Object Persistence for Synthetic Creatures

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ABSTRACT
We present methods for anticipatory behavior in simulated graphical creatures. We discuss in general terms the importance of anticipatory behavior through explicit expectation formation. We present an in-depth description of a specific type of expectation-formation, namely location-expectation, or object persistence. A new representation – the Probabilistic Occupancy Map (POM) – is presented, and it is shown how this representation can be used to maintain estimations of the positions of mobile objects in the world based on both positive and negative knowledge provided by the creature's perceptual system. Finally a number of illustrative results are presented that show Duncan, our simulated dog, successfully performing a number of tasks that require a high degree of spatial common sense.

Categories and Subject Descriptors
I.2.0 [**Artificial Intelligence**]: General – *cognitive simulation*

General Terms
Algorithms, Design, Theory.

Keywords
Autonomous agents, graphical agents, object persistence, spatial common sense.

1. INTRODUCTION
As we attempt to build increasingly sophisticated autonomous interactive agents (or "synthetic creatures" as we will call them in this paper) an important contributor to a life-like appearance is the ability to *anticipate*. Anticipation – or expectation formation – can be thought of as the ability to make decisions and react to aspects of the world state that, for one reason or another, cannot be directly perceived. This might include events that occur outside the field of view, are occluded, or that have not yet happened (but are *expected* to happen). There are many potential sources for

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Figure 1: Duncan the Highland Terrier

these expectations, such as reliably observed event correlations (when the button is pushed, the elevator doors are expected to open), theory of mind (given an assumed state of mind, another creature is expected to perform action A), physical intuition (when a ball is released, it is expected to fall), or, as will be discussed at length here, spatial structure (if a ball rolls behind a wall, it is expected to come out again after a certain delay). Not only do these types of expectations make a creature seem more intelligent, but their absence significantly *impairs* any pretensions it might have to common sense. If the ball disappears behind a wall, it would appear either broken or colossally stupid for the creature to then not know where to look for it.

This work presents a model of object persistence, a cognitive phenomenon which we consider equivalent to the ability to form and maintain expectations of object positions over space. While not a general solution to the problem of expectation-formation, it does show an effective solution in a particular domain, a solution which is, moreover, firmly grounded in expectation theory. It also shows a reference implementation of an object persistence system in Duncan, the Virtual Terrier (Figure 1). Duncan lives in a simple graphical environment that he perceives through a synthetic perception system that includes simulated audition and point-of-view rendering (synthetic vision). He is a platform for various aspects of our research, including operant and classical conditioning and motor learning.

Section 2 is a brief discussion of expectation theory in general. Section 3 discusses in depth the problem of location-expectation. Section 4 introduces Probabilistic Occupancy Maps (POMs) as a means of maintaining location-expectation distributions. Section 5 presents some example results and concluding remarks are given in Section 6.

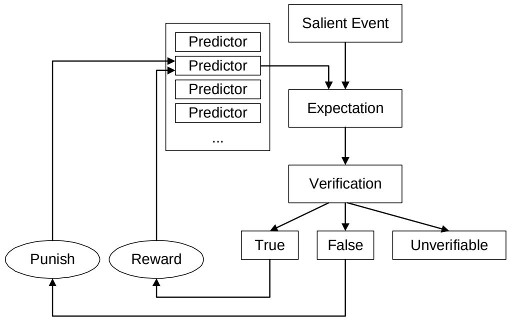
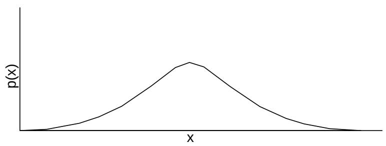
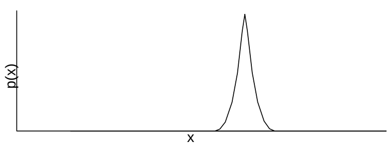


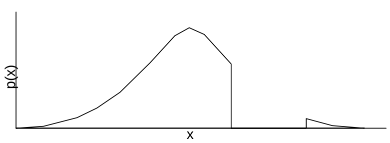
Figure 2: The expectation/verification loop



(a)



(b)



(c)

Figure 3: Incorporating positive and negative observations.

A distribution (a) represents a space of predictions with the indicated confidence. An observation of the true state (b) results in a tightening of the distribution while the negation of some region of the state space (c) zeroes the distribution in that region, and scales the rest of the distribution up as appropriate.

