

Quantifying Residual Feed in a Fence-line Feedlot Bunk using Depth Camera Imaging Techniques

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Summary with Implications

Feed bunk management requires intensive labor and relies on manual observation to estimate the amount of residual feed in the bunk. Alternative and innovative technologies were used to estimate the weight of residual feed in a concrete fence-line bunk using a depth camera. Depth cameras capture the distance between the camera and the object in their field of view. This study used a time-of-flight depth camera (Azure Kinect, Microsoft) to estimate the weight of residual feed in a partial fence-line concrete bunk using 11 common feed ingredients. The depth camera was fastened approximately 3.3 ft above the center of the bunk to collect images for individual ingredients added at a constant weight increment of 2.2 or 4.5 lb. The feed ingredients inside the bunk were stirred randomly after each picture collection to simulate the shape of residual feed after cattle's feeding event. Individual ingredients were then weighed using a scale for comparison with the image-estimated weights. Linear regression showed that the scale-measured weights and image-estimated weights were linearly related, with an R^2 ranging from 0.9833 to 0.9992. Results indicate that depth cameras are capable of accurately estimating the weight of residual feed in the bunk. Overall, this experiment demonstrates a first step in the development of feed bunk management tools using precision livestock management techniques.

Table 1. Eleven commonly used ingredients in Nebraska feedlot mixed diets. The bulk densities of ingredients ranged from 2.56 to 40.2 lb/ft³

Ingredient	Bulk density (lb/ft ³)	Actual weight measurement range (lb)	Weight increment during image collection (lb)
Low bulk density ingredients			
Corn Stalks (CSt) ²	2.55	0.7–20.23	2.2
Wheat Straw (WB) ²	2.62	0.88–20.26	2.2
Grass Hay (GH) ²	4.27	1.96–20.33	2.2
Alfalfa Hay (AH) ²	5.09	0.95–20.15	2.2
Corn Silage (CSi) ¹	14.1	0.77–20.26	2.2
High bulk density ingredients			
Sweet Bran (SB)	23.47	3.4–50.3	4.5
Steam Flaked Corn (SF)	24.64	2.98–52.55	4.5
Dried Distiller's Grains (DDG)	34.54	1.5–50.3	4.5
High Moisture Corn (HMC) ¹	35.33	3.53–50.3	4.5
Modified Distiller's Grains (MDG) ¹	36.06	0.37–50.16	4.5
Dry Rolled Corn (DRC)	40.2	3.99–50.22	4.5

¹ingredient had some mold present while collecting bulk density

²ingredient contained dust while collecting bulk density

Introduction

Precision Livestock Farming (PLF) has the potential to provide solutions to alleviate challenges that the U.S. beef industry is facing by using advanced technology as management tools. For the U.S. cattle industry, there were about 13.4 million head of cattle and calves on feed for slaughter in 2021. These cattle go through feedlots for an intensive feeding period that can range from 90 to 200 days. To maintain appropriate daily intake of the cattle and make prompt decisions on the next-day feed delivery, feedlot managers rely on manual observations of skilled workers as a feed bunk management protocol. This management protocol is prone to error and can cause feed waste that tends to increase the cost of production. The objective of this experiment was to develop image processing algorithms to predict the weight of residual feed in the bunk using depth images.

Procedure

Eleven common feed ingredients were used in this experiment: dried distillers' grains (DDG), alfalfa hay (AH), corn silage (CSi), corn stalks (CSt), dry rolled corn (DRC), high moisture corn (HMC), grass hay (GH), modified distiller's grains (MDG), sweet bran (SB), steam flaked corn (SF), and wheat straw (WS). Table 1 shows each ingredient's bulk density and the measured range of the actual weights during data collection. Bulk densities were measured by weighing a nine-liter sample of each feed ingredient. For each bulk density measurement, the ingredients were carefully added in the bucket to reduce compaction and over-packing of the bucket. The ingredients were divided into two categories based on their bulk densities (low bulk density ingredients and high bulk density ingredients). The low bulk density ingredients ranged from 2.56 to 14.1 lb/

ft³ and were imaged with a 2 lb weight increment, while the high bulk density ingredients ranged from 23.5 to 40.2 lb/ft³ and were imaged with about a 4 lb weight increment (Table 1).

The time-of-flight depth camera was used to measure the distance between the camera and the surface of the ingredients. The depth camera was centrally positioned on top of a fence-line feed bunk facing downwards to capture a two-foot section of the concrete bunk. The camera was positioned at least three feet from the base of the bunk. For each weight level, ten depth images were captured for the residual ingredients. Five depth images with best image quality and pixel consistency, representing different feeding events were selected at each weight level for image processing. An image processing program was developed using the MATLAB data analytic software to estimate the volume of the ingredient using the depth images, and to multiply the estimated volumes to their corresponding measured bulk densities. After the estimated weights were predicted by the image processing program, the image-estimated weights were compared to the scale-measured weights. Linear regression was developed for each ingredient and used to find the R² and the P-value of the relationship between the scale-measured weights and image-estimated weights.

