Tagged Behavior-Based Systems: Integrating Cognition with Embodied Activity

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Abstract

Classical artificial intelligence systems presuppose that all knowledge is stored in a central database of logical assertions or other symbolic representations and that reasoning consists largely of searching and sequentially updating that database. While this model has been very successful for disembodied reasoning systems, it is problematic for robots. Robots are distributed systems; multiple sensory, reasoning, and motor control processes run in parallel, often on separate processors that are only loosely coupled with one another. Each of these processes necessarily maintains its own separate, limited representation of the world and task; requiring them to constantly synchronize with the central knowledge base is probably unrealistic. I will discuss an alternative class of architectures – tagged behavior-based systems – that support a large subset of the capabilities of classical AI architectures, including limited quantified inference, forward- and backward-chaining, simple natural language question answering and command following, reification, and computational reflection, while allowing object representations to remain distributed across multiple sensory and representational modalities. Although limited, they also support extremely fast, parallel inference.

Introduction

Automated reasoning systems are typically built on a transaction-oriented model of computation. Knowledge of the world is stored in a database of assertions in some logical language, indexed perhaps by predicate name (Russell and Norvig 95). When the system is given a query like “are there any blood disorders with symptoms that affect the gastrointestinal tract?” the system might translate the query from natural language into a logical assertion like “there exist X and Y such that X is a blood disorder, X has symptom Y, and Y involves the gastrointestinal tract.” It would then answer the question by attempting to prove or disprove the assertion. The backtracking control structure used by a logic-programming engine to check the assertion would amount to a series of nested loops:

```
for each X such that blood-disorder(X) appears in the database
   for each Y such that symptom(X,Y) appears in the database
      for each Z such that involves(Y,Z) appears in the database
         if Z=gastrointestinal-track
            then return true
return false
```

Of course, this is a very simple case of automated reasoning; it doesn't really use much in the way of inference rules. However, even simple examples like this can be extremely problematic to implement on a robot. Suppose, we instead wish to ask the robot, "are there any predators here that could eat you?" (ignoring the issue that robots aren't particularly digestible). That query would translate into the sentence "there exists X such that X is nearby, X is a predator, and X can eat me." Again, a reasoning system attempting to verify this sentence would need to perform a search that would amount to a set of nested loops:

```
for each X such that nearby(X) appears in the database
   if predator(X) appears in the database
     then for each Y such can can-eat(X,Y) appears in the database
           if Y=me, then return true
return false
```

The problem occurs when we ask how the database is filled in to begin with. Unlike blood disorders, the set of objects near the robot is in continual flux. The only way the robot can know about them is to direct its sensors and sensory processes toward the objects in question and measure whatever properties of them are relevant to the task at hand. However, automated reasoning systems typically have no good way of directing perceptual attention. They either assume that all relevant information is already stored in the database or they provide a set of epistemic actions that fire task-specific perceptual operators to update specific parts of the database. The former approach requires that the perceptual systems run some very expensive loops of their own in parallel with the reasoning system:

```
for each object X in view
   for each property P of X
      measure P(X)
      retract the old value of P(X) from the database
      assert the new value
   for each other object Y in view
      for each spatial relation R
          determine whether R(X,Y) holds
          update the database accordingly
      … etc…
```

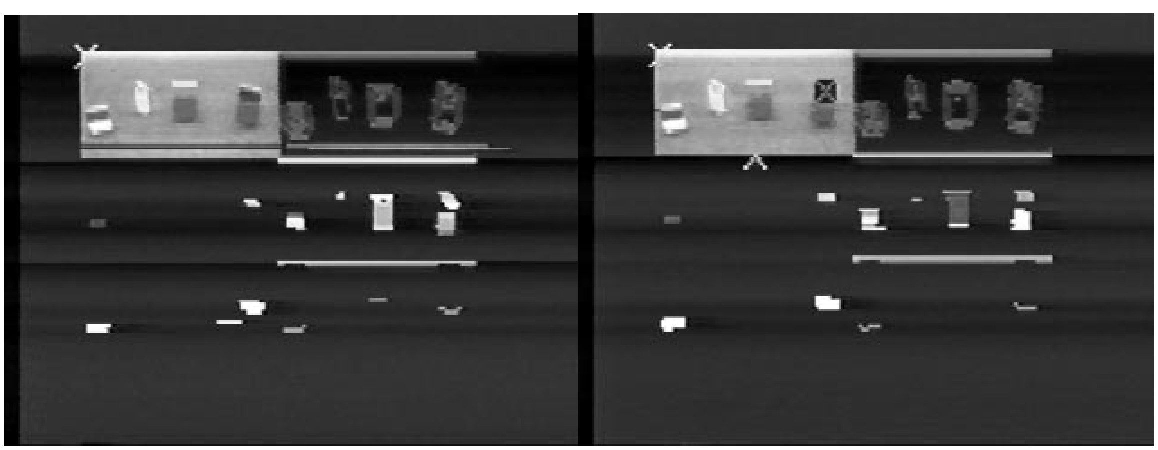
The epistemic action approach requires that the programmer design the rule base to ensure that the appropriate actions are fired at the appropriate times. This is more complicated than it might seem at first. Epistemic actions not only need to be fired when information in the database is missing, but also when it is *out of date*. In effect, the database is functioning as a cache for sensory data. As with any cache system, it must be kept *coherent* with the rest of the system – in this case, the sensory systems, and more importantly, the external world.

This analog of the cache coherence problem is an instance of a more general problem in robot design, which I will call the **model coherence problem**. Real robots consist of a large number of sensory, motor, and reasoning processes operating in parallel, often on separate processors, and often on very simple processors with little or no operating system. Each of these processors has, in some sense, its own limited model of the world and/or of the robot's current task. All these models must be kept consistent with one another and with the external world. This cannot be done by fiat nor, I would argue, can it be done as an afterthought. It must be designed in as a central architectural tenet of the system.