2. EXPECTATION THEORY

Kline's Masters Thesis ([8]) provides an excellent overview of expectation theory. This discussion will largely parallel its conclusions. These concepts will be explored more concretely in the next section.

An expectation, for our purposes, is a guess about some aspect of the world state that is not directly perceivable. Each expectation is accompanied by a degree of *confidence*, which indicates how strongly the expectation is believed to be accurate. In general, it is an observation of some sort – perhaps of an unusually salient stimulus – that leads to an expectation formation by a specialized *predictor* unit. While a creature might act on its expectations as if they were all completely accurate, the ultimate validity of an expectation is ascertained through *verification*. The process of verification can have three possible outcomes:

- Verifiably true: The expectation turned out to be correct.
- Verifiably false: The expectation turned out to be incorrect. This is an expectation violation.
- Unverifiable: The accuracy of the prediction could not be determined.

Typically, a verifiable prediction-outcome is followed by some form of belief revision. The predictor that generated the expectation might also be revised, for example, its reliability rating might be modified according to whether its outcome proved accurate or not. If the prediction accuracy was unverifiable then neither the expectation nor the predictor itself is impacted. This entire process is summarized in Figure 2.

The above formulation applies to discrete true/false predictions. Some expectations, however, are better formulated as a *space* of predictions that might naturally be expressed as a probability distribution over the possible world states, as in Figure 3. Within this space, each infinitesimal element can be considered an individual prediction to be verified as true or false. These individual predictions can affect each other in two ways: first, in that an observation and confirmation of one prediction is equivalent to a negation of all the other predictions, resulting in a "tightening" of the distribution around the observed value (Figure 3b). Second, a verified negation of a sub-region of the state-space (effectively a culling of probability from the distribution) results in a renormalization of the rest of the distribution (Figure 3c).

2.1 Expectation Violations and Salience

We define salience as the degree to which an observation violates expectation. As [8] points out there are two types of expectation violation: unexpected observations and negated expectations (verified false predictions). For the first kind, a straightforward inverse relationship exists between salience and confidence at the observed value (thus unexpected observations are more salient):

$$s(x) = \frac{1 - c(x)}{c(x)} \tag{1.1}$$

This maps salience into the range $[0,\infty]$ (assuming that $c(x)$ has range $[0,1]$). We call this form of salience *surprise*.

For expectation violations of the second kind, the salience can be considered proportional to the amount of confidence culled by the observation. This might be expressed as

$$s(x) = \int_R c(x) \tag{1.2}$$

where R is the region of the state-space of x that has been verified as false (see Figure 3c). We call this form of salience *confusion*.

It is notable that many secondary emotions imply some form of expectation: fear, delight, disappointment, anticipation, confusion, dread, worry, etc. They also imply an extended range of possible interactions. Creatures that can form expectations can be tricked, teased, deceived and more.

3. OBJECT PERSISTENCE

In this section we introduce an extended example of expectation-formation: that of location-expectation. We argue that the ability to maintain reasonable location-expectations is tantamount to a sense of object persistence. Object persistence, as discussed by the

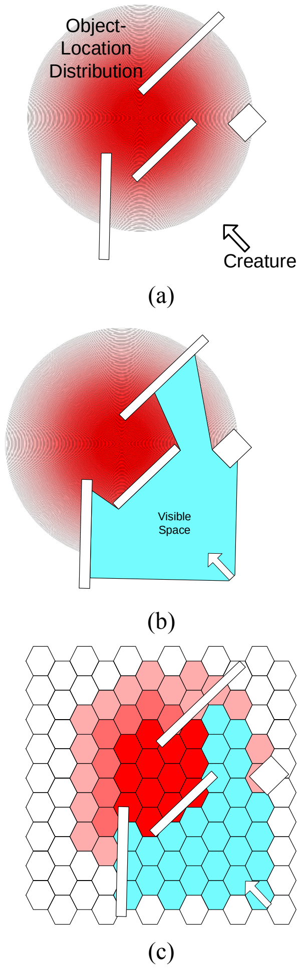


Figure 4: Distribution Representation

A gaussian distribution (a) cannot incorporate negative information about regions of space observed to be empty (b). In this work, we discretize the space itself, and allow each element to become a "bucket" of probability (c).

psychologist Piaget [13], refers to the persistence of mental images of objects after they have stopped being perceived. It also implies the ability to make basic deductions about where objects could be, and to act on those deductions. If a child turns toward a toy that has been hidden from it, it does not forget about the toy, or remain staring at the toy's last known position. Instead it searches for the toy systematically, based on its last observed position and based on the physical structure of the environment – could it have been hidden behind the box, or under the table? The basic problem of object persistence, which we would like our synthetic creatures to be able to solve, is: given that an object is not currently visible, where is it *expected* to be?

