Autonomous Robots 7, 175–186 (1999)

A Robotic Excavator for Autonomous Truck Loading

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Abstract. Excavators are used for the rapid removal of soil and other materials in mines, quarries, and construction sites. The automation of these machines offers promise for increasing productivity and improving safety. To date, most research in this area has focussed on selected parts of the problem. In this paper, we present a system that completely automates the truck loading task. The excavator uses two scanning laser rangefinders to recognize and localize the truck, measure the soil face, and detect obstacles. The excavator's software decides where to dig in the soil, where to dump in the truck, and how to quickly move between these points while detecting and stopping for obstacles. The system was fully implemented and was demonstrated to load trucks as fast as human operators.

Keywords: autonomous excavation, robotic excavator, integrated robotic system, laser rangefinder, software architecture, manipulator, dig planning

1. Introduction

The surface mining of metals, quarrying of rock, and construction of highways require the rapid removal and handling of massive quantities of soil, ore, and rock. Typically, explosive or mechanical techniques are used to pulverize the material, and digging machines such as excavators load the material into trucks for haulage to landfills, storage areas, or processing plants. As shown in Fig. 1, an excavator sits atop a bench and loads material into trucks that queue up to its side. The operator is responsible for designating where the truck should park, digging material from the face and depositing it in the truck bed, and stopping for people and obstacles in the loading zone.

The opportunities for automation are immense. Typically, loading a truck requires several passes, each of which takes 15 to 20 s. Reducing the time of each loading pass by even a second translates into an enormous gain across the entire job. The operator's performance peaks early in the work shift and degrades as the shift wears on. Scheduled idle times, such as lunch and other breaks, also diminish average production across a shift. All of these factors are areas where automation can improve productivity.

Safety is another opportunity. Excavator operators are most likely to be injured when mounting and dismounting the machine. Operators tend to focus on the task at hand and may fail to notice other site personnel or equipment entering the loading zone. Automation can improve safety by removing the operator from the machine and by providing complete sensor coverage to watch for potential hazards entering the work area.

Numerous researchers have addressed aspects of automated earthmoving (Singh, 1997). The lowest and most common level of automation has been teleoperation. Typically, the operator is removed from the scene for reasons of safety. Teleoperated excavators are used in applications that pose a danger to humans, such as the uncovering of buried ordnance (Nease and Alexander, 1993) and waste (Burks et al., 1992; Wohlford et al., 1990), or excavation around buried utilities. A higher level of autonomy is achieved by systems that share control of the excavation cycle with a human operator. Typically, these systems (Bradley et al., 1993; Bullock and Oppenheim, 1989; Huang and Bernold, 1994; Lever et al., 1994; Rocke, 1994; Sakai and Cho, 1988; Salcudean et al., 1997; Sameshima and Tozawa, 1992; Seward et al., 1992) concentrate on the process of digging. An operator chooses the starting location for the excavator's bucket and a control system takes over the process of filling the bucket using force and/or joint position feedback to accomplish the task. At the

Figure 1. Excavator loading a truck with soil in a typical mass excavation work scenario.

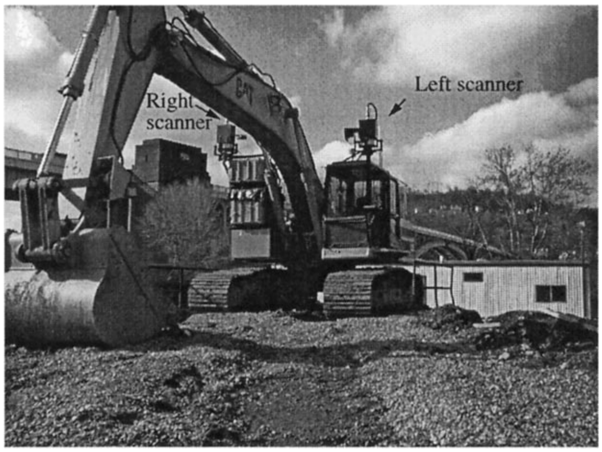

Figure 2. Sensors mounted on excavator.

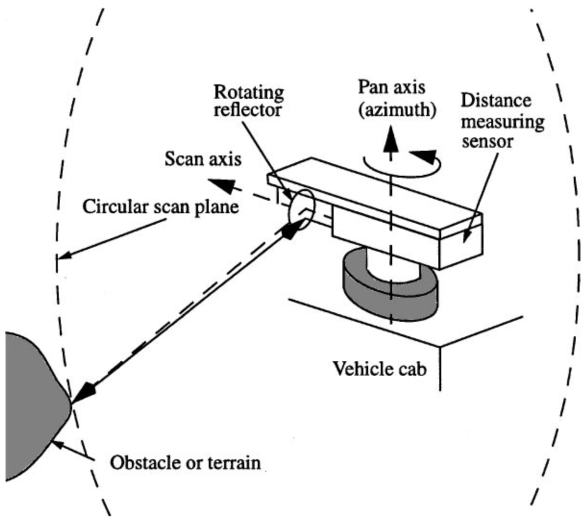

Figure 3. Two axis scanning sensor configuration.

next level of autonomy are systems that automatically select where to dig. Such systems measure the topology of the terrain using ranging sensors (Feng et al., 1992; Singh, 1995; Takahashi et al., 1995) and compute dig trajectories that maximize excavated volume. At the highest level of autonomy are systems that sequence digging operations over a long period (Bullock et al., 1990; Romero-Lois et al., 1989; Singh, 1998).