In this particular case, however, the problem is easily solved by making the perceptual system emulate the database. A typical automated reasoning system implements two functions, **ask** and **tell**, which query and modify the database, respectively, by performing the appropriate database searches. The database, for its part, typically implements simpler versions of these operations. For queries, these operations often amount to enumerating the set of variable bindings that match a given literal. A literal is an expression consisting of an application of a predicate to a set of argument expressions. These argument expressions may or may not contain variables. When the literal contains no variables, the database need only answer whether it appears in the database. When the literal does contain variables, the database needs to act as an abstract iterator, generating a series of values for the variables until either a set of values is found that make the sentence true, or all possible values are exhausted in which case the sentence is false.

Fortunately, these sorts of enumeration operations are relatively straightforward to implement directly in the perceptual system. When the reasoning system asks to enumerate the variable bindings of `red(X)`, the database can defer to the perceptual system. The perceptual system allocates a color tracker, records the fact that it is "bound" to the variable X, and sets it looking for a red object. When the reasoning system asks for the next binding of X, the perceptual system redirects the tracker to a new red object.

The Bertrand system



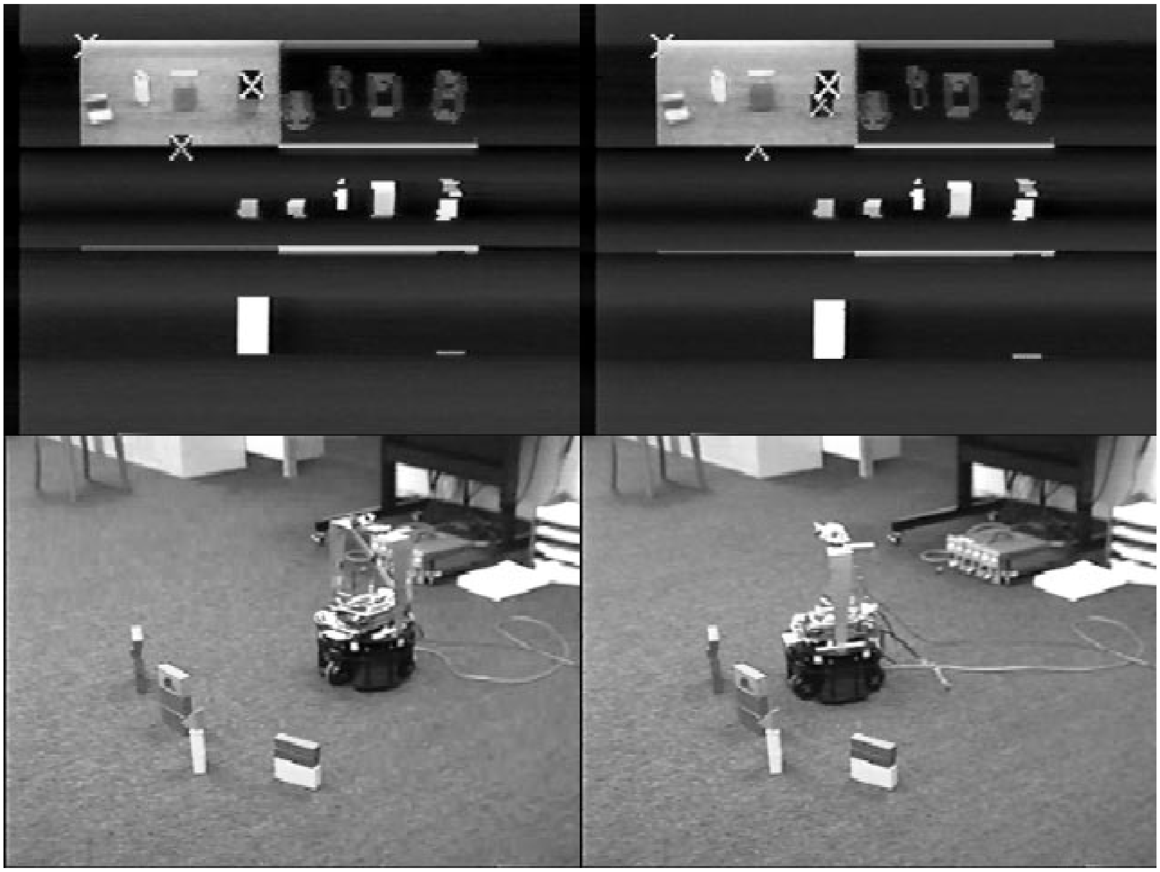


Figure 1: The Bertrand system searches for a blue block stacked on a red block using the query blue(X), on(X,Y), red(Y). Each screen image shows the original NTSC camera image (upper left), the edges detected in the image (upper right), the color blobs extracted from the image (middle right), the salient pixels given the current search criteria (bottom left), and the selected most salient blob (middle left). In the first frame, the system searches for a blue block and finds two blue objects. In the second frame (top right), it happens to select the correct blue object, and binds a tracker to it (the red X). In the next frame, it searches for an object underneath the selected object by highlighting all points immediately beneath it as salient (bottom left frame). Only one object is in the salient region. In the last frame, an other tracker is bound to it (green X). If the system had chosen the wrong blue object in the first step, it would have backtracked when the search for a red object underneath it failed. In the bottom two frames, the external view of the robot is shown as it executes the query and drives to the chosen blocks.

The Bertrand system (Horswill 95) was a "database-free" logic programming system that answered blocks-world queries using real blocks and a real-time vision system. Bertrand used an implementation of current theories of human intermediate-level vision (Ullman 84) to search the scene for specified configurations of colored blocks. Enumeration operations in Bertrand were handled by a *visual routine processor*, a specialized "vision computer" whose "registers" were object trackers[1] and whose "instruction set" consisted of the operations:

- Bind a specified tracker to an object of a specified color
- Bind a specified tracker to a *different* object of its specified color that has not already been searched
- Test a specified tracker to determine its color
- Bind a specified tracker to an object beneath/beside/above the object tracked by another specified tracker
- Bind a specified tracker to a different object beneath/beside/above that has not already been searched
- Test whether the objects tracked by two trackers lie in a specified spatial relationship.

