Tracking a vehicle from a rotating platform with a scanning range laser

Elliot Duff
Autonomous Systems Laboratory, CSIRO ICT Centre
PO Box 883, Kenmore, Qld 4069, Australia
Email: `Firstname.Lastname@csiro.au`

Abstract

This paper describes the development of an algorithm that is able to track the pose of a vehicle as it approaches a rotating platform with a number of scanning range lasers. The target application is path planning and traffic management systems that are able to assist drivers of mining trucks when parking their vehicles with respect to loading machinery (ie. swing-loaders, rope-shovels and excavators). Experiments using a 1/7 scale model of a dump-truck and swing-loader demonstrates the feasibility of the approach.

1 Introduction

Surface coal mining can be categorized into two types: open-cut and open-pit. Open-cut mining is economic when the coal seam is relatively close to the surface and its slope is relatively shallow. In this case, a prime-mover such as a dragline, removes the overburden from above the coal seam and the coal is then removed by dump trucks and shovels/swing-loaders. Open-pit mines target steeper coal seams and generally consist of a series of benches which wind down to an ever decreasing area, usually targeting multiple coal seams. Material is removed through a combination of drills, shovels, excavators and trucks. In both cases, the efficiency of interactions between mobile and fixed machinery is limited by factors such as poor 'path-planning' by machinery operators, poor placement of the vehicle with respect to the loading machine, and poor tracking of 'good' trajectories. Many of these problems can be attributed to poor visibility from the operator's cabin, as shown in Figure 1.

In the manufacturing sector, automation has demonstrated the potential to improve the efficiency of interaction between mobile and fixed equipment. Whilst there are many examples of autonomous earthmoving equipment [Singh, 2002] the state of the art in open-cut mining [Lever and MacAree, 2002] reveals that fully automated mining trucks are not yet commercially available. Existing systems have the capability to navigate a haul route and dump automatically but the interaction with loading equipment is limited. Thus the aim of the work in this paper is to provide enabling technology that can assist with the interactions between truck and shovel, in particular, with driver assistance technology that can provide a staged approach to automation.

Figure 1: Typical truck and shovel interaction.

2 Proposed Solution

The simplest method to guide a driver to a desired position is to place a marker, or markers, in the environment (e.g. H on a Helipad) and let the driver determine their own path. Another solution is to direct the truck with various hand signals (e.g. Marshalling at an airport). Neither technique is suitable in the mining environment. The only practical solution is to provide the driver with a user interface that displays a recommended or desired trajectory. For such a user interface to guide the truck to the desired position, a path must be generated [Usher, 2006]. This task is only possible if we know: the dynamics and kinematics of the truck; obstacles that may hinder its movement; where the truck should be (spotting), and the current location truck (localization). This paper deals with the final task of localization.

Localization techniques relevant to the mining industry are presented in [Kloos *et al.*, 2004]. Although GPS (Global Positioning System) is used widely to track the location of mobile equipment, there are many problems when it is used to control motion. In particular, the obstruction of satellites and effects of multi-path interference can make GPS unreliable. Although the classical solution is to perform data fusion with an INS (Inertial Navigation System), there are still problems with the accuracy of the map. GPS/INS systems are classed as absolute navigation systems. If there is an error in the map; either in the location of the destination (it has moved) or changes in the environment (movement of obstacles or benches) then it is possible that the truck will end up in the wrong location. Once again this problem can be corrected by augmenting the navigation system with obstacle detection, but this can lead to confusion in the control strategies. Alternatively, the map can be manually updated, but this is prone to human error.

An alternative navigation scheme is based upon relative locations [Roberts *et al.*, 2002]. Here the position of truck, shovel and obstacles are measured relative to one another. The advantage of this system is that it does not rely upon maps; rather it relies upon sensors that are aware of the surrounding objects. The accuracy of the system is dependant upon the accuracy of the sensors. The disadvantage of such a system is that it relies upon the sensor visibility. If the sensor is blinded, for whatever reason, the vehicle cannot navigate. Thus, one of the main challenges to automation in the mining environment is the choice of sensors. In particular, there is debate in the mining industry about the suitability of lasers in the mining environment. In our experience, they have proved themselves to be robust, reliable and accurate sensors in the mining environment [Duff, 2000].

