Quantitative Evaluation of Coarse-to-Fine Loading Strategies for Material Rehandling

Martin Magnusson, Tomasz Kucner and Achim J. Lilienthal

Abstract—Autonomous handling of piled materials is an emerging topic in automation science and engineering. A central question for material rehandling tasks (transporting materials that have been assembled in piles) is “where to dig, in order to optimise performance”? In particular, we are interested in the application of autonomous wheel loaders to handle piles of gravel. Still, the methodology proposed in this paper relates to granular materials in other applications too. Although initial work on suggesting strategies for where to dig has been done by a few other groups, there has been a lack of structured evaluation of the usefulness of the proposed strategies. In an attempt to further the field, we present a quantitative evaluation of loading strategies; both coarse ones, aiming to maintain a good pile shape over long-term operation; and refined ones, aiming to detect the locally best attack pose for acquiring a good fill grade in the bucket. Using real-world data from a semi-automated test platform, we present an assessment of how previously proposed pile shape measures can be mapped to the amount of material in the bucket after loading. We also present experimental data for long-term strategies, using simulations based on real-world 3D scan data from a production site.

I. INTRODUCTION

Material rehandling is a common task for wheel loaders; in mining and construction applications, earthmoving, etc. The task is to repeatedly load the bucket of the vehicle with material from piles and transport it to somewhere else.

One example of such an application is depicted in Fig. 1, which shows an asphalt production site. The task of the wheel loader (Fig. 2) is to transport gravel of different granularities from the piles and load it into specific bins (hoppers), feeding into the asphalt production plant.

It is not always evident at which pose it is best to attack a pile in order to ensure high productivity. It may not be sufficient to adopt a greedy strategy, and only attack the pile at the pose where it is expected to get the most volume in the bucket, because such a strategy may, after a number of digs, result in a pile where it is difficult to find a good pose at which to dig. In other words, it may be beneficial to also adopt a global strategy, aiming to maintain a good pile shape over time. In our implementation, these two strategies are governed by a coarse planner (responsible for the global strategy) and a refined planner, which selects an actual attack pose, given a dig region specified by the coarse planner. This implementation follows the ideas first presented by Singh and Cannon [13].

The main contributions of the present paper is a quantitative and qualitative evaluation of such strategies, including to what extent the heuristic pile-shape measures that are typically used actually can be used to predict good fill grades. We also propose a methodology for evaluating pile handling strategies, and we encourage others to use this methodology for developing and testing other strategies for autonomous material rehandling.

The authors are with the Centre for Applied Autonomous Sensor Systems (AASS), Örebro University, Sweden. E-mail: martin.magnusson@oru.se, tomasz.kucner@oru.se, achim.lilienthal@oru.se.

This work was funded in part by the Knowledge Foundation under contract number 20110214 (ALLO).

II. RELATED WORK

When it comes to the refined planner, which locally selects an attack pose for filling the bucket, several options have been proposed in the literature. All methods have three heuristic criteria in common. One such criterion is that the wheel loader’s bucket should enter the pile flat on the ground. If not, it is more difficult to fill the bucket completely, and it will be more difficult to maintain a good pile profile. The pile should also be attacked at a slightly convex point, so that more of the pile volume is in the middle of the bucket than at the edges. Another criterion is to attack the pile so as to prevent an asymmetric load (sideloading the bucket). Using these criteria, the search space for finding an optimal attack pose is one-dimensional: a point along the 2D edge profile of the pile. However, the profile of the pile may be different higher up than
at the bottom edge, and a perpendicular attack pose at a convex point at the pile’s bottom edge may still lead to an uneven load. Therefore, it is not enough to evaluate the pile’s shape using only the 2D edge profile, but a complete 3D model of the pile should be used.