Whereas a conventional compiler for a logic programming language might compile the query "blue(X), above(X,Y), red(Y)" (i.e. "is there a blue object above a red object?") into something like:

```
Find the first instance of blue() in the database
Bind X to its argument
repeat
   find the first instance of above(X, …) in the database
   bind Y to its second argument
   repeat
      if red(Y) appears in the database, return true
      find the next instance of above(X, …) in the database
      rebind Y to its second argument
   until no more instances of above(X, …)
   find the next instance of blue(…) in the database
   rebind X to its argument
until no more instances of blue(…)
```

The execution of this query under Bertrand is shown in figure 1. Bertrand compiled the same query into a series of *visual* operations:

```
find a blue patch in the image and bind tracker 1 to it
repeat
   find a colored patch under the region tracked by tracker 1
   bind tracker 2 to it
   repeat
      if tracker 2 is tracking a red patch, return true
      find the next colored patch beneath tracker 1
      rebind tracker 2 to it
```

[1] Since Bertrand only answered static queries about the scene, it didn't actually track objects, it only searched for them and temporarily stored their positions. I use the term "object tracker" here for consistency with the other systems described here, which do true object tracking.

```
    until the bottom of the image is reached
    rebind tracker 1 to another blue patch
until no more blue patches
```

This allowed Bertrand to execute queries without the need for separate epistemic actions because the inference operations *were* epistemic actions.

The Ludwig system

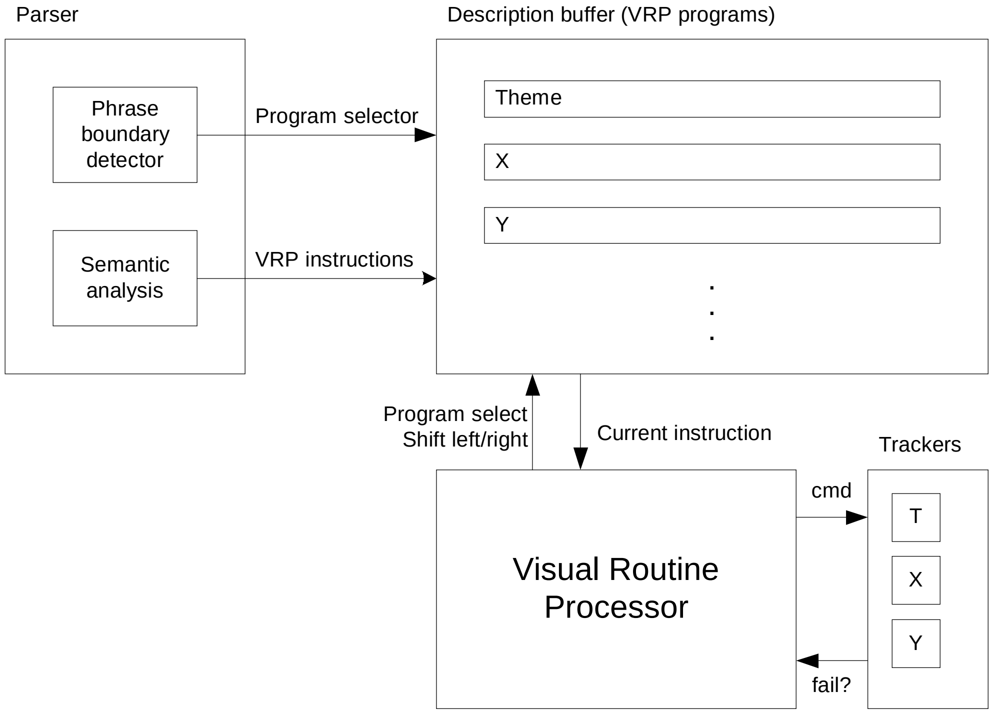


Figure 2: Architecture of the Ludwig system. The parser compiles noun phrases to visual routine processor programs to find their referents and loads them into shift registers in the description buffer. The VRP opportunistically runs these programs in parallel with the parsing process to bind trackers to the referents of the query's noun phrases.

Ludwig (Horswill 95) was a simple natural-language question answering system based on the same approach. It could answer simple queries involving colors and spatial relations, such as "is there a blue block on a red block on a yellow block?" or "is the block on the yellow block blue?" Although syntactically and semantically simple-minded – the only words it paid attention to in "where is the blue block?" were "where," "is," and "blue" – it was unusual in that it was directly grounded in real-time vision.

What made Ludwig most unusual was that it used a behavior-based architecture in the general sense that it was built as a parallel network of communicating finite-state machines similar to Brooks' subsumption architecture (1986). Instead of having a single, centralized representation, information about an object was distributed between different specialized representational mechanisms (figure 2).

Ludwig's parser consisted of a pipeline of finite-state machines built from (simulated) logic gates and latches. Each word from the user's query was presented to the parser as it was typed, one word per cycle. Whenever it saw an adjective or proposition, it compiled it into a visual routine processor instruction; "blue" compiled into "place tracker N on a blue object", for example, while "on" compiled into "place tracker M on the object immediately below tracker N in the image." The parser then latched the instruction into a shift register, gradually accumulating a visual routine processor program, represented within the shift register, which would search for the referent of the noun phrase.

