Real-Time Volume Estimation of a Dragline Payload

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Abstract— **This paper presents a method for measuring the in-bucket payload volume on a dragline excavator for the purpose of estimating the material's bulk density in real-time. Knowledge of the payload's bulk density can provide feedback to mine planning and scheduling to improve blasting and therefore provide a more uniform bulk density across the excavation site. This allows a single optimal bucket size to be used for maximum overburden removal per dig and in turn reduce costs and emissions in dragline operation and maintenance.**

The proposed solution uses a range bearing laser to locate and scan full buckets between the lift and dump stages of the dragline cycle. The bucket is segmented from the scene using cluster analysis, and the pose of the bucket is calculated using the Iterative Closest Point (ICP) algorithm. Payload points are identified using a known model and subsequently converted into a height grid for volume estimation. Results from both scaled and full scale implementations show that this method can achieve an accuracy of above 95%.

I. Introduction

This paper demonstrates the automatic measurement of the bulk density within a dragline bucket on a production dragline. Through the use of a range bearing sensor, a three dimensional model of the bucket and payload is constructed while in motion. The payload is segmented from the bucket to estimate the volume of the material. The density of the payload is then calculated using the weight measured from a third party dragline monitoring package.

Accurate estimates of the bulk density are beneficial to the open cut coal industry as they can provide:

1) a reliable assessment of dig and blast performance,
2) an improved bucket size selection to achieve consistent suspended load targets, and
3) decreased production downtime by reducing probability of bucket overloads and subsequent damage to the dragline.

This paper is primarily concerned with the volume component of the material bulk density as the bucket payload weight is readily available through commercial dragline monitors. Volume estimation of the material in a dragline bucket is difficult as the bucket is not rigidly coupled to the machine as with other excavators. The bucket is attached to free moving ropes and thus the dynamics of the bucket are unknown. Here we use Iterative Closest Point (ICP) [1] to match observed data points on the bucket to a known model and subsequently determine the pose. This pose information, in conjunction with point clustering techniques [2], [3], is used to extract a point cloud representation of the payload. Finally, a height grid is created from the point cloud and used to measure the volume of the payload, which is combined with the weight to provide a density estimate.

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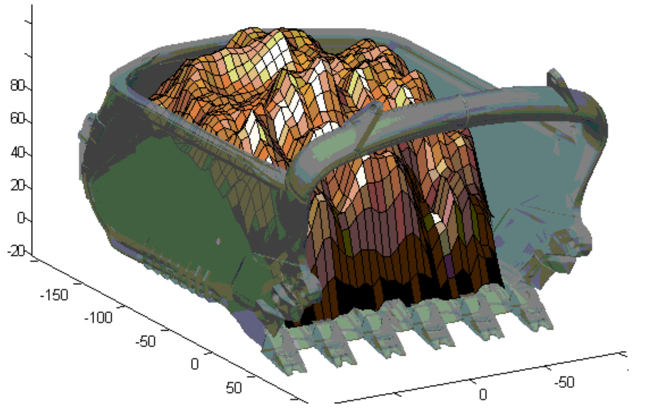

Fig. 1: Processed scaled payload data with superimposed bucket model.

A. Literature Review

Volume estimation of a 3D surface can be efficiently computed using representations such as height grids, voxels, or polygons. In our work, the 3D surface is constructed from a point cloud generated from a laser range finder. Generating an accurate 3D surface from point clouds has been investigated extensively in the computer vision community [4], [5], [6].

Zhang *et al.* generate point clouds from laser measurements and compared two methods to construct the 3D surfaces and subsequently estimate volume [7]. The first method is a Meshed Surface technique that bins collected points into uniformly spaced cells to form a height grid but requires interpolation for sparse data sets. The second method, named Isolated Points, measures volume by setting the area covered by each point to equal the total area scanned divided by the number of points collected. This method suffers from inaccurate estimates due to under-sampling in occluded regions or where reflectivity is low.

In the context of mining, Duff used laser scanners to estimate the volume of the load in a haul truck tray as it passed through a weigh station [8]. In contrast to the ever-changing terrain experienced by a dragline, the environment surrounding the weigh station remains static. In more closely related work, Rowlands *et al.* used a stereo camera to quantify dragline bucket fill volume during the dig phase of a typical dragline cycle [9]. Payload volumes were processed offline as computational resources for stereo vision were not adequate in the late '90s. Unfortunately, the accuracy of Rowland's results are unknown as no ground truth data was collected. Although real-time stereo processing is feasible at present, problems with lighting conditions (especially night operation) still require further study.

