Automated control of a dragline using machine vision

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SUMMARY The research described in this paper is directed toward increasing productivity of draglines through automation. In particular, it focuses on the swing-to-dump, dump, and return-to-dig phases of the dragline operational cycle by developing a swing automation system. In typical operation the dragline boom can be in motion for up to 80% of the total cycle time. This provides considerable scope for improving cycle time through automated or partially automated boom motion control. This paper describes machine vision based sensor technology and control algorithms under development to solve the problem of continuous real time bucket location and control. Incorporation of this capability into existing dragline control systems will then enable true automation of dragline swing and dump operations.

1 INTRODUCTION

Reduction of overburden removal costs has been identified as the most important means of improving the economic performance of open cut coal mines. The dragline is the key component in the overburden removal process, so improvement in dragline productivity will realise an immediate reduction in these costs with significant benefits to the industry. At a cost of $50M to $100M, buying a dragline is a major investment for any coal mine. The technology being developed in this project is expected to increase dragline productivity by up to 4%, which may mean a saving of $3M/year for a typical Australian coal mine — translated to a potential saving of $280M/year for the nation.

The work described in this paper is aimed at developing a swing automation system to improve the productivity of the swing-to-dump and dump-to-dig phases of a draglines operation.

The overall configuration of a dragline and the way the bucket is rigged is shown in Figure 1. During digging, hoisting and dumping, bucket motion is controlled using only the drag rope and hoist rope. The dump rope allows interaction between the other two ropes and enables a loaded bucket to be tipped at an appropriate time by a release of drag rope tension. The entire dragline and boom assembly rotates in order to swing the raised bucket from the digging to the dumping location. The loading, hoisting, and dumping operations are explained in detail in Knights and Shanks[1].

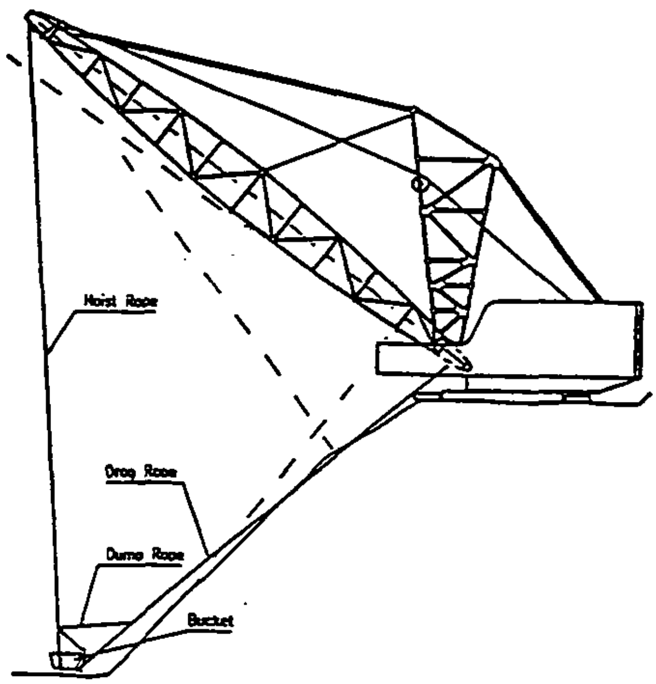

Figure 1: Dragline configuration and bucket rigging.

2 DRAGLINE CONTROL

2.1 Dragline Mathematical Model

The fist step in being able to control a dragline is the development of a mathematical model of the dynamics of a dragline. Ridout[2] gives the full non-linear model for a simple pendulum in the context of crane load control. The unconstrained dragline is a variable-length spherical pendulum, the support point of which moves along a circular arc. This is a coupled and highly non-linear system with chaotic tendencies. The moving constraint placed by the drag rope does make the system better behaved but adds extra complication to the system representation. A mathematical model has been developed with four independent variables:

- Swing angle Ω, the rotation of the dragline with respect to some datum;
- Hoist rope length h;
- Hoist rope angle with respect to vertical θ;
- Horizontal projection of the hoist rope angle with respect to the boom, ψ.

The drag rope length is treated in the model as a holonomic constraint represented by a Lagrange multiplier.

This model is being used to develop and test control algorithms which are to be implemented on a test dragline using machine vision feedback. The non-linear differential equations are solved using fourth-order Runge-Kutta procedures under MATLAB or a custom numerical simulation.

2.2 Control strategies

Ridout[2] provides an excellent summary of anti-swing control for loads suspended by cranes. Although the dragline has an additional rope, the drag rope, for constant rope lengths the dragline dynamics approximate those of a crane. Open-loop control strategies have been proposed and are the basis of several commercially available anti-swing controllers. However open-loop control is critically dependent upon knowledge of the load oscillation period which is a function of rope length. Open-loop control is also unable to compensate for external disturbances such as wind. Systems based on closed-loop control are capable of greater performance and disturbance rejection, but require swing angle sensing.