In parallel with this semantic analysis, another set of finite-state machines performed a simple syntactic analysis to find phrasal boundaries. Verbs (of which Ludwig understood only "is") and the end of an utterance signified phrasal boundaries. However, a noun followed by an adjective, as in "is the block on the blue block • red?" also signals a boundary between two NPs. When the parser encountered a phrasal boundary, it marked the current shift register completed and switched to a new shift register. The really cool thing about Ludwig was that as the new NP was parsed, the visual routine processor would automatically begin searching for the referent of the old NP using the completed shift register. Thus, semantic analysis, syntactic analysis, and visual processing all occurred in a pipelined, parallel fashion.

Ludwig kept track of the relationship between the programs, stored in shift registers, that represented the *description* of an object, and the visual trackers that represented its *position* and *identity*, using a system of associative **tagging**. Object representations, both descriptions (programs) and trackers, are tagged with the names of the objects they represent. For example, in the command "face the green block on the blue block," (Ludwig had a very limited motor control capability) the theme of a sentence is "the green block on the blue block." The description of the theme,

    green(Theme), on(Theme, X), blue(X)

would be stored in a shift-register tagged Theme. When the control system needed the referent of the theme, it would tell the visual routine processor to run the Theme program, knowing that the end effect of this would be that the referent of the description would be tracked by whatever tracker was bound to Theme. The VRP would execute the program tagged Theme, which would involve allocating trackers and tagging them Theme and X. and directing them toward their intended referents. Upon completion of the program, the top-level control system then needs to tell the motor control system to servo toward the Theme. To do this, it need only send the tag Theme to the turn behavior. The behavior then forwards it to the trackers and whichever tracker is tagged Theme responds with the coordinates of the object.

Tagging provides an alternative mechanism for coordinating the different representations of an object. Rather than copying all the data to a centralized database, or passing complicated symbolic expressions between components of the system, components communicate by passing simple tags. Tagged behavior-based systems preserve the simplicity, parallelism, and efficiency of traditional behavior-based systems, while providing additional flexibility and programmability.

Forward-chaining inference for control

While the Bertrand/Ludwig architecture works well for question answering, it doesn't work as well for controlling action. Being a backward-chaining inference engine, its control structure is necessarily *top-down* and *serial*. If the scene changes as the robot scans it, the robot won't notice since (1) it only attends to the particular property or spatial relation it's measuring at the moment and (2) it doesn't keep any sort of dependency graph to link premises to their conclusions; without a dependency network, conclusions can't be retracted when their premises change. This is a problem when we look at control applications. If we build a package delivery system using serial backward-chaining, the system can infer that it needs to pick the package up before driving to the destination, but if the package falls out of the gripper in route, it may not even notice. Current reactive planners often require the programmer to explicitly program when to check these sorts of sensory conditions. When unanticipated changes occur, the robot's behavior can be quite pathological.

What is needed here is a forward-chaining inference system, one where any inference that is computed is continually *recomputed*, or at least recomputed whenever its antecedents change. Compiling forward-chaining propositional inference into parallel networks is relatively simple (see, for example, Kaelbling and Rosenschein 91). For every proposition in the system, we have a wire that holds its truth-value. An axiom such as facingObject and objectNear ⇒ objectGraspable, is implemented by connecting an AND gate to the facingObject and the objectNear wires and using its output to drive the objectGraspable wire.

The problem comes when we try to implement quantified inference (inference with variables). To implement an inference rule like facing(X) and near(X) ⇒ graspable(X), we would need an infinite number of wires, one for each possible value of X, and an infinite number of AND gates. This is not a purely theoretical problem; it is a general problem of connectionist and behavior-based control systems that representing predicate/argument structure in fixed, parallel networks is deeply problematic. In such situations, behavior-based systems often use multiple copies of behaviors to handle all their possible arguments. One behavior-based dialog system, for example, used a separate behavior for each possible utterance of each speaker.

Fortunately, tagging gives us a partial solution to this problem. In a tagged behavior-based architecture, we have a fixed set of tags that we use to identify the objects referred to by a given tracker or memory representation. If we restrict the system's inference to the set of objects actually represented in working memory, then we can represent a predicate graspable with the *set* of tags for which it's true. Assuming the set of tags is relatively small, we can represent a tag set using a fixed vector of bits, one bit per tag. The predicate is true of a given object if and only if the bit position corresponding to its tag is set to one. If the number of tags is manageable (we presently use about 20), then this still allows for a relatively compact network. We simply take the original propositional network and replace individual wires with 20-bit busses, or time-multiplex a single network.

Of course, no one actually builds parallel hardware like this. Real robots are built from loosely coupled networks of microcontrollers, PCs, and other serial processors, not from custom parallel hardware. Fortunately, tagging is also very efficient on conventional serial processors. Instead of using a 20-bit bus to represent a predicate, we use a single 32-bit machine word. The graspable rule above can then be compiled to a simple assignment statement, written here in C++:

```
graspable_tags = facing_tags&near_tags;
```

If, for example, all rules are Horn sentences (implications with conjunctions on the left), then we can compile all the rules into a series of such assignment statements and reexecute them on every cycle of the system's decision loop, effectively recomputing the entire knowledge base on every cycle. While this sounds expensive, it is cheap enough that it is effectively free. Since each rule is compiled to a small number of load, store, and bit-mask instructions, it's possible to run 1000 rules at 100Hz and still use less than 1% of a modern CPU.

Tagging is only a partial solution to the problem of representing predicate/argument structure. It doesn't support term expressions. It's limited to reasoning over the set of objects to which the robot is presently attending. And it is also effectively limited to unary (signal argument) predicates; if there are n tags, then binary predicates would require n^2 wires, ternary relations, n^3 wires, etc. However, tagged architectures are sufficient to do most of the kinds of reactive reasoning that robots do today, only considerably more efficiently.

