Automatic construction of reactive control systems using symbolic machine learning

CLAUDE SAMMUT

Department of Artificial Intelligence, University of New South Wales, Sydney Australia 2052
(email: claude@cse.unsw.edu.au)

Abstract

This paper reviews a number of applications of Machine Learning to industrial control problems. We take the point of view of trying to automatically build rule-based reactive systems for tasks that, if performed by humans, would require a high degree of skill, yet are generally performed without thinking. Such skills are said to be sub-cognitive. While this might seem restrictive, most human skill is executed subconsciously and only becomes conscious when an unfamiliar circumstance is encountered. This kind of skill lends itself well to representation by a reactive system, that is, one that does not create a detailed model of the world, but rather, attempts to match percepts with actions in a very direct manner.

1. Introduction

Traditional control theory requires a mathematical model of a physical process to predict its behaviour so that appropriate control decisions can be determined. Unfortunately, many processes are either too complicated to model accurately or insufficient information is available about the process' environment. In such cases, heuristic methods often prove useful. But where do the heuristics come from? They may be hand-crafted, based on the knowledge of experts, but this is often not possible since many control skills are sub-cognitive, that is, they are performed without thinking and without any conscious knowledge of the skill. For this reason, machine learning plays an important role in building knowledge-based control systems.

How a dynamic system is controlled depends very much on the time scales involved. A good example of a highly dynamic system is an aircraft. Suppose we wish to control a large plane, such as a 747. This system is so large that the response time for a control decision may be quite long. Say, for example, that the pilot wishes to lower the flaps on a landing approach. Depending on the angle of the flaps, this may take quite a few seconds. Given the inertia of such a large aircraft, the effect of lowering the flaps is further delayed. In fact, piloting a large commercial aircraft, under normal circumstances, requires a high degree of conscious planning and forethought. On the other hand, suppose we are piloting a highly responsive aircraft, such as a fighter or aerobatics plane. In this case, the aircraft responds to control decisions very quickly and therefore, much of the pilot's decision making must be correspondingly fast, in fact, so fast that conscious thought is not possible.

Many of our skills are sub-cognitive, just like the fighter pilot's skill. In 1911, the mathematical philosopher A.N. Whitehead wrote:

> It is a profoundly erroneous truism ... that we should cultivate the habit of thinking what we are doing. The precise opposite is the case. Civilisation advances by extending the number of important operations which we can perform without thinking about them.

In this paper, we are concerned, not with the conscious planning and control that a 747 pilot might engage in, but rather in the subconscious control of a fighter pilot.

Such skills are not limited to exotic domains. When we do not have good model of a dynamic system, we usually resort to "seat-of-the-pants" control. As an example, consider a system such as a container crane. Very large gantry cranes are used to transport heavy loads, on a swinging rope, from the dock to a ship and *vice versa*. Because of their non-linear nature, traditional control theory is unable to provide optimal control strategies to maximise the throughput of these cranes, yet some human operators are known to perform much better than others and better than automated systems. Somehow, they have acquired a skill that enables them to perform very efficiently, yet they are unable to articulate that skill because it is sub-cognitive.

Human sub-cognitive skills are "tacit" in the sense that the owner of such a skill is unaware of its mode of operation. However, a skilled human operator of a plant is usually conscious of the goals and sub-goals he or she is attempting to achieve. Each of these goals may be served by a separate sub-cognitive procedure. Machine-executable forms of such sub-cognitive skills can be used to simplify the construction of practical control systems by introducing a "multi-agent" architecture where low-level agents may be regarded as expert solvers for a particular problem. A chairman, who has global access to the problem-solving environment, selectively invokes members of a committee of specialists each of which has access to a different, very limited, part of the environment. The chairman embodies explicit knowledge that is easily articulated and therefore can be hand-crafted. The specialists implement low-level real-time control skills that, in a human, are not performed at a conscious level and therefore cannot be articulated. To create this kind of knowledge, each agent may be separately derived by inductive learning of production rules from recorded human performance of the skilled task.

Complex control skills in humans are built of components which their possessors cannot explicitly communicate. However, given sufficient sampling of subarticulate input-output, machine learning programs can construct rules which result in behaviours similar to those of the original exemplars (Michie, 1986). These "clones", i.e. exemplar-derived agents, are in effect, symbolic representations of subsymbolic behaviours.

In this paper, we first look briefly at heuristic control systems and at how control skills can be specified by a symbolic representation. We then review systems that learn such control rules. Note that we confine ourselves to a discussion of techniques for learning symbolic representations. One of the primary aims of the work surveyed is to produce explicit descriptions of sub-cognitive skills that can be read and understood. There are two reasons for this: one is that such explicit representations may shed light on the nature of the skill; the second is that the skill's description may lead to improved training methods. There is a considerable body of literature on neural, genetic and reinforcement learning for control problems. While much of this work has been extremely productive, we do not include it in our survey since the output from these algorithms are often difficult to interpret.

2. Reactive Procedures

Tacit skills can be represented by "situation-action" rules. We illustrate this with a new formalism developed by Nilsson (1994).

> A teleo-reactive(T-R) sequence is an agent control program that directs the agent toward a goal (hence *teleo*) in a manner that takes into account changing environmental circumstances (hence *reactive*). In its simplest form, it consist of an ordered set of production rules.

Two T-R procedures for controlling a mobile robot are shown below:

```
goto(Loc)
    position = Loc                    →   nil
    heading = course(position, Loc)   →   move
    otherwise                         →   rotate

amble(Loc)
    position = Loc                    →   nil
    clear_path(position, Loc)         →   goto(Loc)
    otherwise                         →   amble(new_point(position, Loc))
```

The left hand side of a production rule consists of tests on sensor data and the right hand side consists of calls to action procedures. The first rule of the `goto` procedure simply states that if the robot is at the desired location then do nothing. If the heading of the robot is the same as the course required to reach the desired location then move forward, otherwise rotate. These production rules are continuously evaluated in the order they are written. As the robot rotates, the heading is continuously compared with the required course. When they are the same, the second production rule takes priority, so rotation stops and the robot moves forward. If the robot drifts off course then the third rule will be invoked until the heading is correct again.