The proposed solution to the problem of vehicle tracking is a compromise between absolute (global) and relative (local) coordinate systems. This is achieved by dividing the space around the shovel into three zones (see Figure 2): the outer zone, where the trucks are ignored by the shovel; the hand-over zone, where the shovel starts to direct the trucks movement; and the work zone, where the truck is within range of the shovel sensors. As the vehicle moves from the outer zone into the hand-over zone (say 200m away from the shovel), the truck is made aware that the shovel wishes to manage the trucks movements. In this zone, the position of the truck is monitored from a fusion of GPS and inertial sensing. As the vehicle crosses into the work zone (e.g. 50m), the shovel is able to see the truck with a variety of on-board sensors. The position of the truck is then measured relative to the position of the shovel. If the sensors on the shovel are able to see the bench and other obstacles in the work zone, then the shovel is also able to direct the truck around obstacles as they appear in the work zone, and park the trucks as close to the bench as practical (called spotting). In other words, since the shovel is actively aware of its environment, it is able to deal with changes to the environment as they occur.

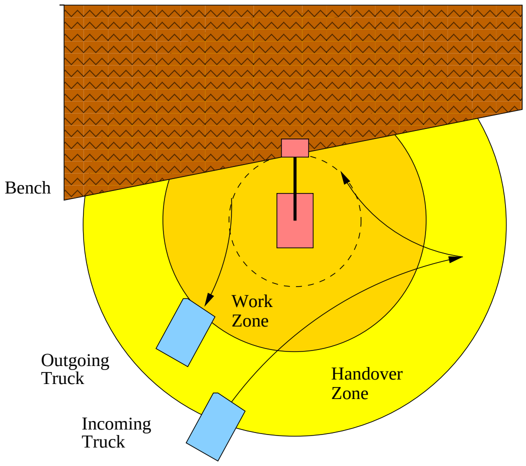


Figure 2: Multi-zoned traffic management strategy.

This paper describes the development of a system to localize the truck with respect to the shovel. The next section briefly reviews the literature on outdoor localization. Section 3 then describes the experimental platform. Section 4 describes the implementation of the vehicle tracking algorithm. Section 5 concludes the paper and provides directions for future research.

3 Outdoor Localization

There are many techniques that are able to localize a vehicle in the outdoor environment. The most obvious (and popular) is GPS. Although promising, the weakness of GPS are well known to the mining industry. The performance of high resolution GPS in an open cut mine is discussed in great detail [Walker, 1999], which highlights the problem of satellite availability, particularly when the satellites fall below the rim of a pit. Improvements have been suggested [Kloos *et al.*, 2004], with the addition of Ad-Hoc WiFi network, but in practice, GPS is not sufficiently reliable and alternative solutions or technologies are required.[1]

One solution is to use RF tag technology. With this technology, the truck is fitted with an RF tag, and a number of RF receivers are placed in the environment around the shovel. These receivers measure the time of flight of a broadcast signal from the RF tag and triangulate the position of the vehicle. Unfortunately, the benches that surround the shovel are likely to create multi-path interference which lead to errors of more than 1m. This error is too large for accurate pose control of the truck that is less than 6m in width.[2]

Another solution is to install passive tags in the environment and mount a sensor that can detect the tags on each

---

[1] Although this is being addressed by the commercial release of PsuedoLite GPS Systems (www.novariant.com).

[2] Although this is being addressed by new ultra-wide band communications systems.

truck. For example, a scanning laser range finder can be fitted to the vehicle and reflective beacons placed at surveyed locations in the environment [Howard *et al.*, 2004]. This technology is robust, reliable and provides good pose information. An alternative solution is use the laser to estimate the pose of the vehicle from natural structures in the environment (e.g. with angle histograms [Weiss *et al.*, 1994] or neural networks [Dubrawski and Siemiatkowska, 1998]). The disadvantage with both of these technologies is that they require each truck to have its own scanning laser (A$8000). A cheaper solution would be to use video cameras and coloured/shape beacons. This technology works well in indoor environments, but does not work very well in extreme lighting conditions encountered outdoors [Tews *et al.*, 2005]. The problem with any “beacon-based” technique is that the beacons require maintenance, and a map of their location must be regularly updated. This is an issue for mining, where the environment is undergoing continuous change.

