



Experiments Suggest the Possibility of Achieving Autonomous Robotic Excavation in Moving Towards Construction Automation

Robotic Excavation in Construction Automation

Construction is of prime economic significance to many industry sectors. Intense competition, shortages of skilled labor, and technological advances are forcing rapid change in the construction industry, thus motivating construction automation [1]. Earthmoving machines, such as bulldozers, wheel loaders, excavators, scrapers, and graders, are common in construction. Excavation-based operations are used in general earthmoving, digging, and sheet-piling for displacing large amounts of material. On a smaller scale, operations such as trenching and footing formation require precisely controlled excavation. Although the fully automated construction site is still a dream of some civil engineers, research developments have shown the promise of robotics and automation in construction [2]. Despite the apparent economic importance of excavation in construction, there have been few implementations of autonomous or teleoperated excavators.

A number of researchers have investigated the feasibility of automating excavation. Many of these studies have addressed the possible use of autonomous excavators during unmanned phases of establishing manned Lunar or Martian research stations [3], [4]. Much of the work on terrestrial excavation has focused on teleoperation, rather than on the system requirements for autonomous operation. Although there have been a number of valuable theoretical and experimental contributions to the field of autonomous, robotic or teleoperated excavation [5]–[8],

autonomous operation of a full-scale excavator has not been commercially demonstrated.

Many of the experimental studies reported in the literature involve using conventional industrial robots fitted with buckets to excavate in a bed of loose sand. While there are parallels between “classical” robotics and robotic excavation, there are also some pronounced differences. In particular, an excavator is not fixed relative to the work piece; it plastically deforms the work piece by applying large forces and is caused to move relative to the soil by the same large forces. Furthermore, strategic and bucket trajectory planning must necessarily occur in a dynamic environment; if the excavator is not changing the profile of the soil being worked, it is not doing useful work.

This article presents some results of the autonomous excavation project conducted at the Australian Centre for Field Robotics (ACFR) with a focus on construction automation. The application of robotic technology and computer control is one key to construction industry automation. Excavation automation is a multidisciplinary task, encompassing a broad area of research and development

- ◆ planning
- ◆ monitoring
- ◆ environment sensing and modeling
- ◆ navigation
- ◆ machine modeling and control.

The ultimate goal of the ACFR excavation project is to demonstrate fully autonomous execution of excavation tasks in

**BY QUANG HA, MIGUEL SANTOS,
QUANG NGUYEN, DAVID RYE,
AND HUGH DURRANT-WHYTE**

common construction, such as loading a truck or digging a trench. A number of difficult theoretical and practical problems must be solved to achieve this objective. The problems fall into three main groups: excavation planning, sensing and estimation, and control.

Experimental Robotic Excavator

A number of experimental studies of robotic excavation [4], [6], [7] have been conducted by using a conventional industrial robot fitted with a bucket as the end-effector. Although this approach has yielded valuable information, we are firmly of the belief that typical “excavator technology” should be used to develop autonomous excavation capabilities. Consequently, we have used a Komatsu PC05-7 hydraulic mini-excavator as the basis for our experimental work. This 1.5-tonne machine has been extensively modified [9] to meet the requirements of the research and development project. The experimental excavator has eight hydraulic actuators: right and left travel motors, a cab slew motor, and two-way hydraulic cylinders on the boom swing, boom, dipper arm, bucket, and back-fill blade axes. The excavator cabin and all operating levers have been removed and the original manually actuated direction control valves replaced by electrohydraulic servovalves. Ancillary equipment added to support the servovalves includes an accumulator with an unloading valve, solenoid check valves, and an oil-to-air radiator. Fig. 1 shows the modified robotic excavator during a trench-forming task, while the electrohydraulic servovalves, accumulator, and oil radiator can be seen in Fig. 2. The excavator is extensively instrumented with joint angle encoders, pressure transducers, and load pins. Control is achieved through Moog proprietary digital controllers in conjunction with an IBM-compatible industrial PC. The system is fully self-contained, with power derived from the excavator’s electrical system.

Sensing and Estimation

When operating an excavator, a human uses senses such as sight and hearing together with reasoning based on knowledge and experience to control and monitor the digging process. In robotic excavation, sensing, modeling, and decision-making hardware and software must be used in lieu of the operator.

A number of vehicle and environment sensors are fitted to the experimental robotic excavator. The hydraulic system is instrumented with transducers that measure the actuator pressures and the valve spool positions. Strain-gauge force sensors enable direct force measurement during digging. Sensing of the machine’s external environment is essential for planning and controlling platform motion and autonomous digging operations and for monitoring progress towards task completion. A commercial time-of-flight laser measurement system is used to scan the terrain on either side of the bucket, providing a surface profile with 10-mm resolution and a statistical error of ± 15 mm within a sensing range of 1–8 m.

Parameter estimation and system identification is an important consideration in robotic excavation. Although a number

of states in the control state space are directly measured by machine sensors, estimation of some inaccessible states is required for control and monitoring purposes. Furthermore, there is also a need to estimate the uncertain forces arising from interaction between the bucket and the soil, and other external disturbances such as friction and load inertia changes, in order to reject their influence and achieve robust performance. A variety of robust estimation techniques can be used. In general, the term “robust estimation” refers to the design of deterministic observers in the presence of system uncertainties, delays, modeling errors, disturbances, and other unknown factors. Observers based on variable structure systems [10] are of interest, as they can provide robust estimations. A variable structure systems approach to friction estimation and compensation [11] has been proposed and applied to electrohydraulic servo systems [12] for external disturbance rejection in force and position control of the robotic excavator. This approach is summarized here.

Assuming that the disturbance force is slowly time-varying, the state model for 1-D motion occasioned by an actuator force w can be written as

$$\dot{v} = w - F_L, \quad \dot{F}_L = 0, \quad \dot{y} = v, \quad (1)$$



Figure 1. The robotic excavator in a trench-forming task.