The `amble` procedure describes a simple plan for obstacle avoidance. If the robot is at the desired location then do nothing. If there is a clear path from the current position to the desired location then go to that location, otherwise determine a new point to one

Table 1. Yaw Control Rule

	Yaw rate very negative	Yaw rate negative	Yaw rate ok	Yaw rate positive	Yaw rate very positive
Yaw positive	$\frac{1}{4}$ thrust	no thrust	$-\frac{1}{4}$ thrust	$-\frac{1}{2}$ thrust	– full thrust
Yaw ok	$\frac{1}{2}$ thrust	no thrust	no thrust	no thrust	$-\frac{1}{2}$ thrust
Yaw negative	full thrust	$\frac{1}{2}$ thrust	$\frac{1}{4}$ thrust	no thrust	$-\frac{1}{4}$ thrust

side of the obstacle and call `amble` recursively. Some procedures, either sensor or motor, are built it. For example, the current heading may be determined by reference to an onboard compass which is accomplished by special purpose code. Primitive actions include move, rotate, etc. Actions, whether primitive or user defined, can be used in planning provided that additional information is available, namely, the preconditions necessary for an action to achieve a goal, the postconditions of the action and side effects, such as conditions which become true or false after performing the action.

In effect, the current situation is used as an index into a set of pre-arranged action sequences. If the rules cover all possible situations in which an agent can find itself, these plans are said to be *universal* (Schoppers, 1987). We give a simple, but practical example of a universal plan in the following section.

2.1. Satellite Control

If the attitude of a satellite in Earth orbit is to be kept stable by means of thrusters, the control system must contend with many unknown factors. For example, although very thin, the Earth' s atmosphere can extend many hundreds of kilometres into space. At different times, the solar wind can cause the atmosphere' s density to change, thus altering the drag on the space craft. Indeed, the solar wind, itself highly variable, can affect the satellite' s attitude. These are factors which earth-bound designers cannot predict, and even after nearly four decades of space flight, attitude control is still a major problem.

Sammut and Michie (1991) developed a strategy for firing roll, pitch and yaw thrusters by using a simple table look up, which corresponds very closely to Nilsson’s T-R paradigm. We illustrate this with the yaw table, reproduced in Table 1. Pitch and roll have similar control strategies.

Using a high-fidelity simulator of a space craft, Sammut and Michie found that although roll, pitch and yaw are coupled, the control systems for each can be separated. Each axis is discretised so that when the state variables indicate that the system falls in a particular table entry or box, the appropriate action is taken. Roll, pitch and yaw are treated independently, but even though a torque in one direction can cause precession in another, the rules implicitly correct for interactions. Originally, Sammut and Michie used pure bang-bang control. While this was able to control the satellite, it wasted fuel and caused unnecessary accelerations. The strategy shown in Table 1 is fuel efficient and relatively smooth.

Discretisation of the state space was a trivial matter. The designers of the spacecraft indicated regions of optimum performance; acceptable performance and unacceptable performance. These specifications were used to set the boundaries of the boxes.

This application illustrates some advantages of a reactive control system. Because system builders are often unable to predict variations in environment, a system may be designed so that it responds in reaction to the current situation rather than following a pre-defined plan which may become inappropriate when conditions change. The attitude control problem is one in which it is relatively easy to cover all expected situations, provided that all the thrusters are operating normally. Later we will discuss how failures can be handled.

In this example, it was possible to write comprehensive control rules, however, an obvious difficulty with reactive control systems, especially universal ones, is that number of rules required may become impossibly large in some domains. How can we anticipate all possible circumstances? Where will all of these rules come from? Machine Learning provides one answer.

3. Learning Situation-Action Rules by Behavioural Cloning

Behavioural cloning seeks to build situation-action rules by learning from the traces of a skilled operator's behaviour. Thus, if a human is capable of performing some task, rather than ask him or her to explain how the task was performed, we ask to be shown how. Machine learning is used to create a symbolic description of the skill where introspection by the human operator fails because the task is performed without thinking. The first demonstration of behavioural cloning was by Michie, Bain and Hayes-Michie (1990) on the task of pole balancing. Since then, a number of practical applications have been developed. The method of behavioural cloning is best understood by looking at some of these applications.

3.1. Learning to Fly

Sammut, Hurst, Kedzier and Michie (1992) modified a flight simulation program to log the actions taken by a human subject as he or she flies an aircraft. The log file is used to create the input to an induction program. The quality of the output from the induction program is tested by running the simulator in autopilot mode where the autopilot code is derived from the decision tree formed by induction.

The central control mechanism of the simulator is a loop that interrogates the aircraft controls and updates the state of the simulation according to a set of equations of motion. Before repeating the loop, the instruments in the display are updated.

3.1.1. Logging Flight Information

The display update was modified so that when the pilot performs a control action by moving the control stick or changing the thrust or flaps settings, the state of the simulation is written to a log file. Three subjects each 'flew' 30 times.

At the start of a flight, the aircraft points North, down the runway. The subject is required to fly a well-defined flight plan that consists of the following manoeuvres:

1. Take off and fly to an altitude of 2,000 feet.
2. Level out and fly to a distance of 32,000 feet from the starting point.
3. Turn right to a compass heading of approximately 330°. The subjects were actually told to head toward a particular point in the scenery that corresponds to that heading.
4. At a North/South distance of 42,000 feet, turn left to head back towards the runway. The scenery contains grid marks on the ground. The starting point for the turn is when the last grid line was reached. This corresponds to about 42,000 feet. The turn is considered complete when the azimuth is between 140° and 180°.
5. Line up on the runway. The aircraft was considered to be lined up when the aircraft' s azimuth is less than 5° off the heading of the runway and the twist is less that ±10° from horizontal.
6. Descend to the runway, keeping in line. The subjects were given the hint that they should have an 'aiming point' near the beginning of the runway.
7. Land on the runway.