The truck parking problem is one in which an approaching vehicle is homing towards a frame of reference whose origin is located at the shovel. Hence the logical site for the primary sensors, which monitor the closure of the vehicle relative to the shovel, is on the shovel itself. From information derived from the primary sensors, the truck can be advised of the optimal approach, parking location and departure path from the loader. This is the same concept already used in air traffic control[3]. The location of the primary sensors on the loader is consistent with the approach taken to automate the loading operations from a back-hoe excavator to a dump truck with the aid of a scanning laser[Stentz *et al.*, 1998].

The problem of placing sensors on the shovel are likely to be associated with the need to obtain sufficient sensory range to observe incoming vehicles, as well as the problem of temporary loss of contact resulting from a restricted field of view or the presence of dust clouds. In the literature, there are many examples of automotive vehicle tracking. Typically, the tracking involves a combination of Kalman filter with a dynamic model [Zhao and Thorpe, 1998] statistical analysis [Lu and Tomizuka, 2003] and line/corner detection [MacLachlan, 2004]. Although some of the technology is quite mature, the techniques are overly complex for the task at hand.

4 Experimental Platform

This section describes the design and construction of the scale-model shovel and truck. The purpose of the scale-model is to demonstrate that it is technically feasible to assist truck drivers optimally park their vehicle relative to the swing loader or shovel. The scale-model truck is a Toro ride-on lawn mower (i.e the red tractor) which has been retro-fitted with sensors, actuators, control systems, and a computer, enabling either full computer control, remote operation or manual control of the vehicle’s operations. All control and computing occurs on-board, whilst the display for the guidance feedback to the operator is a laptop computer mounted in such a manner that the operator can see the display and safely drive the vehicle at the same time. Comprehensive models of the vehicle have been identified [Usher *et al.*, 2003a; 2003b] allowing for testing of model-based control techniques and for extensive development in simulation.

In accordance with the scale of the truck, the scale-model shovel was designed to 1/7 scale (see Figure 3). It consists of a rotating platform that can support a control computer and sensors, a servo controller that can be directed to rotate the platform to a specified angle, an embedded computer to communicate with the sensors and servo-controller, and three scanning laser range finders: two mounted horizontally on either side of the shovel to scan for approaching trucks and another mounted vertically along-side the boom to generate a 3D digital terrain map of the surrounding environment.

Figure 3: Scale model shovel and truck.

5 Implementation

The placement of the horizontal lasers is shown in Figure 4, where the two lasers are 1.4m apart on either side of the scale model shovel. Since each laser is able to scan 180^o, the data from both lasers can be mapped onto a 360^o range map that is centred on the centre of rotation of the shovel. Note, that there is a blind spot in front and behind the shovel. As the shovel turns, the angle of rotation is measured by an encoder in the motor drive that enables the range data to be correctly mapped onto the 360^o range map. As the shovel continues to swing around, the 360^o range map is update with the minimum range. This “minimum range map” is defined as the *background*.

---

[3] The airspace over a given country is divided into a number of zones, and each zone is divided into sectors. As the aircraft travels from one sector/zone to another, the air traffic controller responsible for the sector/zone passes it off to the new controller.

