Measuring What You Can See: Video Applications for Feeding Management

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Abstract

Feed costs in the United States represent approximately 50% of the cost of milk production on dairy farms; with over 9.3 million lactating dairy cattle this represents over $25 billion dollars spent annually on feed costs. Dairy cattle are fed diets that are a combination of forages and concentrates, with the composition depending on markets, feed supply, and farm infrastructure. Therefore, the consumed rations vary in appearance, nutrient concentrations, and ingredient composition. Feed management software provides information about the amount of each added ingredient, as well as mixing and unloading times. However, group feeding of animals leaves practitioners and researchers lacking information about intake on a per animal basis. As described here, feed consistency and individual intake are both measurements that can be achieved with video analytics. Continuous assessment of feed consistency and individual feed intake would enable management decisions that could improve the efficiency of each animal's production, health, and welfare. This paper describes the importance of feed and feeding measurements, and how systems performing automated video analytics can provide valuable information that is not currently available.

Introduction

Dry matter intake is fundamentally important in nutrition as it determines the quantity of nutrients available to a dairy cow to be used for maintenance, growth, health, and production (NASEM, 2021). Daily and even per-meal intake is commonly measured for research purposes on feeding behavior studies (Ferris et al., 2006; Halachimi et al., 2016) with results leading to management changes that positively impact dairy cattle well-being and performance (Grant and Albright, 1995; von Keyserlingk et al., 2009). Similarly, consistency of feed, as measured by particle size (Kononoff et al., 2003; Maulfair amd Heinrichs, 2012), nutrient analysis (Weiss et al., 2012; Rossow and Aly, 2013), and tracers incorporated into feed (Buckmaster et al., 2014) has demonstrated benefits in improved milk production and optimized equipment utilization. The recent technology uptake on dairy farms has resulted in an enormous amount of data generated on farms. One type of data is generated by video systems on farms (i.e., Cattle Eye and Viking Genetics). The information captured by video provides an opportunity to automatically measure both intake quantity and consistency; more accurate knowledge of these parameters can continue to improve management decisions and create positive impact. This paper explores recent work on measuring individual feed intake and consistency using video analytics.

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Video analytics is the extraction of information from video. Our research in the space of video analytics for improved dairy management has considered both analysis of the dairy cattle and analysis of their feed. To obtain the video, we have mounted several RGB Ubiquiti UniFi G3 Bullet cameras in the holding area as cows exit the milking parlor, above pens of cattle, and above a feed mixer wagon. These record cows walking from the milking parlor to their pens and feed being mixed prior to delivery, with the recordings automatically stored for later processing. In addition, we have mounted an OAK-D PoE stereo vision camera directly above tiestall feed bunks. This camera system captures 50 frames of stereo video each minute, which is processed in real-time. Our prototype system can provide estimates of feed volume over time. The applications of video analytics to feed consistency and feed intake are described next, followed by some additional applications of video analytics for dairy management.

Feed Consistency

What cattle consume is greatly impacted by the physical presentation of that diet and the consistency of feed throughout the bunk and throughout the day. For decades, dairy nutritionists and consultants have been conducting audits of the feed mixing process on dairy farms to try to improve the consistency of feed delivered to dairy cattle and increase awareness of feed management on farms. Feed consistency can be monitored through monitoring particle size (Kononoff et al., 2003), nutrient analysis of samples across a feed bunk (Oelberg, 2015; Oelberg and Stone, 2014), or using a visible tracer whose frequency can be readily quantified (Buckmaster et al., 2014). Significant increases in milk component production and feed efficiency were demonstrated when particle size was more consistent, even when the diets had the same nutrient composition (Boerman et al., 2021).

Current methods to evaluate feed consistency on farms are expensive and time-consuming. As such, they provide only infrequent snapshots of feed management, and it is not feasible to perform evaluations on every farm that could benefit from this information. Additional information across a longer time frame will provide more meaningful recommendations that will positively change feeding consistency. An automated system that constantly and consistently monitors feed consistency could provide actionable information in near-real-time.