3.1 Distribution Representation

We must come up with some way of representing our spatial probability distributions. One natural representation might be the gaussian distribution – after all, it is compact, and mathematically convenient, with notions of confidence and "best guess" built in. The difficulty with the straight gaussian representation is that it does not lend itself easily to the incorporation of negative knowledge. Figure 4 shows an example of this problem. Figure 4a, shows the distribution for an occluded object. A great deal of negative information – namely, those locations observed to be empty – is being thrown out. The correct distribution, the one in which all probability has been zeroed in all visibly empty space, is shown in Figure 4b. This distribution is clearly not gaussian – it is even disjoint. Since the shape of the distribution relies ultimately on the physical structure of the environment, it can be arbitrarily complex – and arbitrarily messy.

3.2 Probabilistic Occupancy Maps

The general strategy we use to overcome the difficulties of the gaussian representation is to discretize the location-distribution, in what we call a Probabilistic Occupancy Map (POM). In this formulation the environment is partitioned into discrete locations which can be used as "buckets" of probability. Thus the compact gaussian representation is replaced with a vector of discrete activations, each corresponding to the probability that the target object is contained in that location. As Figure 4c shows, this scheme has no problem representing oddly-shaped distributions, though its accuracy obviously depends on the resolution of the map itself.

We use a hexagonal grid overlaid on the environment. Each grid node is connected to six neighbors, and is denoted by a pair of *(i,j)* indices. Each node is annotated with a probability vector, whose element indicate the probability that the node contains a particular object. For simplicity, in the following discussion we will assume that there is one target object, and that each node is annotated with a single probability, $p(n_{i,j})$, of containing that object.

In some experiments the maps themselves were learned, such that higher resolution was used in more "interesting" parts of the environment, such as around prominent landmarks. This strategy is very useful in terms of representational economy. However, it is not essential to the basic implementation, and so will not be discussed here. See [6] for details.

3.2.1 Probability Diffusion

On timesteps in which the target object is not observed, a discrete diffusion step is carried out to reflect the decreased confidence in the target's location. Simple isotropic diffusion works well. The update expression for a single node can be given as

$$p^{t+1}(n) = (1-\lambda)\,p^{t}(n) + \frac{\lambda}{6}\sum_{n' \in neighbors(n)} p^{t}(n') \qquad (1.3)$$

where λ is a diffusion constant in the range [0,1] and $p^{t}(n)$ is the probability of the node *n* at time *t*. Thus at each timestep, each node passes some fraction of its own activation to its neighbors.

In cases where the target was last observed in motion, the probability should diffuse preferentially in the direction of the target's last observed velocity. This can be used in the example in which the target object disappears behind an occluder – the creature can form an expectation about when it should reappear. The most obvious way to achieve this effect is to modify the diffusion rates along the various connections emanating from a particular node so as to favor diffusion in the correct direction. We might set the diffusion rate, λ_i, along the ith connection as

$$\lambda_i = \lambda_c + \max\left(0, \frac{v \cdot l_i}{|l_i|^2}\right) \quad (1.4)$$

where v is the velocity vector and l_i is the position offset between the current node and the node's ith neighbor. λ_c is a constant diffusion rate, ensuring that some probability is diffused to every neighbor, even if that neighbor does not lie in the direction of the velocity vector. Note that this method does not guarantee that the peak probability will follow exactly the straight linear extrapolation of the target's position and velocity, although the result generally approximates it.