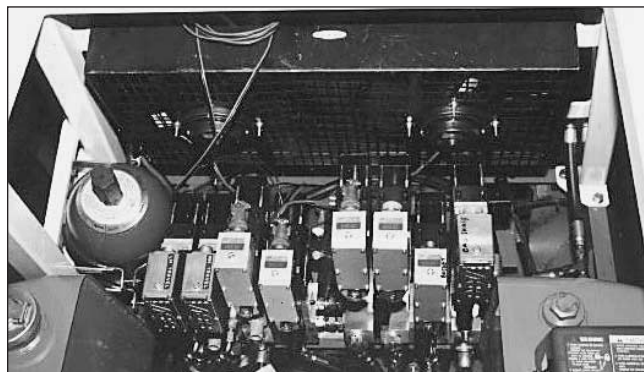


Figure 2. A view of the electrohydraulic servovalve stack.

where y is the displacement, v is the velocity, and F_L is the external disturbance force to be estimated. A schematic diagram of the observer proposed for (1) is shown in Fig. 3. In

Although the fully automated construction site is still a dream of some civil engineers, research developments have shown the promise of robotics and automation in construction.

that figure, a circumflex denotes an estimated quantity, $\sigma = \mu \operatorname{sgn}(e_y)$ with $\mu > 0$, $e_y = \hat{y} - y$ is the output error, and l_1 and l_2 are the observer gains. To reduce chattering associated with the sliding mode of the output error, the signum function $\operatorname{sgn}(e_y)$ is replaced by a sigmoidal expression resulted from fuzzy reasoning:

$$\sigma = \mu \tanh(e_y / \gamma_e). \quad (2)$$

The term γ_e is a positive constant that determines the rate of convergence and allows for chatter reduction as explained in [13].

Lower Level Control

The usual task of a backhoe excavator is to loosen and remove material from its original location and transfer it to another location by lowering the bucket, digging by dragging the bucket through the soil, then lifting, slewing, and dumping the bucket load. In moving towards automatic excavation, there is a need for the development of controllers that are robust to uncertainties associated with these operations [9]. Kinematic and dynamic models of excavators are developed in [14]-[16]. These models assume that the hydraulic actuators act as infinitely powerful force sources. Bucket po-

sition control using a conventional proportional and derivative controller is used in [16], [17] for simulation of the digging process with limited soil interactions. Rather than tracking desired position or force trajectories, interaction control seeks to regulate the relationship between the end-effector position and the force exerted by the bucket on the soil. Impedance control has been proposed [8], [18] as providing a unified approach to both unconstrained and force-constrained motion of an excavator arm.

In our approach, a robust sliding mode control technique is developed to implement impedance control for an excavator using generalized excavator dynamics. The bucket tip is controlled to track a desired digging trajectory in the presence of environment and system parameter uncertainties. As a result of the impedance control strategy, both the piston position and the ram force of each hydraulic cylinder that are required to exert a given bucket force at a particular position in world space can be determined. The problem is then to find the control voltages that must be applied to the servovalves to track these desired commands.

The dynamic model of the excavator can be expressed concisely in the form of the well-known manipulator equations of motion [16]

$$\mathbf{D}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + \mathbf{C}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}})\dot{\boldsymbol{\theta}} + \mathbf{B}(\dot{\boldsymbol{\theta}}) + \mathbf{G}(\boldsymbol{\theta}) = \boldsymbol{\Gamma}(\boldsymbol{\theta})\mathbf{F} - \mathbf{T}_L(F_t, F_n), \quad (3)$$

where $\boldsymbol{\theta} = [\theta_2 \ \theta_3 \ \theta_4]^T$ is the vector of measured joint angles as defined in Fig. 4; matrix $\mathbf{D}(\boldsymbol{\theta})$ represents inertia, and matrix $\mathbf{C}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}})$ represents Coriolis and centripetal effects; vectors $\mathbf{B}(\dot{\boldsymbol{\theta}})$, $\mathbf{G}(\boldsymbol{\theta})$, and $\boldsymbol{\Gamma}(\boldsymbol{\theta})$ respectively represent friction, gravity forces, and functions of the moment arms; \mathbf{T}_L represents the load torques as functions of the tangential and normal components F_t and F_n of the soil reaction force at the bucket, and \mathbf{F} is a vector of the ram forces of the hydraulic actuators that produce the torques acting on the joints. The tangential component F_t of the total soil resistance force is parallel to the

digging direction. The total resistance is considered to be the sum of soil resistance to cutting, friction between the bucket and the ground, the force required to accelerate the cut prism of soil, and the force to cause soil movement within the bucket. According to [19], the tangential component can be calculated as

$$F_t = k_1 bh, \quad (4)$$

where k_1 is the specific digging force in Nm^{-2} , and h and b are the thickness and width of the cut slice of soil. The normal component F_n is calculated as

$$F_n = \psi F_t, \quad (5)$$

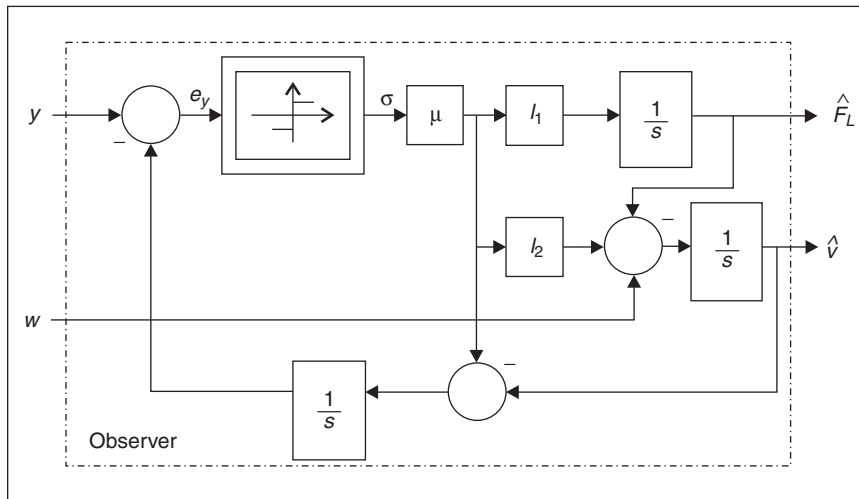


Figure 3. Observer schematic diagram.

