1 Basic Definitions and Concepts

In This Chapter

- What Is Intelligence?
- What Is "Game AI"?
- What Game AI Is Not
- How this Definition Differs from that of Academic AI
- Applicable Mind Science and Psychology Theory
- Lessons from Robotics
- Summary

Welcome to *AI Game Engine Programming*. This book is meant to give the game artificial intelligence (AI) programmer the knowledge and tools needed to create AI engines for modern commercial games. What exactly do we mean by "game AI"? It turns out this isn't as straightforward a question as you would think.

First, the term "game" is somewhat hazy itself. A "game" could refer to a spoken ritual that a class full of kids might play or to a complex technological undertaking by our government for training purposes. For this book, we'll be referring to electronic video games exclusively, although some of the concepts that we'll cover would probably be applicable to board games, or other strategic competitive game-like activities.

Second, we come to the term "AI." Seeing as its foundations were created in the 1950s, the science of AI is relatively young. The usage of AI techniques within games is even more contemporary, because of the computation and storage-space limitations of earlier game machines (not to mention the simplistic nature of many early games). The field's immaturity means that the definition of game AI is not clear for most people, even those who practice game production. This chapter will define the term *game AI*, identify practices and techniques that are commonly mistaken for game AI, and discuss areas of future expansion. Later in the chapter, relevant concepts from other fields, including mind science, psychology, and robotics, will be discussed regarding game AI systems.

What Is Intelligence?

The word intelligence is fairly nebulous. The dictionary will tell you it is the capacity to acquire and apply knowledge, but this is far too general. This definition, interpreted literally, could mean that your thermostat is intelligent. It acquires the knowledge that the room is too cold and applies what it learned by turning on the heater. The dictionary goes on to suggest that intelligence demonstrates the faculty of thought and reason. Although this is a little better (and more limiting; the thermostat has been left behind), it really just expands our definition problem by introducing two even more unclear terms, thought and reason. In fact, the feat of providing a true definition of intelligence is an old and harried debate that is far beyond the scope of this text. Thankfully, making good games does not require this definition.

Actually, this text will agree with our first dictionary definition, as it fits nicely with what we expect game systems to exhibit to be considered intelligent. For our purposes, an intelligent game agent is one that acquires knowledge about the world, and then acts on that knowledge. This is not to say that our notion of intelligence is completely reactive, since the "action" we might take is to build a complex plan for solving the game scenario. The quality and effectiveness of these actions then become a question of game balance and design.

What Is "Game AI"?

Let us start with a rigorous, academic definition of AI. In their seminal AI Bible, *Artificial Intelligence: A Modern Approach*, Russel and Norvig [Russel 95] say that AI is the creation of computer programs that emulate acting and thinking like a human, as well as acting and thinking rationally. This definition encompasses both the cognitive and the behavioral views of intelligence (by requiring emulation of both actions and thinking). It also includes, yet separates, the notions of rationality and "humanity" (because being human is sometimes far from rational, but is still considered intelligent; like running into a burning building to save your child).

In contrast, games don't require such a broad, all-encompassing notion of AI. Game AI is specifically the code in a game that makes the computer-controlled elements appear to make smart decisions when the game has multiple choices for a given situation, resulting in behaviors that are relevant, effective, and useful. Note the word "appear" in the last sentence. The AI-spawned behaviors in games are very *results*-oriented, and thus, we can say that the game world is primarily concerned with the behavioralist wing of AI science. We're really only interested with the responses that the system will generate, and don't really care how the system arrived

at it. We care about how the system acts, not how it thinks. People playing the game don't care if the game is using a huge database of scripted decisions, is making directed searches of a decision tree, or is building an accurate knowledge base of its surroundings and making inferred choices based on logical rules. The proof is in the pudding as far as game AI goes.