3.2.2 Observation

On timesteps in which the target object was observed, we pick the node n^* that is closest to the target's position. We tighten the distribution around this node by setting its probability to 1, and zeroing the probabilities of all other nodes:

$$\forall n_{i,j} \neq n^*, p(n_{i,j}) \leftarrow 0 \quad (1.5)$$

$$p(n^*) \leftarrow 1 \quad (1.6)$$

As in section 2.1, we determine a salience for the observation with the expression

$$s = \frac{1 - p(n^*)}{p(n^*)} \quad (1.7)$$

While this gives a valid mapping for a salience in the range $[0,\infty]$, it has one undesirable property: that when the distribution is very diffuse, even the most likely location (the location with the highest p^*) returns a high salience if confirmed. Since the desired behavior should be for the most expected prediction not to be considered salient when confirmed, we normalize the previous expression by $p_{highest}$, the probability of the most likely location. Thus,

$$s = \frac{p_{highest} - p(n^*)}{p(n^*)} \quad (1.8)$$

3.2.3 Verification

Positive verification in this domain is simply the observation of the target where it was expected to be. Negative verification is more complicated, requiring us to use information about locations observed to be empty. If a map node with a certain probability is considered a prediction about an object's location, then the observation of that location without the corresponding observation of the object can be considered a negation of that prediction. If a location is confirmed to be empty, that information can be incorporated into the POM by zeroing the probability content of the corresponding map node.

On timesteps in which the target object was not observed, the map nodes are divided into a visible set, V, and a non-visible set, N. A total amount of culled probability p_{culled} is calculated as

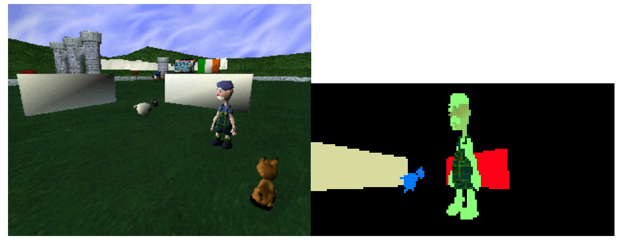


Figure 5: Duncan's Synthetic Vision

$$p_{culled} = \sum_{n \in V} p(n) \quad (1.9)$$

Then the probabilities of all visible nodes are set to zero:

$$\forall n \in V, p(n) \leftarrow 0 \quad (1.10)$$

Finally the remaining probabilities are renormalized

$$\forall n \in N, p(n) \leftarrow \frac{1}{1 - p_{culled}} p(n) \quad (1.11)$$

Note that by the definition given by equation (1.2), the value p_{culled} is also the measure of the surprisingness of the failure to observe the target object.

4. IMPLEMENTATION

The POM scheme was implemented on top of C4, a character simulation platform described in [2] and [7]. Currently, Duncan (Figure 1) is our most sophisticated character, and it was in his brain that most of the following was implemented and tested.

4.1 Synthetic Vision

A simple model of synthetic vision was used as the primary source of perceptual information for Duncan, in a manner similar to schemes used in [1] and [18]. The vision model consisted of a rendering of the world from the point of view of Duncan's left eye. This rendering was color-coded (as shown in Figure 5) such that individual objects were recognized by color (i.e. no shape-analysis was performed). From these renderings, screen-space object-centroids were extracted, and combined with the contents of the depth-buffer to produce eye- and then world-space coordinates. Two implications of this strategy are that an object is considered visible if *any* portion of that object is visible, and that the location is taken as the centroid of the visible portion.

4.1.1 The Test-point Method

Another crucial function of the vision system is to determine the visibility of map-locations for the purposes of negative verification (i.e. in separating the N and V sets, from section 3.2.3). A number of schemes are possible here, the "truest" one probably involving pixel-sampling over the expected screen-space extent of the node. This scheme is not used due to run-time considerations.

Instead, we use a vastly simplified *Test-Point* approximation, in which a single point is imagined floating half a body-height above the world location of the map-node to be tested. The world-coordinates of this point are transformed back into NDC coordinates. The depth-buffer is then queried to see whether an object at that point would be visible. If the depth of the pixel to which the test-point transformed is less then the NDC-depth of the test-point, then the test-point is hidden, and the entire location is considered non-visible (and placed in the *N* set). If the depth is greater, then the location is considered visible (and placed in the *V* set).

Unlike object-observation, in which the view of any part of the object counts as a full observation, it is generally advantageous in location-visibility to err on the side of non-visibility. In other words, it is advantageous to demand that the *entire* location be visible before the corresponding node is considered visible. This is simply to ensure that the true location of the object is never discounted simply because *part* of the location was visible. Note, however, that our test-point method does not follow this guideline.