1) Identifying Points of Interest: The intial step in generating a 3D surface and subsequent volume estimation is to identify the points of interest in the data and extract them from the surrounding noise. In our case, we want to identify the payload and segment it from the bucket and other external objects such as terrain. We focus on cluster analysis of points and learn a model to classify the clusters.

The large range of existing point cluster techniques can be classified as either partitioning or hierarchical [10]. Partitioning techniques such as the classical k-means [11], [12] typically do not perform well on data containing noise or non-convex cluster shapes as experienced in our work. More recent hierarchical methods such as DBSCAN [2], OPTICS [13], CURE [10] or SNN [3] overcome these drawbacks by simultaneously detecting clusters based on density connectivity and identifying low density points as noise. DBSCAN's ability to distinguish between points of varying density is limited while SNN can identify uniformly low density clusters by analysing the shared nearest neighbours between points. We make use of both the DBSCAN and SNN algorithms.

We use supervised classification of the resultant clusters to identify the bucket data points. Supervised classifiers are numerous and varied [14]. For simplicity we train a Bayes classifier offline from manually labelled clusters and use the learnt model to identify bucket and payload points. Other automatic methods, such as unsupervised Bayesian classification [15] with class mixing could also be used, but are more complicated.

2) Pose Estimation: Once the payload and bucket data points are isolated, a 3D surface can be constructed. However, to compute the volume, the internal surfaces of the bucket which define the lower surfaces of the payload must be determined. Here we match the observed points to a predetermined model of the bucket using pose estimation. As the bucket is dynamic in nature, the problem is exacerbated when compared to [8].

Pose estimation in a dragline context has been investigated by McInnes who devised formulae for measuring the out-of-plane motion of a dragline bucket by sensing the strain at two points on the boom [16]. This coupled with hoist and drag rope length information enabled determination of the four degrees of freedom of the bucket [17]. Ridley and Corke dynamically estimated the pose of a dragline bucket through the use of a kinematic model of the boom and bucket rigging [18].

We take a different approach of matching a model to the observed points, commonly used in the robotics community. This type of approach includes techniques such as least squares fitting [19] and Iterative Closest Point (ICP) [1] allowing the determination of the six degree of freedom transformation between the observed points and the model. The least squares fitting solution proposed by Arun solves the regression problem of finding the rotation and translation through the use of singular value decomposition (SVD) [19].

ICP iteratively matches a set of data points to a set of model points and estimates the transformation between these sets. Only the closest model point to each data point is considered per iteration. The transformation between the data points and the closest model point subset is calculated through a least squares minimisation process [19]. This paper makes use of the ICP algorithm as it does not depend on the number of data or model points, feature matching is not required, and with a good initialisation an accurate pose estimate can be computed within a small number of iterations, enabling real-time performance.

3) Paper Outline: Section II provides a system overview, while section III explains the classification of laser data for bucket identification. Bucket dynamics and shape reconstruction is approximated in Section IV by measuring the horizontal sway and rope lengths as the bucket passes through the scan plane. Methods for evaluating the reconstructed bucket pose are discussed in Section V. Section VI details how the payload is filtered and the volume calculated. Section VII demonstrates the accuracy of the system implemented on both a scaled test bed and a full scale production machine. The findings and future applications are outlined in Section VIII with acknowledgements given in Section IX.

II. System Setup

A typical dragline cycle consists of digging, swinging, dumping and returning. During the dig, the bucket is dragged through the ground filling as it nears the machine. After lifting a full bucket with hoist ropes the machine swings through an arc of generally 120 degrees to dump the load. While doing so it releases the drag rope moving the bucket out under the boom tip where the bucket rigging allows the material to be dumped. Finally the machine swings back for the next dig. The bucket motion is controlled by the operator adjusting hoist and drag rope velocities to move the bucket to the dump zone. Additionally swing accelerations cause the bucket to move in a normal direction to the boom plane.

A Sick LD-MRS laser mounted to a pan tilt unit (PTU) was chosen for imaging the bucket from an access platform located on the boom (Fig. 2). The LD-MRS is an all weather laser which operates in rain and dusty conditions. The laser is set to focused mode where central angles have a finer resolution. This is beneficial in this application as this is typically where the bucket is located. During the swing, the payload surface of the loaded bucket is sampled by the laser with the resulting point cloud used to compute the payload volume. The laser is orientated to scan across the width of the bucket allowing the magnitude of the sway to be observed.