The prior work addresses many subproblems important for autonomous truck loading, however in order to field a fully automated system that performs at the level of its manually operated equivalent, a much broader set of problems must be solved than just digging. Sensors are needed to sense the dig face, recognize and localize the truck, and detect obstacles in the workspace. Perception algorithms are needed to process the sensor data and provide information about the work environment to the planning algorithms. Planning and control algorithms are needed to decide how to work the dig face, deposit material in the truck, and move the bucket between the two.

We have developed a complete system for loading trucks fully autonomously with soft materials such as soil. The Autonomous Loading System (ALS) was implemented and demonstrated on a 25-ton hydraulic excavator and succeeded in loading trucks as fast as an expert human operator. The rest of the paper describes the ALS and presents results from experimental trials.

2. System Overview

The Autonomous Loading System uses two scanning laser rangefinders which are mounted on either side of the excavator's linkage (see Fig. 2) to sense the dig face, truck, and obstacles in the workspace. Two scanners are needed for full coverage of the workspace and to enable concurrent sensing operations. Each sensor has a sample rate of 12 kHz, and a motorized mirror sweeps the beam circularly in a vertical plane. The mirror spins at approximately 1800 rpm providing 30 circles of sensor data per second. Additionally, each scanner can pan at a rate of up to 120 degrees per second, enabling this circle to be rotated about the azimuth, as shown in Fig. 3. The lasers have an effective range of 200 m and are eye-safe when the mirror is spinning.

The scanner positioned over the operator's cab is called the "left scanner", and it is responsible for sensing the workspace on the left hand side of the excavator. The "right scanner", which is located at a symmetric position on the right, is responsible for sensing the workspace on the right hand side of the excavator.

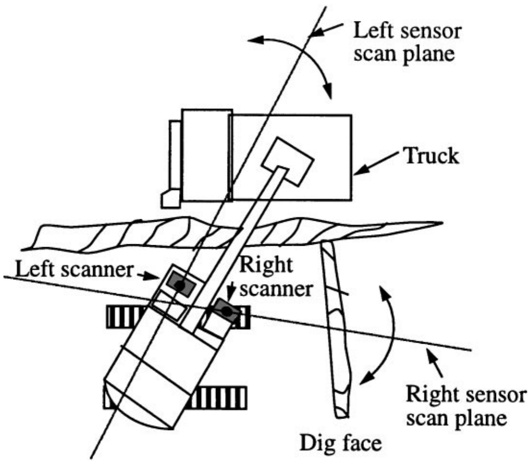

Figure 4. Top view of sensor configuration.

The excavator uses its scanners in the following fashion when loading a truck (Fig. 4). While the excavator digs its first bucket, the left scanner pans left from the dig face across the truck both to detect obstacles and to recognize, localize, and measure the dimensions of the truck. Using this information, a desired location in the truck to dump the material is planned, and the bucket swings toward the truck. During this swing motion, the right scanner pans left across the dig face to measure its new surface, and the next location to dig is calculated. The right scanner continues to pan toward the truck.

After the soil is dumped into the truck, the right scanner pans back across the dig face to detect obstacles in the way of the implements. The excavator swings back to the next dig point. During this swing, the left scanner pans across the truck to measure the soil distribution in the truck bed, and the next desired dump location is calculated. This process repeats for each subsequent loading pass until the truck is full, with the exception that truck recognition is only necessary for the first pass for each new truck. Typically, six passes are needed to load our 20 ton truck with our excavator testbed.

All of the perception and motion planning software is run on an on-board array of four MIPs processors. The software architecture is shown in Fig. 5. The boxes are software modules that can run on one of the system processors. Circles are hardware components such as sensors. Lines represent communication channels between different software modules.

The *sensor interfaces* receive data from the two scanners and control the panning motion of the devices. Sensor data from the interfaces are passed to *scanline*

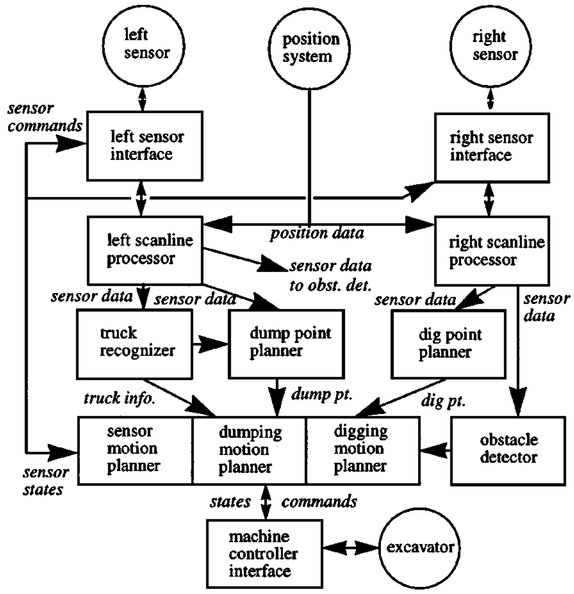

Figure 5. ALS software architecture.

processors, where they are converted from spherical, sensor coordinates to Cartesian, world coordinates using corresponding data from the *position system*. These three-dimensional range points are then made available to whatever perception software modules require them.