Sarata et al. have published a number of papers describing the development of an automated wheel loader [10, 12, 11, 5]. In their work, the pile is modelled as a set of columns, where each column stores the mean height of the points within the column — in other words, an elevation map. Their selection of attack poses is performed using a model of the moments acting on the bucket, computed from the column model. For each column i inside the trajectory that is followed by the bucket when it has entered the pile, the moment is computed from the height $h_i$ of the column and the lateral distance $w_i$ to the bucket’s centre. The selected pose is the one that minimises $A' = \sum h_i w_i$. In our implementation, the columns are clipped (using Sutherland-Hodgman polygon clipping) so as to include only the part of each column that falls inside the bucket trajectory, as opposed to using discrete columns. In other words,

$$A = \sum v_i w_i,$$

with $v_i$ denoting the partial volume of column i that is inside the bucket trajectory. Strictly speaking, the physical unit of $A$ is m$^2$, which is used in lieu of Nm (the height of the column is assumed to be proportional to the force it exerts on the bucket).

Singh and Cannon [13] use a 2D bucket model split in two, and examine the area that falls into each half in order to judge the convexity and sideload at each attack pose. We have previously shown [6] that this two-part bucket model is inadequate for real-world 3D pile scans. An extension of their approach is to use a three-part bucket instead. Specifically, let $V_c$ be the volume inside the centre third of the bucket and $V'_l$ and $V'_r$ the left and right thirds. The convexity can then be modelled as

$$C_C = \frac{V_c}{\max(V'_l, V'_r)}.$$  

Convex areas have $C_C > 1$ and concave areas have $C_C < 1$. The three-part sideload is measured as

$$C_S = \frac{|V'_l - V'_r|}{V'_l + V'_r}.$$  

Another approach is to fit a quadric surface to a bucket-sized region of the pile, and assess the convexity and sideload from the surface parameters [6].

$$z = ax^2 + bxy + cy^2 + dx + ey$$

The quantities used for evaluating attack poses are taken from (4), with convexity and sideload

$$D_C = -a,$$

$$D_S = |d|.$$  

In our previous work [6], we evaluated the consistency of the above pile-shape measures. A good shape measure should give consistent values independently of the viewpoint at which the pile is observed or the sensor configuration. We found the quadric method ($D_C$ and $D_S$) to be least sensitive to differences in viewpoint and scan configuration. However, the question of how useful the measures are is the topic of the present paper. That is, which measures are useful for predicting the poses where we can expect to fill the bucket well?

The above measures are tools to find out “where to dig”. The next question is “how to dig”; or, in other words, developing a bucket-fill controller that will actuate the bucket at the given attack pose so as to fill it. This is an important question in its own right, although we don’t study it in depth in this paper. We use an automated bucket-fill controller that is implemented on our test platform (shown in Fig. 2), which is based on the work of Almqvist [1].

III. PILE-SHAPE MEASURES

A. Evaluation methodology for shape measures

The following strategy was implemented in order to assess the relevance of the pile shape measures. We have collected data at the site depicted in Fig. 1.

When approaching a pile (at around 20 m distance from the pile), we acquire a 3D scan using an actuated Sick lidar. This scan, which we call the “request scan,” is later used to extract pile-shape measures.

The attack pose is selected to be the point on the pile edge that is located straight in front of the loader, and the loader is set to drive straight towards this attack pose. The pile and its bottom edge is segmented as described in our earlier work [6]. Because of inaccuracies in odometry and control, it might not end up exactly at the selected attack pose, but the actual attack pose is found as described later in this section.

When reaching the attack pose, the loader proceeds to execute an automated bucket-fill manoeuvre [1].

At the same time, the lidar is tilted downwards to scan the bucket of the wheel loader. After the bucket has been filled, the loader is stopped and a scan of the bucket is acquired. Using this 3D scan, we compute an estimate of the volume of gravel inside the bucket (see Fig. 3).

The real attack pose is estimated as follows. The lidar is continuously scanning while driving towards the pile. Because of the slow update rate of the 3D scanner (around 1 Hz) compared to the driving speed (around 3 m/s), the scans will be distorted. They are corrected using a per-scan graph-based SLAM approach [2]. The last scan before the loader’s bucket enters the pile is registered to the request scan using 3D-NDT registration [7, 8], in order to compensate for odometry drift. The actual attack pose is estimated by computing the intersection between the pile edge and a line drawn from the loader’s centre position (at the time of this scan) in the direction of the bucket tip.
The pile-shape measures are computed at the attack pose computed as described above, using the request scan. We compare the following measures: quadric convexity $D_C$ and sideload $D_S$, three-part convexity $C_C$ and sideload $C_S$, and moment $A$. The notation is consistent with Magnusson and Almqvist [6], and further details about the properties of the individual measures can also be found in that publication.