In recent work (Santos et al., 2024), we apply video analytics to measure total mixed ration **(TMR)** uniformity in near-real-time. Video was captured during the mixing process using cameras mounted above a mixing wagon (Figure 1). By comparing the contents of a video frame from before mixing with a frame from after mixing, we can explore the change in TMR uniformity. Specifically, in each frame, we sample 5 regions of interest **(ROI)** within the mixer wagon. For each ROI, we compute the histogram of the pixel intensities. The Earth Mover Distance **(EMD)** or Wasserstein Distance, is a distance measure that computes the distance between two histograms. A smaller distance indicates more uniformity, because it indicates that different regions of the TMR inside the mixer wagon are more similar. Therefore, we compute the distance between each pair of ROI, to obtain 10 distances for the first frame (before mixing), and similarly 10 distances for the final frame (after mixing). Our results indicate a statistically significant difference between the two frames, where the mean distance for the first frame is 55 while the mean distance for the final frame is 15.

Feed Intake

Currently the average herd size in the United States is over 300 dairy cows, with farms

over 1,000 cows becoming more frequent. As a result, producers and nutritionists rely on averages of the group when formulating diets. However, in controlled research settings where individual intake is routinely measured, a considerable amount of variation exists for dry matter intake. As a result, there is an increased focus on genetic selection for animals with greater efficiency, that consume less feed than predicted (Tempelman et al., 2015). In research settings, this enhances the opportunity for greater sustainability through more efficient cows. However in the group settings, measuring feed efficiency has been significantly more difficult. In group settings, several factors impact the intake of individual animals, including dietary characteristics, environmental conditions, and management decisions, as well as individual cow characteristics.

When predicting an individual animal's intake, current models estimate what an individual animal will consume using inputs that include body weight, body weight change, milk production, milk components, reproductive status, environmental conditions, and the distance animals walk daily (NASEM, 2021). However, because animals are housed in groups, these estimates are typically averages across a pen, which ignores the large amount of variation that exists between cows. Residual feed intake **(RFI)**, a measurement of feed efficiency, is a heritable trait (Tempelman et al., 2015); therefore, researchers and commercial companies alike focus on improving feed efficiency by selecting for cattle that consume less feed to produce the same outputs (i.e., growth and milk). Currently, neither residual feed intake nor feed efficiency can be measured on individual cows in commercial settings because we lack tools to measure per-animal intake when group housed.

Building on preliminary work by Rogers (2022), we have designed and implemented a non-invasive system that uses stereo vision to continuously estimate the volume of feed on offer throughout the day (Flinders et al., 2024; Rao et al., 2024). Our system leverages parallel processing which enables it to operate in real-time; it also stores any necessary data so that reproducible experiments are possible. Using the OAK-D POE camera, the system captures the depth of objects from the camera. Depth is converted to a point cloud and subsequently to volume estimates. Final estimates and intermediate images are presented to the user on an interactive dashboard (Figure 2). Experiments have considered the impact of lighting and the shape of the feed pile on the accuracy of the volume estimation (Rao et al., 2024). Additional experiments measured feeding behavior and intake over a 12-hour period (Flinders et al., 2024). These demonstrated that the system was able to detect changes in volume before and after a meal, and that it was able to identify when a cow was present based on the depth estimate. The estimates of feed volume were similar to manually measured volumes.

Additional Video Analytics for Dairy Management

To obtain reliable daily intake records for each animal, the above information must be combined with automated recognition of each individual. Ideally, this can be further combined with information obtained by observing and quantifying animal behavior, appearance, and health status.

Video imaging systems have been designed to assess dairy cows to estimate body condition (Spoliansky et al., 2016) and lameness or locomotion irregularities (Li et al., 2022). However, robustness of these systems has not yet been verified on commercial farms, where

environmental conditions like dust, fences, and irregular lighting add significant challenges to video processing.

Cattle recognition through computer vision techniques has also received significant attention. A series of papers presents identification of individuals in a herd of Holstein cows when they are observed from an overhead camera (Andrew et al., 2017; Gao et al., 2021). However, these methods do not translate easily into new herds of cows, and adding a single new cow to the collection is cumbersome and requires retraining the system. An approach that applies ArcFace, the state-of-the art technology for human face recognition (Deng et al., 2019), for recognizing cows faces from frontal views has been developed recently (Xu et al., 2022). Techniques used for pig and sheep face detection have also been tested (Xue et al., 2021; Wang and Liu, 2022). These studies only consider a limited number of animals and have not been applied to commercial settings.