One consumer of this processed sensor data is the *truck recognizer*, which recognizes the truck and measures both its dimensions and location. Two others are the *dig point planner*, which plans a sequence of dig points for eroding the dig face, and the *dump point planner*, which plans a sequence of dump points for loading soil into the truck bed. A fourth sensor data consumer, the *obstacle detector*, processes data from the scanner that is sweeping in advance of excavator's motion and sends a request to stop the machine if an obstacle is detected in its path.

The motion planners receive and use the information that is produced by the sensor data consumers. The *digging motion planner* controls the excavator during digging at the specified location. The *dumping motion planner* dumps the bucket of soil into the truck and returns to the dig face. The *sensor motion planner* controls the panning for both scanners to coordinate scanner and excavator motion, following the scenario described earlier. The *machine controller interface* communicates commands to the low level machine joint controller, which executes the commands and sends excavator state information back to the planning modules.

3. Hardware Subsystem

The ALS hardware subsystem consists of the servo-controlled excavator, on-board computing system, perception sensors, and associated electronics. In this paper we focus primarily on the perceptual sensors which provide the data from which the truck is identified, the dig location is chosen, obstacles are avoided, and ultimately the mass excavation process is achieved.

With the target application of earthmoving, we concentrated on developing a laser based scanning system that would be able to penetrate a reasonable amount of dust and smoke in the air. The laser itself would need to be able to accurately measure range from a variety of target materials (e.g., metals, wood, dirt, rock, snow, ice, and water), colors and textures. We also needed a system that would be robust to dust and dirt accumulating on the protective "exit" window (glass or plastic which protects the laser and optics from weather and dirt, though permits the beam to pass).

Over the past decade, a variety of laser based scanners have been produced. With the exceptions of the Dornier (Shulz, 1997) and Schwartz (Schwartz) scanners, most have either been research devices or limited to indoor usage. None that we know of address the problems of dust penetration or a partially occluded (i.e., dirty) exit window.

We have developed two different time-of-flight scanning ladar systems that can be used in reasonable amounts of ambient dust. The first uses a "last-pulse" technique that observes the waveform of the returned light and rejects early returns that can arise from internal reflections off of a dirty exit window, or from a dust cloud obscuring the target (see Fig. 6). In general, the next-to-last pulse returns are due to dust in the scene and are indicative of what a normal "first pulse" rangefinder would see. For instance, in Fig. 6, a first pulse rangefinder would detect the dirty exit window and would be unable to "see" the target. Even if the window were clean, the first pulse unit would still "see" the dust cloud instead of the target.

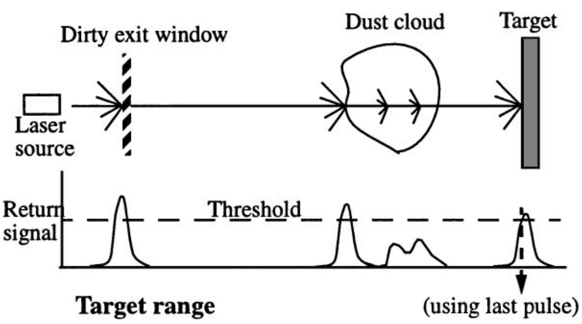

Figure 6. Last pulse detection concept.

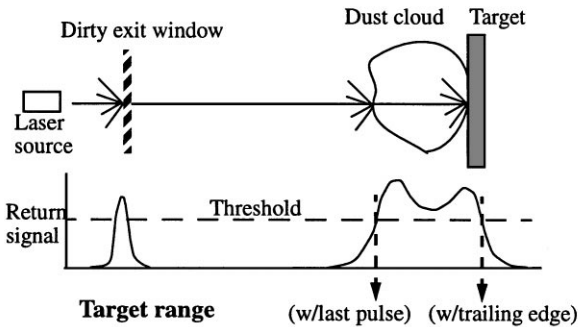

Figure 7. Trailing edge detection of target when target is obscured in dust cloud.

Since reflections off the exit window are rejected with the last pulse technique, the unit can be environmentally sealed using an inexpensive transparent cover that does not have to be optically perfect or clean. Another advantage is that the laser system can also report when multiple returns occur, giving a warning that dust is present. This is important because overall ranging reliability and accuracy is decreased in dusty conditions, so an autonomous machine might need to adopt a slower, more conservative motion strategy.