B. Results

Fig. 4 shows the volume in the bucket as a function of the individual pile-shape measures. These plots are the results of 23 dig points where the loader succeeded in filling the bucket to some extent. More data points would be required to make more certain claims about the relationships between shape measures and fill outcome, but these data can be used as an indication. The plots shown in Fig. 4 were computed using Gaussian process (GP) regression.

The nominal bucket volume is 3.4 m$^3$. Please note that it is possible to fill the bucket with more than the nominal volume, as the material (after a good fill) typically rises up slightly above the bucket’s top edge. The measured volumes in these 23 data points range between 2.3 m$^3$ and 3.7 m$^3$.

It would appear that currently unmodelled factors also play an important role here. These include the execution of the bucket-fill controller, but also properties of the material which can vary from day to day. For example, wet materials behave differently than dry ones, and when the pile has been untouched for a longer period of time, it settles and becomes harder, which also affects the performance of the bucket-fill controller.

Keeping these sources of uncertainty in mind, the results shown in Fig. 4 indicate that the moment and sideload measures proposed in the literature ($A$, $C_S$, $D_S$) have little relevance to the dig result, but that convexity ($C_C$, $D_C$) is a better indicator.

Both sideload measures $D_S$ and $C_S$ are very scattered. Although (in our data) they don’t help much in assessing the final bucket volume, they do correspond to the sideload in the bucket. In production, one does not only want to maximise the volume in the bucket, but also have an even distribution in order to minimise the risk of spilling material when transporting it to the dump point. Therefore, we use both convexity and sideload for the refined strategy in our subsequent tests.

Performing GP regression with a Gaussian ARD (automatic relevance detection) covariance function [9], we get the following characteristic length scales:

- $D_C$: 0.34
- $D_S$: 0.34
- $C_C$: 1.47
- $C_S$: 0.69
- $A$: 9.41

The characteristic length scales of the ARD covariance function indicate the relevance of each parameter. As described by Rasmussen and Williams [9], when the value of the length scale is large, the covariance will become less dependent of that input, decreasing its influence on the result. In other words, the smaller the length scale, the more relevant the parameter.

We note that the length scales for the quadric method (sideload and convexity $D_S$ and $D_C$) are significantly smaller than the corresponding measures for the three-part method ($C_A$), which motivates our choice of using a combination of $D_S$ and $D_C$ for the refined planner in the subsequent tests (Section IV).
The length scale for the moment measure $A$ is very large. This finding is in line with our previous results [6], which showed that $A$ had large spreads for the same point in a pile, depending on the viewing range and direction.

Judging from Fig 4d, a good quadric convexity measure should be where the predicted mean is highest, which is at $D_C \approx -0.1$. As our refined planner, given a set of candidate attack poses $a_i$, we first remove poses where $D_C > 0.05$ and then select the one that minimises $\arg \min_a |D_S|$.

IV. COARSE LOADING STRATEGIES

This section describes our implementation of a course-to-fine loading strategy, and quantitative evaluations of the effect of using a global, coarse, strategy compared to only using a local, greedy, planner.

A. Implementation

We have adapted the coarse planning strategy proposed in Singh and Cannon [13], which is concerned with hillside backhoe excavators and short-cycle operation of wheel loaders, to a material rehandling scenario. The general idea is still to work the “front face” of the pile in a sequential fashion: moving in order from left to right. An outline of the algorithm is provided below.

1) Preprocessing: Before the coarse planner can run, we need to provide 3D models of the piles in the environment, which can be extracted from a 3D map of the site.

As a starting point, we create such a 3D map by collecting and fusing 3D scans from a lidar (either an actuated Sick LMS211, as in Fig. 1b, or a Velodyne HDL-64E, as in Fig. 8). The scans are registered to a consistent map using 3D-NDT registration [7, 14, 8] from the open-source perception_oru1 ROS packages.

