interactions within the herd. This allowed us to build the temporal social network of the cows, also known as a time-varying network, a network whose links are active only at certain points in time. The nodes of the network corresponded to the cows and the links corresponded to the social distance between two cows.

We aimed to select proximity events between cows situated within 1–1.5 m of one another. This distance allows the detection

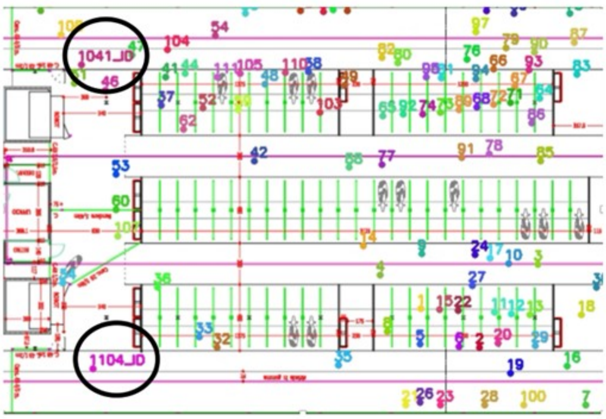

Figure 9. Screenshot of the primiparous dairy cows tracking video. Black circles indicate the real unique IDs assigned.

of a close-contact situation, during which social interactions between animals might occur [25].

However, our final goal was to understand how social interactions can influence milk production and the health and welfare of the cows. To achieve this goal, we needed to associate the temporary unique ID assigned during the tracking with the real unique ID (a constant and unique ID identifying each cow) to match the information obtained by the social network with those obtained by the AMSs. We made this ID change the first time a cow, identified by the temporary ID (no real ID associated), was registered by the milking robot.

The pipeline for real ID assignment followed the object detection and tracking phases. The required inputs were the data extracted from the milking robot (time of milking and real ID of the cow) and the position of each dairy cow obtained by the tracking module. To assign the real IDs to the dairy cows we merged the data coming from these two data sets. We first delimited the two areas right outside the milking robots to catch when a dairy cow went out of the robot. Then, when the tracker recognized a dairy cow in whichever one of these areas, we checked if in the milking robot data set there was information on that specific time frame. If so, we assigned to the cow in the target area the real unique ID coming from the milking robot data set. From there forward the tracking continued with the cow's real unique ID (Figure 9).

This allowed us to study how the cows' social interactions can influence the quantity, and the quality of milk produced and to build a social network using the real unique IDs. This represents a crucial tool for the herd management able to help smart farmers in improving their management practices and, eventually, prevent welfare issues and disease.

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