During a flight, up to 1,000 control actions can be recorded. With three pilots and 30 flights each, the complete data set consists of about 90,000 events. The data recorded in each event are:

on_ground	boolean: is the plane on the ground?
g_limit	boolean: have we exceeded the plane's g limit
wing_stall	boolean: has the plane stalled?
twist	integer: 0 to 360° (in tenths of a degree, see below)
elevation	integer: 0 to 360° (in tenths of a degree, see below)
azimuth	integer: 0 to 360° (in tenths of a degree, see below)
roll_speed	integer: 0 to 360° (in tenths of a degree per second)
elevation_speed	integer: 0 to 360° (in tenths of a degree per second)
azimuth_speed	integer: 0 to 360° (in tenths of a degree per second)
airspeed	integer: (in knots)
climbspeed	integer: (feet per second)
E/W distance	real: E/W distance from centre of runway (in feet)
altitude	real: (in feet)
N/S distance	real: N/S distance from northern end of runway (in feet)
fuel	integer: (in pounds)
rollers	real: ±4.3
elevator	real: ±3.0
rudder	real: not used
thrust	integer: 0 to 100%

flaps integer: 0°, 10° or 20°

The elevation of the aircraft is the angle of the nose relative to the horizon. The azimuth is the aircraft's compass heading and the twist is the angle of the wings relative to the horizon. The elevator angle is changed by pushing the mouse forward (positive) or back (negative). The rollers are changed by pushing the mouse left (positive) or right (negative). Thrust and flaps are incremented and decremented in fixed steps by keystrokes. The angular effects of the elevator and rollers are cumulative. For example, in straight and level flight, if the stick is pushed left, the aircraft will roll anti-clockwise. The aircraft will continue rolling until the stick is centred. The thrust and flaps settings are absolute.

When an event is recorded, the state of the simulation at the instant that an action is performed could be output. However, there is always a delay in response to a stimulus, so ideally we should output the state of the simulation when the stimulus occurred along with the action that was performed some time later in response to the stimulus. But how do we know what the stimulus was? Unfortunately there is no way of knowing. Human responses to sudden piloting stimuli can vary considerably but they take at least one second. For example, while flying, the pilot usually anticipates where the aircraft will be in the near future and prepares the response before the stimulus occurs.

Each time the simulator passes through its main control loop, the current state of the simulation is stored in a circular buffer. An estimate is made of how many loops are executed each second. When a control action is performed, the action is output, along with the state of the simulation as it was some time before. How much earlier is determined by the size of the buffer.

3.1.2. Data Analysis

Quinlan's C4.5 (Quinlan, 1993) program was used to generate flight rules from the data. Even though induction programs can save an enormous amount of human effort in analysing data, in real applications it is usually necessary for the user to spend some time preparing the data.

The learning task was simplified by restricting induction to one set of pilot data at a time. Thus, an autopilot has been constructed for each of the three subjects who generated training data. The reason for separating pilot data is that each pilot can fly the same flight plan in different ways. For example, straight and level flight can be maintained by adjusting the throttle. When an airplane's elevation is zero, it can still climb since higher speeds increase lift. Adjusting the throttle to maintain a steady altitude is the preferred way of achieving straight and level flight. However, another way of maintaining constant altitude is to make regular adjustments to the elevators causing the airplane to pitch up or down.

The data from each flight were segmented into the seven stages described previously. In the flight plan described, the pilot must achieve several, successive goals, corresponding to the end of each stage. Each stage requires a different manoeuvre. Having already defined the sub-tasks and told the human subjects what they are, the learning program was given the same advantage.

In each stage four separate decision trees are constructed, one for each of the elevator, rollers, thrust and flaps. A program filters the flight logs generating four input files for the induction program. The attributes of a training example are the flight parameters described earlier. The dependent variable or class value is the attribute describing a control action. Thus, when generating a decision tree for flaps, the flaps column is treated as the class value and the other columns in the data file, including the settings of the elevator, rollers and thrust, are treated as ordinary attributes. Attributes that are not control variables are subject to a delay, as described in the previous section.

C4.5 expects class values to be discrete but the values for elevator, rollers, thrust and flaps are numeric. A preprocessor breaks up the action settings into sub-ranges that can be given discrete labels. Sub-ranges are chosen by analysing the frequency of occurrence of action values. This analysis must be done for each pilot to correctly reflect differing flying styles. There are two disadvantages to this method. One is that if the sub-ranges are poorly chosen, the rules generated will use controls that are too fine or too coarse. Secondly, C4.5 has no concept of ordered class values, so classes cannot be combined during the construction of the decision tree.

An event is recorded when there is a change in one of the control settings. A change is determined by keeping the previous state of the simulation in a buffer. If any of the control settings are different in the current state, a change is recognised. This mechanism has the unwanted side-effect of recording all the intermediate values when a control setting is changed through a wide range of values. For example, the effects of the elevator and rollers are cumulative. If we want to bank the aircraft to the left, the stick will be pushed left for a short time and then centred, since keeping it left will cause the airplane to roll. Thus, the stick will be centred after most elevator or roller actions. This means that many low elevator and roller values will be recorded as the stick is pushed out and returned to the centre position.

To ensure that records of low elevator and roller values do not swamp the other data, another filter program removes all but the steady points and extreme points in stick movement. Control engineers are familiar with this kind of filtering. In their terms, the graph of a control's values is differentiated and only the values at the zero crossings of the derivative are kept.

3.1.3. Generating the Autopilot

After processing the data as described above, they can be submitted to C4.5 to be summarised as rules that can be executed in a controller.

Decision tree algorithms are made noise tolerant by introducing *pruning*. If the data contain noise, then many of the branches in a decision tree will be created to classify bad data. The effects of noise can be reduced by removing branches near the leaves of the tree. This can either be done by not growing those branches when there are insufficient data or by cutting back branches when their removal does not decrease classification accuracy.

The flight data are very noisy, so decision trees are generated using conservative setting for pruning and then tested in the simulator. Pruning levels are gradually increased until the rule ‘breaks’, ie. it is no longer able to control the plane correctly. This procedure results in the smallest, and thus most readable, rule the succeeds in accomplishing the flight goal.

3.1.4. Linking the Autopilot with the Simulator

To test the induced rules, they are used as the code for a autopilot. A post-processor converts C4.5’s decision trees into if-statements in C so that they can be incorporated into the flight simulator easily. Hand-crafted C code determines which stage the flight has reached and decides when to change stages. The appropriate rules for each stage are then selected in a switch statement. Each stage has four, independent if-statements, one for each action.