where $\psi=0.1-0.45$ is a dimensionless factor that depends on the digging angle, digging conditions, and the wear of the cutting edge. For a comprehensive description of (3), see [16]. By systematically assigning Cartesian coordinate frames $\{O_1 x_1 y_1 z_1\}$, $\{O_2 x_2 y_2 z_2\}$, $\{O_3 x_3 y_3 z_3\}$, and $\{O_4 x_4 y_4 z_4\}$, as shown in Fig. 4, (3) can be cast in Cartesian space as

$$\mathbf{H}(\mathbf{x})\ddot{\mathbf{x}} + \mathbf{C}_x(\mathbf{x}, \dot{\mathbf{x}})\dot{\mathbf{x}} + \mathbf{B}_x(\dot{\mathbf{x}}) + \mathbf{G}_x(\mathbf{x}) = \mathbf{J}^{-T}\mathbf{\Gamma}\mathbf{F} - \mathbf{F}_e = \mathbf{u} - \mathbf{F}_e, \quad (6)$$

where \mathbf{J} is the Jacobian matrix,

$$\begin{aligned} \mathbf{H} &= \mathbf{J}^{-T} \mathbf{D} \mathbf{J}^{-1}, \\ \mathbf{C}_x &= \mathbf{J}^{-T} (\mathbf{C} - \mathbf{D} \mathbf{J}^{-1} \dot{\mathbf{J}}) \mathbf{J}^{-1}, \\ \mathbf{G}_x &= \mathbf{J}^{-T} \mathbf{G}, \\ \mathbf{B}_x &= \mathbf{J}^{-T} \mathbf{B}, \end{aligned}$$

and $\mathbf{u} = \mathbf{J}^{-T} \mathbf{\Gamma} \mathbf{F}$ is a control vector of generalized forces exerted at O_4 . The generalized forces of interaction between the bucket and the soil are $\mathbf{F}_e = \mathbf{J}^{-T} \mathbf{T}_L$, with force entries for the coordinates (x_4, z_4) and a torque entry around y_4 .

Let $\mathbf{x}_r(t)$ be the desired trajectory of the bucket tip. Typically, the target impedance is chosen as a linear second-order system to mimic mass-spring-damper dynamics

$$\begin{aligned} \mathbf{Z}_i(s) \mathbf{e}_p &= (\mathbf{M}_i s^2 + \mathbf{B}_i s + \mathbf{K}_i) \mathbf{e}_p \\ &= \mathbf{M}_i \ddot{\mathbf{e}}_p + \mathbf{B}_i \dot{\mathbf{e}}_p + \mathbf{K}_i \mathbf{e}_p = \mathbf{e}_F, \end{aligned} \quad (7)$$

where s is the derivative operator, and the constant positive-definite $n \times n$ target matrices \mathbf{M}_i , \mathbf{B}_i and \mathbf{K}_i are the matrices of desired inertia, damping, and stiffness. The position error \mathbf{e}_p and the force error \mathbf{e}_F are defined as

$$\mathbf{e}_p = \mathbf{x}_r - \mathbf{x}, \quad \mathbf{e}_F = \mathbf{F}_r - (-\mathbf{F}_e), \quad (8)$$

where $\mathbf{F}_r(t) = \mathbf{M}_i \ddot{\mathbf{x}}_r + \mathbf{B}_i \dot{\mathbf{x}}_r + \mathbf{K}_i \mathbf{x}_r$ is the force set-point. The control problem is to drive the system state so as to implement asymptotically the relationship (7), even in the presence of uncertainty. If the position error \mathbf{e}_p approaches zero, the force error \mathbf{e}_F also approaches zero, and vice versa, according to the specified dynamic relationship defined by the numeric values of the target matrices \mathbf{M}_i , \mathbf{B}_i and \mathbf{K}_i in (7). Let us define the sliding functions $\mathbf{s} = [s_1(\mathbf{x}), s_2(\mathbf{x}), \dots, s_n(\mathbf{x})]^T$ as follows [20]

$$\mathbf{s} = -\dot{\mathbf{e}}_p - \mathbf{M}_i^{-1} \mathbf{B}_i \mathbf{e}_p - \mathbf{M}_i^{-1} \mathbf{K}_i \int \mathbf{e}_p d\tau + \mathbf{M}_i^{-1} \int \mathbf{e}_F d\tau = \dot{\mathbf{x}} - \dot{\mathbf{x}}_s, \quad (9)$$

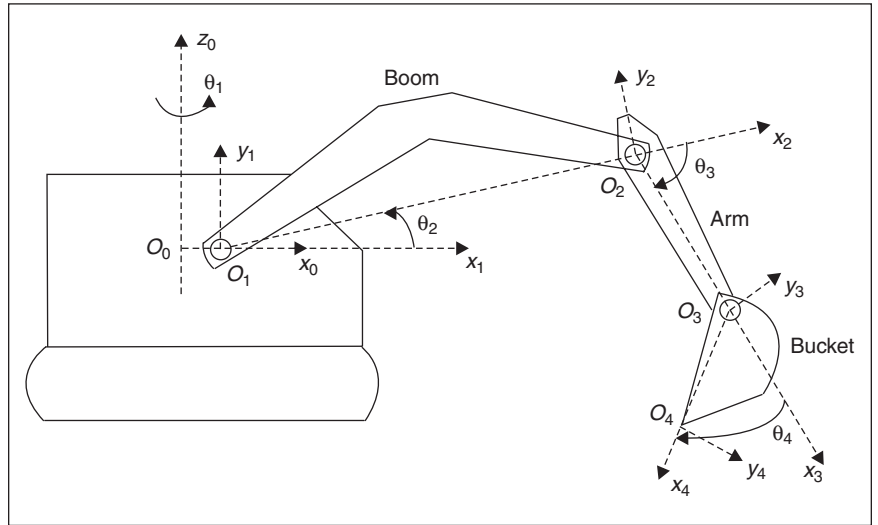


Figure 4. Excavator joint variables assigned using the Denavit-Hartenberg convention.