III. Bucket Identification

The laser constantly samples the environment with or without the bucket present. Identifying the bucket in the scan data is not a trivial task as the terrain is constantly changing and the bucket position differs each cycle. Bucket

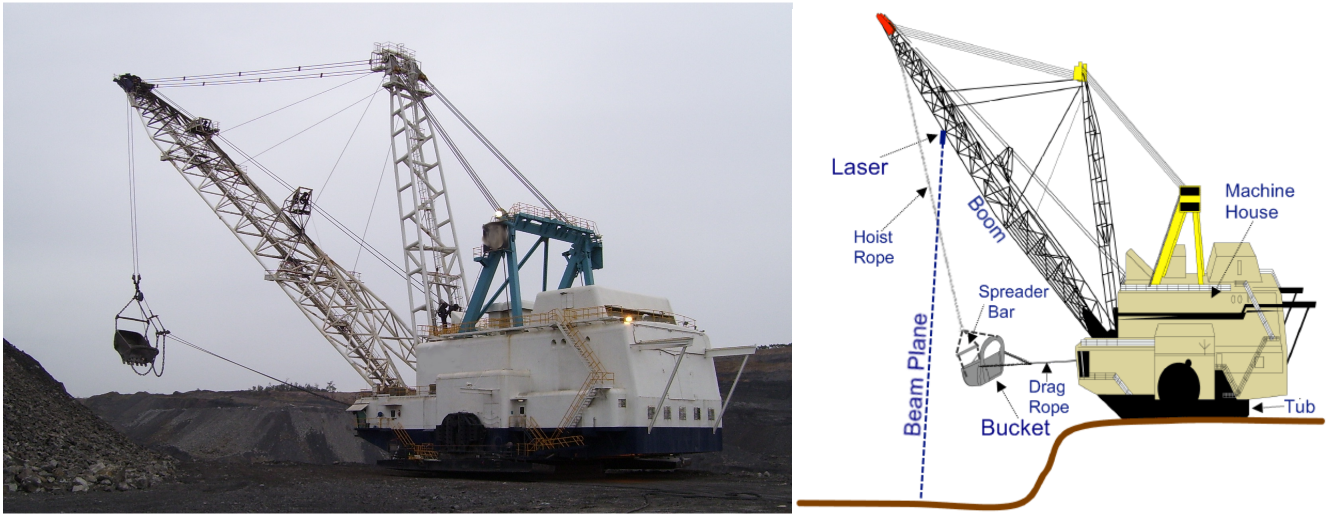

Fig. 2: System Overview. Left: Photo of BE1370 returning from dump position. Right: Illustration of dragline detailing major components of the system. The laser samples the bucket as the drag rope is released during the swing phase.

identification is critical in isolating the relevant data from background noise such as points from the terrain. To identify points associated with the bucket, we firstly group points from a single scanline into clusters and then assign labels to each cluster.

A. Clustering

In our work clustering is performed on each individual 2D scanline and to filter bucket points from payload points. We use SNN [3] for the former and DBSCAN [2] for the latter. Advantages of these schemes include the ability to segment non convex shapes, identify noise, and automatically estimate the number of partitions in a data set. We describe these two algorithms in more detail in the following paragraphs.

Both algorithms recursively group points into clusters dependent on neighbourhood density. In DBSCAN the neighbourhood is defined as the set of points within a Euclidean volume with radius ε, while density is the number of points within this fixed volume. SNN defines a neighbourhood as a set of k nearest neighbours (kNN) to a given point, while SNN density is the number of links in this neighbourhood. SNN links are made from a point p to any point q in its kNN such that p is a member of q kNN [3].

SNN and DBSCAN clusters are constructed based on density reachability and density connectivity, where density is defined by two parameters: the radius of a point's neighbourhood ε (or k for SNN), and the minimum threshold of the number of points in the ε neighbourhood *minPts* [2].

Points p and q are density connected if there is a point o, such that p and q are both density reachable from o. Points with at least *minPts* in their ε neighbourhood are considered to be core-points while border-points are points neighbouring core-points with less than *minPts* neighbours. Noise points can be identified as points without any core points in their ε neighbourhood [2].

