SELECTIVE ATTENTION AND ACTION IN AN ARTIFICIAL, EVOLVED AGENT: REACTIVE INHIBITION

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We analyzed the mechanisms for selective attention and action in an artificial, evolved agent. Our analysis shows the agent selectively responds to targets through reactive inhibition of nontarget items. Reactive inhibition, in which suppression of nontargets is in proportion to their salience, has been previously shown to be a means of selection in people. Our results suggest that reactive inhibition may be a fundamental process in selective control of action.

1. Control of action

Agents operating in complex environments can have competing demands for action. A simple example is a frog eyeing two flies. If the frog selects one fly for action, it may succeed in catching it. The "intermediate" response, attacking a midpoint between the two flies, is useless. Effective action must therefore be selective -- response mechanisms must be focused on selected targets, and these same mechanisms must be insulated from the possibilities for action offered by nontargets. Theories of attention have proposed different accounts how selection links perception and action. One influential account assumes that perceptual processes lead to the relatively unselective activation of numerous potential actions. Control of action is achieved by inhibitory mechanisms that suppress activation of all but the desired action (e.g. Tipper et al, 1998, Houghton & Tipper, 1996). Another approach uses biased competition (Duncan et al, 1997), and demonstrates how distributed representations of objects can be linked to distributed representations of action, through a competitive selection process (Ward, 1999). This model shows how a stable state of selective network activation, representing one object and its implications for behaviour, can arise from a confluence of what, where, and how information.
In these and other psychological models of attention (e.g., Schneider, 1995), there is a single episode of filtering which defines the target for action. There is a rich literature of computational models of attention, exploring mechanisms for selecting a single target from a static array of nontargets. However, filtering is only part of the problem when considering the control of action. For example, we can return to the case of the frog and the flies to illustrate some of the complexities of selective action. First, the two flies must be prioritized for action, so that a first target is selected. Second, there must be a means for keeping response mechanisms tied to the movements of the first fly, and for insulating responses from movements of the second. In other words the effects of the second fly on action systems must be filtered. However, if possible, sensory processing of the second fly should continue, so that once the first is caught, the frog will be able to rapidly acquire the second. After the first fly is caught, the second fly, once insulated from response mechanisms, must now be allowed to control them. That is, the frog must reallocate selective processing mechanisms. Thus, multiple potential targets for action in a dynamic environment create demand for selective response, a separation of perceptual and response processing, and the reallocation of selective processing from one target to the next.

Current psychological models of attention have generally not addressed this range of processes necessary for selective action in a dynamic environment. Or more accurately, perhaps the theories (e.g. Tipper et al, 1998; Duncan et al 1997) are meant to be applied to such environments, but the computational implementations of these theories (e.g. Houghton & Tipper, 1994; Ward, 1999) have been limited to much simpler worlds. This is a problem, because we don't know how or if psychological mechanisms like distractor inhibition (Tipper et al, 1998) and biased competition (Duncan et al, 1997) work, when brought out of static worlds and into more complex ones.

The aim of this research is to explore the psychological underpinnings of models of perception, attention, and action that operate in dynamic environments, and in which perception, attention, and action are temporally extended processes. We examine these processes in working but tractable artificial agents. Our approach is similar in some ways to comparative psychology. Our aim is to uncover the principles underlying the operation of the agent, and to then compare these principles with models of selective processing in the psychological literature. In comparing the solutions of the artificial agent to the psychological literature, we hope to enrich our understanding of computationally adequate, psychological models of selective action.
Models of embodied, situated, and dynamical (ESD) agents stress what Clark (1998) calls "the unexpected intimacy between the brain, body, and world". The ESD approach emphasizes the contextually-bound nature of solutions to cognitive problems, as opposed to isolated but general-purpose attention, perception, or motor subsystems. Important for our purposes is the "minimally cognitive" form of ESD agent, as developed by Beer (1996). This approach attempts to create simple artificial agents that instantiate interesting cognitive behaviors. Such agents serve as model systems, allowing a tractable analysis of the cognitive processing going on in more complex systems.