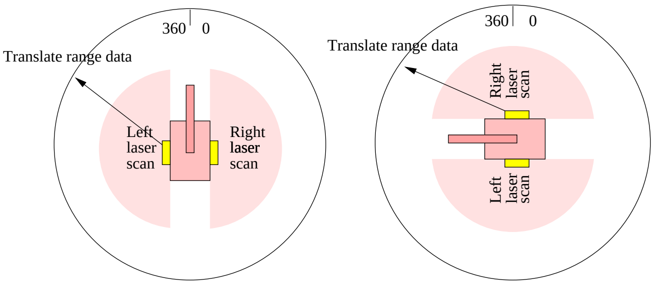


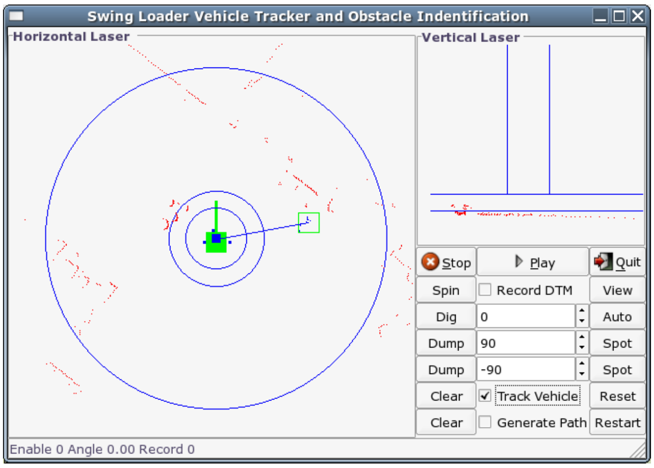
Figure 4: Mapping range data from two lasers onto single 360^o range map, independent of orientation.

Once the *background* range has been recorded, any object that moves in front of the background is labeled as a *target*. This is shown in Figure 5. In the left hand window (labeled Horizontal Laser) the green solid rectangle represents the current orientation of the shovel (in this case, it is pointing up at 0^o). The blue rings represent critical zones - the outer ring at 10m is the hand-over zone, whilst the two inner rings represent the spotting arcs. The red dots represent range data of the background (ie. buildings and obstacles etc). The blue dots represent targets that require tracking (range data that is in front of the background range). If the target is of sufficient size (i.e. more than a few pixels) the target is tracked by a minimum enclosing box (green box) and a blue line is drawn from the centre of the shovel to the centre of the target. In this case, the tractor has approached the shovel from the right and has been identified as being 5m away at a bearing of 80^o. In Figure 6, the tractor is still being tracked at 3m. As the tractor approaches the shovel the tractor splits into two targets (see Figure 7). This reflects the fact that the lasers are scanning at a height that bisects the foot-well of the tractor. This can be corrected by merging targets that are sufficiently close. This of course would not be a problem for real trucks, but if the truck were sufficiently high relative to the shovel, it might be possible to see under the tray. The system must be able to account for the fact that the ground is not flat and that the lasers are measuring a 2D cross section of a 3D world.

In practice, it is likely that more than one vehicle will enter the detection range (work-zone) of the shovel. This is shown in Figure 8, where a car drove across the compound, approximately 20m from the shovel. To cope with this situation, the identity of the target (the truck we wish to track) is maintained if any pixel in the next scan lie within the enclosing box.

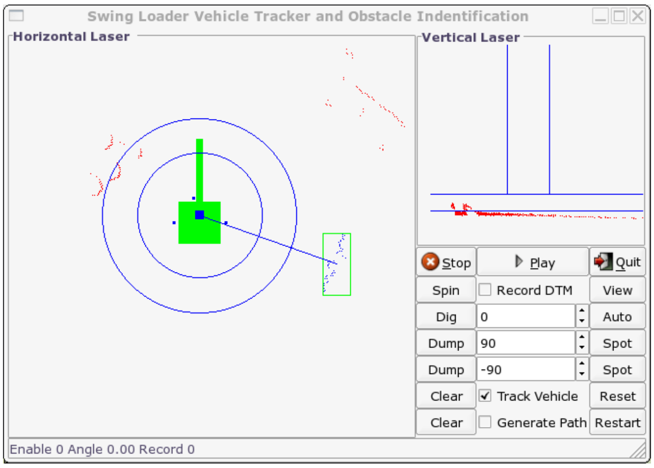
5.1 Position Estimation

The results of tracking the tractor are presented in Figure 9. The shovel is located at (0m,0m) and the tractor starts approximately 7m to the right of the model shovel. It approaches the shovel and then turns left, making a loop, before reversing approximately 3m away from the shovel, it then moves forward to make another loop, to reverse to less than 2m. Although this correctly reflects the behavior of the vehicle, the path (position) is rather noisy. To understand why this is so, it is necessary to re-examine the tracking method. The tractor in the spotting zone is shown in Figure 6. The position of the tractor is assumed to be the centre of the enclosing rectangle. This is an incorrect assumption: since the range data only records the position of points on one side of the vehicle. To be accurate, the width and length of the vehicle must be taken into account. The problem with this is that we don't know the orientation of the vehicle. In Figure 6 it is possible to observe the complexity of the distribution of range data within the enclosing box. The complexity makes it difficult to identify the features of the tractor from which we could estimate its orientation. One solution would be to add artificial features (reflective targets) — but this creates issues with maintenance. Another solution is to recognize that all trucks (and tractors) are essentially rectangular in shape, and that a rectangle that defines the size of the tractor/truck should enclose all of the observable range data.