There is, however, a limitation to last-pulse rangefinding. When the target is within or adjacent to a dust cloud, the receiver electronics can have difficulty separating the dust and target returns (see Fig. 7). We have built a second dust penetrating scanner system that identifies that target by locating the "trailing edge" of the last return signal as is shown in Fig. 7. Like the last pulse system, this device is also robust to occlusions on the exit window making it ideal for construction and mining environments. Though the trailing edge detection technique forgoes some range accuracy, we believe it is a superior approach for environments where the dust may frequently surround the target.

The television monitor pictured in Fig. 8 shows range points plotted from a single scanline for both the last pulse and trailing edge scanners. Range increases from the left to the right of the monitor. The top monitor screen shows scans of the rear of a dump truck. The bottom screen shows scans of the same truck but shrouded in a heavy dust cloud. Note that the last pulse device is unable to separate the dust cloud from the truck and reports the front of the cloud. The trailing edge device

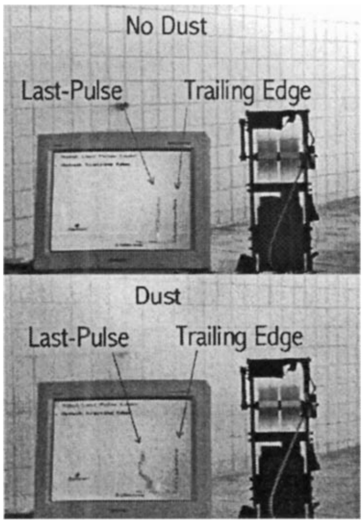

Figure 8. Last pulse vs. trailing edge detection when target is within dust cloud.

correctly reports range to the truck regardless of the presence of dust.

It is important to note that both dust penetrating techniques are physically limited by very heavy dust levels that attenuate the return target signal below the point of detectability.

4. Software Subsystem

The software subsystem consists of several software modules that process sensor data, recognize the truck, select digging and dumping locations, move the excavator's joints, and guard against collision. In this section, the algorithms employed by key software modules in the software architecture are described.

4.1. Truck Recognition

In order to properly load a truck, an excavator operator must verify that it is a loadable vehicle, determine its location, and determine its dimensions. This information is essential for calculating a loading strategy and for planning the sequence of joint motions that implements this strategy. In some scenarios, such as surface mining, the loaders are serviced by a mine-owned fleet of haulage trucks. An automated system could acquire the truck information by equipping each truck with a global positioning system (GPS) sensor and an identification transponder. However, in other scenarios such

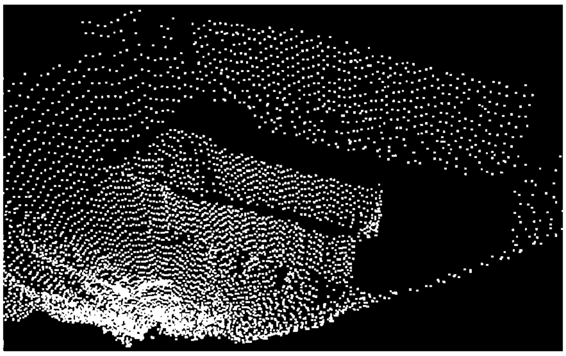

Figure 9. Raw range data of a truck.

as highway construction, the loaders are serviced by a variety of independently owned, on-highway trucks of varying dimensions, so equipping each and every truck with such sensors could be infeasible. For such scenarios, an automated system could acquire the necessary information using rangefinder data.

The truck recognizer uses range sensor data to automatically recognize, localize, and dimension haulage trucks. As the excavator digs its first bucket of soil, the left scanner pans across the truck, which is assumed to be parked to the excavator's side. The raw sensor data are shown in Fig. 9. The scanner pans from right to left at 30°/s, so data from a 90° sector of the workspace would require 3 s to obtain. Each rotation of the mirror returns one scanline of data, created by intersecting the vertical scan plane with the truck. Each scanline is processed into line segments which are grouped with coplanar line segments from other scanlines to form planar regions.

Using an interpretation tree approach (Grimson, 1990), a simple model for a truck bed is matched to the segmented data region by region. The model consists of six planes representing the sides, bottom, and canopy of the truck bed. Depth-first search is used to hypothesize model-to-scene planar region matches. At each level in the tree, constraints are used to prune the search and to check for consistency with previously hypothesized matches. The interpretation that matches most of the model and survives the verification stage is selected as the correct one.

In order for the truck recognizer to recognize a class of truck models rather than just a single model, the truck bed model uses parameter ranges rather than single parameter values. Ranges are used on the sizes of the planar regions in the model, the locations of their centroids relative to each other, and the angles between the planes. These parameter ranges are checked for

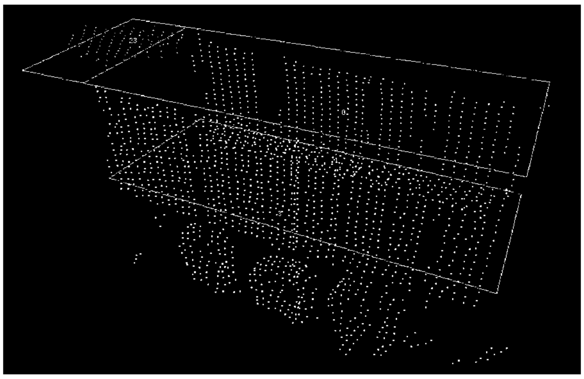

Figure 10. Truck model fit to segmented data.

consistency at every level in the interpretation process to prune the search. This specification allows the truck recognizer to identify trucks of varying sizes and truck bed shapes.