4.2 Working Memory and Object Matching

Duncan maintains a Working Memory model that consists of a recent perceptual history of all objects in the world. On each timestep, the perceptual input from each object – color, shape and location – from the vision system is bundled up into a *belief* object. These beliefs are compared to a list of persistent beliefs stored in the creature's Working Memory. Since many of the new beliefs probably represent a new observation of an old belief (if it represents the newest data from an object that has been tracked over multiple timesteps, for example), all incoming beliefs undergo a process of *belief matching*, in which the "distances" between the new belief and each of the old ones is found. If the lowest of these "distances" is below a threshold, the two are considered a match, and the data contained in the new belief is added onto the perceptual history contained in the old one. If the lowest distance is above the threshold, then the new belief is considered to represent a new object, and is itself added to Working Memory.

In finding the distance between two perception tuples (each consisting of <*color, shape, location*>), each component in one tuple is compared with the corresponding component of the other. The total distance is then considered the sum of the component-distances. For the purpose of this system, both shape and color are symbolic binary matches returning distance infinity or zero depending on whether there is an exact symbolic match or not (e.g. "red" = "red"). In comparing location however, we can again make use of the location distributions of the POM, since ultimately we are more interested in the *likelihood* of the target appearing at the new location than its straight distance from the last one (although straight distance is often used as a convenient approximation). This likelihood is exactly what the POM gives us. When a new observation is made, the incoming location data can be ascribed a nearest node, n^*. This node holds some probability, $p(n^*)$ of containing the target object. To find the "distance" between a location-distribution, and a new observation at n^*, we use

$$d = \frac{p_{highest} - p(n^*)}{p(n^*)} \tag{1.12}$$

where $p_{highest}$ is again the highest probability value of any node in the map. This is, of course, simply a re-casting of the salience function of equation (1.8). This follows the intuition that if an observation is too unexpected, we might reject it altogether.

When a new belief is merged into the old one, the appropriate distribution tightening, as per equations (1.5) and (1.6) occurs. For all non-visible objects, the appropriate distribution culling is carried out, as in equation (1.10), followed by the diffusion of all location-distributions, as in equation (1.3).

4.3 Action Selection and Motor Control

Having updated his perceptual image of the world, Duncan must decide what to do. Though the problem of Action Selection is a major focus of our research (particularly with regards to learning), it is largely irrelevant to this work. In many of the experiments conducted on this system, Duncan was given just three behaviors: "look at target", "approach target" and "approach shepherd" (the shepherd being a user-controlled character inhabiting the same space). Duncan decided between these behaviors deterministically at the instruction of the shepherd. These high-level behaviors are translated by the action selection system into low-level navigation and motor commands. A Navigation System was use to control locomotion toward a goal and obstacle avoidance, and a Motor System was used as the lowest-level interface with the graphics system to control Duncan's animation.

5. RESULTS

This section presents a few scenarios as examples of Duncan's new spatial capabilities with the POM system in place.

5.1 Salient Moving Objects

One result of the POM system is that moving objects –especially irregularly moving objects – automatically become salient. If an object remains still, its distribution looks like a roughly gaussian cluster of probability centered on the observed location of the object. When the object starts moving, the object is matched into a relatively unlikely part of this distribution – thereby making that observation salient. When velocity-based (anisotropic) diffusion is used, an object that zigzags is more salient than an object that moves at a constant speed in a constant direction.

5.2 Search Behaviors

There are a number of examples of "emergent search" that fall out of the POM system almost for free.

5.2.1 Emergent Look-Around

Intelligently moving the eyes over a visual scene, from an animation point of view, can be important in maintaining the illusion of life [16]. However, there is no practical point to this if the negative information about empty space is not used. Typically, the "look-around" behavior is a canned animation. However, a convincing "look-around" happens naturally with the POM system. Consider a situation in which a target (in this case, a sheep) has not been seen in some time (and has been moved since it was last observed), and is represented by a wide, diffuse distribution. When instructed to look at the sheep, Duncan turns towards the most likely position for the sheep, namely the center of the distribution. Not finding it there, he looks first one way, then the other, always looking at the current most likely position. The result is an alternating sweep-left, sweep-right behavior, until the sheep is found at its new location.

5.2.2 *Emergent Search*

If Duncan is instructed to approach the sheep, rather than just look at it, then the emergent look-around becomes an emergent search. As in the emergent look-around, Duncan approaches at every point the most likely location for the target object. He is preceded by his gaze however, which rules out open areas of the environment. This leaves only areas occluded by barriers, and the resulting behavior is what looks like a systematic search of these occluded areas.