In the commercial space, technology companies such as Ever.Ag (formerly Cainthus) apply video analytics on dairy farms; an application of this technology is to estimate how much feed is available for cows to consume and to trigger events like feed push up. CattleEye monitors cows for body condition score and locomotion score, using a model that accounts for an animal's typical score to indicate when a change is observed. VikingGenetics has a Cattle Feed InTake **(CFIT)** system that identifies a cow in a commercial farm based on its coat pattern, estimates its weight, and quantifies its food intake, all using 3D cameras. While data are being gathered for their system on several commercial farms, feed intake results were reported only for 24 replicates and recognition accuracies were not reported (Lassen et al., 2022).

In our research, we have considered three applications that focus on the dairy cattle themselves: identifying a cow's structure using keypoints, estimating bodyweight, and recognizing Holstein cows. The first step was to accurately and automatically recognize where the cow is in an image; this is essential to make subsequent analyses more intuitive and explainable. We designed and developed a system that identifies a cow's structure using keypoints, when the cow is viewed from the side (Figure 3). We demonstrated that our method is effective, even when there are obstructions like fences and visually cluttered backgrounds created by many additional cattle (Liu et al., 2020). Our approach significantly outperforms segmentation approaches like Mask-RCNN (He et al., 2017).

Our second focus was to apply the cow's structural model to create a system that estimates the cow bodyweight visually. This bodyweight estimation system combines the side-view keypoints and information extracted from a front view of each cow, and it estimates weight within 34 kg when there are no obstructions (Liu et al., 2023). These body weight estimations can be used as an input into diet formulation models to better define characteristics of the animals.

Our third application was to design a recognition system for Holstein cows using a top-view video. When a new cow enters the herd, this system requires only a single image of it to begin to identify the individual (Ramesh et al., 2023). In comparison, other approaches would require dozens of views of a single cow to learn a new individual during recognition system training (Gao et al. 2021; Gao et al., 2022). For each cow image, our system begins by locating the 10 keypoints shown in Figure 4; the image is then aligned to a template using the process indicated in Figure 5. This aligned image is then binarized to create a bit-vector that is stored in a

catalog. New images can be processed similarly, and the new bit-vector can be compared to those in the catalog to identify the cow.

Combined, these video-based applications that focus on the dairy cattle themselves have enabled localization and identification of animals, as well as estimation of the animal's weight and appearance, all automatically obtained from the captured video. We believe that, combined with the estimates of the volume of feed on offer, this can provide a powerful tool for continuous per-animal real-time estimates of individual feed intake.

Conclusions

Video analytics can be used as a tool to extract useful information about feed and feeding management on dairy farms. Localization and identification of animals may be required to determine both appearance and behavior, including feeding behavior and attributes of dairy cattle. While commercial implementations of video analytics are becoming available and research into its theory is accelerating, more work is needed to ensure these advances can be integrated into effective systems for dairy farms. The most appropriate video analytics system and methods for analysis are still dependent on the question being asked and requires domain knowledge. Our long-term goals is to seamlessly integrate the information extracted from video with existing information available about feed management and animal outputs to inform management decisions on dairy farms.

References

Andrew, W., C. Greatwood, and T. Burghardt. 2017. Visual localisation and individual identification of Holstein Friesian cattle via deep learning. In Proceedings of the IEEE International Conference on Computer Vision. https://ieeexplore.ieee.org

Boerman, J.P., W. Hornback, D. Beever, P. Doane, M. Ceceva, A.L. Lock, S. Hansen, M. Drewnoski, M. Murphy, and J.K. Drackley. 2021. Effects of physical preparation of diets and inclusion rate of modified wet distillers grains with solubles, production and rumen measurements of lactating dairy cows. J. Dairy Sci. 104:1680-1695.

Buckmaster, D.R., D. Wang, and H. Wang. 2014. Assessing uniformity in total mixed rations. Applied Engineering in Agriculture 30(5):1-6. https://doi. 10.13031/aea.30.9783

Deng, J., J. Guo, N. Xue, and S. Zafeiriou. 2019. Arcface: Additive angular margin loss for deep face recognition. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. https://ieeexplore.ieee.org

Ferris, C.P., T.W.J. Keady, F.J. Gordon, and D.J. Kilpatrick. 2006. Comparison of a Calan Gate and a conventional feed barrier system for dairy cows: Feed intake and cow behavior. Irish J. Agric.Res. 45:149-156.