Role passing

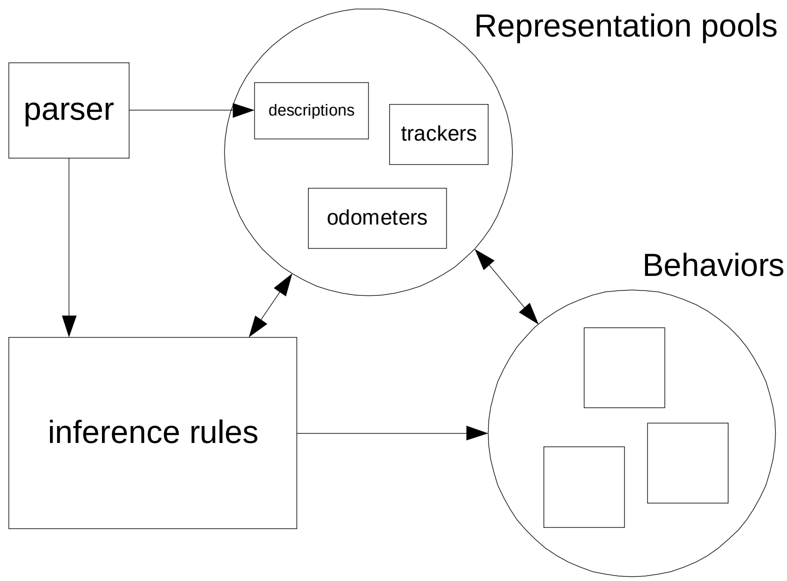


Figure 3: Role-passing architecture used on the Kluge robot. Nearly all data passed between subsystems is in the format of tag sets (roles).

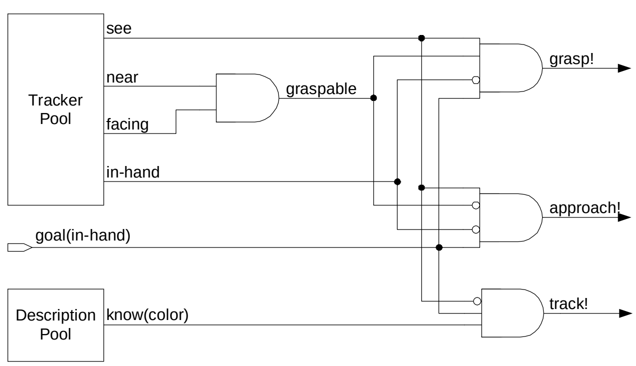


Figure 4: Equivalent control circuit for the grasping inference rules given in the text. Note that each wire here is really a bus with one bit per role and that logic operations are bitwise ANDs and NOTs on these bit-vectors. Data flows from the goal input, the description pool, and the vision system and its outputs drive the grasp, approach, and visual tracking behaviors. Inferences are recomputed with each successive frame of the video stream.

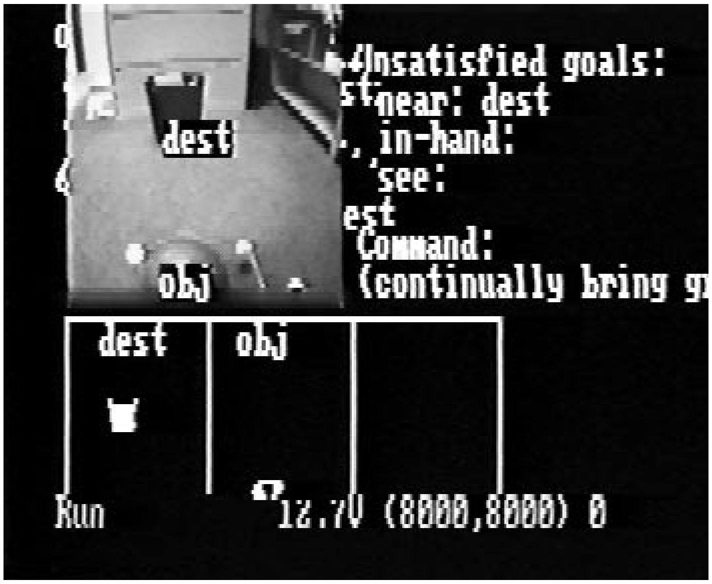


Figure 5: Kluge follows the command "continually bring green to blue." The parser binds the object role to the color green and the destination role to blue, then asserts the goals in-hand(object) and near(destination). The robot grasps the green ball then drives toward the blue trashcan.

We've used this feed-forward tagging scheme to program a robot, Kluge, to follow simple natural language commands, such as "get the green ball," "go to the blue ball," "follow me," etc. (Horswill 98). Kluge uses a custom 25MIP DSP board with an attached frame grabber (the DIdeas Cheap Vision Machine) and video camera. The electronics are housed on a commercial synchrodrive base (a Real World Interface B14S). The robot can track up to three colored objects simultaneously and performs visual navigation at about 1m/s. The vision system runs at 10 frames/second and the inference engine and motor control behaviors completely update themselves on every frame.

Kluge can represent objects in three different modalities (figure 3). It can remember what color it is by tagging one of a set of color representations held in its *description pool*. Given the color, it can allocate a visual tracker from its *tracker pool*, assigning it an appropriate tag, and set it searching for that color. And when the object goes out of view, it can still keep a rough idea of its location using an *odometric tracker pool*.

As with Ludwig, Kluge uses a finite-state parser whose "output" is set of tag bindings in the other components of the system, specifically the representation pools. In this system and subsequent systems, we have adopted the practice of using linguistic role names, such as agent, patient, etc. as our tags. So when the user types "get the green ball," the parser binds the role object to the the color green in its pool of color descriptions and asserts that in-hand(object) is a goal (see below).