When the data from the human pilots were recorded, a delay to account for human response time was included. Since the rules were derived from these data, their effects should be delayed by the same amount as was used when the data were recorded. When a rule fires, instead of letting it effect a control setting directly, the rule’s output value is stored in a circular buffer. There is one for each of the four controls. The value used for the control setting is one of the previous values in the buffer. A lag constant defines how far to go back into the buffer to get the control setting. The size of the buffer must be set to give a lag that approximates the lag when the data were recorded.

Rules could set control values instantaneously as if, say, the stick were moved with infinite speed from one position to another. Clearly this is unrealistic. When control values are taken from the delay buffer, they enter another circular buffer. The controls are set to the average of the values in the buffer. This ensures that controls change smoothly. The larger the buffer, the more gentle are the control changes.

3.1.5. Flying on Autopilot

An example of the rules created by cloning is the elevator take-off rule generated from one pilot’s data:

```
elevation > 4 : level_pitch
elevation <= 4 :
| airspeed <= 0 : level_pitch
| airspeed > 0 : pitch_up_5
```

This states that as thrust is applied and the elevation is level, pull back on the stick until the elevation increases to 4°. Because of the delay, the final elevation usually reaches 11° which is close to the values usually obtained by the pilot. `pitch_up_5` indicates a large elevator action, whereas, `pitch_up_1` would indicate a gentle elevator action.

A more complex case is that of turning. Stage 4 of the flight requires a large turn to the left. The rules are quite complex. To make them understandable, they have been greatly simplified by over-pruning. They are presented to illustrate an important point, that is that rules can work in tandem although there is no explicit link between them. The following rules are for the rollers and elevator in the left turn.

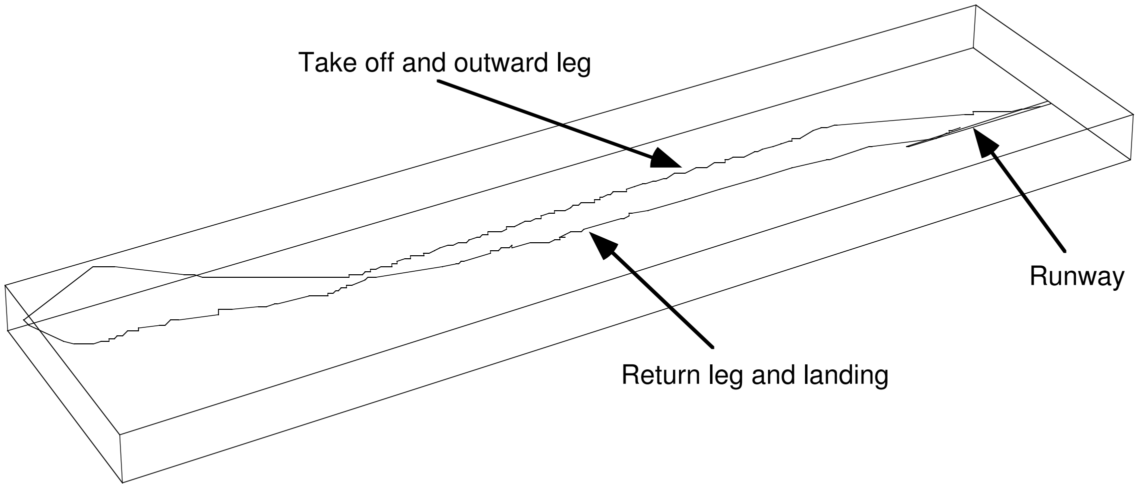


Figure 1. Flight profile

```
azimuth > 114 : right_roll_1
azimuth <= 114 :
| twist <= 8 : left_roll_4
| twist > 8 : no_roll

twist <= 2 : level_pitch
twist > 2 :
| twist <= 10 : pitch_up_1
| twist > 10 : pitch_up_2
```

A sharp turn requires coordination between roller and elevator actions. As the aircraft banks to a steep angle, the elevator is pulled back. The rollers rule states that while the compass heading has not yet reached 114°, bank left provided that the twist angle does not exceed 8°. The elevator rule states that as long as the aircraft has no twist, leave the elevator at level pitch. If the twist exceeds 2° then pull back on the stick. The stick must be pulled back more sharply for a greater twist. Since the rollers cause twist, the elevator rule is invoked to produce a coordinated turn. The profile of a complete flight is shown in Figure 1.

Like Michie, Bain and Hayes-Michie (1990), this study found a "clean-up effect". The flight log of any trainer contains many spurious actions due to human inconsistency and corrections required as a result of inattention. It appears that the effects of these inconsistent examples are pruned away by C4.5, leaving a control rule which flies very smoothly.

3.2. Container Crane Control

Urbančič and Bratko (1994) also used behavioural cloning to construct a control system for a container crane, illustrated in Figure 2.

The task of the operator is to pick up a load from some point and transport the load to a specified goal point. The operator can control the speed of the trolley and can change the length of the rope to lift and deposit the load. The dynamics of this system are quite complex since the load can swing on the rope, thus causing the trolley to

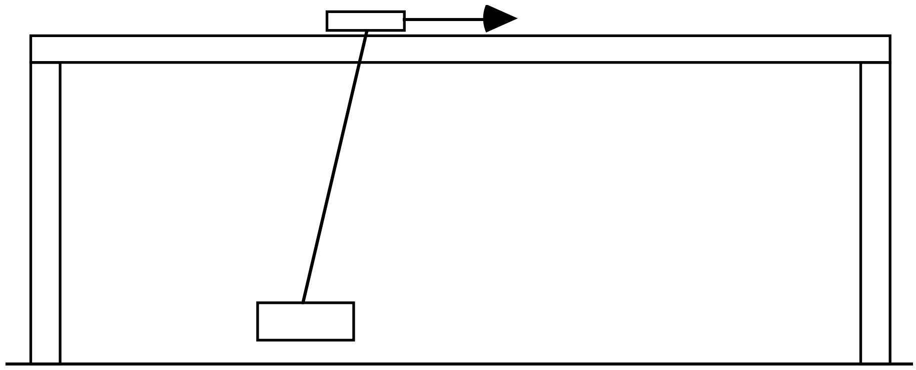


Figure 2. A container crane

accelerate and decelerate. In addition, the load must not be swinging when it is lowered to the ground, thus, the operator must dampen all swing to succeed.