Flinders, M.N., P. Rao, D. Buckmaster, A.R. Reibman, and J.P. Boerman. 2024. Near-real-time feeding bunk monitoring for dairy cattle using stereo vision. Abstract Accepted for the American Dairy Science Association Annual Meeting.

Gao, J., T. Burghardt, W. Andrew, A.W. Dowsey, and N.W. Campbell. 2021. Towards self-supervision for video identification of individual Holstein-Friesian cattle: The Cows2021 Dataset. Computer Vision for Animals Workshop. https://ev4animals.com

Gao, J., T. Burghardt, and N.W. Campbell. 2022. Label a Herd in Minutes: Individual Holstein-Friesian Cattle Identification. ICIAP Workshop on Learning in Precision Livestock Farming. https://doi.org/10.48550/arXiv.2204.10905

Grant, R.J. and Albright, J.L. 1995. Feeding behavior and management factors during the transition period in dairy cattle. J. Anim. Sci. 73:2791-2803. https://doi:10.2527/1995.7392791x

Halachmi, I., Y. Ben Meir, J. Miron, and E. Maltz. 2016. Feeding behavior improves prediction of dairy cow voluntary feed intake but cannot serve as the sole indicator. Animal 10(9): 1501-1506. https://doi:10.1017/S1751731115001809

He, K., G. Gkioxari, P. Dollár, and R. Girshick. 2017. Mask R-CNN. Proceedings of the IEEE International Conference on Computer Vision, pgs. 2961-2969.

Kononoff, P.J., A.J. Heinrichs, and D.R. Buckmaster. 2003. Modification of the Penn State forage and total mixed ration particle separator and the effects of moisture content on its measurements. J. Dairy Sci. 86(5):1858-1863. https://doi: 10.3168/jds.S0022-0302(03)73773-4

Lassen, J., J.R. Thomasen, and S. Borchersen. 2022. CFIT – Cattle Feed InTake – a 3D camera based system to measure individual feed intake and predict body weight in commercial farms. 12th World Congress on Genetics Applied to Livestock Production. https://doi.org/10.3920/978-90-8686-940-4_132

Li, Z., Q. Zhang, S. Lv, M. Han, M. Jiang, and H. Song. 2022. Fusion of RGB, optical flow and skeleton features for the detection of lameness in dairy cows. Biosyst. Eng. 218: 62-77.

Liu, H., A.R. Reibman, and J.P. Boerman. 2020. Video analytic system for detecting cow structure. Comput. Electron. Agric. 178:105761. https://doi.org/10.1016/j.compag.2020.105761

Liu, H., A.R. Reibman, and J.P. Boerman. 2023. Feature extraction using multi-view video analytics for dairy cattle body weight estimation. Smart Agric. Tech. 6:100359.

Maulfair, D.D., and A.J. Heinrichs. 2012. Review: Methods to measure forage and diet particle size in the dairy cow. Prof. Anim. Sci. 28:489-493.

National Academies of Sciences, Engineering, and Medicine. 2021. Nutrient requirements of dairy cattle: Eighth revised edition. https://doi.org/10.17226/25806

Oelberg, T.J. 2015. Effective outcomes of TMR audits. In Proc. Tri-State Nutrition Conference. https://www.tristatedairy.org/proceedings

Oelberg, T.J. and W. Stone. 2014. Monitoring total mixed rations and feed delivery systems. Veterinary Clinics of North America: Food Animal Practice 30(3):721-744. https://doi.org/10.1016/j.cvfa.2014.08.003

Ramesh, M., A.R. Reibman, and J.P. Boerman. 2023. Eidetic recognition of cattle using keypoint alignment. Electronic Imaging, pp. 279-1 - 279-6.

Rao, P., M.N. Flinders, D. Buckmaster, A.R. Reibman, and J.P. Boerman. 2024. Real-time Cattle Intake Monitoring using Stereo Vision. Electronic Imaging. https://www.imaging.org

Rogers, M. 2022. Volume measurement of biological materials in livestock or vehicular settings using computer vision. Doctoral Dissertation, Purdue University, West Lafayette, IN.