Modern game developers also use the term AI in other ways. For instance:

- Some people refer to the behavioral mechanics of the game as AI. These elements should actually be thought of as *gameplay*, but any time the AI controlled agents do something, people tend to think of it as AI, even if it's using the exact mechanism that the human players use.
- Many people think of game AI primarily as animation selection. Once a game entity makes a decision as to *what* to do, animation selection then makes a lower level decision as to *how* (on a visual level) to perform the move. Say that your AI controlled baseball pitcher has decided to throw a curveball. The exact animation that he goes through performing that decision is animation selection. How does the windup go, where does he look, does he tip his hat, etc.? Perceptions are polled, and an intelligent contextual decision is made. But this kind of low-level decision making is much more short range than the kind of intelligence we are talking about. People that think of animation selection as AI tend to be working on games with very simple AI requirements, games that don't require heavily strategic solutions.
- Even the algorithms that govern movement and collision can sometimes fall under this label (if the game uses animation-driven movement, rather than physics-based methods).

In fact, the term "AI" is a broadly-used moniker in the game-development world. When discussing AI with someone else in the industry (or even within the company at which you work), it's important to know that you both agree on the meaning and scope of the term; miscommunication can occur if your notion of AI is vastly different from the other person's (be it simpler or more complex, or just at opposite ends of the responsibility spectrum). So, let's be clear. When this book refers to AI, it will use the rather narrow definition of character-based behavioral intelligence. We care only about the behavioral smarts exhibited by some character within the game (the main character, a camera, an overseeing "god," or any other agent within a game world).

In the old days, AI programming was more commonly referred to as "gameplay programming," because there really wasn't anything intelligent about the behaviors exhibited by the CPU-controlled characters. See Figure 1.1 for an overall game AI timeline.