where

$$\dot{\mathbf{x}}_s = \dot{\mathbf{x}}_r + \mathbf{M}_i^{-1} \mathbf{B}_i \mathbf{e}_p + \mathbf{M}_i^{-1} \mathbf{K}_i \int \mathbf{e}_p d\tau - \mathbf{M}_i^{-1} \int \mathbf{e}_F d\tau. \quad (10)$$

The control input proposed [18] is

$$\mathbf{u} = \hat{\mathbf{u}} - \mathbf{Q} \operatorname{sgn}(\mathbf{s}) - \mathbf{K} \mathbf{s}, \quad (11)$$

where

$$\begin{aligned} \hat{\mathbf{u}} &= \hat{\mathbf{H}} \ddot{\mathbf{x}}_s + \hat{\mathbf{C}}_x \dot{\mathbf{x}}_s + \hat{\mathbf{G}}_x + \hat{\mathbf{F}}_e, \\ \mathbf{Q} &= [Q_1 \operatorname{sgn}(s_1), \dots, Q_n \operatorname{sgn}(s_n)]^T, \quad Q_i > \beta_i, \\ \mathbf{K} &= \operatorname{diag}[K_i(s_i)], \\ K_i &= K_{i \max} \left[1 - \exp\left(-|s_i|/\delta_i\right) \right], \end{aligned}$$

and where β_i , $K_{i \max}$, and δ_i ($i=1,2,\dots,n$) are some positive constants to be determined during design.

By using a trigonometric mapping [21] between a joint angle θ_i , $i=2,3,4$, and the linear displacement y_i of the associated hydraulic cylinder, the cylinder positions $\mathbf{y} = [y_2 \ y_3 \ y_4]^T$ required to position the bucket tip can be determined. Using the impedance control action \mathbf{u} in (6), together with the transformation between excavator joint space and Cartesian space, the ram forces \mathbf{F} of the machine hydraulic actuators can also be determined. The vectors \mathbf{y} and \mathbf{F} then form the reference inputs to the excavator axis control system.

The actuators driving the boom swing, boom, dipper arm, and bucket attachments of the excavator are axial hydraulic cylinders, and the flow of hydraulic oil to each cylinder is regulated by an electrohydraulic servovalve. For simplicity, the following linear expression can be used with little loss of accuracy for frequencies up to 200 Hz

$$x_v = K_v u_v, \quad (12)$$

where x_v is the servovalve spool displacement, and u_v is the valve input voltage. By assigning each hydraulic cylinder force F to be a state variable, a model for electrohydraulic systems that actuate machine axes can be obtained [12] as

This methodology can be extended to coordinated control of complicated autonomous machines at many scales with a variety of distinct dynamic operating regimes.

$$\begin{aligned} \dot{y} &= v \\ \dot{v} &= \frac{1}{M} [F - F_L] \\ \dot{F} &= a_{12}v + a_{13}F + a_{14}P_1 + b_1u_v \\ \dot{P}_1 &= a_{22}v + a_{23}F + a_{24}P_1 + b_2u_v, \end{aligned} \quad (13)$$

where P_1 is the piston head-side fluid pressure, and a_{ij} and b_i are time-varying coefficients with nominal values \bar{a}_{ij} and \bar{b}_i . The piston velocity v and load disturbance F_L are estimated using the observer shown in Fig. 3.

Let us define control errors

$$\begin{aligned} e_1 &= y - \gamma_r, & e_2 &= v - v_r, \\ e_3 &= F - F_r, & e_4 &= P_1 - P_{1r}, \end{aligned} \quad (14)$$

where v_r and P_{1r} are respectively the desired piston velocity and the head-side pressure. The following nonlinear dynamics can be derived for the error vector $\mathbf{e} = [e_1 \ e_2 \ e_3 \ e_4]^T$

$$\dot{\mathbf{e}} = \mathbf{A}(\mathbf{x}, \mathbf{x}_r) + \mathbf{B}(u + f), \quad (15)$$

where

$$\mathbf{A}(\mathbf{x}, \mathbf{x}_r) = \begin{pmatrix} \hat{v} - v_r = e_2 \\ \frac{F - \hat{F}_L}{M} - \dot{v}_r = \frac{e_3 - \hat{F}_L}{M} \\ a_{12}\hat{v} + a_{13}F + a_{14}P_1 - \dot{F}_r \\ a_{22}\hat{v} + a_{23}F + a_{24}P_1 - \dot{P}_{1r} \end{pmatrix}, \quad \mathbf{B} = \begin{pmatrix} 0 \\ 0 \\ b_1 \\ b_2 \end{pmatrix},$$

and f encapsulates all uncertainty arising from parameter variations and modeling errors. We now define the switching function

$$S = \mathbf{C}\mathbf{e} = e_3 + c_2e_2 + c_1e_1, \quad (16)$$

where $\mathbf{C} = [c_1 \ c_2 \ 1 \ 0]$ and c_i ($i=1,2$) are positive constants to be chosen according to the desired dynamics of the closed-loop system. The following control law is proposed [12]

$$u_v = u_{eq} + u_{sw} + u_{ft}, \quad (17)$$

where

$$\begin{aligned} u_{eq} &= -(\mathbf{CB})^{-1}(\mathbf{CA}) \\ &= -\bar{b}_1^{-1} \left[(c_1 + \bar{a}_{12})\hat{v} + \left(\frac{c_2}{M} + \bar{a}_{13} \right) F + \bar{a}_{14}P_1 - r - \frac{c_2}{M} \hat{F}_L \right] \\ u_{sw} &= -\rho_{sw} \operatorname{sgn}(\varphi), \\ u_{ft} &= -u_{f_m} \tanh(\varphi / \gamma_t), \end{aligned}$$

and where $r = c_1\dot{x}_r + c_2\ddot{x}_r + \dot{F}_r$, $\varphi = \mathbf{SCB} = Sb_1$, and u_{f_m} and γ_t are some positive constants to be determined.