Most of the communication between the parser, inference engine, and peripheral systems consists of passing sets of linguistic roles in this bit-vector representation. On every control cycle, the vision system grabs a new frame and processes it. The different tracking systems independently determine whether their targets are nearby. The vision system ORs together the roles (represented as bit-vectors) of all the trackers with nearby targets. The result is the extension of the predicate near, which it passes to the inference engine. Similarly, it ORs together the roles of all tracked objects it is facing to form the facing predicate. In parallel, the odometry system, which tracks the locations of objects using dead reckoning, determines which of its targets are nearby and/or faced by the robot, and ORs their tags into the bit-vectors representing near and facing. These bit-vectors are cheap to compute compared to the cost of doing the tracking in the first place, so they can be recomputed on every decision cycle.

Kluge then uses a set of inference rules to control the firing of different behaviors. A simplified version of the rules used to control grasping and approaching objects is:[2]

> near(X), facing(X) ⇒ graspable(X)
> goal(in-hand(X)), not in-hand(X), graspable(X) ⇒ grasp!(X)
> goal(in-hand(X)), not in-hand(X), not graspable(X) ⇒ approach!(X)

These rules are transformed into the feed-forward logic network shown in figure 4. The inference engine ANDs the near and facing bit-vectors to form the bit-vector for the graspable predicate. It ANDs this with the bit-vector of objects it wants to have in its hand and with the complement of the bit-vector of objects it already has in its hand (as determined by the vision system). The result is a bit-vector specifying the object to try and grasp, if any. By feeding this bit-vector to the grasp! behavior, the inference engine can control grasping. When the bit-vector is non-zero, the behavior fires and tries to grab the specified object. When the behavior succeeds in grasping the object, the in-hand predicate will change, automatically deactivating the behavior. Since these bit-vector inference operations are cheap to perform, Kluge can recomputed them on every cycle of its decision loop, continually updating its knowledge base. So if the object slips out of the gripper after being grasped, the grasp behavior immediately re-fires.

For its part, the grasp! behavior doesn't need to know which tracker is tracking the object, or even which sensory modality is tracking it. It simply passes the tag on to the tracking systems. All trackers match the tag to their own tags in parallel and the matching tracker drives the behavior's input bus with the coordinates of the object. Again, this matching and transmission is performed on every cycle, so the behavior is able to close a feedback loop around the tracked position of the object. Since nearly all the data coordination between the various subsystems of the robot is performed by passing sets of linguistic roles, we call this flavor of tagged architecture "role passing."

Unfortunately, the inference rules above are useless unless the vision system is tracking the object. When the robot is told "get the green ball", the parser only binds the role object to the description pool; it doesn't do anything to the vision system. In order to even know whether it's facing the object or not, Kluge has to direct its visual attention toward the relevant objects. It does this using the inference rules:

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[2] In the real system, grasp! isn't an atomic behavior. Separate rules are used to open and close the gripper, to drive toward the object, etc.

see(X) $\Rightarrow$ know(near(X))
see(X) $\Rightarrow$ know(facing(X))
see(X) $\Rightarrow$ know(in-hand(X))
goal(see(X)), not see(X), know(color(X)) $\Rightarrow$ track!(X)

The first three rules state that it knows whether objects are nearby, etc. when it can see them, that is, when the vision system is tracking them. The last rule says that if it wants to see something but doesn't, and it knows what color the object is, then it should fire the track! behavior on it. The track! behavior allocates a tracker, binds it to the specified role, and sets it searching for the right color. These rules are also compiled into the control network shown in figure 4. A screen capture from the running robot is shown in figure 5 as it tries to deliver a green ball to a blue target which a mischievous human repeated steals the ball from it.

The Cerebus Project

Figure 6: The hardware used by Cerebus. A commodity laptop with USB frame grabber, and NTSC board camera mounted on an RWI Magellan robot base.

The unifying theme of all these systems is the attempt to import the useful features of traditional symbolic AI systems into behavior-based systems without also importing the model-tracking and model-coherence problems. I've argued that you can implement forward- and backward-chaining inference for useful subsets of predicate logic using the kinds of parallel, distributed computations commonly employed in behavior-based systems.

My group's current effort in this direction is the Cerebus system (figure 6), an attempt to build, within a nominally behavior-based architecture, a "self-demoing robot."[3] The goal is for Cerebus to be capable not only of interacting with the world, but of using reflective knowledge about its own capabilities to interactively describe and demonstrate those capabilities. Cerebus combines a set of perceptual-motor systems with reflective knowledge about those systems, allowing it to perform limited reasoning about its own capabilities. Cerebus distributes its representations of itself and its world through a number of semi-autonomous representational systems linked by role-passing:

- **Tracker** and **description pools**, as in Kluge
- A pool of place nodes in a **topological map**. Places can be bound to roles and the map reports the role of the robot's current location (if any) and the direction of the next waypoint on the path from the current location to the goal location.
- A **lexicon pool**, entries of which are automatically bound to roles by the parser as the user types an utterance.

Cerebus also includes a set of *reflective* pools that give the robot access to its own internal state:

- The **behavior pool** holds bindings between tags and specific robot behaviors. Each behavior continually compares its tag to the set of tags on a global call signal. Whenever a behavior detects a match, it activates itself.[4] Active behaviors also drive a global running? signal with the bit-vector of their tags. The signal therefore holds the tags of all running behaviors, allowing any part of the system monitoring the signal to determine whether the behavior bound to a given tag is running.
- The **proposition pool** holds bindings between tags and specific binary-valued signals in the system. The pool generates a true? signal comprised of the set of all tags bound to propositions that are presently true. This allows one component of the system to "pass" a signal to another component by binding it to a tag that has been agreed upon in advance. The receiving component can then monitor the signal by inspecting the appropriate bit of the true? signal.
- The **predicate pool** holds bindings between tags and unary predicates. The predicate pool generates vector of signals, indexed by role, whose elements hold the extensions of all bound predicates – role 0 in element 0, role 1 in element 1, etc. Again, this provides an indirection facility for passing signals between components.