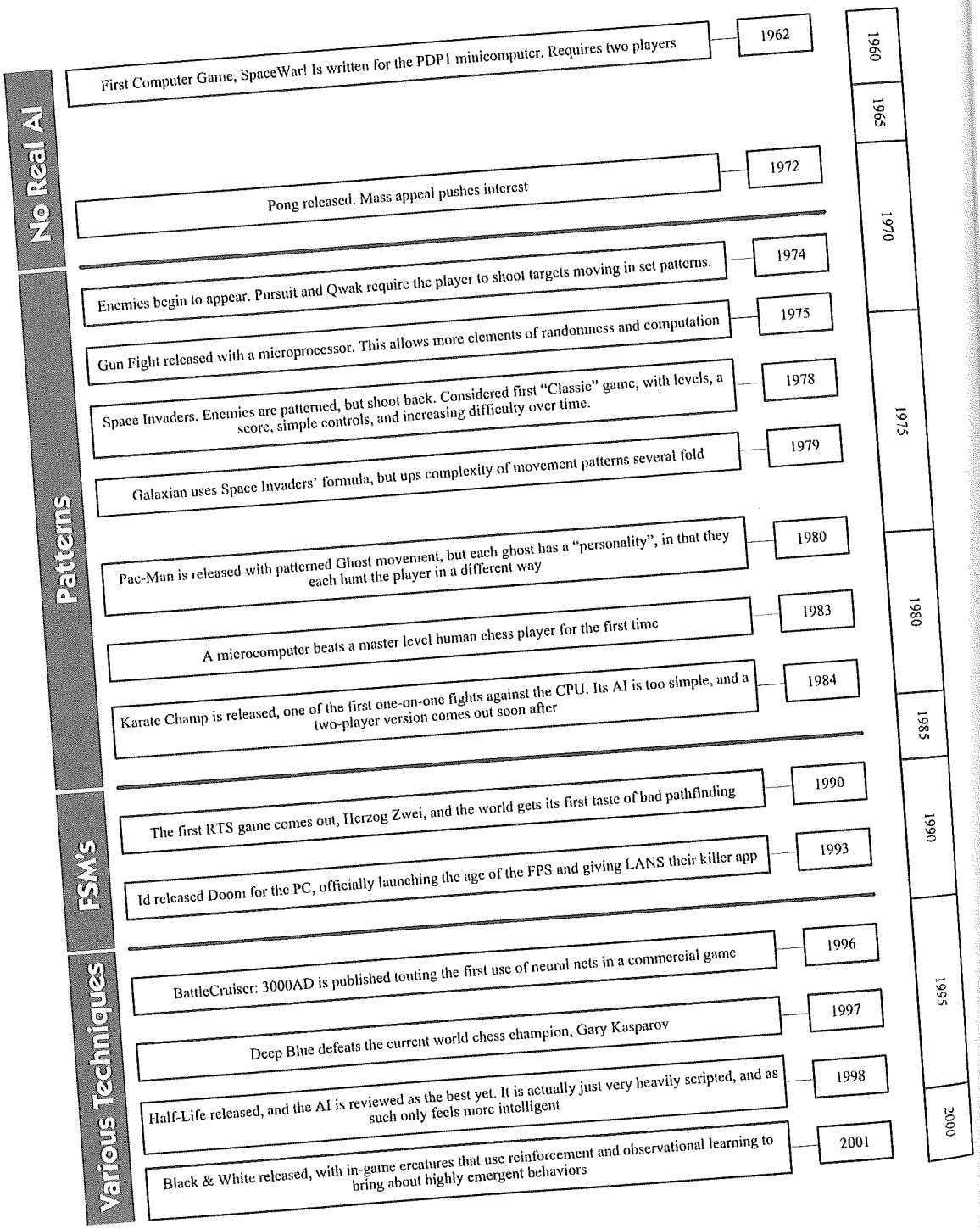
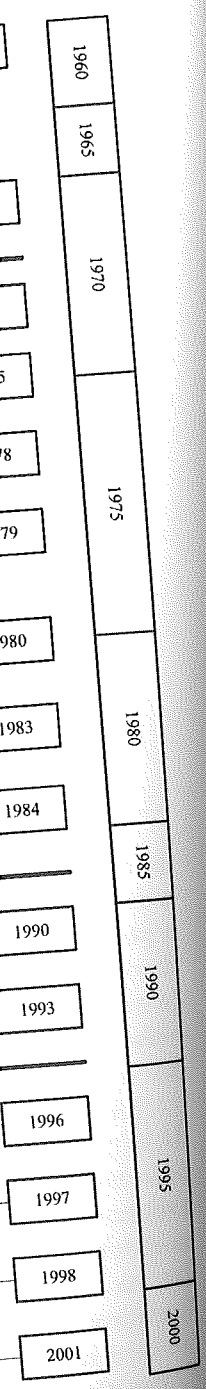


FIGURE 1.1 Game AI timeline.



In the early days of video gaming, most coders relied on patterns or some repetitive motions for their enemies (for example, *Galaga* or *Donkey Kong*), or they used enemies that barely moved at all but were vulnerable to attack only in certain "weak points" (like *R-Type*). The whole point of many of these early games was for the player to find the predetermined behavior patterns so that the player could easily beat that opponent (or wave of opponents) and move on to another. The extreme restraints of early processor speed and memory storage lead naturally to this type of game. Patterns could be stored easily, requiring minimal code to drive them, and required no calculation; the game simply moved the enemies around in the prescribed patterns, with whatever other behavior they exhibited layered on top (for instance, the *Galaga* enemies shoot while moving in a pattern when a player is beneath them).

In fact, some games that used supposed "random" movement could sometimes lead to a pattern. The random number generator in many early games used a hard-coded table of pseudo-random numbers, eventually exposing a discernable sequence of overall game behavior.