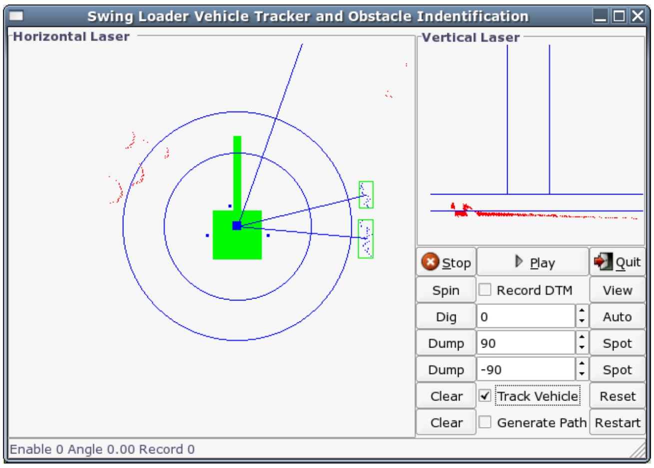
Enable 0 Angle 0.00 Record 0

Figure 5: Tracking of tractor at 5m.



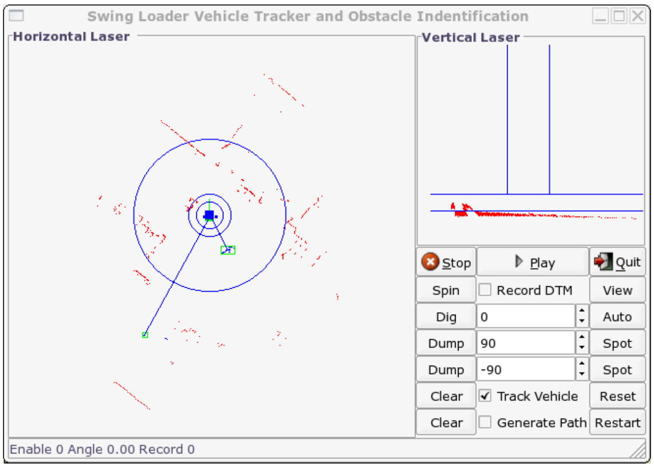
Enable 0 Angle 0.00 Record 0

Figure 6: Tracking of tractor at 3m.



☐ Record DTM
Dig 0
Dump 90
Dump -90
☑ Track Vehicle
☐ Generate Path
Enable 0 Angle 0.00 Record 0

Figure 7: Tractor splitting into two targets.



☐ Record DTM
Dig 0
Dump 90
Dump -90
☑ Track Vehicle
☐ Generate Path
Enable 0 Angle 0.00 Record 0

Figure 8: Tracking of tractor and other vehicle (lower left).

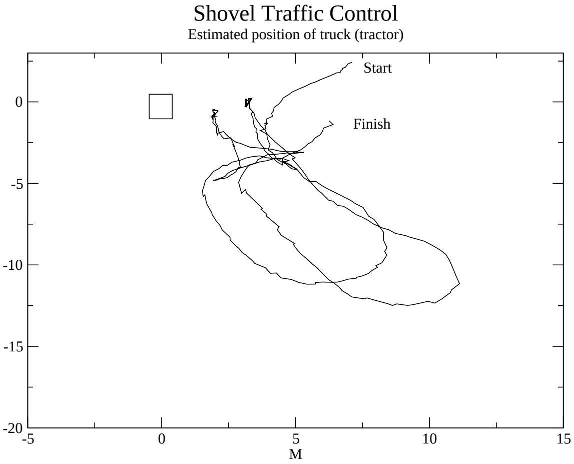


Figure 9: Position of tractor with respect to model-shovel.