Beginners in this task perform very slowly because they cannot predict the effects of the swing and therefore must wait for oscillations to dampen by slowing the trolley down. An experienced operator anticipates the swing by starting the trolley going, then slowing down, allowing the load to overtake the trolley and then speeding up again to catch up with load just above the target location so that the load can be deposited with minimal swing.

Because of the non-linearities involved, this crane control is still a challenging problem for traditional control theory. Thus, there is considerable economic advantage to be gained from "cloning" expert human operators.

In their experiments, Urbančič and Bratko, volunteers trained on a simulator of an actual crane. The parameters of the simulator were made as realistic as possible. There are six measured variables: the position and velocity of the trolley, the rope angle and angular velocity and the rope length and velocity. Two control actions are available to the operator: applying a horizontal force to the trolley and applying a vertical force to the rope.

The simulator had two modes of display. It could show the state of the system as a graphical reproduction of the crane (similar to Figure 1) or it could show "instruments" indicating the values of the six state variables. Six volunteers learned to control the crane using the graphical display and six learned using the instrument display. The latter group did not know that the system was a crane at all. They were only told to bring all of the state variables to certain values using two controls of an unspecified nature. The interesting point of this experiment is that the second group did just as well as the first. This indicates that having a physical model of the system gave no advantage. This conforms with what we would expect of a sub-cognitive skill since the time required to make a decision is shorter than the time required for consciously reasoning about a physical model.

Once the volunteers had become skilled in the task, traces of their behaviour were recorded as in learning to fly. Rather than using a classification tree method (such as C4.5), Urbančič and Bratko experimented with regressions trees, ie. the output of the decision rules are numeric values rather than discrete classes. These experiments succeeded and also avoided the problem of discretising the class variable. Other than the learning algorithm, the only significant difference between the cloning methods was that crane control does not have to be divided into different stages, since there does not appear to be any advantage to creating sub-goals for this task.

Like Sammut *et al*, experiments with the crane also showed the clean-up effect where the clone out-performed the trainer. Also, like learning to fly, these experiments created control rules that are brittle. That is, the rules cannot deal with much variation in the initial conditions or disturbances during the performance of the task. Later work on flight control by Arentz (1994) showed that in order to build a more robust clone, the training examples must be acquired from a “noisy” simulator that includes disturbances such as turbulence. For example, in straight and level flight, if there is no turbulence then once the aircraft is at the desired altitude and heading, the pilot need do no more. The induction program will not be given sufficient examples of how to recover when the aircraft is not in the desired state. Arentz showed that the introduction of random disturbances leads to the production of robust control rules that can cope with variations in the operating conditions of the aircraft.

The crane control rules have another problem in common with the flight control rules. They do not always correspond to human intuition. In attempting to construct pure situation-action rules, we have ignored goal-directed behaviour. Taking the example of straight-and-level flight again, a pilot will know that if the aircraft is below the desired altitude then a positive climb rate is required. In order to achieve that the pilot may increase the throttle or the elevation of the aircraft. The reactive behaviour takes place in using that strategy to achieve that goal. However, the cloning methods described so far use only very gross goal specifications and rely almost solely on reactive behaviour for the entire task.

Later, we will discuss how goal-directed behaviour can be combined with reactive behaviour, more in keeping with Nilsson’s *teleo-reactive* systems. However, before we do, we will discuss one more application of behavioural cloning, namely, learning to schedule a production line.

3.3. Learning to Schedule an Unbalanced Production Line

> The complexity and variability in manufacturing systems makes it difficult to develop automated scheduling systems using analytical methods. To manufacture competitively however, it is important to react rapidly to changes in the manufacturing environment., using current shop floor status so as to minimise the effects of disruptions (Kerr & Kibira, 1994).

Kerr and Kibira have developed a reactive scheduler for a telephone manufacturing plant using behavioural cloning of a skilled human scheduler.

A simulation model was developed so that data could be obtained from the human scheduler more quickly than by performing observations of the actual process. A schematic diagram of the plant is shown in Figure 3.

The resources on the shop floor are organised as a flowline consisting of a series of workstations that execute different operations. 90% of the assembly is done automatically by equipment that inserts components into printed circuit boards. The remaining odd-shaped components are inserted manually, followed by soldering. The printed circuit board assemblies (PBAs) are inspected for defects, repaired and retested. Final assembly consists of adding a keypad and fitting the assembly to the telephone casing. The completed telephone and already assembled handsets are packed in the same box. A conveyor belt links the various workstations.

Each workstation has "buffer" or storage area for incoming boards, yet to be processed. There is also a start-of-shift buffer and an end-of shift-buffer. The scheduling operations consists of assigning labour to the various workstations in order taking into account the size of the start-of-shift buffer, the desired size of the end-of shift-buffer and the volume throughput.

Reactive scheduling is useful because process times may vary, component failures lead to unpredictable delays, machines breakdown or go down due to planned maintenance and labour absenteeism is also unpredictable. The task of the scheduler is to allocate labour to balance the line and thus improve throughput while reducing inventory levels.

A general scheduling strategy is predetermined as:

if *beginning of shift or*
any of scheduled breaks or
any buffer level exceeds a given threshold or
any buffer level falls below a given threshold or
here is an equipment breakdown or
repairs in previously broken down equipment have completed or
there is a sudden drop in the total labour capacity

then *reallocate labour on the entire production line on the basis of current buffer levels, additional phones to be produced, time into the shift, equipment status and labour capacity.*

To construct the clones, the decisions of the human scheduler were logged each time labour was reallocated. Four sets of decision trees were constructed, one for each of the workstations: Automatic Insertion, Manual Assembly, Solder Touch Up and handset assembly and test. In addition, a shift is divided into three stages for the beginning, middle and end since different scheduling strategies are used to begin a process, end the process and for the steady-state. The attributes used to build each of the sets of decision trees are shown in Table 2. Examples were taken from 200 shifts.