Another commonly used technique in the past (and sadly, the present) to make games appear smarter was to allow the computer opponents to cheat; that is, to have additional information about the game world that the human player does not have. The computer reads that a player pushed the punch button (before the player has even started the punch animation) and responds with a perfectly timed blocking move. A real-time strategy (RTS) game employing AI cheating might have its workers heading toward valuable resource sites early in the game, before they had explored the terrain to legitimately find those resources. AI cheating is also achieved when the game grants *gifts* to the computer opponent, by providing the opponent additional (and strategically timed) abilities, resources, and so forth that the opponent uses outright, instead of planning ahead and seeing the need for these resources on its own. These tactics lead to more challenging but ultimately less satisfying opponents because a human player can almost always pick up on the notion that the computer is accomplishing things that are impossible for the human player to accomplish, because the "cheats" are not available or given to the human player.

One of the easier-to-notice and most frustrating examples of this impossible behavior is the use of what is called *rubber banding* in racing games. Toward the end of a race, if a player is beating the AI-controlled cars by too much, some games simply speed up the other cars until they've caught up with the human player, after which the AI-controlled cars return to normal. Sure, it makes the race more of a battle, but for a human player, watching a previously clueless race car suddenly perform miracles to catch up to him or her borders on ridiculous. The opposite case can be equally frustrating. The AI-controlled cars are so far ahead of the player that the game reacts by having the leaders suddenly crash, screw up, or just slow down until the human catches up. Most players realize they're being coddled; they don't feel as much of a sense of accomplishment when the computer gives up.

In modern games, the old techniques are being abandoned. The primary selling point of games is slowly but surely evolving into the realm of AI accomplishments and abilities, instead of the graphical look of the game as it was during the last big phase of game development. This emphasis on visuals is actually somewhat causal in this new expansion of AI importance and quality; the early emphasis on graphics eventually led to specialized graphics processors on almost every platform, and the main CPU is increasingly being left open for more and more sophisticated AI routines. Now that the norm for game graphics is so high, the "wow" factor of game graphics is finally wearing thin, and people are increasingly concentrating on other elements of the game itself.

So, the fact that we now have more CPU time is very advantageous, considering that the current consumer push is now for games that contain much better AI-controlled enemies. In the 8-bit days of gaming or before, 1 to 2 percent of total CPU time was the norm, if not an overestimation, for a game's AI elements to run in. Now, games are routinely budgeting 10 to 35 percent of the CPU time to the AI system [Woodcock 01], with some games going even higher.

Today's game opponents can find better game solutions without cheating and can use more adaptive and emergent means—if for no reason other than that they have access to faster and more powerful processors driving them. Modern game AI is increasingly leading towards "real" intelligence techniques (as defined by academic AI), instead of the old standby of pre-scripted patterns or behaviors that only mimic intelligent behavior. As games (and gamers' tastes) become more complex, game AI work will continue to be infused with more complex AI techniques (heuristic search, learning, planning, etc.).

What Game AI Is Not

The term game AI can be used as quite the broad label, often loosely used when referring to all sorts of areas within a game: the collision avoidance (or pathfinding) system, the player controls, the user interface, and sometimes the entire animation system. To some extent, these elements do have something to add to the AI world and are elements that, if done poorly, will make the game seem "stupider," but they are not the primary AI system in a game. An exception to this might be a game in which the gameplay is simple enough that the entire smarts of the enemies are in moving around or choosing the right animations to play.

The difference is this: Game AI makes intelligent decisions when there are multiple options or directions for play. The above-mentioned secondary-support systems, while making decisions from a pool of options/animations/paths, are more "find the optimal" (read: singular) solution for any particular input. The main AI in contrast might have many equally good solutions, but needs to

consider planning, resources, player attributes (including esoteric attributes like personality type or things like character flaws), and so on to make decisions for the game's bigger picture.