In one example, Duncan is introduced to the environment shown in Figure 6. After a brief view of the environment and the objects in it, Duncan is called to the shepherd. Behind his back, the sheep is moved behind the nearest wall. When told to approach the sheep, Duncan immediately goes to search behind the correct wall. Duncan is called away again, and this time the sheep is moved from its original hiding place to a new one behind the other wall. When again instructed to approach the sheep, Duncan first looks in the original hiding place. Not finding it there, he comes out and again scans the scene, this time concluding that the only place the sheep can now be is behind the second wall. Again, he finds the sheep in its hiding place.

What is perhaps most interesting about this example, is that at a behavioral level – at the level of the Action Selection mechanism – Duncan has only two behaviors to chose from: “approach the sheep” and “approach the shepherd”. However, the result is much more sophisticated, and has the *appearance* of deliberative reasoning.

This “emergent search” behavior is extremely important for keeping the process of action-selection clean. If “search” needed to be included at this level of the system, it would need to be listed explicitly as a strategy for “approaching the sheep,” “approaching the shepherd,” “biting the sheep”, “eating the sheep” etc. Matters would be even worse if we expected learning to occur at this level of control – thus pushing onto the learning mechanism the burden of deciding when “biting the sheep” necessitates a “search.” With the architecture described here – in which some of the decision-making has been pushed up into the perceptual/memory system and down into the navigation/motor system – some degree of search capability is implied in *all* targeted behaviors.

5.3 Distribution-Based Object-Matching

To show the advantage of distribution-based object-matching, a scenario was set up as shown in Figure 7. Like in a previous example, Duncan tracks a moving sheep as it passes behind a long wall. This time, however, the wall has a large gap in it. The scene is staged, because at a certain time where the sheep, unimpeded, might have expected to come out from behind the right wall, a second sheep, initially hidden, appears there. A single sheep would have been observed to pass through the gap. Since it did not, the intelligent observer is forced to conclude that there are, in fact, two separate sheep. Happily, Duncan makes the same determination, since his constant viewing of the space between the two walls keeps any of the probability from diffusing from behind one wall to behind the other. Thus when the second sheep appears, it appears in a location for which the first sheep’s location-distribution is zero. Since it is impossible for the two observations to represent the same object, the belief-matching step fails and a new persistent belief is added to Working Memory.

Figure 6: The search task environment

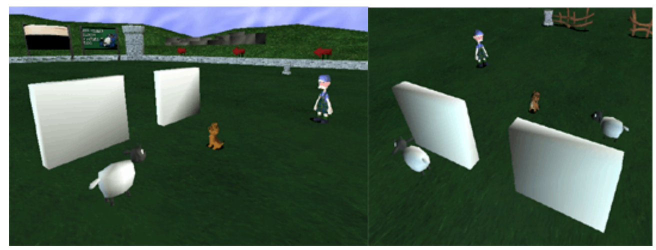


Figure 7: The object-matching task environment

This is apparent, because when Duncan is subsequently asked to approach the nearest sheep, he looks behind the left wall first.

This is an exciting result for two reasons. First, it shows a very different kind of “reasoning” from the previous examples – a kind of negative reasoning, reflecting the ultimate determination that the two objects are not the same. Second, it shows a kind of reasoning that is highly distributed: the vision system provides observation data, the Verification System extracts visible locations, the Spatial System maintains the POM itself, and the Working Memory system makes the ultimate decision to allocate a new persistent belief. In the best sprit of the Society of Mind [9], it is the confluent effect of all these systems that results in the “intelligent” behavior.

5.4 Emotional Behavior

Duncan maintains a list of variables to represent various aspects of internal state. Some of these variables are explicit “emotional” variables. In one series of experiments, Duncan was given the variables of “surprise”, “confusion” and “frustration”. The first two of these were simply the outputs of equations (1.8) and (1.9) run through an asymmetric low-pass filter (for sharp rising edges and soft falling ones). The “frustration” variable grew by some factor on every timestep that Duncan’s target was not directly observed. Figure 8 shows a stereotypical trace of these variable values over time in a “search for the sheep” task.

Currently, the only effect that these variables have is to change Duncan’s facial expression. However, the ultimate hope would be to feed these emotional variables back into Duncan’s basic decision-making processes, such that, for example, frustration could act as a signal to “stop whatever you’re doing and try something else”, and surprise could indicate “examine more carefully your object of attention” etc.