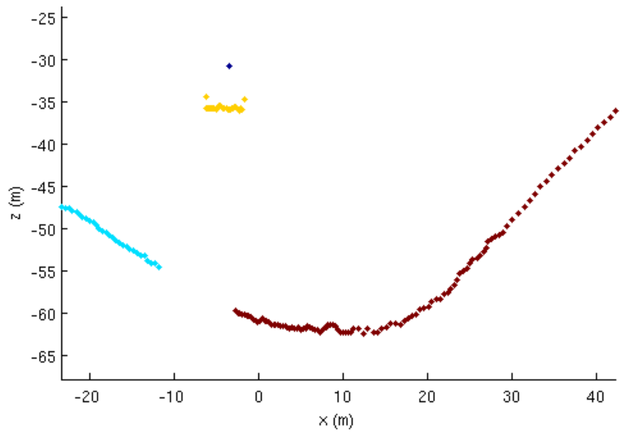

Fig. 3: Scanline points clustered using SNN. Yellow indicates bucket points while blue and brown indicate terrain points. Additionally this scan shows that simple thresholding methods cannot segment the bucket based on height alone.

SNN outperforms DBSCAN for clustering data with varying Euclidian density as experienced in the scanline shown in Fig. 3. DBSCAN is later used to filter the payload by removing outliers further than a fixed Euclidean distance from the main payload cluster.

B. Bucket Classification

Once the scan data has been grouped into clusters, the next step is to assign labels to these unclassified clusters. Fig. 3 shows that the relative position of the terrain can potentially be higher then the typical bucket position causing thresholding methods to fail.

As such, classification of the clusters was performed using a Bayes method. A training set of over 1000 clusters was used to learn a multivariate Gaussian Mixture Model (GMM). These clusters were manually labelled bucket, ter-

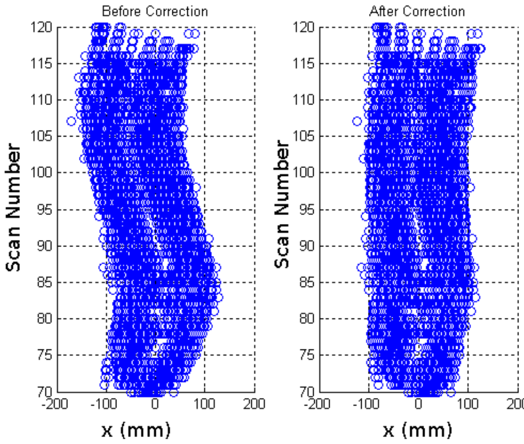

Fig. 4: Top view of bucket point cloud before (left) and after (right) sway correction is applied. A single scanline consists of points along the x axis.

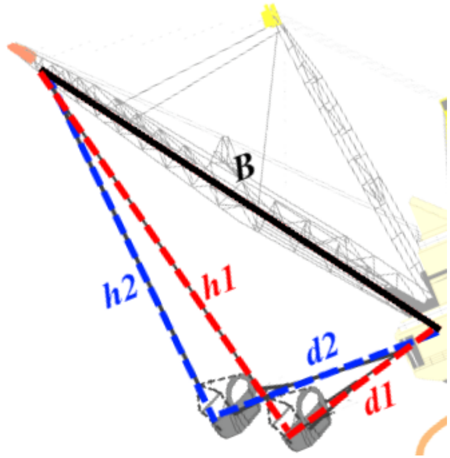

Fig. 5: Bucket position estimated from rope lengths provided by a third party dragline monitor.

rain or noise. The multidimensional feature vector for each cluster consisted of the three dimensions of each cluster's bounding box (height, width and depth), the cluster's position relative to the sensor, and the number of points in the cluster. Once the model parameters were learnt, clusters were automatically assigned a label using maximum likelihood.

IV. Bucket Reconstruction

After identifying which clusters in each of the 2D scanlines corresponded to the bucket, these clusters needed to be reconstructed to produce a 3D surface. This was not a trivial task, as the dynamics of the bucket passing through the laser scan plane were significant. The reconstruction process needed to compensate for lateral movements (sway), as well as changes in velocity (in the hoist and drag rope directions) between scanlines. Bucket rotation (twist) was considered negligible in typical dragline operation.