An alternative way of thinking about this differentiation is that these support systems are much more low-level intelligence, whereas this book will focus mostly on the high-level decisions that an AI system needs to make. For example, you get out of your chair and walk across the room to the refrigerator. The thought in your mind was, "I want a soda out of the fridge." But look at all the low-level intelligence you used to accomplish the task: your mind determined the right sequence of muscle contractions to get you out of the chair (animation picking), and then started you moving toward the fridge (behavior selection), threading you through all the things on the floor (pathfinding). In addition, you slightly lost your balance but regained it quickly (physics simulation) and scratched your head on the way there (secondary behavior layering), in addition to a myriad of other minor actions. None of these secondary concerns changed the fact that your entire plan was to go get a soda, which you eventually accomplished. Most games split up the various levels of decision making into separate systems that barely communicate. The point is that these low-level systems do support the intelligence of the agent but, for this book's purposes, do not define the intelligence of an AI-controlled agent.

A completely separate point to consider is that creating better game AI is not necessarily a result of writing better code. This is what puts the "A" in AI. Many programmers believe that AI creation is a technical problem that can be solved purely with programming skill, but there's much more to it than that. When building game AI, a good software designer must consider balancing issues from such disparate areas as gameplay, aesthetics, animation, audio, and behavior of both the AI and the game interface. It is true that a vast number of highly technical challenges must be overcome by the AI system. However, the ultimate goal of the AI is to provide the player with an entertaining experience, not to be a demonstration for your clever code. Gamers will not care about your shiny new algorithm if it doesn't feel smart and fun.

Game AI is not the best code; it is the best *use* of code and a large dollop of "whatever works." Some of the smartest-looking games have used very questionable methods to achieve their solutions, and although this book is not advocating poorly written code, nothing should be thrown away if it helps to give the illusion of intelligence and enhances the fun factor of the game. Plus, some of the most elegant game code in the world started out as a mindless hack, which blossomed into a clever algorithm later, upon retrospection and cleanup.

On a less serious note, game AI is also not some kind of new life form—a disconnected brain that will eventually take over your PlayStation® and command you to feed it regularly. Hollywood routinely tells us that something sinister is probably what AI has in store for us, but the truth is likely far less dramatic. In the future,

we will most likely have access to a truly generic AI paradigm that will learn to competently play any game, but for now this is not the case. Right now, game AI is still very game-specific and very much in the hands of the coders who work on it. The field is still widely misunderstood by the non-programming public, however, and even by those people working in game development who don't regularly work with AI systems.

How This Definition Differs from That of Academic AI

The world of academic AI has two main goals. First is to help us understand intelligent entities, which will, in turn, help us to understand ourselves. Second is to build intelligent entities, for fun and profit, you might say, because it turns out that these intelligent entities can be useful in our everyday lives.

The first goal is also the goal of more esoteric fields, such as philosophy and psychology, but in a much more functional way. Rather than the philosophical, "Why are we intelligent?," or the psychological, "Where in the brain does intelligence come from?," AI is more concerned with the question, "How is that guy finding the smart-sounding answer?" The second goal mirrors the nature of the practical economy (especially in the western world), in that the research that is most likely to result in the largest profits is also the most likely to win the largest funding.

As stated earlier, Russel and Norvig [Russel 95] define AI as the creation of computer programs that emulate four things:

1. thinking humanly
2. thinking rationally
3. acting humanly
4. acting rationally

In academic study, all four parts of this definition have been the basis for building intelligent programs. The Turing test is a prime example of a program specifically created for acting humanly—the test states that if you cannot tell the difference between the actions of the program and the actions of a person, that program is intelligent. Some cognitive theorists, who are helping to blend traditional human mind science into AI creation, hope to lead towards human-level intelligence by actually getting a computer to think humanly. Sheer logic systems try to solve problems without personal bias or emotion, purely by thinking rationally. Lastly, many AI systems are concerned with acting rationally—always trying to come up with the correct answer that, in turn, directs the system to behave correctly.