Once the clone was built, it was tested on simulations of 25 shifts, which included

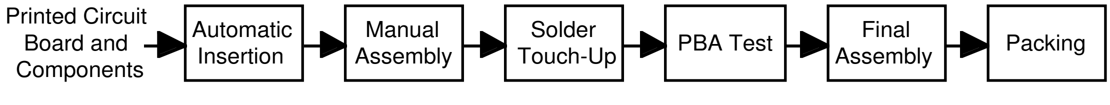


Figure 3. Basic stages in the manufacturing process.

random variations to test the robustness of the scheduler. In comparison with an automatic scheduler built using traditional optimisation techniques, the clone gave significantly better throughput with better balanced line. According to Kerr and Kibira (1994), the clone also did as least as well as the human who provided the training examples.

Table 2. Attributes used to build scheduler

Workstation	*Attributes*
Automatic Insertion	• Difference in buffer levels at: Manual Assembly, Solder Touch Up and PBA test.
	• Number of phones left to meet shift production target
	• Time into shift
Manual Assembly	• Difference in buffer levels at: Solder Touch Up and PBA test.
	• Number of phones left to meet shift production target
	• Time into shift
Solder Touch Up	• Difference in buffer levels at: PBA test.
	• Number of phones left to meet shift production target
	• Time into shift
Handset Assembly and Test	• Difference in buffer levels at: packing.
	• Number of phones left to meet shift production target

4. Learning to Achieve Goals

One of the interesting features of behavioural cloning is that the method can develop working controllers that have no representation of goals. The rules that are constructed are pure situation-action rules, i.e. they are reactive. However, this feature also appears to result in a lack of robustness. When a situation occurs which is outside of the range of experience represented in the training data, the clone can fail entirely. To some extent, a clone can be made more robust by training in the presence of noise. However, because the clone does not have a representation of how control action can achieve a particular goal, it cannot choose actions in a flexible manner in totally new situations.

In this section, we discuss a different application of machine learning in which goals are learned explicitly and then a second phase of learning constructs rules for applying actions to achieve the desired goals. We conclude the section with a discussion on how cloning a learning goal structures can be combined.

4.1. Leech

Leech (1986) describes an application of machine learning to controlling a chemical process which consists of converting Uranium hexa-fluoride gas to Uranium dioxode powder and then pressing the powder into cylindrical pellets which are sintered. According to Leech, the process is so complex that no human expert understands the integrated process behaviour. Also, the results of standard statistical analysis are difficult for the plant's operators to interpret and use. Thus, prior to the application of machine learning, much of the control of the plant was done by "seat-of-the-pants" adjustment by the operators.

Machine learning was applied in two stages to produce a simple and understandable control system which resulted in very significant improvements in the process yield. The first stage of learning was concerned with identifying the variables that determine high, medium or low yield. Seven attributes of the process were measured during the normal operation of the plant. At the same time, the yield of the plant was also recorded. These example were input to a decision-tree learning program, similar to ID3. The output was a decision tree which predicts the yield of the plant based on the values of the measured variables. An example of such a tree is shown below.

```
if (Y1 < 5865)
          if (Y7 < 585)
                   yield = very_low
          else
                   yield = high
else
          yield = high
```

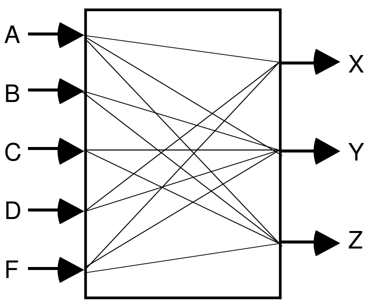
Y1 and Y7 are the names of variables measured from the plant. The decision tree was converted into a set of rules, such as:

```
yield = very_low   if Y1 < 5865 & Y7 < 585
yield = high       if Y1 < 5865 & Y7 >= 585
yield = high       if Y1 >= 5865
```

One of the immediate benefits of this analysis was that it revealed that many of the measure variables were irrelevant to determining the yield of the plant. The next step was to work out the correct settings for the control variables so that they achieve the values of the measured variables that result in high yield.

It was found that only three measured variables were significant in determining yield. Training examples were collected for each of these three variables. The attributes of the examples were the values of the eleven control variables for the plant and the class value was the measure variable. Thus, decision trees were built which would predict the value of each measured variable, given the control settings for the plant. An example of the decision tree for Y1 is shown below.

```
if (C4 < 172.5)
          if (C2 < 134.5)
                   if (C7 < 294.5)
                             Y1 = low
                   else
                             Y1 = ok
          else
                   Y1 = ok
else
          if (C2 < 127.5)
                   Y1 = low
```



Controls	Goals X	Goals Y	Goals Z
A	0.8	0.1	0.2
B	0.0	0.4	0.4
C	0.0	0.7	0.2
D	0.4	0.4	0.0
F	0.1	0.2	0.6

Effector set allocations			
SET	X	Y	Z
UE	—	—	—
ME	A	C	F
SE	D,F	B,D,F,A	B,A,C

Figure 4. (a) An example of a plant (b) perceived influences between control inputs and output goals (c) agent's effector view of system

```
else
         if (C8 < 143.5)
                  if (C2 < 131.0)
                           Y1 = low
                  else
                           Y1 = ok
         else
                  Y1 is ok
```

Note that the Y1 values have been discretised into the ranges 'low', 'ok' and 'high'. Again, the decision tree is converted into a set of rules:

```
Y1 = low  if C4 < 172.5 & C2 < 134.5 & C7 < 294.5
Y1 = ok   if C4 < 172.5 & C2 < 134.5 & C7 >= 294.5
Y1 = ok   if C4 < 172.5 & C2 >= 134.5
Y1 = low  if C4 >= 172.5 & C2 < 127.5
Y1 = low  if C4 >= 172.5 & C2 >= 134.5 & C8 < 143.5 & C2 < 131
Y1 = ok   if C4 >= 172.5 & C2 >= 134.5 & C8 < 143.5 & C2 >= 131
Y1 = ok   if C4 >= 172.5 & C2 >= 134.5 & C8 >= 143.5
```

We now have two sets of rules. The first tells the control system the desired values of the plant outputs (or measured variables). The second set of rules tells the control system the values of the plant inputs (or control variables) required to obtain the desired outputs. From these, it is relatively straight forward to build the complete control system.