An application of the 'minimally cognitive agent' approach to problems of perception, attention, and action was demonstrated recently by Slocum et al (2000) and Goldenberg et al (2004). Slocum et al (2000) used genetic algorithm (GA) methods to evolve a small continuous time recurrent neural network (CTRNN) capable of performing a selective attention task. The "visual agent" (VA) was constrained to run along the bottom of a 2D environment, moving left or right to catch two balls falling from the top of the environment. We extend this work, exploring the operation and abilities of such an minimally cognitive agent in detail. This chapter summarizes some of the findings of Ward and Ward (submitted), in which fuller details and analyses can be found.

2. Methods

2.1. The agents

A key part of our research strategy was to consider two types of VAs: a "reflexive" and a "controlled" agent. The reflexive visual agent (RVA) has direct links from the sensory units to the motors with no intervening hidden units. In RVA, perceptual inputs drive motor output directly, and there is no possibility for selective processing of one ball over the other. In contrast, the "controlled" visual agent (CVA) has an intermediate hidden layer, so that potentially at least, CVA can focus processing activity on one target. RVA also used a linear activation function, while CVA used the standard sigmoid activation function. The capabilities of the RVA therefore serve as a baseline by which the effectiveness of selective processing in CVA can be assessed.

For both agents, the input layer consisted of units driven by oriented proximity sensors. The sensors signaled the distance between the VA and a "solid" surface intersecting the sensor ray (as in Slocum et al, 2000). An array of 7 sensors evenly covered 6° of visual angle. The output layer of both agents contained 2 motor units, one for controlling left and one for right movement. In
the CVA but not the RVA, the motor units were connected to each other. The hidden layer of the CVA contained 8 fully inter-connected units, each receiving inputs from all sensors and each with reciprocal connections to the motor units. These networks are illustrated in Figure 1.

![Diagram of the CVA and RVA](image)

Figure 1. Architectures of the two visual agents. Connections between layers, indicated by arrows, represent bilaterally symmetric connections. Connections within layers are indicated by the shading of the outlining box. Filled boxes indicate that each unit is connected to every other unit within the layer using bilaterally symmetric weights. Unfilled boxes indicate no intralayer connections. The sensor neurons all have the same parameters: gain, bias, and time constant. Similarly, each motor has identical parameters. The hidden layer neurons, however, have bilaterally symmetric parameters.

### 2.2. Training

Both VAs were trained to catch targets falling from the top of the simulated environment to the bottom, by moving underneath them before the targets impacted (see Figure 2). There were two types of trials: Divided Attention trials, in which two targets fell, and Focused Attention trials where only a single target fell. First we describe the Divided Attention trials. The two targets, T1 and T2, were identical objects dropped simultaneously at the start of each trial. On a given trial, T1 and T2 fell with a constant vertical velocity and with zero horizontal velocity. However, by definition, T1 traveled faster than T2, and therefore this target needed to be prioritized for response. Once T1 impacted, it was removed from the environment so that it no longer blocked the sensors. The VA always began each trial centered along the bottom of the environment.

The starting position and speed of targets in training were varied factorially. There were four factors describing Divided Attention trials: T1 Side (T1 started 24 units Left or Right of center); T2 Side (T2 was positioned to the Left or Right of T1); Spatial Separation (T1 and T2 were either relatively Near [24 units] or Far [48 units] from each other); and Temporal Separation (again Near or Far; on
Temporal Near trials, T1 and T2 fell at close to the same speed [4 and 3] and so impacted at near the same time; on Temporal Far trials there was greater difference in speed [5 and 2] and they impacted further apart in time). This factorial design creates 16 trials types. For greater generalization, these 16 trials were each presented three times each epoch, with a global offset of 8 units to the left, 8 to the right, and with 0 offset.

In addition to the Divided Attention trials described above, a training epoch consisted of Focused attention trials, in which a single target appeared. Focused trials were created by simply removing one target from the Divided set, so that there were 48 Focused T1 trials in which T1 was presented without T2, and 48 Focused T2 trials in which T2 appeared without T1. There was then a total of 144 trials in each epoch, requiring the catch of 192 targets.

There are several notable factors about the training set. First, the training set was constructed to ensure T2 catch was possible after T1 catch. The ratio of the final distance separation and the catch time separation were determined so as to be a maximum of about one-half (~55%) of the maximum agent velocity. That is, after catching T1, the agent had to travel at most 55% of its max velocity to catch T2. Second, the 6° spread of the VA sensor array was enough to span both targets at their maximal separation when between 10 and 100% of the sensor range. Finally, the Far Space/Near Time trials were a particular challenge. On these trials, a VA that is centered under T1 at the time of impact will have no sensor contact with T2 (as illustrated in Figure 2). That is, if VA makes an accurate catch of T1 on these trials, it will subsequently be looking at empty space. This leaves VA with two options to avoid failure on T2: initiate a blind search for T2, or remember the last seen location of T2 and move towards that remembered location.