But, the vast majority of academic AI study is heavily biased towards the rationality side. If you think about it, rationality lends itself much more cleanly to a computing environment, since it is algorithmic in nature. If you start with a true statement, you can apply standard logical operators to it and retain a true statement. In contrast, game AI focuses on acting "human," with much less dependence on total rationality. This is because game AI needs to model the highs and lows of human task performance, instead of a rigorous search toward the best decision at all times. Games are played for entertainment, of course, and nobody wants to be soundly beaten every time.

Say you're making a chess game. If you're making this chess game as part of an academic study, you probably want it to play the best game possible, given time and memory constraints. You are going to try to achieve perfect rationality, using highly-tuned AI techniques to help you navigate the sea of possible actions. If instead, you are building your chess game to give a human player an entertaining opponent to play against, then your goal shifts dramatically. Now you want a game that provides the person with a suitable challenge, but doesn't overwhelm the human by always making the best move. Yes, the techniques used to achieve these two programs might parallel in some ways, but because the primary goal of each program is different, the coding of the two systems will dramatically diverge. The people who coded Big Blue did not care if Kasparov was having fun when playing against it. But the people behind the very popular Chessmaster games surely spend a lot of time thinking about the fun factor, especially at the default difficulty setting.

Chess is an odd example because humans playing a chess program usually expect it to perform pretty well (unless they're just learning and have specifically set the difficulty rating of the program to a low level). But imagine an AI-controlled Quake "bot" deathmatch opponent. If the bot came into the room, dodged perfectly, aimed perfectly, and knew exactly where and when powerups spawned in the map, it wouldn't be very fun to play against (not for very long, anyway). Instead, we want a much more human level of performance from a game AI opponent. We want to play against an enemy that occasionally misses, runs out of ammo in the middle of a fight, jumps wrong and falls, and everything else that makes an opponent appear human. We still want competent opponents, but because our measure of competence, as humans, involves a measure of error, we expect shortcomings and quirks when determining how intelligent, as well as how real, something is. Anything that is too perfect isn't seen as more intelligent; it is usually seen as either cheating, or alien (some might say "like a computer").

Academic AI systems are generally not trying to model humanity (although there is the odd rare case). They are mostly trying to model intelligence—the ability to produce the most rational decision given all the possible decisions and the rules. This is usually their one and only requirement and, as such, the reason why

all our limitations in games (such as time or memory) are not given thought. Also, by distancing themselves from the issues of humanity, they don't run into the sticky problems in dealing with questions about what constitutes human intelligence and proper problem solving. They just happily chug along, searching vast seas of agreed-upon possibility for the maximum total value.

Eventually, computing power, memory capacity, and software engineering will become so great that these two separate fields of AI research may no longer be dissociated. AI systems may achieve the kind of performance necessary to solve even the most complex of problems in real time, and as such, programming them might be more like simply communicating the problem to the system. Game programmers would then use the same general intelligence systems that any programmer would.

Applicable Mind Science and Psychology Theory

Thinking about the way that the human mind works is a great way to flavor your AI programming with structural and procedural lessons from reality. Try to take this section with a grain of salt, and note that different theories exist on the workings and organization of the brain. This section is meant to give you ideas and notions of how to break down intelligence tasks in the same ways that the human mind does.

Brain Organization

Classically, the brain is divided up into three main subsections: the hindbrain (or brain stem), the midbrain, and the forebrain. Most people may have heard these divisions somewhat wrongly referred to as the reptilian brain, the mammalian brain, and the human brain, but recent research has shown this sort of clear-cut, species-related division to be false. Almost all animal brains have all three parts, just in different sizes and, in some cases, in dramatically different locations (thus, snakes have a mammalian brain region).