Higher Level Control

Task planning and execution are important considerations in autonomous excavation. Traditionally, a planner is used to determine a sequence of primitive actions that, when executed, will transform the world from an initial state to a goal state. As there is a duality between world states and machine tasks, planning is thought to be hierarchical. At the highest level, a planner “ought to abstract the world and worry about goals while lower levels incrementally flesh out the directives” [6]. For example, in excavation planning, the bucket trajectories may initially be conservative, planned to shear a thin layer of homogeneous soil during the “drag” phase of an excavation step [22]. The objective is to generate trajectories that will fail marginally in the absence of sensing and control. Another view of planning is that it should be deliberative. A machine employing deliberative reasoning requires relatively complete knowledge of the world and uses this knowledge to predict the outcome of its operations [23].

In our work on robotic excavation, we propose to combine behavior-based and hierarchical architectures to produce strategies for planning and controlling the machine at higher levels. Practically, excavation tasks can be decomposed into behaviors that activate an appropriate set of suitable controllers. Approximate reasoning with fuzzy logic is incorporated to encapsulate human expert knowledge of earthmoving operations. The description of a particular behavior is based mainly on observation and study of how expert operators command excavators when digging.

Using a hierarchical-behavioral approach [24], we propose a layered control hierarchy of lower and higher levels within a global controller [22]. Lower level controllers are activated upon the technical resolution of conflicts and also of resource sharing, and the management of the control flow and the data flow using statecharts [25] and fuzzy reasoning. At the higher control level, the proposed hybrid architecture involves control schemes that are based on the decomposition of typical

excavation tasks into states or state elements. Each task is represented by a state in a statechart. At the lowest level in the statechart hierarchy are state elements to be used for the control of machine axes.

Unlike finite-state machines [26], statecharts allow for component reuse, concurrency, and for complex nested states (superstates), if required. A statechart is used to represent a state machine consisting of states and transitions between states together with synchronization states and pseudostates [25]. Every state object has entry and exit actions and executes the particular behavior or activity until a transition is set and the state is exited [22]. Transition conditions can be refined to have event priorities if more than one condition is true at the same time or can be seen as if/else or switch/case structures. For transition between state elements, a characteristic function γ_i associated with the state S_i is defined here as follows

$$\gamma_i = \begin{cases} 1, & \text{transition from } S_i \text{ to } S_j \\ 0, & S_i \text{ is active, } i=1,2,\dots,r. \end{cases} \quad (18)$$

A task element base, $\{\tau_i, i=1,2,\dots,r\}$, can contain one or more feasible elemental operations of the machine actuators [22]: perhaps τ_1 —adjust the engine throttle to maintain a constant speed, τ_2 —maintain the current position for a certain time, τ_3 —curl the bucket inward, and τ_4 —curl the bucket outward, and so on.

To illustrate this control architecture, consider the tasks of loading and of digging a trench to a certain depth. In loading, one pass in the task of removing soil from a pile can be decomposed as consisting of the states of positioning the bucket with a specified attack angle, penetrating the soil by curling the bucket inward, lifting and swinging the boom, and then dumping soil by curling the bucket outward.

Trenching, another common construction task, can be decomposed to the following sequence of states within a statechart:

- 1) Position the bucket over the trench start.
- 2) Lower the boom to the ground surface.
- 3) Penetrate the ground by curling the bucket.
- 4) Drag the bucket teeth in a straight line by moving the arm and the boom simultaneously.
- 5) Curl the bucket to collect soil into the bucket.
- 6) Raise the boom out of contact with ground.
- 7) Dump the bucket contents at the side of the trench.
- 8) Check the necessity of doing another dig cycle according to the specified trench dimensions. If necessary, repeat steps 1-8, or else terminate the task.

Associated with each phase of the task decomposition described above are states $S_i, i=1,\dots,5$, including **LowerBoom** (S_1), **Penetrate** (S_2), **Drag** (S_3), **Capture** (S_4), and **LoadToTruck** (S_5). The digging portion of the excavation work cycle and the dump cycle are considered as sub-states of this statechart. The transition between task elements is determined mainly by estimating if the digger has reached a position predetermined according to expert excavator-operator heuristics by measuring the Cartesian position error.