For each complete interpretation (i.e., an attempt to match all model regions to scene regions), the truck recognizer performs a verification. The verification consists of finer-grained consistency checking of truck parameters, and the identification of the four "corner points" in the sensor data that define the opening of the truck bed. For the selected interpretation, the corner points are used to calculate the position and orientation of the truck bed. This information is used by other software modules to produce a dumping strategy. Fig. 10 shows the truck model matched to the planar regions segmented from the raw sensor data.

4.2. Coarse-to-Fine Dig Point Planning

Automated earthmoving operations such as leveling a mound of soil are distinguished from typical planning problems in two important ways. First, soil is diffuse and therefore a unique description of the world requires a very large number of variables. Second, the interaction between the robot and the world is very complex and only approximate models that are also computationally tractable are available. The large state space and complex robot-world interaction imply that only locally optimal planners (i.e. per dig) can be created.

In order to deal with the practical issues of excavating large volumes of earth in applications, we have developed a multi-resolution planning and execution scheme. At the highest level is a coarse planning scheme that uses the geometry of the site and the goal configuration of the terrain to plan a sequence of "dig-regions." In turn, each dig region is searched for the "best" dig that can be executed in that region. Finally, the selected dig is executed by a force based closed loop control scheme (Singh and Cannon, 1998). Treatment of the problem at three levels meets different objectives. The coarse planner ensures even performance over a large number of digs. The refined planner chooses digs that meet geometric constraints (reachability and collisions) and which locally optimize a cost function (e.g. volume, energy, time). At the lowest level is a control scheme that is robust to errors in sensing the geometry of the terrain. Fig. 11 shows the process of coarse-to-fine planning for the excavator.

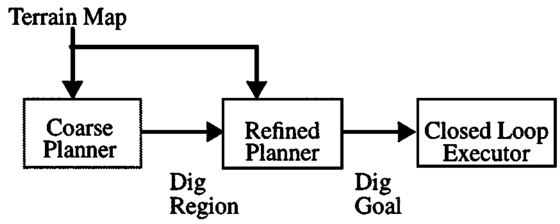

Figure 11. Coarse-to-fine planning strategy.

The coarse planner takes processed sensor data as input which it places in a terrain map (a 2-D grid of height values). The output is a sequence of dig regions, each of which is in turn sent to a refined planner. Fig. 12 shows a strategy for removing material that was recommended by an expert excavator operator. Each box indicates a region, and the number within the box indicates the order in which the region is provided to the refined planner. In this strategy, material is removed

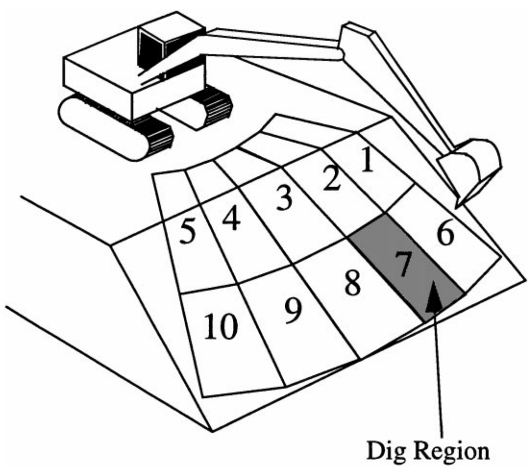

Figure 12. Coarse plan for an excavator.

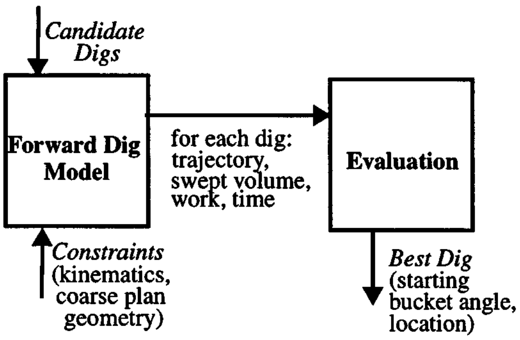

Figure 13. Operation of refined planner.

from left to right, and from the top of the face to the bottom. There are several reasons for choosing this strategy. In most cases, the truck is parked on the operator's left hand side so that the operator has an unobstructed view of it. By digging from left to right, the implements do not need to be raised as high to clear material when swinging to the truck. In digging from top to bottom, less force is required from the implements because it is not necessary to work against the weight of the material up above. In addition, clearing material away from the top minimizes the range shadows cast on the face of the terrain given a scanning range sensor that is mounted on the cab.