Results

The scale-measured weights were plotted against the image-estimated weights for each ingredient to evaluate the relationship between the two variables, and the results are shown in Fig. 1. The average coefficient of determination (R²) for all ingredients was 0.99. The linear relationship between the scale-measured weights and the image-estimated weights was strong and significant (*P*-value < 0.0001) for all ingredients. Fig. 1 shows that the R² of all the ingredients ranged from 0.9833 for GH to 0.9992 for SF and a *P*-value < 0.0001. The ingredients with lower R² values were GH, DRC, and SB, with a value of 0.9833, 0.9876 and 0.9888, respectively. SF had the highest R² value of 0.9992, followed by HMC and MDG with an R² value (= 0.9984). Other

ingredients like AH, CSi, and WS had a high R² of 0.9972, and DDG and CST had an R² of 0.9963 and 0.9949, respectively. The results from this study show that the depth camera can estimate 99.4% of the residual

feed weight in the fence-line concrete bunk. In future experiments, depth cameras will be used to evaluate the accuracy to quantify the volume and estimate the weight of mixed diets in the bunk.

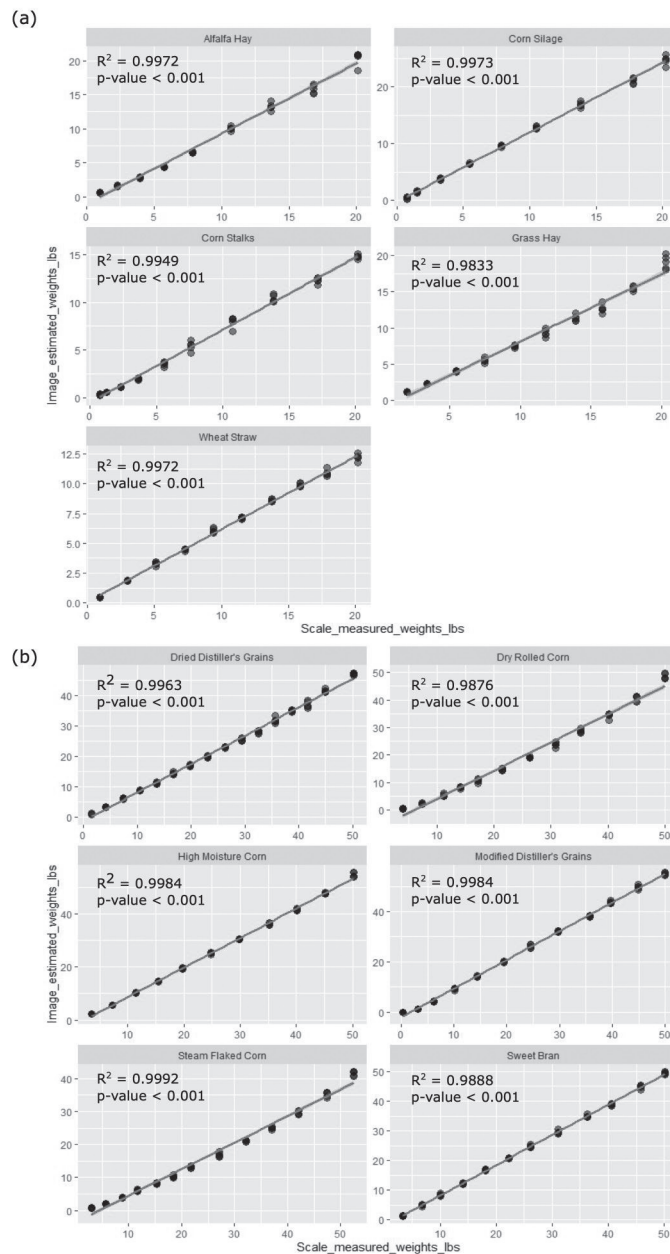


Figure 1. Comparison of the scale-measured weights (X-axis) and the image-estimated weights (Y-axis) of the eleven ingredients. (a) shows the linear relationship for the low bulk density ingredients, and (b) shows the linear relationship for ingredients with high bulk densities. The measured weight range ranged from 0.7 to 20.23 lb for (a) low bulk density ingredients, while the measured weight range for high bulk density ingredients (b) ranged from 1.5 to 50.3 lb. The *P*-value was smaller than 0.0001 for all the ingredients.

Conclusion

This experiment demonstrated that the depth sensing method is a promising tool to estimate the weight of residual feed in a concrete fence-line feedlot bunk. This tool offers an alternative solution to increase the capacity and the production efficiency in commercial feedlots. With this tool, managing a large quantity of feed bunks at once may require less labor and provide accurate

predictions of residual feed in the bunk. For large feedlots, accurate residual feed predictions can reduce the cost of production by allocating feed resources more efficiently and reducing feed spoilage and waste.

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