Rossow, H.A. and S.S. Aly. 2013. Variation in nutrients formulated and nutrients supplied on 5 California dairies. J. Dairy Sci. 96:7371-7381. https://doi: 10.3168/jds.2013-7084

Santos, I.G.M.A., A.R. Reibman, D.R. Buckmaster, L.J. Pfeiffer, and J.P. Boerman, 2024. Assessing Total mixed ration uniformity in a mixer wagon using image analysis. Tri-State Dairy Conference Proceedings. https://tristatedairy.org

Spoliansky, R., Y. Edan, Y. Parmet, and I. Halachmi. 2016. Development of automatic body condition scoring using a low-cost 3-dimensional Kinect camera. J. Dairy Sci. 99:7714-7725.

Tempelman, R.J., Spurlock, D.M., Coffey, M., Veerkamp, R.F., Armentano, L.E., Weigel, K.A., de Haas, Y., Staples, C.R., Connor, E.E., Lu, Y., and M.J. VandeHaar. 2015. Heterogeneity in genetic and nongenetic variation and energy sink relationships for residual feed intake across research stations and countries. J. Dairy Sci. 98:2013-2026.

von Keyserlingk, M.A.G., J. Rushen, A.M. de Passille, and D.M. Weary. 2009. Invited review: The welfare of dairy cattle - key concepts and the role of science. J. Dairy Sci. 92:4101-4111.

Wang, Z., and T. Liu. 2022. Two-stage method based on triplet margin loss for pig face recognition. Comput. Electron. Agric. 194:106737.

Weiss, W.P., D. Shoemaker, L. McBeth, P. Yoder, and N. St-Pierre. 2012. Within farm variation in nutrient composition of feeds. Tri-State Dairy Nutrition Conference. 103-117. https://tristatedairy.org

Xu, B., A. Wang, L. Guo, G. Chen, Y. Li, Z. Cao, and S. Wu. 2022. CattleFaceNet: a cattle face identification approach based on RetinaFace and ArcFace loss. Comput. Electron. Agric. 193:106675.

Xue, H., J. Qin, C. Quan, W. Ren, T. Gao, and J. Zhao. 2021. Open set sheep face recognition based on Euclidean Space Metric. Mathematical Problems in Engineering 2021:1-15.

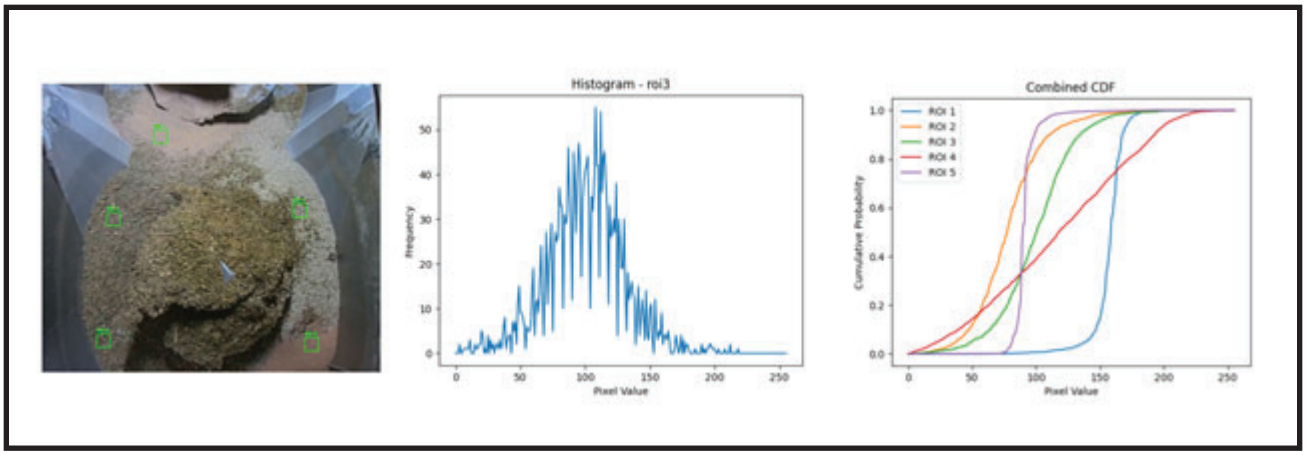

Figure 1. Measuring feed consistency: an example image extracted from video, and data generated from that frame of the video. The first panel represents an image viewing a mixer wagon from above with regions of interest identified by green boxes. The second panel represents an example histogram of pixel intensities for one region of interest. The third panel represents the cumulative distribution functions for each of the five regions of interest which can be used to determine feed uniformity. Greater uniformity will produce more similar cumulative distribution functions. Images provided by I. G. M. A. Santos.