Using this map, piles are segmented based on local surface slope and roughness [6] (see example output in Fig. 1b). Spurious false positives can easily be removed by setting a threshold on the minimum size of a pile. Please note that the output shown in Fig. 1b contains no false negatives (missed piles) and few false positives (non-pile areas detected as piles).

Each pile can then be given as input to a coarse-to-fine planner.

2) Sequential Planner: Given a 3D pile model, first identify a set of bottom-edge and top-edge points from the pile. If the point cloud has been triangulated, the bottom points can be selected as all boundary points that are within a small distance of the ground plane, and the top points are the remaining boundary points. Forgoing triangulation, bottom and top points can be selected based on the height of points in a local neighbourhood. Let $z$ be the height of a point $p$, $z_m$ the mean height of the $n$ points closest to $p$, $z_b$ the minimum height of the neighbouring points within some radius $r$, and $z_t$ the maximum height in the neighbourhood. Furthermore, let $z_1$ and $z_2$ be the max and min height of all the points in the pile. Assume (without loss of generality) that the ground plane is at height 0. Using two thresholds $t_z$ and $t_g$ that are selected based on the average point density ($t_z = 0.75$ and $t_g = 0.5$ has worked well in our experience), bottom points can be selected using the criterion $z < z_m - t_z(z_m - z_b)$ and $z < t_g(z_t - z_b)$. Similarly, top points can be selected using the criterion $z > z_m - t_z(z_t - z_m)$ and $z > t_g(z_t - z_b)$.

In the next step, the bottom points are ordered radially around the pile’s centroid.

Then, we iterate over the sorted points, finding the pair of points with the largest distance. We assume that this largest gap is the rear edge of the pile. Typically, this gap between bottom points stems from the ramp on which construction vehicles drive up on the pile when adding new material to it. If such a ramp does not exist, the distinction between front and back edge may not be relevant, and the largest gap may be at an arbitrary position along the pile’s bottom edge. In any case, we refer to the line connecting the point pair with the largest distance as the pile’s rear edge.

The direction towards the front face of the pile is given from the vector that goes from the centre of the rear edge through the pile’s centroid.

The “working edge” of the pile, then, consists of all bottom points that are in front of the front-most top point. The output of the coarse planner is a sequence of regions, ordered radially around the pile centroid. Each region is placed one bucket width (2.7 m for our vehicle) to the right of the previous one. The centre points of these regions are marked with red in Fig. 5a. Output from the motion planner used in our system [3] is shown in Fig. 5b, although the present evaluation is not dependent on any specific motion planner.

Given dig regions determined by the coarse planner, the refined planner then selects the bottom point inside the region that has the “best” pile-shape parameters. For the experiments shown in Fig. 6 and 7, the refined planner selects the point with the smallest $D_S$ value, where also $D_C < 0.05$.

B. Evaluation methodology for coarse-to-fine planning

While the shape measures have been evaluated using real-world dig data (in Section III), the long-term effects of the coarse-to-fine strategy has been evaluated in simulation. One reason for this is that the simulation allows us to evaluate the results of the strategy without considering noise that would enter the data in real-world tests, since there is no guarantee that the wheel loader always attacks the pile at the exact pose that is selected by the coarse-to-fine planner. Another factor is, of course, that long-term tests would be labour intensive. At the time of this paper’s submission, the integration of autonomous planning and control is not complete, and running long-term tests on the test site also requires scheduling the trials in coordination with the commercial production on the site.

For these reasons, we have evaluated the long-term coarse-to-fine strategy in simulation. The simulation uses 3D maps reconstructed from real-world data, just as the finished system would, but the pile shape after removing material is simulated.

The gravel simulator implemented for this evaluation is similar to the ones used by Sarata [10] and Halbach and Halme [4], with the main difference that we work with triangle meshes instead of

1http://wiki.ros.org/perception_oru
column models. At the selected attack pose, removal of gravel is simulated by sweeping the bucket volume through a J-curve similar to the one targeted by the real bucket-fill controller [1]. The material inside this sweep is removed from the pile, by moving the corresponding vertices to the bottom of the swept volume. After this step, the flow of material is simulated as follows. We iterate through all vertices in the pile model. As the model has been triangulated, each vertex is connected to a number of neighboring vertices. For edges where the vertical incline is steeper than the material’s angle of repose, we decrease the height of the topmost vertex and increase the height of the bottom vertex, thus transferring a quantum of volume. This process is iterated until no more volume can be transferred. The output of the gravel simulation can be seen in Fig. 6 and Fig. 7.