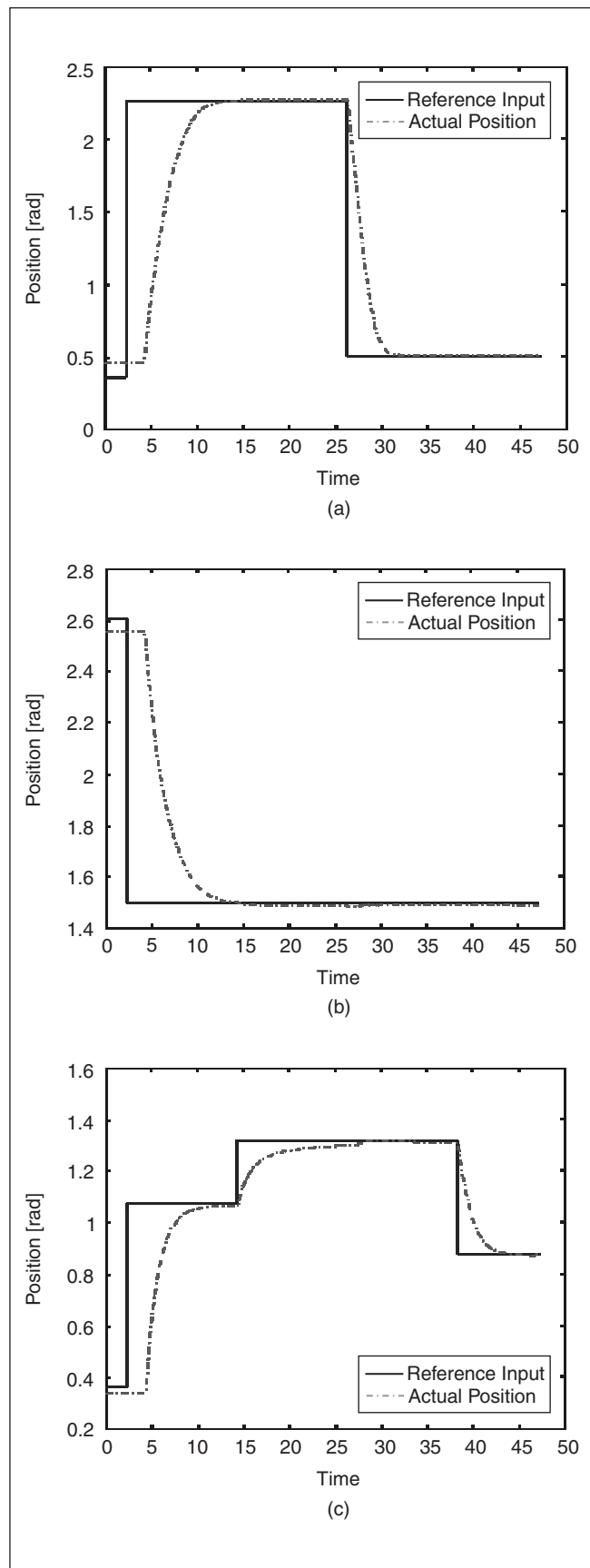


Figure 5. Loading a truck with impedance control: (a) bucket, (b) arm, and (c) boom joint angles.

Experimental Results

Experiments have been performed using the robotic excavator shown in Fig. 1. Data acquisition and control algorithms are written in C++ and executed under the *Windows NT* operating system. The sampling time is chosen to be 0.010 s, and data is communicated between the five control system processors by message-passing over a controller area network (CAN) bus at 250 kb/s. Some typical excavation tasks in construction automation can be demonstrated with our robotic machine.

Loading, for example, is a common earthmoving task. In an experiment, the duration for one-pass loading is set at 50 s. As the excavator operates under computer control, machine data from joint encoders and pressure transducers, together with environment data obtained by laser-scanning the soil pile, are continually gathered. These data determine, in real-time, the flow of control within the statechart, thus causing the required digging action. Transition between task elements (i.e., states) is determined mainly by testing estimated joint positions against allowable position errors. Given specific values of the target impedance matrices in (7), experimental responses of the boom, dipper arm, and bucket joints to reference position inputs are as shown in Fig. 5. Fig. 6 shows the ram force that actuates the bucket for one loading cycle of digging and dumping the soil. The results obtained verify the validity and feasibility of our proposed robust control scheme for autonomous operation of the robotic excavator, taking into account tool-soil interactions.

Fig. 1 shows one phase of a trenching task, executed with the decomposition detailed in the “Higher-Level Control” section. The average task duration for the digging portion of the trenching cycle is 15 s, which is an average time for a human operator to complete this task. The recorded data for the entry and exit points of the dragging phase are utilized to generate the desired trajectory in joint space for the next digging cycle. Field tests have been conducted that involve trenching in soils categorized as soft, medium, and hard. The three parts of Fig. 7 show the measured Cartesian trajectories of the bucket tip when digging in these three soil types. In the figure, segments AB, BC, CD, and

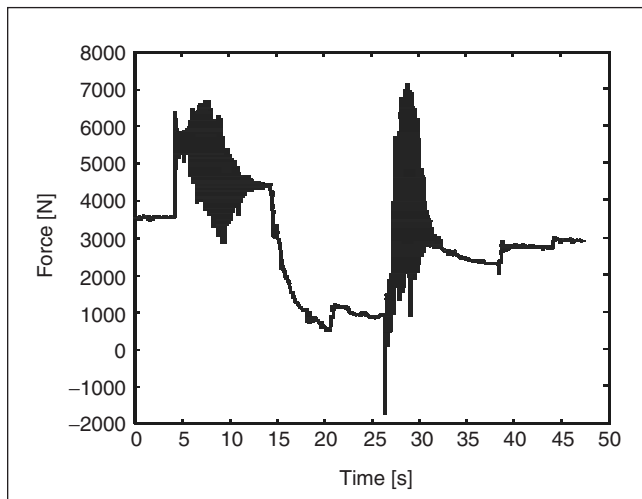


Figure 6. Bucket ram force during a loading task.