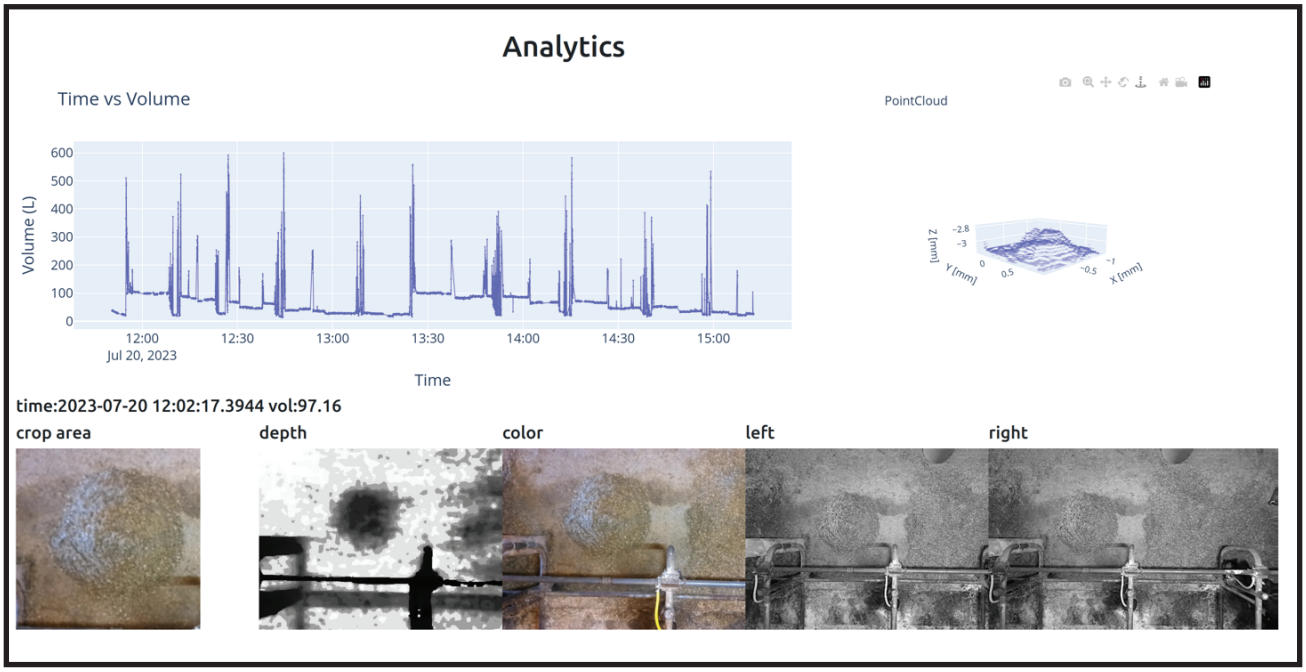

Figure 2. Measuring feed intake: our system dashboard. The top left panel illustrates a graph for the estimated volume as a function of time during a 3-hour period. The top right is an interactive display of the point cloud estimated from the feed. The bottom row illustrates, from right to left, the right and left greyscale images of the stereo camera, the central color image of the stereo camera, the computed depth image (in greyscale), and the close-up cropped region of the central color image. Images provided by P. Rao.