[3] The name "Cerebus" is not a reference to the cerebrum of the brain, but rather to a barbarian aardvark in a satirical comic book series written by artists Dave Sim and Gerhard. Like our robot, Cerebus is short, brutish, stupid, and only speaks of itself in the third person.
[4] Of course, behaviors can also be activated in all the normal ways, including bottom-up self-activation.

Finally, Cerebus includes a marker-passing **semantic net**. Nodes within the net can be bound to role tags and then propagated as markers along links in the net to perform retrieval and inference from long-term memory.

It is important to understand that a given object or concept might be represented in several of these pools simultaneously, with each pool representing different aspects of the object. This is supported in part by allowing elements of different pools to share a single tag register. For example, the lexicon pool entry for the word "show," the behavior show, and the semantic net node representing information about the behavior, all share a common tag register. Therefore, when the parser binds "show" to a role, the behavior that can implement the verb is automatically bound to the same role at the same time. Conversely, if some other process binds the behavior to a role, the lexical entry is automatically bound, thereby insuring that the robot will be able to name the behavior verbally, should it be necessary.

Allowing system components such as behaviors and signals to be tagged gives the system the ability to *reify* those components – to make them data objects that can be manipulated, inspected, and passed as parameters in their own right. Allowing them to be associated with nodes in the semantic net gives the system the ability to store *reflective knowledge* about its own structure and capabilities.

Reification of behaviors allows Cerebus to implement *higher-order behaviors*: behaviors that are parameterized by other behaviors. One trivial example of a higher-order behavior is handle-imperative. Suppose the user types the command "show me freespace following." Cerebus' parser reads keypresses in real time as it continues with its other activities and breaks it into words. It finds the verb of the sentence, "show," which it binds to the activity role, and identifies its objects, "me" and "follow-freespace," the latter of which is treated as a single word. Based on the verb's lexical entry, it knows that the first object should be bound to destination, that the second should be bound to object, and that the subject should be bound to agent. Since the subject is absent the parser defaults it to "Cerebus." Cerebus happens to have behaviors by the names show and follow-freespace, each of which shares its tag register with its respective entry in the lexicon. Therefore, upon completion of the parse, the show behavior is bound to activity and the follow-freespace behavior is also bound to object.

The handle-imperative behavior automatically activates itself whenever agent is bound to the word "Cerebus" and activity is bound to a behavior. It responds by driving the call bus with the bit-vector representing activity, thereby activating the show behavior. It then waits until the running? signal no longer includes the activity role, the signal that show, or whatever other behavior was specified by the user's command, has terminated, at which point handle-imperative deactivates itself.

For its part, show, another higher-order behavior, works by driving the call bus with the object tag, thereby activating whatever behavior was bound to that tag by the parser, in this case, follow-freespace. It then waits for 60 seconds and then stops the behavior by driving another global bus, the stop bus, with the object tag, which stops the freespace follower.

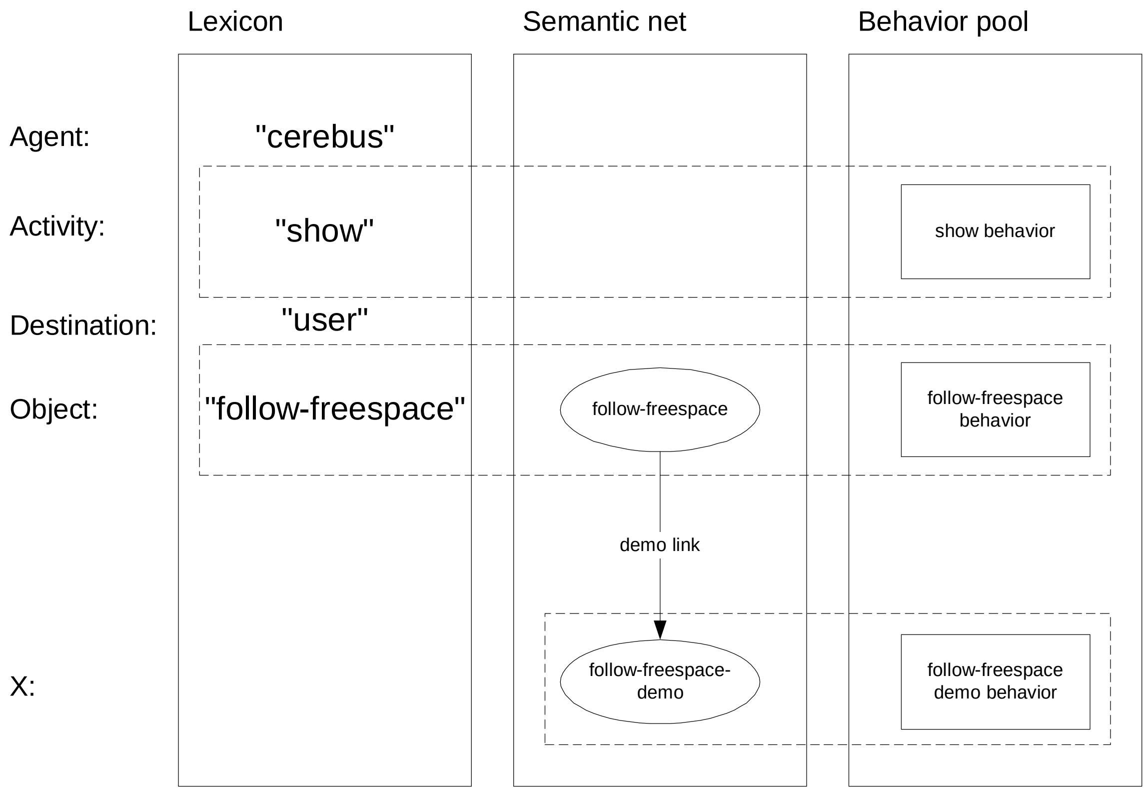

Figure 7: Tag bindings in the task "show me freespace following". Tags are shown on the left, and their respective bindings within pools are shown on the right. Objects which share a single tag register are shown linked in dashed rectangles. The parser established the initial bindings of agent, activity, destination, and object in the lexicon. Activity and object are then implicitly bound in the semantic net and behavior pools by virtue of register sharing. The show behavior, then binds follow-freespace-demo to the scratch role X, by performing a marker passing operation in the semantic net.