A. Sway Correction

Large angular accelerations during the swing phase cause the bucket to act like a pendulum and sway out of the boom plane. As the laser scan plane is orthogonal to the boom plane, the bucket sway can be directly measured in the scan (Fig. 4 left). This sway was measured using the mean horizontal coordinate of each scanline. As outliers in these coordinates can adversely affect the alignment, polynomial regression was used for smoothing. The smoothed mean coordinates were subsequently used to translate the scanlines, thus correcting for sway (Fig. 4 right).

B. Velocity Correction

Changes in the velocities of the hoist and drag ropes result in differences in spacing between each scanline. For example, a slow velocity will result in concentrated scanlines while faster velocities will result in well separated scanlines. Thus, it is essential to estimate the magnitude of the inter-scanline spacing to accurately reconstruct the bucket and payload in 3D from the scanline data. The bucket position was approximated using the hoist and drag rope lengths to form a triangle with the boom (Fig. 5). For every scanline, rope length data is collected from a third party dragline monitor, and used to estimate the relative bucket position in each scan. This calculated position yields the third dimension of each scanline, completing the 3D reconstruction process.

V. Bucket Pose Estimation

Once the bucket has been segmented from the background and the 3D surface has been recovered, the next step is to evaluate the bucket pose relative to a reference model. Knowledge of the bucket pose is vital as the reference model aids in defining the inner surfaces of the bucket and therefore the boundaries of the payload.

We used ICP to estimate the pose of the scanned bucket relative to a known model (Fig. 6). Points potentially occluded by payload material are excluded from the model point set. As with most iterative methods ICP required a good initial transformation to ensure convergence to the global minimum. A translation equal to the difference in means between the model and data point sets was adequate for this purpose.

VI. Volume Estimation

Once the bucket is reconstructed and we know the pose, we can compute the payload volume by removing the non-payload bucket data points and differencing the known reference bucket profile with the measured profile.

A. Payload Filtering

Knowledge of the bucket structure with pose information allows for the direct removal of non-payload features such as the arch, rim, and spreader bar. Once these features are removed the remaining point cloud consists of a dense cluster of payload points with a few outliers introduced from dust. These outliers were removed using DBSCAN to identify low density noise. DBSCAN parameters were set to match the expected point density of the bucket surface. The resulting

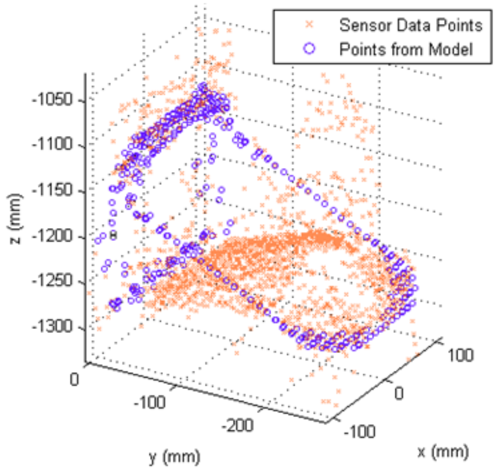

Fig. 6: Result of ICP model fitting to the scaled reconstructed data points.

point cloud is a smooth continuous surface with all outliers removed.

B. Volume Representation

Once the payload points are segmented, they need to be represented in a form that readily allows volume computation. There are several representations capable of efficiently measuring volume such as height grids, voxels, and polygons formed from Delaunay triangulation. Due to simplicity, we use height grids which are are constructed by binning points into cells of fixed size based on their x, y values and assigning the cell height to the average z value. The volume of each cell is basically the cell height multiplied by the cell area.

VII. Results

Due to the high cost of a dragline's production time initial trials were carried out using a 1:20 scaled dragline. After viewing the results of the pilot study, Anglo Coal granted 90 minutes of production time (typical cost \$300/minute) for data acquisition on a BE1370 at Drayton Mine. This allowed a ground truth dataset to be acquired by performing high resolution sweep scans over static loaded buckets.

A. Pilot Study

The scale dragline test facility was used to conduct initial algorithm testing. The scale facility allowed various initial experiments to be performed without impacting production on an actual dragline. Data was logged from a series of realistic experiments with empty and loaded buckets imparted with typical motion experienced in a mine setting.

A range bearing laser was setup on the scaled dragline midway along the boom while the orientation of the sensor was selected from analysing actual dragline data. The scanning parameters of the laser were set to simulate the same sampling resolution on the full scale system. The laser data was post processed using the algorithms described in this paper, implemented and visualised with Matlab. The results of the scaled system trials are summarised in Table I and illustrate a volume estimate with an accuracy of greater than 95%.