The refined planner operates on an abstract representation of an atomic action (i.e. a single dig). Rather than searching for a bucket trajectory, the refined planner searches through compact task parameters within the bounds specified by the coarse planner. In order to select the best digging action, the refined planner evaluates candidates through the use of a forward model that simulates the result of choosing an action (in our case the starting location of the bucket). An evaluation function scores the trajectory resulting from each action, and the action that meets all constraints and optimizes the cost function is chosen. This process is shown in Fig. 13.

4.3. Template-Based Dump Planning

The truck must be loaded evenly and completely. Because of uncertainty in soil settlement, the dumping strategy may need to be revised for each successive bucket load. The dump point planner applies a template-based approach to robustly find the low regions of soil distribution in the truck bed.

Sensor data are gathered after each bucket of soil has been dumped in the truck as the excavator is swinging back to the dig face. Like the dig point planner, the sensor data are placed in a 2-D terrain map. The dump point planner also requires information about the location of the truck, provided by the truck recognizer module, so it can filter out any irrelevant sensor data that are outside of the truck bed. The terrain map is then smoothed using a Gaussian filter to eliminate any sensor noise. The current grid cell resolution of the truck bed terrain map is 15 cm, with a typical map containing on the order of 500 cells.

Occlusion of the deposited soil by the truck bed walls is a serious problem. Rather than assuming that nothing is in the unseen regions of the truck bed, the dump point planner fills in any unknown grid cells with the average elevation of the known grid cells. This results in some slight inaccuracies in the perceived soil distribution at first, but they diminish as more soil is placed in the truck bed.

Finally, a specific terrain shape template is convolved over the entire truck bed terrain map to produce a score for each grid cell. This small 5×5 or 7×7 grid cell template looks for a certain profile of the material in the truck bed, such as a slope or a hole. Simple templates of constant elevations can be used to find the lowest elevation in the truck bed terrain map as well. The convolution operator produces a score which represents how well the template matched the particular region in the truck bed, and the location of the cell with the best score is returned as the desired dump location.

4.4. Script Based Motion Planning

The motion planning software coordinates the motions of the excavator's joints for each loading pass, beginning immediately after digging a bucket of soil and ending when the bucket has returned to the next dig point. The main objectives of the motion planner are to plan motions which place the soil at the desired dump location, avoid all known obstacles in the workspace such as the truck, and execute each loading cycle as quickly as possible.

Because of power constraints and joint coupling effects of the excavator's hydraulic system, as well as the difficulty in accurately modeling the dynamics of such a machine, traditional optimal trajectory generation schemes do not work well. Instead, recognizing the fact that the excavator's motions are highly repetitive and very similar from loading cycle to loading cycle, and that it operates in a relatively small portion of its total workspace, a script based approach to motion planning was adopted (Rowe and Stentz, 1997). A *script* is a set of rules which define the general motions of the excavator's joints for a certain task, in this case loading trucks. These rules contain a number of variables, known as *script parameters*, which get instantiated on every different loading pass based on the current task conditions.

The rules of script were designed with the input of an expert human excavator operator and implicitly constrain what the excavator is and is not allowed to do. For example, if it was advised that moving two particular joints simultaneously was a bad idea, then the rules of the script make that motion impossible. The left hand side of the rules are functions of the excavator's state, and the right hand side of the rules are the commands which the planner sends to the excavator's low level joint controllers. Thus, when the left hand side of a particular rule evaluates to true, its corresponding command gets sent to the excavator. The rules get re-evaluated at a fixed rate as state information is obtained, 10 Hz for example, during the execution of the excavator's motion.

Fig. 14 shows the script rules for the truck loading task. The numbers in boldface are one example set of script parameters, which will be described in more detail below. The θ's are the excavator's state, in this case the angular positions of the joints. The definitions of the joints along with their lines of reference are shown in Fig. 15. The commands are desired angular joint

Joint 1: Swing	Command
1) When digging finishes, wait	θ_1 = **5°**
2) If θ_2 > **14°**, swing to truck	θ_1 = **101°**
3) If θ_4 > **10°**, swing to dig	θ_1 = **0°**
4) If θ_1 = **0°**, stop and execute dig	
Joint 2: Boom	**Command**
1) When digging finishes, raise	θ_2 = **18°**
2) If θ_1 < **60°**, lower to dig	θ_2 = **6°**
Joint 3: Stick	**Command**
1) When digging finishes, wait	θ_3 = **-100°**
2) If θ_1 > **31°**, move to spill point	θ_3 = **-76°**
3) If θ_4 > **-30°**, move to dump point	θ_3 = **-92°**
4) If θ_1 < **65°**, move to dig	θ_3 = **-75°**
Joint 4: Bucket	**Command**
1) When digging finishes, curl	θ_4 = **-90°**
2) If θ_1 > **60°** and θ_3 > **-89°**, open	θ_4 = **30°**
3) If θ_1 < **60°**, move to dig	θ_4 = **7°**

Figure 14. Truck loading script for an excavator.