Figure 2. Schematic of catching task with two targets. The two targets are indicated by the down arrows. VA is located at the bottom of the environment, and can move left and right by activation of its two motor units. VA is here under T1. The rays emitting from VA represent its sensors. The leftmost and two rightmost sensors detect nothing, and the others have intersected T1. At this time T2 (on the right) is out of view. Copies of the simulator and associated data files are available for download at http://www.psychology.bangor.ac.uk/ward.
The weights of each CTRNN were selected with a genetic algorithm (GA) procedure. GA search was halted when the best population member did not change after 1000 generations and the agent had evolved at least 5000 generations. Searches were terminated at 15,000 generations if the above conditions were not met. In all cases, the lowest performing population member was nearly equal to the highest performing member, which is indicative of near convergence. The search objective was to minimize the total miss distance divided by the total number of targets processed. Miss distance was calculated as the center-to-center separation between a target and the VA when the target’s bottom vertical position equaled or exceeded the top of the VA’s vertical position.

2.3. Test trails

After training, performance was assessed on a set of 1500 randomly generated test trials, for Divided, Focused T1, and Focused T2 conditions. Five hundred Divided attention trials were constructed as follows. T1 position was randomly sampled in the interval of 169 to 209. T2 was offset a random distance from T1 in the range of 24-48 units left or right of T1. T1 speed was generated as a real number between 4 and 5, and T2 speed in the range of 2 to 3. Focused trials repeated the Divided attention trials, omitting one of the targets.

3. Results

3.1. Selective attention to T1

Before investigating possible selective processing in CVA, we had to first verify that CVA was actually capable of selective action. Selectivity was assessed by a simple question: how much did the presence of T2 interfere with the catch of T1? This is illustrated in Figure 3. Looking first at RVA performance, we can see that catch accuracy was almost perfect with single targets in Focused Attention conditions. But relative to Focused Attention, the presence of T2 in Divided Attention conditions produced significant interference on T1. Interference from T2 is

![Figure 3. Catch accuracy (% overlap between the agent and the target) on 1500 random test trials. Agents show near-perfect performance with single targets in Focused Attention. When two targets must be caught in Divided Attention conditions, CVA improves significantly relative to RVA.](image)
best described as a 'capture effect', so that RVA would miss T1 by positioning itself between T1 and T2. This tendency to miss towards rather than away from T2 was highly significant, \( t(498)=26.5, p<.0005 \). For CVA, the interference in Divided Attention conditions was much reduced, as evidenced by the significant interaction of Agent Type (CVA or RVA) x Attention Demand (Focused or Divided), \( F(1,992)=428, p<0.00005 \). Relative to the RVA baseline, CVA was clearly capable of selectively responding to T1, and preventing interference from T2.

3.2. Memory for T2

Selective processing of T1 created a problem for CVA. When CVA took up a position directly underneath T1, T2 could fall outside of the sensor array (especially Far Space/Near Time trials, see section 2.2). We called these cases "out-of-view" (OOV) trials. On OOV trials, after the T1 catch, CVA would be looking at a completely blank sensor array. Which way should CVA move in such case? To solve the problem of OOV trials, CVA developed a memory for position of the unseen T2. We assessed this memory by determining whether CVA's first move after T1 catch on OOV trials was towards or away from T2. Our training set had the virtue that the position of T1 was uninformative about the direction in which T2 might lie. A random first move would be towards the unseen T2 only 50% of the time. CVA does much better than chance, making the correct first move in 100% of the OOV training trials, on 84% of the OOV trials in our first test set. These levels of performance were significantly better than chance, chi-squared(1) > 78, \( p < .000005 \). CVA must therefore have developed a memory for T2 position, established earlier in the trial, while T2 was in view.