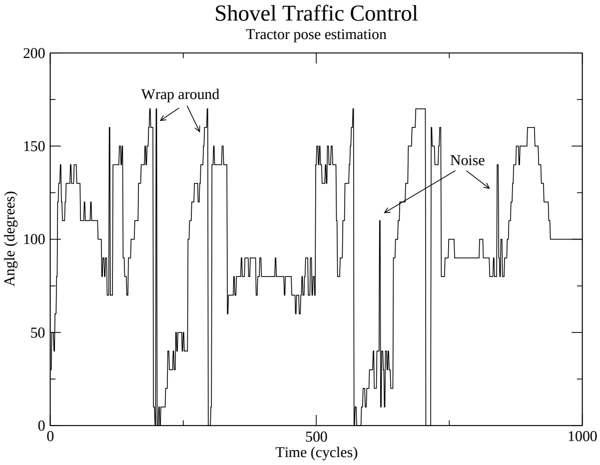


Figure 10: Orientation with respect to model-shovel.

5.2 Orientation Estimation

A technique used in shape analysis is called Feret Analysis [Thomas *et al.*, 1989] which is based on the idea of calculating the minimum enclosing rectangle for a number of different angles. This is shown in Figure 11, where there are 3 data points, enclosed by rectangles at 0^o, 10^o, 20^o and 30^o. From this analysis it can be seen that the enclosing rectangle with the smallest volume (i.e. the minimum enclosing rectangle) is at 30^o. It is apparent that further rotations will not find a smaller volume. Since the tractor can also be enclosed by a rectangle, the following assertion is made:

> *The tractor's orientation is defined by the minimum enclosing rectangle.*

The results of this analysis at 10^o intervals is presented in Figure 10. Since the technique is unable to discriminate between the back or front of the tractor there is a wrap-around at 180^o. This feature and associated noise can be corrected with a Kalman filter.

5.3 Improvement

The position estimation can be improved by using the minimum enclosing rectangle, the orientation and knowledge about the real size of the tractor (the projected tractor rectangle). The tractor rectangle (0.6m x 2.0m) is projected from a corner, or edge, of the minimum enclosing rectangle. The choice of corner is based upon the estimated orientation and bearing of the tractor. This technique is shown in Figure 12, where the tractor is 90^o to the scanning laser. In this situation, the Feret angle is 0^o and the tractor rectangle is projected from left edge. In Figure 13, the tractor is at 45^o, so the bottom left corner is used. Whilst in Figure 14, the tractor is at 0^o, so the bottom edge of the rectangle is used. Similar rules can be made for all orientation and bearing angles. The results of this improved position estimation are shown in Figure 15.

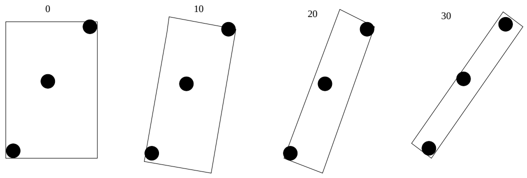


Figure 11: Feret analysis from $0^o$to 30^o.

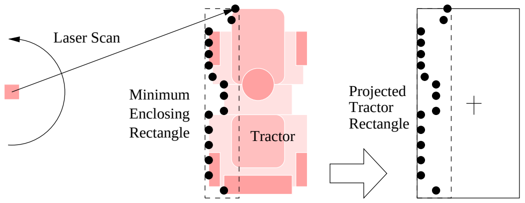


Figure 12: Projected tractor rectangle, laser at 90^o.

6 Conclusion

In this paper, a multi-zoned traffic management strategy is proposed to address the problems associated with the interaction of mining trucks and loading equipment. In this strategy, there is a transition from absolute to relative localization as mining trucks approach the loading equipment. This transition recognizes and takes advantage of the natural strengths of each localization technique:

- Absolute localization techniques (e.g. GPS and beacons) are best suited to static environments, such as those found on haul roads, where there is little change to the environment and the mine can afford to install and maintain the appropriate infrastructure (i.e. re-survey the road whenever required).
- Relative localization techniques (e.g. laser, radar or vision) are suited to dynamic environments, such as those found around the loading equipment. This environment is under going continual modification, and it is impractical, and often impossible, to install and maintain infrastructure.