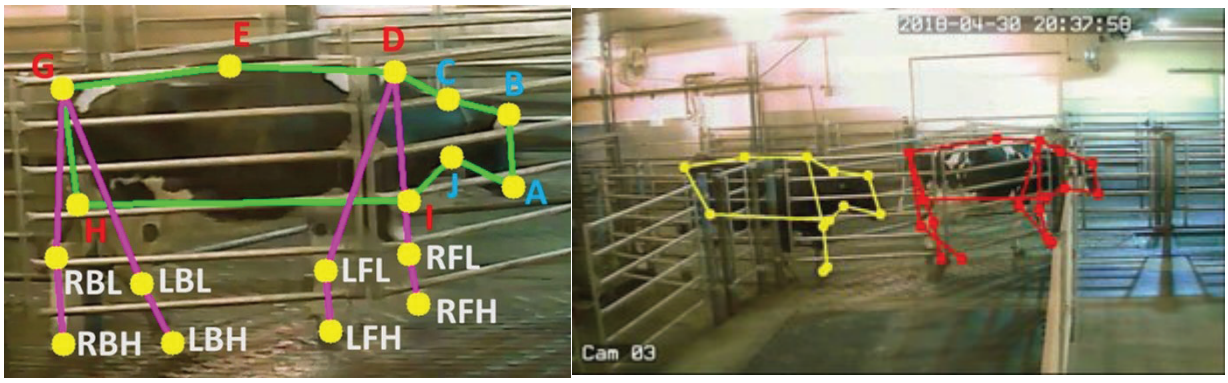

Figure 3. Identifying a cow's structure through keypoints. Left panel: 17 keypoints, where keypoints A-I (in green) correspond to the body and head, and the legs (in purple) are the remaining keypoints. Right panel: Automatically identified keypoints on two cows simultaneously, despite heavy occlusion from fences. Images from H. Liu.