3.3. Reactive inhibition: A mechanism for selective action

We have seen that CVA selectively responds to T1, and insulate its response mechanisms from the effects of T2. However, after T1 is caught, CVA must reallocate processing to the previously ignored T2. In people, this kind of cognitive reallocation produces robust costs in the form of "negative priming". Negative priming refers to costs in performance when a previously ignored object must be subsequently attended and reported (see Figure 4). The Houghton and Tipper (1994) model of reactive inhibition proposes that the strength of negative priming directly reflect competition for attention. According to the model, a target is selected by inhibiting all nontarget items. The more salient the nontarget -- that is, the more powerfully it tends to attract attention -- the greater
the inhibition needed to prevent the object from gaining control of behavior. Thus, more negative priming is observed for highly salient nontargets than for less salient ones (Grison & Strayer, 2001).

Given that CVA must switch its processing from T1 to the previously ignored T2, we looked for a similar "negative priming" cost. We observed a marked hesitation in CVA movement after the T1 catch, so that, on average, CVA was immobile for roughly 30 timeslices. We measured this period of hesitation when T2 was in-view and OOV after T1 catch. For the intact CVA, the hesitation period was longer for in-view than OOV T2s, F(1, 498) = 95.9, p < .0005.

This may seem like a counter-intuitive result. After all, once T1 is caught and removed from the environment, CVA must now catch T2. And on in-view trials, T2 is setting right in front of CVA --- shouldn't this facilitate T2 catch? This intuition is countered by the predictions of the reactive inhibition model. According to reactive inhibition, a T2 that is visible for longer periods during the trial would be expected to receive greater inhibition, to prevent it from being the target of selective action. Thus, the in-view T2 would be expected to receive more inhibition than an OOV T2. The decay of this inhibition would result in a longer hesitation for in-view T2's.

Reactive inhibition fits the pattern of hesitation we observe, but can we find direct evidence of inhibition? An inhibition model predicts that, during the buildup to T1 catch, CVA is developing an inhibitory signal, acting to keep CVA away from the T2 during the T1 catch. Under normal conditions, once T1 is caught, the external input from T2 would act in opposition to this internal signal. The external input would attract CVA towards T2, while the internal inhibition would keep CVA away from T2. However, as the inhibition of T2 decays, CVA...
will move gradually in the direction of this external input. We can isolate any internal inhibitory signal by disconnecting sensor inputs right after T1 impact. By doing so, we remove the counteracting external input from T2. CVA is now subject only to the inhibitory signal and should move away from T2. This is what we see in Figure 5. The first move of the intact CVA, following T1 catch, is towards T2, on 417 of 417 trials. With the sensor input of CVA disconnected, this pattern completely reverses. After catching T1, CVA now moves away from T2, on 414 of 417 trials.

4. Summary and conclusions

We analyzed mechanisms for selective action in an artificial evolved agent. We found that our agent, CVA, utilized a reactive inhibition mechanism, strikingly similar to proposals in the psychological literature for control of action (Houghton & Tipper, 1994). In particular, CVA demonstrated costs when reallocating its selective processing, to respond to a previously ignored item. This cost varied significantly with the salience of the ignored item: the more salient the ignored item, the greater the subsequent costs for reallocation. We were also able to directly confirm that selective processing was achieved by inhibition of nontargets. We were able to isolate an inhibitory signal, applied to nontargets, and generated within the internal recurrent connections of CVA. This inhibitory signal allowed CVA to catch the target without interference from the nontarget, but did not prevent CVA from perceptual processing of the nontarget, and in particular from forming a memory for nontarget location. Greater detail and analysis on these and other points is available in Ward and Ward (submitted).

The use of reactive inhibition in CVA is notable for several reasons. First, this is the first demonstration of reactive inhibition in an embodied, dynamic agent. The reactive inhibition model appears suitable for selective action involving behaviors extended over time and space. Second, reactive inhibition emerged as a solution for control, despite the simplicity of CVA and its environment. There was nothing in the architecture of CVA to obviously encourage reactive inhibition. This is particularly notable when comparing CVA’s architecture to the relatively complex and sophisticated "wiring" of
Houghton and Tipper (1994). Furthermore, the CVA network is about as primitive as one could imagine, in its sensory and motor capabilities, and in its 8-unit hidden layer. The environment in which CVA operates is also about as simple as any environment can be that requires selective action over time. Reactive inhibition may therefore be a fundamental mechanism for selective control, in all sorts of selective agents and dynamic environments.

References