It is also worth noting that the haul roads are often in open environments which favour the performance of GPS and RF based systems, unlike the loading equipment which is often at the bottom of pits, where radio performance can be poor.

Since the work presented in the paper is primarily concerned with the development of technology to assist truck drivers park their vehicle alongside the loading equipment, this paper has investigated algorithms to track the pose of the truck as it approaches a rotating platform (which is what loaders do). To this end, a simple technique based on Feret Analysis has been developed and tested.

This paper has demonstrated the feasibility of using a Feret Analysis to estimate the pose of an approaching vehicle. The system is robust to internal outliers (outliers that lie within the confines of the vehicle (i.e. laser penetrating into vehicle internal structure) but sensitive to external outliers (i.e. outliers that are not in the vehicle). This behavior is contrary to that of conventional line/corner detection techniques.

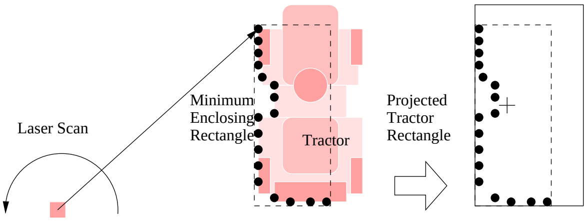


Figure 13: Projected tractor rectangle, laser at 45^o.

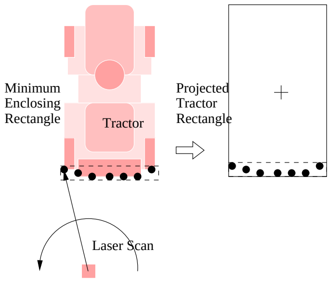


Figure 14: Projected tractor rectangle, laser at 0^o.

The Feret analysis technique is generic and should work for any vehicle that lies within a known rectangular footprint. Since the accuracy of the laser is absolute, there is an expectation that an increase of scale to a full size truck will increase the precision of the technique. Future work will include:

- Test software on data from real trucks.
- Use Kalman filter to smooth orientation.
- Use GPS to transition from hand-over zone.

7 Acknowledgments

This work was funded though the Australian Coal Research Program project number C13041. The author would like to thank the rest of the CSIRO ICT Autonomous Systems Lab for their invaluable technical expertise and assistance.

References

[Dubrawski and Siemiatkowska, 1998] A Dubrawski and I Siemiatkowska. A method for tracking the pose of a mobile robot equipped with a scanning laser range finder. In *Proceedings. 1998 IEEE International Conference on Robotics and Automation*, volume 3, pages 2518–2523, 1998.

[Duff, 2000] Elliot Duff. Automated volume measurement of haul-truck loads. In *Proceedings of Open Cut Coal Operations Conference*, Mackay, Queensland, Australia, 2000.

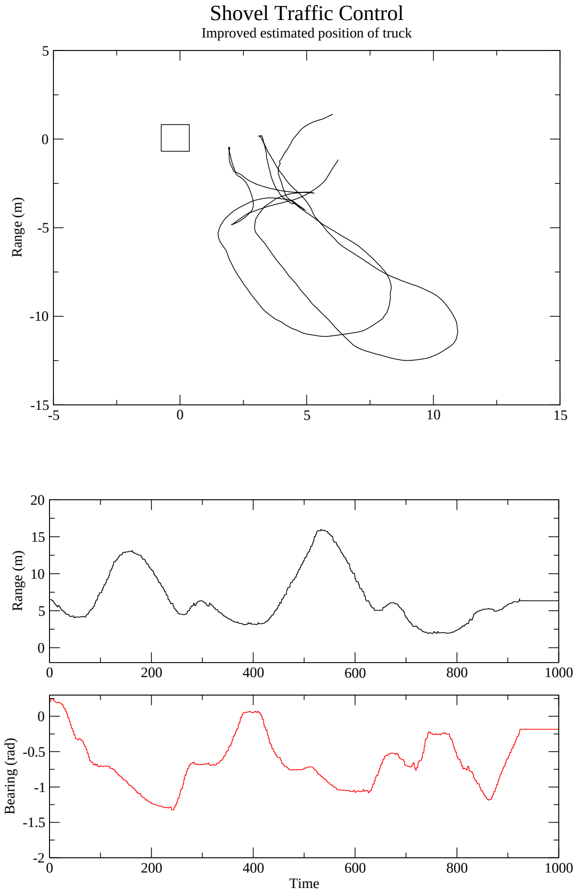


Figure 15: Improved tractor position.