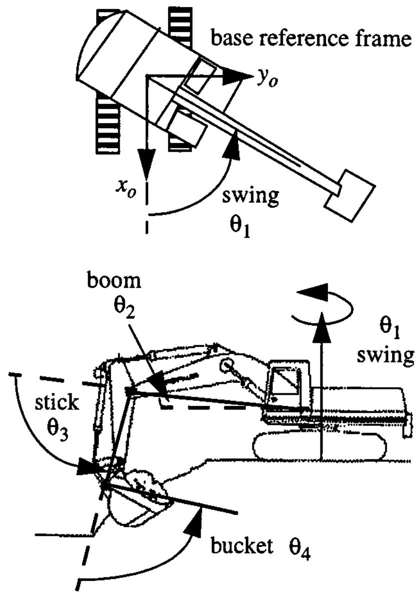

Figure 15. Joint names and reference positions for the excavator.

positions. Notice that each joint has its own separate script. Therefore, only one rule per joint may be active at a time.

The script parameters are computed before each loading pass starts using the information about the truck's location and the desired dig and dump points which it receives from the truck recognizer, dig point planner, and dump point planner software modules respectively. There are two types of script parameters, those which appear in the left hand side of the script rules and affect which commands are sent by the planner, and the joint commands themselves which appear on the right hand side of the rules.

The command script parameters in the right hand side of the rules are primarily computed by geometric and kinematic means. For example, consider the command of 18° from step 1 of the boom joint's script in Fig. 14. That is the boom angle which is required for the excavator's bucket to safely clear the top of the truck, and is a kinematic function of the height and location of the truck relative to the excavator. Similarly, the stick joint commands are computed using knowledge about the radial distance of the truck from the excavator, and the swing joint's commands are found from the desired dig and dump points.

The script parameters in the left hand side of the rules are found through a combination of simple excavator dynamic models and heuristics. These dynamic models capture first order effects of the excavator's closed loop behavior when given desired angular position commands. These models provide information about the length of time that it would take to move a particular joint from a start to a goal location. This information is used to intelligently coordinate the different joint motions resulting in faster loading times.

For example, consider the case when the excavator has finished digging, and the bucket is raising up out of the ground. The excavator does not need to wait until the bucket has raised to its full truck clearance height before swinging to the truck. Instead, it can begin swinging sooner as the bucket is still raising. The dynamic models compute how long it would take to fully raise the bucket and to swing to the truck. From this timing information, the script parameter which determines the precise point to begin swinging to the truck, but still avoid a collision, is found and used in the parameterized script.

The parameterized script approach is an appropriate solution for this motion planning problem. Because the excavator's motions are explicitly scripted, problems with hydraulic power limitations, which result from moving all of the joints simultaneously, are eliminated. By the same token, however, script rules that are too limiting may result in suboptimal performance by the autonomous excavator. The parameterization of the script also provides flexibility in the motions of the excavator as opposed to a simplistic playback of a single, canned motion.

4.5. Obstacle Detection

A major requirement for automated loading is detecting and stopping for people and other obstacles which pose a threat for collision. Obstacle detection software has been developed which uses range sensor data to perceive objects in the excavator's workspace, and simple dynamic models to predict where the excavator's linkage will be for a short time in the future as the excavator swings back and forth between the dig face and the truck. The predicted excavator linkage locations are compared to the range sensor data, and if there is an intersection, the excavator is immediately commanded to stop. It is crucial that the sensors scan far enough ahead of the excavator's motion, and the prediction is far enough in the future, for the excavator to have enough time and space to come to a complete stop and avoid hitting the obstacle. This look-ahead distance is a function of the swing joint's maximum velocity and was found through experimentation to be

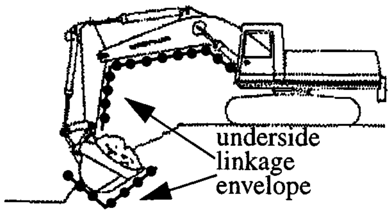

Figure 16. Depiction of the points that are calculated on the underside of the linkage.

between 40° to 50° in front of the excavator's swing joint.

The prediction of the excavator's linkage locations is done using the simplified models of the excavator's closed loop dynamic behavior. Not only is the obstacle detection algorithm predicting what the excavator itself will do, it must also simulate what the script-based motion planner will do using the predicted excavator state. It performs this prediction at the same rate of the script rule base update, 10 Hz for instance. The final result is a list of predicted excavator linkage locations for some amount of time. The look-ahead time was found empirically to be between 2–3 s.

For each predicted linkage location, the coordinates of points on the envelope underneath the linkage are computed. This is done using the forward kinematics of the excavator and simple linear models of the shapes of the linkages. This is shown in Fig. 16. Each point on the underside of the linkage for each predicted linkage location is then compared to the 2-D elevation map of range sensor data. If any point on the underside of the linkage is lower than the elevation of the grid cell that coincides with it, then a predicted collision is reported and the excavator is commanded to stop.