Leech's work demonstrates that goal-directed behaviour for reactive systems can be learned. However, the method used for the chemical plant cannot be directly applied to other control tasks such as flying or driving container cranes, since the concept of "yield" is not present. In the next section, we describe a semi-automatic method for building goal-directed controllers.

4.2. CHURPS

CHURPS (or Compressed Heuristic Universal Reaction Planners) were developed by Stirling (1995) as a method for capturing human control knowledge. Particular emphasis was placed on building robust controllers that can even tolerate actuator failures.

Where behavioural cloning attempts to avoid questioning an expert on his or here behaviour, Stirling's approach is to obtain from the expert a starting point from which a controller can be generated automatically. The expert is asked to supply "influence factors". These are numbers in the range 0 to 1 which indicate how directly a control input affects an output goal. This is illustrated in Figure 4. Here, control action, A, has an influence of 0.8 on goal variable, X. This means that, A, is the main effector that influences that value of the measure variable, X. Action, A, also has lesser effects on variables Y and Z. A is also classed as the main effector for goal variable X. From the influence matrix, control actions are grouped into three sets for each goal variable:

A *Unique Effector (UE)* is the only effector which has any influence on a goal variable.

A *Maximal Effector (ME)* has the greatest influence over a particular goal variable. However, other effectors may have secondary influence over that goal variable.

Secondary Effectors (SE) are all the effectors for a goal variable, except the main effector

The UE, ME and SE sets are used by Stirling's Control Plan generator *CPG* algorithm to generate operational control plans. The algorithm assigns appropriate effectors to control various output goals in order of importance. Informally, the CPG algorithm is:

```
Create an agenda of goals which consist of output variables whose values deviate from a
set point. The agenda may be ordered by the importance of the goal variable.
while the agenda is not empty
    select the next goal
    if deviation is small then
            attempt to assign an effector  in the order, UE, SE, ME.
    if deviation is large then
            attempt to assign an effector  in the order, UE, ME, SE.
    examine influencee's of the effector that was invoked and add them to the agenda.
    remove selected goal
```

The selection of an effector is qualified by the following conditions:

- A controller which is a UE of one goal should not be used as an ME or SE for another goal.
- When choosing an SE, it should be one that has the least side-effects on other goal variables.

This procedure tells us which control actions can be used to effect the desired change in the goal variables. However, the actions may be executed in a variety of ways. Stirling gives the following example. Suppose variables X, Y and Z in Figure 4, are near their desired values. We now wish to double the value of Y while maintaining X and Z at their current levels. Following the CPG algorithm:

1. Y initially appears as the only goal on the agenda.
2. Y had no unique effector and since the required deviation is large, we try to apply an ME, namely, C.
3. Since C also affects Z, Z is appended to the agenda.

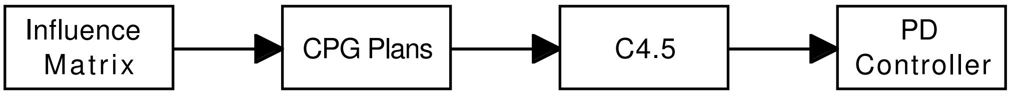


Figure 5. CHURPS Architecture

4. Since Y is the current goal and an effector has successfully been assigned to it, Y is removed from the agenda.
5. Z becomes the current goal. Let us assume that the deviation in Z is small.
6. We attempt to assign as SE to control Z. B is selected since C is already assigned to control Y. A could have been selected, but it would have a side effect on variable X, causing a further expansion in the agenda.
7. The agenda is now empty and terminates with the assignments {Y/C, Z/B}, which can be read as "control goal Y to its desired state via effector C and control goal Z to its desired state via effector B".

This plan can be executed sequentially, by first using C to bring Y to its desired value and then using C to bring Z to its desired value. A loop would sample the plant at regular intervals terminating each phase when the desired value is reached. Alternatively, both actions could be executed in parallel. The first strategy corresponds to one that might be followed by a novice, whereas experts tend to combine well practised behaviours since they do not have to think about them.

As a model of human sub-cognitive skill, the CPG method does not capture the notion that pre-planning is not normally carried out. That is, a skilled operator would not think through the various influences of controls on outputs, but would act on the basis of experience. This is usually faster than first trying to produce a plan and then executing it. To try to simulate this kind of expert behaviour, Stirling used the CPG algorithm as a plan generator which exhaustively generated all combinations of actions for different possible situations. This large database of plans was then compressed by applying machine learning to produce a set of heuristics for controlling the plant. The architecture of this system is shown in Figure 5.

To create the input to the learning system (Quinlan's C4.5) each goal variable was considered to have either a zero, small or large deviation from its desired value. All combinations of these deviations were used as initial conditions for the CPG algorithm. In addition, Stirling considered the possibility that one or more control action could fail. Thus plans were also produced, for all of the combinations of deviations and all combinations of effector failures.

In a style somewhat similar to Leech's, Stirling devised a "goal centred" control strategy in which learning was used to identify the effectors that are required to control particular goal variables. Thus if there is a deviation in goal variable *Y*, a decision tree is built to identify the most appropriate control action, including circumstances in which some control actions may not be available due to failure. An example of a tree for goal variable *X*, is shown below:

```
if (control A is active)
```

```
            if (deviation of X is non-zero)
                    use control A
            else
                    if (control D is inactive)
                            use control A
                    else
                            if (control F is active)
                                    use control D
                            else
                                    use control A
    else
            if (control D is active)
                    use control D
            else
                    use control F
```

Once the control action has been selected, a conventional proportional controller is used to actually attain the desired value.

The CHURPS method has been successfully used to control a simulated Sendzimir cold rolling mill in a steel plant. It has also been used to control the same aircraft simulation used by Sammut *et al*. Like that work, the flight was broken into seven stages. However, one major difference is that CHURPS required the goals of each stage to be much more carefully specified than in behavioural cloning. For example, the original specification of stage 4, the left turn was:

> At a North/South distance of 42,000 feet, turn left to head back to the runway. The turn is considered complete when the compass heading is between 140° and 180°

In CHURPS this is translated to

> At a North/South distance of 42,000 feet, establish a roll of 25° ±2° and maintain pitch at 3 ±5°, airspeed at 100 knots ±40 knots and climb speed at 1 ft/sec ±5 ft/sec.
>
> When the plane's compass heading is between 140° and 180°, return the roll to 0° ±2° and maintain all other variables at the same values.

