**Application**

Artificial intelligence with cameras and wearables has unlocked numerous applications in Precision Livestock Farming (PLF), facilitating farmers in timely management of production, health and welfare. Here we demonstrate its expansion to extensive longitudinal coverage of a whole dairy herd to underpin next-generation research in dairy welfare and sustainability.

**Introduction**

The John Oldacre Centre for Diary Welfare and Sustainability (JOC) at Bristol Veterinary School has been built on top of our established 200-cow commercial dairy farm where cows are milked in a herringbone parlour and housed all year round in a free stall system typical of UK dairy farms. Equally-sized groups (by age) are separated within the single barn, giving us the opportunity to achieve continuous video monitoring of all cows. Current PLF research and commercial systems focus on using one or a small number of cameras to directly detect the physical manifestations of later stage clinical disease, such as gait abnormalities characteristic of lameness. Conversely, spotting the early, subclinical stages of disease is essential for successful treatment, maintenance of high welfare standards and sustainable intensification [1]. For research purposes, therefore, dynamic changes in activity, behaviour and social interactions are of fundamental importance, in terms of their links to subclinical disease and interplay with management practice, breeding, social hierarchy and emissions. Machine vision has the promise to characterise behaviour far more deeply than wearables or indoor positioning systems can, but requires several challenges to be overcome including: the reliable detection of each cow in crowded groups; the identification of each individual over long periods including the re-identification of the same cow between cameras; the accurate identification of behaviour patterns and the associated huge expert annotation burden needed to train fine-grained behavioural classifiers; and maintenance of reliable performance in diverse lighting and climatic conditions.

**Material and methods**

We have installed a total of 58 CCTV cameras with night vision and have optimised the dynamic range and shutter speed dependent on their locations.

* 6 wide-angle (2.4mm) 5MP ceiling-mounted cameras cover our transition pen, which provides a self-contained pilot study area with feeding, water and loafing.
* 6 further 2.4mm cameras cover cubicles in the main barn.
* 20 6MP fisheye cameras cover the remainder of the cubicles in the barn extension, needed as the ceiling is lower.
* 14 4MP cameras with 2.8mm lens cover the length of the feed face, angled to give a clear view of feeding behaviour.
* 5 ceiling mounted 2.4mm cameras monitor the cattle in the collecting yard before milking and a further 4 track them through the race after milking.
* 2 cameras are setup on the race optimised for manual body condition and mobility scoring.

A final camera uses Optical Character Recognition to read the output of the ear tag reader gate. This enables us to link the tracked movement data for each cow back to its veterinary and production records.

The data collection platform architecture was designed to address the concerns of a privacy impact assessment as well as ensure data security. Each camera records motion-triggered video to its internal 256Gb encrypted SD card and is connected through a private network to a gateway server. Here, we have developed a load-balancing script to pull the encrypted video data from each camera through the server to a small cluster of workstations each containing 4 Nvidia RTX GPUs. The workstations run our cow tracking AI [2-4], extracting only the motion of the cows themselves for archival and subsequent analytics.

**Results**

Our published cow tracking methodology relies on a continual reidentification approach, thus avoiding the classical tracking issues of objects losing their identifiers over long periods, particularly when moving between cameras. In addition, we spearheaded the deep metric learning paradigm for cattle re-identification that learns to differentiate between coat patterns generically rather than specifically differentiating between the cows in a training dataset. The system does not therefore need to be retrained when new cows transition into the herd [2] and can also be trained on a new herd with little human involvement [3]. Single frame accuracy is now 99.91% [4], which leads to very few errors when results are integrated across video sequences, although more research is needed to determine the limits of the approach (e.g. when crowding occurs in the collection yard, infrared night-time tracking).

**Conclusion**

We have built a new research platform to link health, welfare and sustainability parameters to detailed longitudinally observation of a whole dairy cattle herd using an automated machine vision approach. Building on this, we are focussing on two aspects concurrently:

1. Implementation of a 20-week intensive data collection period across the camera network and including fortnightly mobility scoring, body condition scoring, and saliva and milk sampling (for salivary serum amyloid A and somatic cell counts as a markers for pre-clinical diseases and mastitis [1], as well as full midinfrared spectroscopy).
2. Development of a framework for fine-grained behavioural classification. Key aspects here are an AI-driven annotation tool for facilitating the generation of labels for supervised classifiers, and definition of a controlled vocabulary / ontology to describe the complex ethogram of behaviours that is shared between biological researchers and machine vision experts.

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