However, a much more interesting case is when show uses information from the semantic net to determine how to demonstrate the behavior (figure 7). In reality, the freespace follower also shares a binding register with a node in the semantic net, which can hold reflective information about the behavior. When that node is linked to another node by a demo link, the other node is assumed to contain information about how to demonstrate the behavior. In particular, show assumes the other node will be linked to a special “demo” behavior used to show off the freespace follower. When the show behavior detects that the object role is bound to a semantic net node with a demo link, it binds the linked node to another role. Since the new net node shares a tag register with the actual demoing behavior it represents, the behavior is tagged at the same time, allowing show to activate it using the call bus.

Cerebus is still very much a work in progress. Its parser can resolve references to objects in its various pools, and its primitive natural language generator can produce descriptions of the object bound to a given role, regardless of the representational system(s) tracking it. However, most of the work on Cerebus has gone into building infrastructure – the paser/generator, the reification system, the semantic net, etc. – rather than filling that infrastructure up with content. Thus, as of this writing, there is a limit to what Cerebus can actually do with a user. A typical interaction with Cerebus might be:

> *Cerebus*: Hello.
> *User*: What can you do?
> *Cerebus*: cerebus can do follow-freespace, follow-color, follow-human, and answer-question.
> *Users*: Show me freespace following.
> *Cerebus*: ok. cerebus show user freespace-following.
> … Cerebus shows off freespace following …
> *User*: (Interrupting) Stop.
> *Cerebus*: ok. cerebus stop.
> *User*: Give a talk.
> *Cerebus*: ok. cerebus give user talk.
> … Cerebus does a simple tree-walk of its semantic net to generate a largely pre-scripted talk
> *User*: (Interrupting) Stop.
> *Cerebus*: ok. cerebus stop.
> *User*: Die.
> *Cerebus*: ok. cerebus die.
> … the Cerebus program exits.

Note that Cerebus is pointedly dysfluent. This is partly because it generates sentences by walking the bindings of its internal representations (semantic net, lexicon, reified behaviors, etc.), which are fairly simple to begin with. Thus, it cannot generate complex noun phrases, or even noun phrases with determiners (a, the, some). However, we have also intentionally exaggerated that dysfluence, for example by having it refer to itself in the third person. If the robot only generates simple sentences, hopefully the user will only give it simple sentences.

Conclusion

It is common to see behavior-based systems and symbolic reasoning systems presented as distinct, or even incompatible, approaches to intelligent control. This view has left behavior-based systems representationally impoverished, and therefore, highly limited. However, not only is symbolic reasoning compatible with behavior-based systems, it's *implementable by* behavior-based systems. The relevant distinction is not between symbolic and non-symbolic computation, but rather between a transaction-based model of computation and a circuit-based model of computation. Although nearly always implemented in conventional programming languages, behavior-based systems have traditionally used styles of computation that are analogous to parallel circuits. This style of computation is typically easier to interface to sensors and effectors and, since it recomputes everything on every clock tick, is highly reactive. Symbolic reasoning systems have traditionally been implemented in LISP, or more recently, Java. However, the same input/output behavior can often be implemented in circuit-style computation, allowing greater reactivity, and easier interface to sensory systems.

Of course, just because something is possible doesn't necessarily mean it's a good idea. Hand-engineered rules in straight logic have many limitations. Learning approaches, as well as probabilistic or fuzzy reasoning systems, have also shown great promise. However, these systems, like behavior-based systems, have traditionally been representationally impoverished. Hopefully the techniques described here can also be used to extend these systems to more powerful representations. And, of course, many things are not implementable in this framework and probably never will be. Full-blown, domain-independent planning, for example, necessarily involves unbounded search and so cannot be done with a fixed parallel network. When such techniques are necessary, a tagged architecture would need either to make out-calls to a more traditional LISP program or effectively emulate a LISP interpreter. Both approaches are worth investigating.

These caveats aside, I believe that there is a rich, and largely untouched, area of research in trying to extend parallel distributed control architectures to support more expressive representations. Even if tiered architectures do ultimately prove necessary, their performance can be improved dramatically by pushing as much work as possible down from the deliberative components into the behavior-based components. There is a great deal of interesting work still to be done: What other techniques beside tagging can be used to extend distributed representations? How can exception handling and meta-level reasoning be incorporated into these architectures? Can on-line statistical learning techniques be extended to more expressive representations? If so, can it leverage those representations to improve performance? The answers are by no means obvious, but any advances that can be made will have a high payoff.

As a final comment, I would like to suggest that one of the reasons that behavior-based systems have lagged behind traditional symbolic systems is because we haven't yet found the right set of tools for building them. While symbolic reasoning systems have very advanced languages, compilers and development environments for them, most behavior-based systems are still written in procedural languages like C++ that don't have built-in notions of circuits or finite-state machines, much less of reified behaviors. Programmers therefore have to in some sense program in two languages at once. They first conceive of their program within some higher-level behavior-based architecture, then hand-compile it to C or Java code. As modifications are made, they must solve problems at both these levels and incrementally recompile manually. The process tends to be painful and error prone. Debugging has to be done at the C level rather than at the architectural level – assuming some kind of thread-safe parallel debugger is available at all. In my own work, I have used a functional language for circuit layout (Horswill 2000). While it's been a big help – we couldn't have built Cerebus without it – it's still far too limited. What's needed is some equivalent of a LISP or Prolog integrated development environment for behavior-based systems.

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