An attempt to control a production dragline at Curragh colliery in Central Queensland [3] was unsuccessful because the empirical approach took no account of the system's changing dynamics as the position of the bucket changed. This attempt at dragline swing control clearly identified that the key to the control was the determination of bucket position. There are a number of technologies available for bucket position determination but most have to be rejected because of the operational environment of the bucket. It is not feasible to have complex instrumentation located on the bucket. For these reasons a passive non-contact vision system has been developed. The selection of vision as the sensory input gives rise to a visual servo system for the control of a dragline's swing cycle.

2.3 Laboratory demonstration

A laboratory demonstration has been used to demonstrate the feasibility of closed-loop control using machine vision sensing of load position. A PUMA 560 robot with outstretched arm represented the dragline and its boom, and a weight suspended from the robot's gripper represented the dragline bucket. A camera mounted on the gripper looked downward and was able to determine the lateral displacement of the suspended weight. The robot was controlled by a custom VMEbus computer system running the ARCL robot control software[4]. The camera image was digitised, thresholded and median filtered by Datacube MaxVideo10 image processing modules prior to binary image feature extraction. The last function is performed by an APA-512+ module[5], a locally developed and manufactured device, which is capable of computing the zeroth to second moments, perimeter and bounding box of all connected regions in the scene at video rates. The binary image features allow computation of the weight's centroid at 50 Hz with minimum latency. If the swinging weight is modeled as a simple pendulum it can be shown that proportional-derivative control will stabilize the weight's position. In the demonstration, vision derived weight position and velocity were fed back with adjustable gains. Suitable gain settings were determined by experiment and allowed the suspended weight to traverse a set path with very little overshoot. The experiment clearly established the feasibility of the general approach.

3 MACHINE VISION SENSING OF BUCKET LOCATION

During digging, hoisting and dumping, bucket motion is controlled using two ropes, the drag rope and the hoist rope. Bucket motion in the vertical, boom, plane can be determined by triangulation from measurement of rope lengths and tensions. However this does involve some approximation since in practice the drag rope is a catenary not a straight line. Instrumentation to obtain rope length and tension data is already routinely installed on production draglines.

In the plane orthogonal to the boom, the rope suspension system allows the bucket to swing freely, essentially as a simple pendulum. This swing, or slew motion of the bucket is very important, and is effectively used by the operator to optimise boom motion. For closed-loop bucket position control, the angle ψ must be known. Knowledge of hoist rope length, h, allows this angle to be determined from the measured lateral displacement of the bucket which can be determined from a single camera viewpoint. Thus full three dimensional measurement is not required, and this greatly simplifies the system to be implemented.

3.1 Camera Positioning

An important consideration in the proposed system is the location of the camera. If a camera is mounted in a position where its field-of-view covers the appropriate 2D projection of bucket motion, bucket position can be derived from the suitably scaled offset of the bucket image from the centre of the image. Our investigations suggest that the most suitable camera position is at the end of the dragline boom looking vertically downwards. For a full size machine, where the boom is 100 m long, this location may pose accessibility and maintenance problems. It may also be necessary to explicitly account for structural compliance in the boom which will increase the order of the dynamic model.

3.2 Image Segmentation

The most important part of the machine-vision based bucket identification system is to reliably segment the moving bucket from the background, given the constraints of 'real time' operation. The segmentation must be robust enough to work under lighting conditions varying from bright sunshine with strong shadows to night operation with floodlamp illumination. Other effects such as dust clouds and rain must also be considered.

The bucket is fabricated from steel and does not have a particularly high contrast with respect to the mine floor. During the swing-to-dump cycle the bucket is filled with overburden and is even harder to distinguish from the mine floor. Segmentation techniques based on differential motion cannot be applied since both the dragline-mounted camera and the bucket are moving at different rates relative to the background. In fact it is this relative motion of the two objects, moving with respect to background, that is the quantity to be measured.

In order to increase the contrast of the bucket with respect to the mine floor, we have modified the scene in a manner that is both robust and inexpensive. This allows segmentation to be performed very quickly using simple thresholding techniques. The spreader bar and arch areas of the bucket structure, which have been observed not to suffer abrasion during filling, have been painted a bright green colour in order to provide sharp contrast with the predominantly grey mine floor background. This green component can be extracted through colour filters or electronically as the green component of a colour video image. Both approaches are being investigated. An additional benefit of this simple approach is that it increases bucket visibility for the dragline operator, particularly in the presence of dust.

The segmentation process consists of the following steps:

- thresholding of raw image;
- morphological processing of thresholded image;
- bucket centroid determination.

The thresholding of the raw video image converts a grey scale image to a binary image. Morphological processing then removes unwanted background artifacts and noise in the bucket arch and spreader bar regions. Currently a chain coding technique is used to compute the centroid associated with the bucket arch and spreader bar regions in the morphologically processed binary image.

The required rate of image segmentation and centroid determination can be estimated from the dynamics of the suspended bucket. The hoist rope length of a dragline during normal operation varies from 10 m to 90 m. Assuming the bucket behaves as a simple pendulum, this will result in a range of natural frequencies between 0.05 Hz and 0.2 Hz. Using the general rule of thumb that the sampling rate in a digital control system be 10 times the closed loop bandwidth, this results in a required visual sampling rate of 2 Hz. The corresponding sample interval is 10 CCIR frame times. Recent work by Corke[6] has demonstrated robot visual closed loop control at 50 Hz (CCIR frame rate) which far exceeds the requirements for the dragline case.