Recalling that the influence matrix was constructed by hand, CHURPS requires much more help from the human expert than behavioural cloning. However, so far, CHURPS have produced smoother and more robust controllers. The question arises, can some combination of behavioural cloning and the CHURPS method used to produce robust controllers requiring minimal advice from the expert?

In preliminary experiments, Bain (Bain & Sammut, 1995) has shown that it is possible to use induction on behavioural traces to produce a controller similar in style to CHURPS and Leech's method. The purpose of the influence matrix is to determine which control inputs should be assigned to which goal outputs. Suppose we have a behavioural trace of a pilot flying an aircraft, rather than try to map situations to actions directly, an induction algorithm can be applied to determine the effect of controls on output variables. For example, if we wish to know how to control climb speed, we may preprocess the behavioural trace to distinguish changes in climb speed as the class variable that we wish to predict. The control actions available become the attributes of the example (along with the other measured variables). The result is a decision tree which tells us which control to apply to affect a change in climb speed under different circumstances. The CPG algorithm can then proceed as before.

A more difficult problem, which is still being investigated is how the goal structure of a complex task can also be learned by induction.

5. Conclusion

In this paper, we have reviewed recent research in the application of symbolic machine learning techniques to the problem of automatically building controllers for dynamic systems. By capturing traces of human behaviour in such tasks, it is possible to build controllers that are efficient and robust. This type of learning has been applied in a variety of domains including the control of chemical processes, manufacturing, scheduling, and autopiloting of diverse apparatus including aircraft and cranes.

Learning control by observing expert behaviour is best suited to tasks where there is little articulated knowledge about the problem but there is a source of tacit knowledge in the expert. This approach contrasts with other systems that can learn control tasks but which assume that background knowledge is available. For example DeJong's (1994, 1995) Explanation-Based Control system builds a controller by using a domain specific theory of qualitative physics to explain an observed trace and then generalise to a control strategy. Behavioural cloning starts with no such knowledge.

Pure behavioural cloning attempts to capture simple situation-action rules from traces. However, situation-action rules have their limitations in that there must be a rule for every likely situation, otherwise the control will not be robust. One of the major directions for future research is the coupling of goal-directed behaviour with pure cloning. This has the effect of breaking a complex task in to more manageable sub-tasks. Several promising methods were for achieving this synthesis were discussed but it remains for future research to demonstrate their success.

References

Arentz, D. (1994) *The Effect of Disturbances in Behavioural Cloning*. Computer Engineering Thesis, School of Computer Science and Engineering, University of New South Wales.

Bain, M., & Sammut, C. (1995). A framework for behavioural cloning. In K. Furukawa, D. Michie, & S. Muggleton (Eds.), *Machine Intelligence 15*. Oxford: Oxford University Press.

Benson, S., & Nilsson, N. J. (1995). Reacting, planning and learning in an autonomous agent. In K. Furukawa, D. Michie, & S. Muggleton (Eds.), *Machine Intelligence 15*. Oxford: Oxford University Press.

DeJong, G. (1994). Learning to plan in continuous domains. *Artificial Intelligence*, **64**(1), 71-141.

DeJong, G. (1995). A case study of explanation-based control. In A. Prieditis & S. Russell (Ed.), *International Conference on Machine Learning*, (pp. 167-175). Tahoe City, California: Morgan Kaufmann.

Kerr, R.M. & Kibira, D. (1994). Intelligent reactive scheduling by human learning and machine induction. *IFAC Conference on Intelligent Manufacturing Systems.* Vienna.

Leech, W. J. (1986). A Rule Based Process Control Method with Feedback. In *Proceedings of the ISA/86*. Research Triangle Park, NC 27709: The Instrumentation Society of America.

Michie, D. (1986). The superarticulacy phenomenon in the context of software manufacture. *Proceedings of the Royal Society of London*, **A 405**, 185-212. Reproduced in D. Partridge and Y. Wilks (1992) *The Foundations of Artificial Intelligence*, Cambridge University Press, pp 411-439.

Michie, D., Bain, M., & Hayes-Michie, J. E. (1990). Cognitive models from subcognitive skills. In M. Grimble, S. McGhee, & P. Mowforth (Eds.), *Knowledge-base Systems in Industrial Control*. Peter Peregrinus.

Michie, D., & Camacho, R. (1994). Building symbolic representations of intuitive real-time skill from performance data. In K. Furakawa, D. Michie, & S. Muggleton (Eds.), *Machine Intelligence 13*. (pp. 385-418). Oxford: The Clarendon Press, OUP.

Nilsson, N. J. (1994). Teleo-Reactive programs for agent control. *Journal of Artificial Intelligence Research*, **1**, 139-158.

Quinlan, J. R. (1993). *C4.5: Programs for Machine Learning*. San Mateo, CA: Morgan Kaufmann.

Sammut, C., & Michie, D. (1991). Controlling a 'Black-Box' simulation of a spacecraft. *AI Magazine*, **12**(1), 56-63.

Sammut, C., Hurst, S., Kedzier, D., & Michie, D. (1992). Learning to fly. In D. Sleeman & P. Edwards (Ed.), *Proceedings of the Ninth International Conference on Machine Learning*, Aberdeen: Morgan Kaufmann.

Schoppers, M. J. (1987). Universal plans for reactive robots in unpredictable domains. In *Proceedings of IJCAI-87*. San Francisco: Morgan Kaufmann.

Stirling, D., & Sevinc, S. (1992). Automated operation of complex machinery using plans extraced from numerical models: Towards adaptive control of a stainless steel cold rolling mill. In *Proceedings of the 5th Australian Joint Conference on Artificial Intelligence*,

Stirling, D. (1995) *CHURPs: Compressed Heuristic Universal Reaction Planners*. Ph.D. Thesis, University of Sydney.

Urbančič, T., & Bratko, I. (1994). Reconstructing human skill with machine learning. In A. Cohn (Ed.), *Proceedings of the 11th Europena Conference on Artificial Intelligence*, John Wiley & Sons.

Whitehead, A. N. (1911). *An Introduction to Mathematics*.