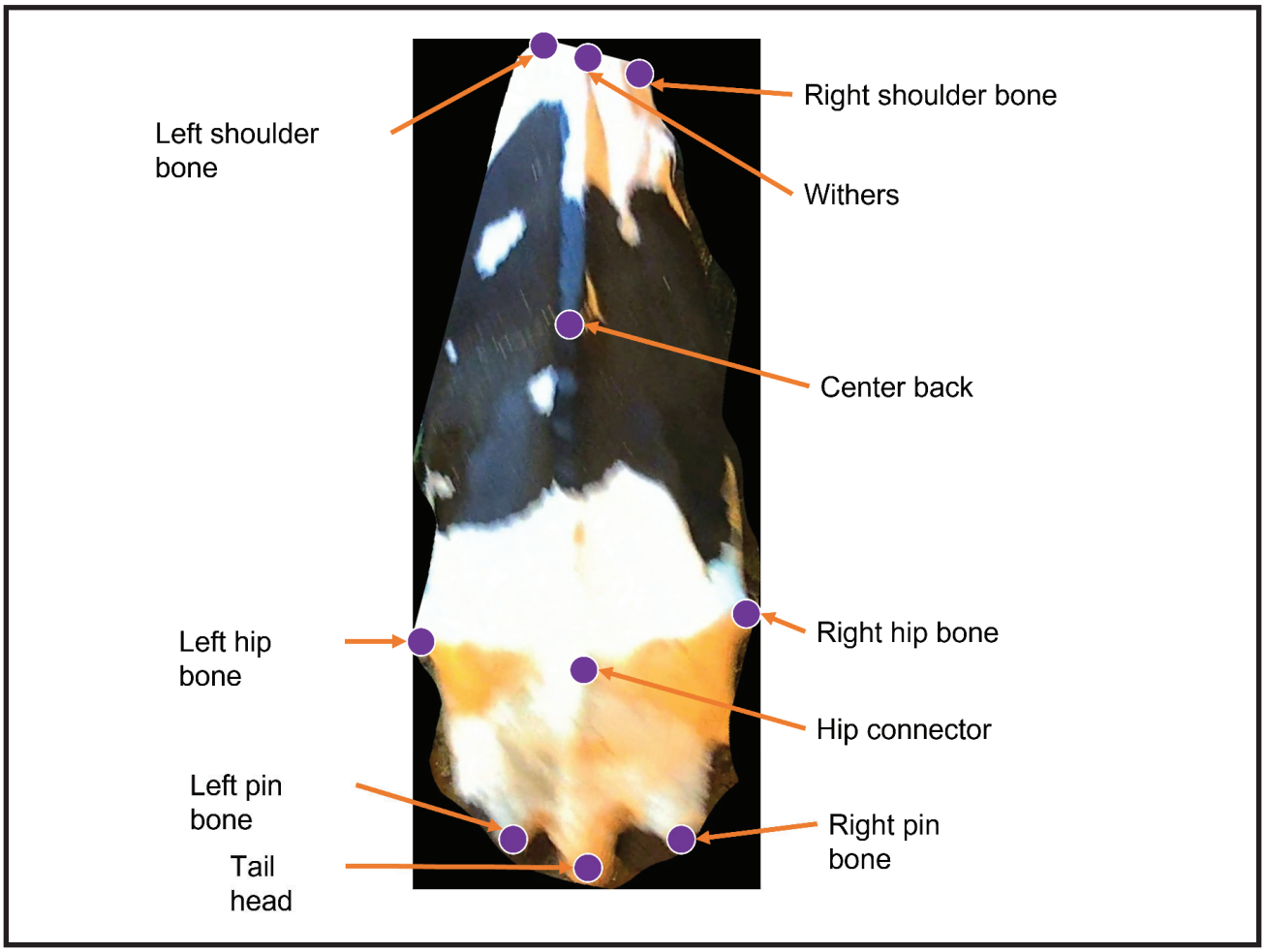

Figure 4. Recognizing a Holstein cow from a top-view image: keypoints. Image from M. Ramesh.

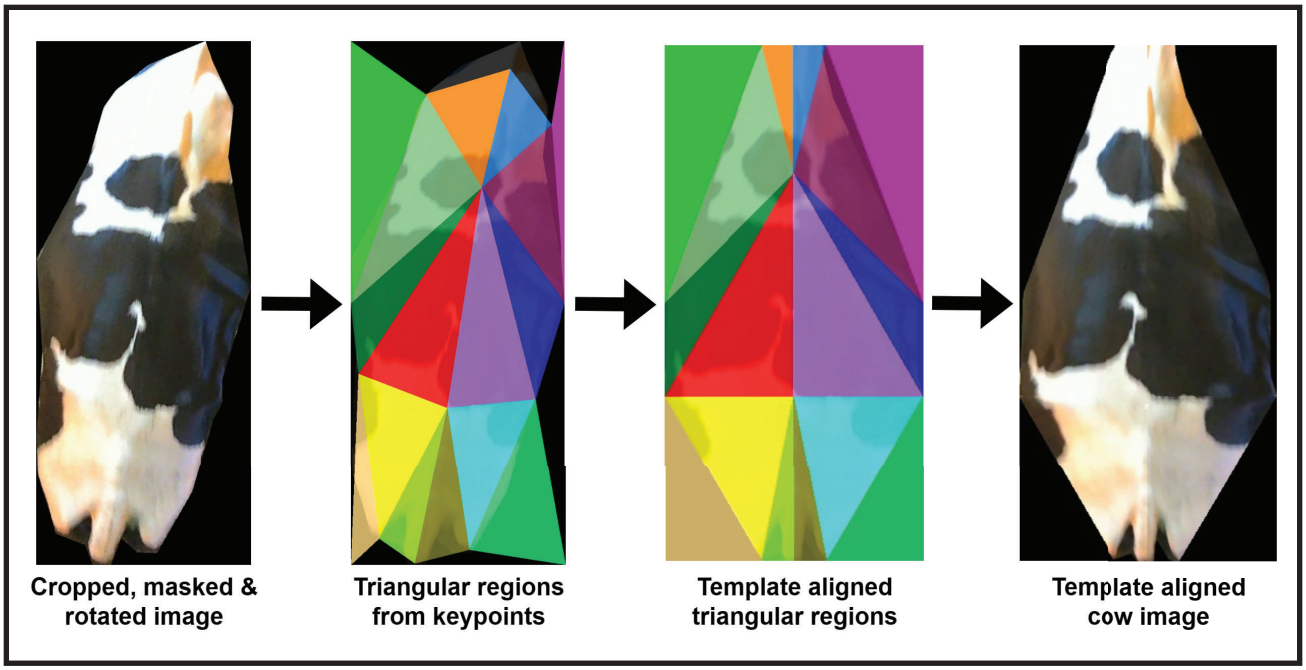

Figure 5. Recognizing a Holstein cow from a top-view image: aligning a cow's keypoints to a template. Image from M. Ramesh.