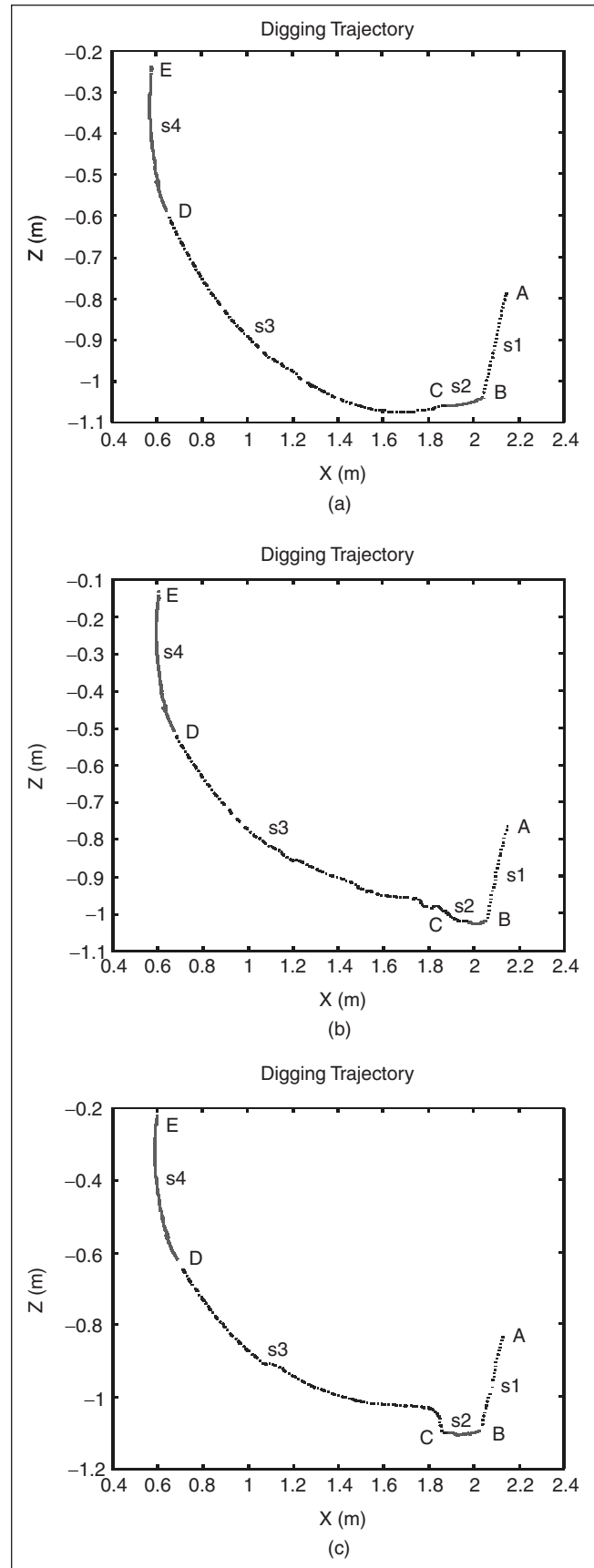


Figure 7. Bucket tip trajectory, digging (a) soft, (b) medium, and (c) hard soil.

DE respectively correspond to the previously defined phases S_1 , S_2 , S_3 , and S_4 . In the absence of hard inclusions, the tip motion during the dragging phase is observed in Fig. 7(a) and (b) to satisfy a desired tolerance of 5 cm. Fig. 7(c) shows that the bucket teeth cannot, however, penetrate hard soil smoothly because the required soil cutting force exceeds the excavator's force capacity. The bucket must then be lifted and the surface scratched with the bucket teeth in order to loosen the soil underneath.

Conclusion

An overview of the robotic excavation project at the Australian Centre for Field Robotics at The University of Sydney has been presented. The experimental machine, retrofitted from a commercial mini-excavator, and its instrumentation are described. Estimation and control strategies applied to the robotic excavator digger are briefly presented. Variable-structure-based techniques are employed to implement impedance control of excavator dynamics, and position/force control of the electrohydraulic systems for each working axis. This control takes into account uncertainties in modeling, friction, and bucket-soil interactions.

Behavioral and hierarchical approaches are combined for decomposition and execution of some excavation tasks that are common in construction. The control architecture is designed with a view to managing hierarchical complexity and facilitating the application of formal verification methods, software reuse, and lower-level robust control results. It is believed that the methodology can be extended to coordinated control of complicated autonomous machines at many scales with a variety of distinct dynamic operating regimes. The experimental results described here suggest the technical possibility of achieving autonomous robotic excavation in moving toward construction automation.

Acknowledgments

The Australian Centre for Field Robotics is a Commonwealth Key Centre of Teaching and Research. Support from the Australian Research Council, NS Komatsu Pty. Ltd., and Cooperative Research Centre for Mining Technology and Equipment is gratefully acknowledged.

Keywords

Robotic excavation, construction automation, lower and higher level control, impedance control, statecharts.