Beyond being interesting from a procedural animation point of view, we consider these types of emotions to be an important part of intelligent, *expressive* behavior. Emotions like confusion and frustration can prove convenient indicators of overall system state or recent history, and are, moreover, easily interpreted even by naïve observers.

6. CONCLUSIONS

In this paper, we have presented a model of object persistence and a representation – the Probabilistic Occupancy Map – that implements it. We draw a number of major conclusions.

Architecturally, the POM is an important lesson in multi-layer decision-making. The section on emergent search shows that even with a simple explicit behavior-selection layer, many complicated behaviors can result with the right perception/space-modeling mechanisms. The behavioral level could be completely user-directed, or scripted, or could be run by a complex automatic behavior simulation system. Whatever the case, there is clear benefit to separating out this series of spatial competencies into separate layers.

Another important point is that a good representation is worth a lot. In this case, the POM structure was tuneable enough to be useful, but also general enough to account for many interesting effects. For example, it was fairly simple to incorporate a sense of momentum for velocity-based probability diffusion. It was also general enough that unforeseen behaviors emerged without being designed for.

Most importantly, this work is an illustration of the expectation theory that is presented in section 2. It should show that (a) representations based on this theory are conceptually simple and easy to implement, (b) the representations are powerful, and lead to interesting behaviors and abilities and (c) these new abilities contribute substantially to a creature's believability and apparent common sense. It is hoped ultimately that this work can serve as a model for how other kinds of expectation formation abilities might be incorporated into a behavior simulation framework.

Much work yet remains to be done. Among the chief problems of the current system is the problem of scalability. The environments used for the experiments outlined here were all fairly simple and fairly limited in size. As the number of target objects and the size of the world increases, it will become increasingly difficult to run the algorithms described here at interactive rates. A possible solution to this might be to use some form of hierarchical space-representation, which would allow the simulation to run accurately in locations near the creature, and coarsely in others. An indoor environment consisting of rooms connected by doors would certainly benefit from this type of representation.

7. RELATED WORKS

The field of artificial life is relatively new, but already has such seminal works as [1] and [15]. More recently, work by Terzopoulos and his colleagues (e.g. [5] and [18] and) has proved very impressive, and relevant to the current work for their concern with higher-level cognitive processes and cognitive modeling.

There has been work on expectation theory. [12] points out a source of surprise not treated in this work: events for which there were no expectations but that are inherently unusual. The example given by the author is that of a brick flying through a window: no

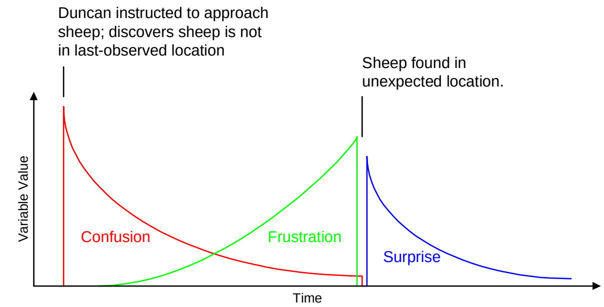


Figure 8: Trace of emotional variables in a search task.

prior expectation existed over where or when such an event would occur, but it should nonetheless register a surprise. We believe that such models of inherent salience could easily be incorporated into our framework. As already mentioned before, [8] was very influential to this work.

Drescher did work specifically on cognitive processes leading to object persistence [3] though only in a toy world. His work was itself an exploration of the computational side of Piaget's theories (as in [13]).

Probabilistic Occupancy Maps are clear derivatives of the Occupancy Grids, or Evidence Grids used in the mobile robotics literature (e.g. [10]). The major difference is that the "probability" held by each spatial element in Occupancy Grids refers to the probability of that element being occupied, rather than the probability that it should contain any particular object. Occupancy Grids are not position-distributions over space, rather they are a method for sensor-fusion over space.

More generally, there has been a tremendous amount of work done on the modeling of emotions, such as [11], [14], and [19] to name but a few. Recent work on modeling emotional social agents has come out of the Synthetic Characters group itself, with [17]. In terms of emotion modeling, the current work seeks to go beyond the simple happiness/sadness models of emotion (e.g. [4]) to secondary emotions such as confusion or surprise that express more subtle aspects of a character's internal state.

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