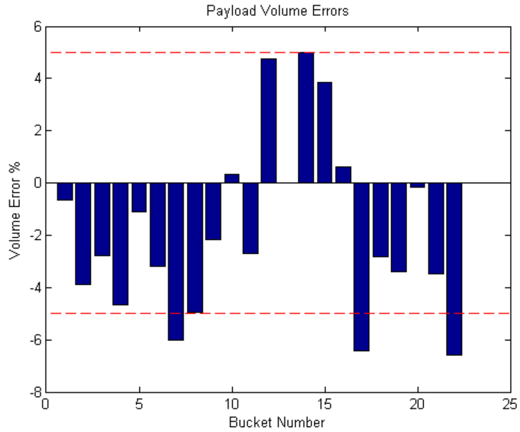

Fig. 7: Volume errors for each production bucket payload with 5% target as the red dashed line. Error is measured as percentage difference from ground truth payload volume.

TABLE I: Results from both scaled and full scale trials

	Scaled Trial	*Full Scaled Trial*
RMS Error	4.9%	3.7%
Mean Error	0.5%	-1.8%
Standard Deviation	4.9%	3.3%
Sample Size	40	22

B. Full Scale Trial

The algorithms used in the pilot study were re-implemented in C++ to achieve real-time performance on a full scale production machine. Using this full scale implementation, a ground truth dataset was collected to verify the accuracy of the system. Additionally, a larger, operational dataset was collected.

1) Ground Truth Data Collection: To measure the accuracy of the system we collected ground truth data by performing high resolution sweep scans over a stationary bucket. A dynamic scan as explained in previous sections was then performed and compared to the high resolution ground truth scan. On completion of each dig, the operator rested the bucket on the pad in a position directly under the laser sweep plane. Four high resolution sweeps, each producing over 6000 samples on the bucket surface were collected. This is approximately ten times the number of samples collected using a dynamic scan during normal operation of the dragline. The speed and resolution of the sweep scans were set to achieve an accuracy of above 99% for an individual sweep. The duration of each sweep was approximately 45 seconds.

Validation of this ground truth was carried out on a static empty bucket. This method resulted in an estimation within 0.56% of the rated bucket capacity.

The results of individual buckets are illustrated in Fig. 7, while Table I shows an RMS error of 3.7% and a negative

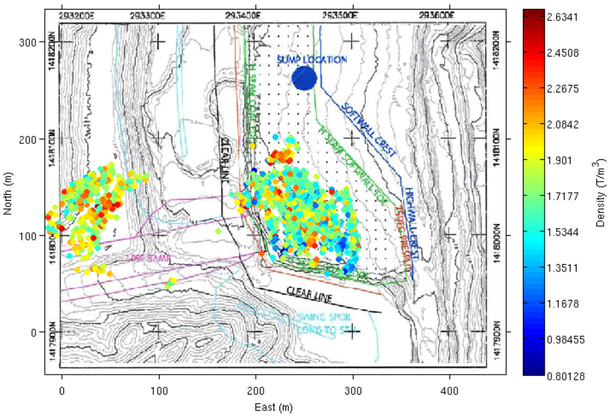

Fig. 8: Scatter plot of bulk densities overlaid on dig design map. Point color indicates the bulk density measured at a particular geographic location.

mean error of -1.8% for the entire trial. This is in very good agreement with the scaled system and also illustrates the validity and reliability of the methods presented in this paper.

2) Operational Data Collection: Having confirmed the accuracy of the volume estimates, we used data from multiple shifts to compute the bulk density of over 1600 buckets, as a preliminary demonstration of how the system could be used on a mine site. The bulk densities were mapped back to their original dig positions using a combination of GPS and encoder information from the dragline monitor (Fig. 8). There are two main dig sites apparent from the data with variance in the density between them. The mine staff noted that one of these areas consisted of re-handled material, accounting for the difference. This information can be used by the mine site to aid in future blast design and in bucket selection for specific dig sites.

VIII. Conclusions and Future Work

The results show that our system can accurately measure the in-bucket payload volume with a mean accuracy above 95%. This full scale data also reflects on the quality of the scale system with 95% performance achieved in the initial pilot studies.

We wish to extend this work to be used as a tool for understanding bulk density variation in blasts and to aid in bucket choice for draglines. A relationship between in-bucket bulk density and that of the terrain is required to achieve this. Future research will focus on investigating this relationship.

IX. Acknowledgments

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