References

- [1] R.L. Tucker, "Construction automation in the USA," in *Proc. 16th Int. Symp. on Automat. Robotics Construction*, Madrid, Spain, 1999, p. vii.
- [2] J. Yagi, "Automation and robotics in construction in Japan," in *Proc. 16th Int. Symp. Automat. Robotics Construction*, Madrid, Spain, pp. iii-vi, 1999.
- [3] L.E. Bernold, "Experimental studies on mechanics of lunar excavation," *J. Aerosp. Eng.*, vol. 4, no. 1, pp. 9-22, 1991.
- [4] P.A. Lever and F.Y. Wang, "Intelligent excavation control system for lunar mining system," *J. Aerosp. Eng.*, vol. 8, no. 1, pp. 16-24, 1995.
- [5] D.V. Bradley and D.W. Seward, "The development, control and operation of an autonomous robotic excavator," *J. Intelligent Robot. Syst.*, vol. 21, pp. 73-97, 1998.
- [6] S. Singh, "Synthesis of tactical plans for robotic excavation," PhD dissertation, Robot. Inst., Carnegie Mellon Univ., Pittsburgh, PA, 1995.
- [7] L.E. Bernold, "Motion and path control for robotic excavation," *J. Aerosp. Eng.*, vol. 6, no. 1, pp. 1-18, 1993.
- [8] S.E. Salcudean, S. Tafazoli, K. Hashtrudi-Zaad, and P.D. Lawrence, "Evaluation of impedance and teleoperation control of a hydraulic mini-excavator," in *Proc. 5th Int. Symp. Experimental Robot.*, Barcelona, Spain, pp. 187-198, 1997.
- [9] A.T. Le, Q.H. Nguyen, Q.P. Ha, D.C. Rye, H.F. Durrant-Whyte, M. Stevens, and V. Boget, "Towards autonomous excavation," in *Field and Service Robotics*, A. Zelinsky, Ed. New York: Springer-Verlag, 1998.
- [10] C. Edwards and S.K. Spurgeon, "On the development of discontinuous observers," *Int. J. Contr.*, vol. 59, no. 5, pp. 1211-1229, 1994.
- [11] Q.P. Ha, A. Bonchis, D.C. Rye, and H.F. Durrant-Whyte, "Variable structure systems approach to friction estimation and compensation," in *Proc. IEEE Int. Conf. Robot. Automat.*, San Francisco, CA, pp. 3543-3548, 2000.
- [12] Q.P. Ha, Q.H. Nguyen, D.C. Rye, and H.F. Durrant-Whyte, "Force and position control of electrohydraulic position systems of a robotic excavator," in *Proc. 16th Int. Symp. Automat. Robot. Construction*, Madrid, Spain, pp. 483-489, 1999.
- [13] Q.P. Ha, D.C. Rye, and H.F. Durrant-Whyte, "Fuzzy moving sliding mode control with application to robotic manipulators," *Automatica*, vol. 35, no. 4, pp. 607-616, 1999.
- [14] P.K. Vaha and M.J. Skibniewski, "Dynamic model of an excavator," *J. Aerosp. Eng.*, vol. 6, no. 2, pp. 148-158, 1993.
- [15] A.J. Koivo, "Kinematics of excavators (backhoes) for transferring surface material," *J. Aerosp. Eng.*, vol. 7, no. 1, pp. 17-31, 1994.
- [16] A.J. Koivo, M. Thoma, E. Kocaoglan, and J. Andrade-Cetto, "Modeling and control of excavator dynamics during digging operation," *J. Aerosp. Eng.*, vol. 9, no. 1, pp. 10-18, 1996.
- [17] P.K. Vaha and M.J. Skibniewski, "Cognitive force control of excavators," *J. Aerosp. Eng.*, vol. 6, no. 2, pp. 159-166, 1993.
- [18] Q.P. Ha, Q.H. Nguyen, D.C. Rye, and H.F. Durrant-Whyte, "Impedance control of a hydraulically-actuated robotic excavator," *Automat. Construction*, vol. 9, no. 5, pp. 421-435, 2000.
- [19] T.V. Alekseeva, K.A. Artem'ev, A.A. Bromberg, R.L. Voitsekhovskii, and N.A. Ul'yanov, *Machines for Earthmoving Work: Theory and Calculations*. Rotterdam: A.A. Balkema, 1986.
- [20] Z. Lu and A.A. Goldenberg, "Robust impedance control and force regulation: Theory and experiment," *Int. J. Robot. Res.*, vol. 14, no. 3, pp. 225-254, 1995.
- [21] S. Tafazoli, P.D. Lawrence, S.E. Salcudean, D. Chan, S. Bachmann, and C.W. de Silva, "Parameter estimation and actuator friction analysis for a mini-excavator," in *Proc. 1996 IEEE Int. Conf. Robot. Automat.*, Minneapolis, MN, pp. 329-334, 1996.
- [22] M. Santos, Q.P. Ha, D.C. Rye, and H.F. Durrant-Whyte, "Global control of robotic excavation using fuzzy logic and statecharts," in *Proc. 17th Symp. Automat. Robot. Construction*, Taipei, Taiwan, 2000, pp. 559-565.
- [23] R.C. Arkin, *Behaviour-Based Robotics*. Cambridge, MA: MIT Press, 1998.
- [24] E. Coste-Manière and R. Simmons, "Architecture, the backbone of robotic systems," in *Proc. 2000 IEEE Int. Conf. Robot. Automat.*, San Francisco CA, pp. 67-72.

[25] B.P. Douglass, *Real-Time UML: Developing Efficient Objects for Embedded Systems*. Reading, MA: Addison-Wesley, 1999.

[26] K.Y. Fok and M.R. Fabuka, "A automatic navigation system for vision-guided vehicles using a double heuristic and a finite state machine," *IEEE Trans. Robot. Automat.*, vol. 7, pp. 181-188, Feb. 1991.

Quang Ha received a B.E. in electrical engineering from Ho Chi Minh City University of Technology, Vietnam, in 1983; a Ph.D. in engineering science from Moscow Power Institute, Russia, in 1992; and a Ph.D. in electrical engineering from the University of Tasmania, Australia, in 1997. From 1997-2000, he was a senior research associate at the Centre for Field Robotics at The University of Sydney. He is currently a lecturer at the University of Technology, Sydney, Australia. His research interests include nonlinear control, variable structure systems, robotics, and applications of artificial intelligence in engineering.

Miguel Santos received a B.S. in electrical engineering from the Universidad Nacional de Ingenieria, Peru, in 1988 and a M.S. in engineering science from the University of New South Wales, Australia, in 1995. His research interests include robot architectures, fuzzy control, artificial intelligence, and its applications to construction and mining.

Quang Nguyen received a B.S. In electrical engineering from Hanoi University of Technology, Vietnam, in 1993. He recently graduated with a PH.D. from the Australian Centre for Field Robotics, The University of Sydney, Australia. His research interests include nonlinear control, robotics and software engineering.

David Rye received a B.E. from Adelaide University, Australia, and a Ph.D. from The University of Sydney, Australia,

both in mechanical engineering, in 1980 and 1986, respectively. From 1986 to December 1987, he served as a lecturer in mechanical engineering at the Department of Mechanical Engineering at the University of Newcastle, Australia. Since 1988, he has been with the Department of Mechanical and Mechatronic Engineering, The University of Sydney, Australia, as a lecturer and then senior lecturer in mechanical engineering. Dr. Rye is a Deputy Director of the Australian Centre for Field Robotics. His research interests include intelligent and nonlinear control, autonomous excavation, crane dynamics and control, mechatronics and automation.

Hugh Durrant-Whyte received the B.S. in mechanical and nuclear engineering from the University of London, UK, in 1983, and an M.S.E. and Ph.D. in systems engineering from the University of Pennsylvania, USA, in 1985 and 1986, respectively. From 1987-1995, he was a University Lecturer in Engineering Science, Oxford University, UK. Since July 1995, he has been Professor of Mechatronic Engineering at the Department of Mechanical and Mechatronic Engineering, The University of Sydney, Australia. Prof. Durrant-Whyte is the Director of the Australian Centre for Field Robotics. His research interests include sensor data fusion, sensor systems, and mobile robotics.

Address for Correspondence: Dr. David Rye, Australian Centre for Field Robotics, Rose Street Building J04, The University of Sydney 2006, Australia. Phone: +61-2-9351-7126; Fax: +61-2-9351-7474; E-mail: rye@acfr.usyd.edu.au; Web site: <http://www.acfr.usyd.edu.au/>.