5. Results

Development and testing of the Autonomous Loading System was done on a 25 ton hydraulic excavator. The excavator testbed was equipped with joint resolvers, cylinder pressure sensors, electrohydraulic controls, and low level joint controllers. Additional hardware required for autonomously loading trucks, such as the on-board computing and laser scanners, was added to the machine over the course of project development.

Fig. 17 shows the autonomous excavator loading a truck in our test site at the Robotics Engineering Consortium, an off-campus research facility of Carnegie Mellon University. The test site was designed

Figure 17. Typical dig for truck loading.

Figure 18. Truck is loaded after six passes.

to emulate a typical loading configuration where the excavator is elevated above the truck, and the truck is loaded to the side of the excavator, like the scenario shown in Fig. 1. Fig. 18 shows the truck after it has been loaded with six buckets of soil. The material that was loaded in the truck was soft clay-like soil typically found in Western Pennsylvania. Over the course of the year, the soil's characteristics would change from dry powdery dust during the summer to wet soupy mud during the winter and spring rains. A layer of snow and frozen soil were also not uncommon conditions.

During development and testing, the Autonomous Loading System has successfully loaded our truck hundreds of times. Discounting occasional hardware glitches and fixable software bugs which caused system failures, the Autonomous Loading System failed to work only a handful of times out of the hundreds of trials. Some of the fundamental reasons for these failures are described in the Discussion section. For nearly all of the data recorded for successful truck loading tests, the typical loading times are 15 to 20 s per bucket pass, with six passes needed to fully load the truck. This rate is very close to the loading times logged by an expert operator manually loading trucks in the same configuration using the same excavator. Loading has been done in a variety of weather conditions from bright sun to moderate rain, and even with snow and ice on the ground and truck.

6. Discussion

The Autonomous Loading System is very complex. There are over 70 major system components which include angular and pressure sensors, perceptual sensors and associated hardware, computer processors, and software modules. All must be working together for the autonomous system to function successfully.

Accurate perception is crucial to successful autonomous system operation. Noise and outliers affect system performance, especially for obstacle detection and truck recognition. For instance, noisy sensor data can affect the planar segmentation of the truck recognition algorithm, which results in a slightly inaccurate measurement of the truck dimensions and pose. Although quite a bit of imprecision can be tolerated in the truck's lateral position, accurate measurement of the truck's height is required to avoid a potential collision between the top of the truck and the bottom of the bucket. Precise sensor calibration is also crucial to accurate sensing of the truck, terrain, and obstacles.

Machine control is another major element for the success of the autonomous system. Accurate joint positioning is required for the parameterized script motion planning algorithm. Although control of a large, hydraulic machine can be difficult, the low level joint controllers performed well. Some machine motions, however, such as lowering the boom with a full bucket of soil, are difficult to control and can result in poor system performance. For example, swinging over a long range with a full bucket of soil can result in some overshoot of the swing joint, causing the material that is in the bucket to be dumped outside of the truck bed. For both this motion, and the boom down motion previously mentioned, the motion planning software could detect these conditions and limit the joint velocities.

Finally, the outdoor, real-world nature of this application affects system performance and functionality as well. For example, it is desirable to evenly load the truck in order to distribute the weight on the tires. The placement of the soil in the truck is dependent on the soil conditions. During testing one day, the soil was very dry and non-cohesive. The motion planning script parameters had been adjusted for these soil conditions so that the soil was loaded evenly in the center of the truck bed. Later, after a fairly substantial rain storm, the soil had changed to wet, sticky mud. The Autonomous Loading System was now loading the trucks too heavy on one side because the soil was sticking in the bucket. The script parameters needed to be manually readjusted to deal with this changed condition.

7. Conclusion

We have demonstrated an autonomous loading system for excavators which is capable of loading trucks with soft material at the speed of human expert operators. The system uses two scanning laser rangefinders to recognize the truck, measure the soil on the dig face and in the truck, and to detect obstacles in the workspace. The system modifies both its digging and dumping plans based on settlement of soil as detected by its sensors. Expert operator knowledge is encoded into templates called scripts which are adjusted using simple kinematic and dynamics rules to generate very fast machine motions.

We believe ours to be the first fully autonomous system to load trucks for mass excavation. While the autonomous excavator can match the speed of expert operators over a short period of time, when factored over an entire work shift, the autonomous excavator will greatly outperform the human expert due to fatigue and required rest breaks. We feel this is where the true gains in productivity lie with such an autonomous excavation system.

Acknowledgments

This paper summarizes the work of the Autonomous Loading System team. This team consists of Stephannie Behrens, Scott Boehmke, Howard Cannon, Lonnie Devier, Jim Frazier, Tim Hegadorn, Herman Herman, Alonzo Kelly, Murali Krishna, Keith Lay, Chris Leger, Oscar Luengo, Bob McCall, Ryan Miller, Richard Moore, Jorgen Pedersen, Chris Ravotta, Les Rosenberg, Wenfan Shi, and Hitesh Soneji in addition to the authors.

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