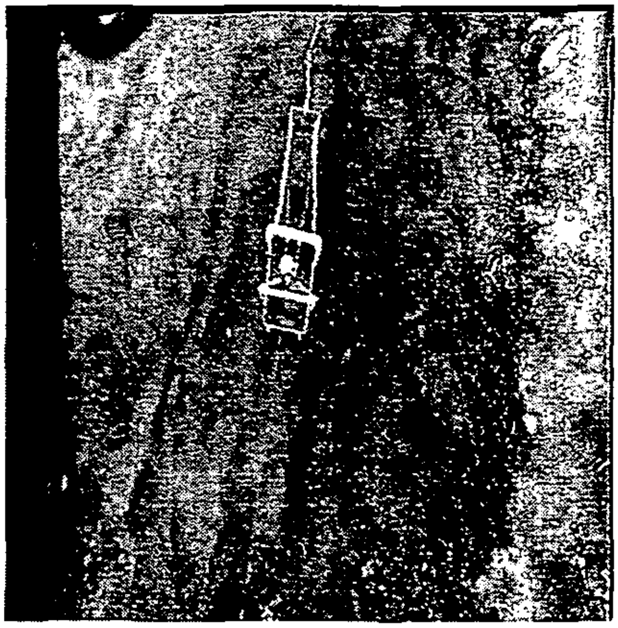

Figure 2: A raw frame from video of bucket on ACIRL dragline.

The vision processing system outlined above computes bucket centroid at 5 Hz, and is sufficient to satisfy the sampling rate criterion. The extra speed and expense of the hardware feature extractor, the APA-512+ used in the robot based demonstration, does not appear to be warranted in this application.

4 EXPERIMENTAL RESULTS

4.1 A model dragline

Australian Coal Industry Research Limited (ACIRL) at Riverview in Brisbane has a Dragline Performance Centre with an operational one-tenth scale dragline. This unit is being used for testing the system components before the automated swing control system is developed for a production dragline.

4.2 Segmentation results

CCIR standard video has been taken of bucket motion on the ACIRL dragline with a camera looking down from the boom. Figure 2 is a representative frame of the raw image. The regions of high intensity correspond to those areas of the bucket that have been painted green. Figure 3 shows a processed frame in which the painted regions of the bucket arc and spreader bar have been extracted. The approximate bucket centroid is computed from the identified bucket arc and spreader bar. The centroid is approximate because currently, no account is made of bucket orientation. The image processing is performed on a Datacube MaxVideo200 image processing computer.

The segmentation process operates on a region of interest in the digitised image frame in order to minimise computation time.

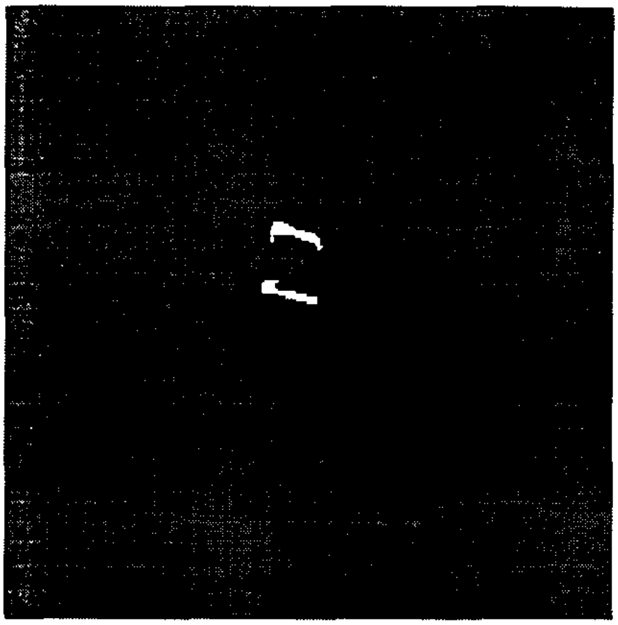

Figure 3: A processed frame of bucket image showing bucket arch and spreader bar.

The position of the region of interest is determined from the known lengths of the dragline's hoist and drag ropes.

4.3 Future work

Currently the existing laboratory system is being transferred to the ACIRL model dragline. The ACIRL dragline control system consists of two parts:

1. a personal computer based dragline control computer;

2. a Sun workstation hosted Datacube image processing computer.

Given the relatively low sample rate, the inter-computer communication will be via a serial communications link.

Rope length and slew transducers have been fitted and tests commenced on the open loop control of the dragline. The next stage, to commence shortly, is for integration of the machine-vision bucket position sensor into a closed loop control system.

5 CONCLUSIONS

This paper has outlined the problem of sensing and controlling the position of a dragline bucket. It has been shown that machine-vision based control of a pendulum, simulating the motion of a dragline bucket, is possible in the laboratory. In addition, promising results have been obtained in experiments in the segmentation of the bucket on the one-tenth scale ACIRL dragline. Future work will involve the incorporation of the vision based position sensor into a visual servo closed loop system to control the bucket motion.

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