C. Results

The outcome of running the coarse-to-fine planner over a long time (50 buckets removed, corresponding to between 50 and 200 minutes of continuous operation, depending on the task) can be assessed both qualitatively and quantitatively.

Figs. 6a and 7a show the segmented piles, before simulation. Figs. 6c and 7c show the pile shape after 50 buckets, using the coarse-to-fine strategy. Comparing these figures with Figs. 6b and 7b, we can see that the sequential strategy maintains a smooth, convex, pile shape; while the strategy that only fulfills the heuristics on sideload and convexity results in a couple of hollows along the pile edge (most pronounced in Fig. 6b).

A quantitative goodness measure of the overall pile shape is the percentage of good points along the edge. When fewer points fulfill the convexity and sideload criteria, the motion planner may need to generate unnecessarily long paths in order to get to a spot where the bucket can be filled well. Both lower fill rates and longer paths for driving decrease productivity. Looking at the plots in Figs. 6 and 7, it is clear that the coarse-to-fine strategy maintains a large number of good pile points: between 80% and 90% over the course of the 50 bucket fills. The greedy (refined) planner, without the aid of the coarse planner, rather quickly drops down to about 60% points that fulfill the criteria.

V. DISCUSSION

The present paper is, to our knowledge, the first attempt at performing a structured evaluation of methods for selecting dig poses for loading piled materials. Although we have collected dig data over time, with several trips to a production site, more dig data should be collected to make a significant assessment of the pile-shape measures used in refined planners. The actual data collection has proven to be more challenging than one might think, because it depends on the availability of the wheel loader test platform and permission to use the production site (without disturbing their normal operation).

Another issue that may affect the result is that we have few data points from digs with extreme sideloads and concavities. The reason is that the bucket fill controller on several occasions failed to fill the bucket at all when approaching the pile at very oblique angles. Instead of adding these attempts as data points with zero volume, we have omitted them from the evaluation.

The coarse-to-fine strategy proposed in this paper could be used both for an autonomous wheel loader, or as operator assistance; for example, by overlaying an arrow at the next planned attack pose on a camera image.

Comparing 3D maps of the site in spring (before the start of the asphalt season) and winter (at the end of the season) gives...
and testing strategies for autonomous material rehandling. Methodology to be used for evaluating material rehandling strategies, in order to make stronger claims. Needed also for the evaluation of the pile-shape measures used in real-world data, rather than using gravel simulation. More data is needed also for evaluating the complete coarse-to-fine strategies on work should also evaluate the complete coarse-to-fine strategies on real-world data, rather than using gravel simulation. More data is needed also for the evaluation of the pile-shape measures used in refined strategies, in order to make stronger claims.

In addition to the above evaluations, we have proposed a test methodology to be used for evaluating material rehandling strategies. We encourage others to use this methodology for developing and testing strategies for autonomous material rehandling.

VI. SUMMARY AND FUTURE WORK

We have presented a comparative evaluation of shape measures that have been used to select attack poses for loading piled materials with a wheel loader, using data from an automated wheel loader test platform. Our results indicate that a convexity measure from a quadric surface fit can be a useful indicator for selecting an attack pose which will result in a good bucket fill.

We have also presented an implementation of a sequential coarse-to-fine strategy, and evaluated the performance for long-term pile handling, in simulation. Our results clearly indicate that using a coarse-to-fine strategy is useful for maintaining a smooth pile shape over time, compared to using a local (greedy) strategy alone.

This paper is the first attempt of performing a methodical performance evaluation of strategies for material handling. Future work should also evaluate the complete coarse-to-fine strategies on real-world data, rather than using gravel simulation. More data is needed also for evaluation of the pile-shape measures used in refined strategies, in order to make stronger claims.

In addition to the above evaluations, we have proposed a test methodology to be used for evaluating material rehandling strategies. We encourage others to use this methodology for developing and testing strategies for autonomous material rehandling.

REFERENCES