[Howard *et al.*, 2004] Andrew Howard, Denis Wolf, and Gaurav Sukhatme. Towards autonomous 3D mapping in urban environments. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 419–424, Sendai, Japan, September 2004.

[Kloos *et al.*, 2004] Gerols Kloos, Jose Guivant, Stewart Worral, Andrew Maclean, and Eduardo Nebot. Wireless network for mining applications. In *Australasian Conference on Robotics and Automation*, 2004.

[Lever and MacAree, 2002] Paul Lever and R MacAree. Open-cut automation scoping study. Technical Report C11054, ACARP, 2002.

[Lu and Tomizuka, 2003] Guang Lu and Masayoshi Tomizuka. A laser scanning radar based autonomous lateral vehicle following control scheme for automated highways. In *Proceedings on American Control Conference*, pages 30–35, 2003.

[MacLachlan, 2004] Robert MacLachlan. Tracking moving objects from a moving vehicle using a laser scanner. Technical Report CMU-RI-TR-05-07 (draft), CMU, 2004.

[Roberts *et al.*, 2002] Jonathan Roberts, Elliot Duff, and Peter Corke. Reactive navigation and opportunistic localization for autonomous underground mining vehicles. *The International Journal of Information Sciences*, 145:127–146, 2002.

[Singh, 2002] S Singh. State of the art in automation earthmoving. In *Proceeding of the Workshop on Advance Geomechatronics*, Japan, Oct 2002. Sendai University.

[Stentz *et al.*, 1998] Anthony Stentz, John Bares, Sanjiv Singh, and Patrick Rowe. Robotic excavator for autonomous truck loading. In *Proceedings of the Intelligent Robots and Systems*, pages 175–186, Victoria BC, Oct 1998. IEEE.

[Tews *et al.*, 2005] Ashley Tews, Jonathan Roberts, Jonathan Roberts, and Kane Usher. Is the sun too bright in queensland? an approach to robust outdoor colour beacon detection. In *Australasian Conference on Robotics and Automation*, Sydney, Australia, 2005.

[Thomas *et al.*, 1989] A.D.H. Thomas, T Davies, and A.R. Luxmoore. Computer image analysis for identification of wear particles. In *Colloquium on Pattern Recognition for Binary Images*, pages 6/1–6/3, 1989.

[Usher *et al.*, 2003a] Kane Usher, Peter Corke, and Peter Ridley. Landmark-based visual homing: Experiments with a non-holonomic vehicle. In *Proceedings of the Conference on Field and Service Robots*, pages 35–40, Tsukuba, Japan, July 2003.

[Usher *et al.*, 2003b] Kane Usher, Peter Corke, and Peter Ridley. Visual servoing of a car-like vehicle – an application of omnidirectional vision. In *International Conference on Robotics and Automation*, pages 4288–4293, Taipai, Taiwan, September 2003. IEEE.

[Usher, 2006] Kane Usher. Human-in-the-loop pose control of a non-holonomic vehicle. In *Proceedings of the International Conference on Robotics and Automation*, page 3948, Florida, USA, 2006. IEEE.

[Walker, 1999] Rodney A Walker. *The Operation and Simulation of GPS Positioning in Harsh Environments*. PhD thesis, Queensland University of Technology, 1999.

[Weiss *et al.*, 1994] G Weiss, C Wetzler, and E von Puttkamer. Keeping track of position and orientation of moving indoor systems by correlation of range-finder scans. In *Advanced Robotic Systems and the Real World, Proceedings of the IEEE/RSJ/GI International Conference on Intelligent Robots and Systems*, volume 1, pages 595–601, 1994.

[Zhao and Thorpe, 1998] L Zhao and C Thorpe. Qualitative and quantitive car tracking from a range image sequence. In *Proceedings on Computer Vision and Pattern Recognition*, page 496, Los Alamitos, CA, USA, 1998. IEEE Computer Society.