These brain regions can be divided into smaller working structures, each of which operate independently by using local working memory areas and accessing neighboring synaptic connections to do specific tasks for the organism (fear conditioning in humans is mostly centered in a brain structure called the amygdala, for example). But these regions are also interconnected, some areas heavily so, to perform global-level tasking as well (the above-mentioned amygdala, through the thalamus and some cortical regions, is also a primary first-step collection spot for emotional data, which will then be sent to another brain structure called the hippocampus for blending with other sensory input and eventual storage into long-term memory). If you think of the brain as being an object-oriented class, the amygdala

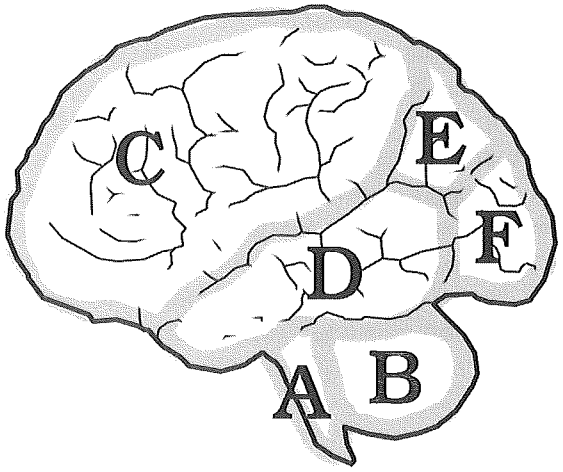
would be a small class, with its own internal functions and data members. But it would also be an internal structure within other classes, like Long-Term Memory, or Forebrain. This object-oriented, hierarchical organizational model of the brain has merit when setting up an AI engine, as seen in Figure 1.2, which shows a nice mirroring between brain and game systems.

By breaking down your AI tasks into atomic modules that require little knowledge of each other (like the brain's small, independent structures), you'll find it much easier to follow good object-oriented programming principles. Combinations of the atomic modules can be blended into more complex representations as needed, without replicating code. This also represents the kind of efficiency we should be trying to achieve in our AI systems. Avoid single-use calculations and code whenever possible, or input conditions that are so rare as to be practically hard-coded. Alas, inefficiency cannot be completely overcome, but most inefficiencies can be eliminated with clever thinking and programming.

Knowledge Base and Learning

Although the inner workings of the human memory system are not fully understood, the common idea is that information is stored in the form of small changes in brain nerve cells at the synapse level. These changes cause differences in the electrical conductivity of different routes through the network and, as such, affect the firing potential of specific nerve cells as well as whole sub-networks. If you use a particular neural pathway, it gets stronger. The reverse is also true. Thus, memory systems use a technique that game designers could learn a lot from (no pun intended), that of plasticity. Instead of creating a set-in-stone list of AI behaviors and reactions to human actions, we can keep the behavior mix exhibited by the AI malleable through plasticity. The AI system could keep track of its actions and make note of whether or not the human consistently chooses certain behaviors in response. It could then recognize trends and bias its behaviors (or the requisite counter measures, as a defense) to plastically change the overall behavior mix that the AI uses.

Of course, an AI memory system would require a dependable way of determining what is "good" to learn. We humans rely on teaching conventions and retrospection to gain insight into which information to value, and which to discard. Without these aids, the human brain would just store everything, leading to misconception, miscommunication, and even delusion. Although very contextually complex, a filter on AI learning would keep the human player from exploiting a learning system by teaching it misleading behaviors, knowing that the system will respond in kind. Does the AI always use a low block to stop the next incoming punch after the player has punched three times in a row? An advanced player would perceive that and punch three times followed by a high punch to get a free



	Organization of:	
	The Brain	A Game AI System
A	Brain Stem - Reflex - Lower Functions/Survival	- Collision - Animation Selection
B	Cerebellum - Motor Center/Sensory Mixing and Coordination	- Physics - Navigation
C	Frontal Lobe - Higher Brain Functions - Emotions - Learning	- Decision Making
D	Temporal Lobe - Memory (Visual and Verbal)	- Learning
E	Parietal Lobe - Sensory Cortex	- Perceptions
F	Occipital Lobe - Visual Processing	- Perception

FIGURE 1.2 Object-oriented nature of the brain related to game AI systems.

hit in on the low-blocking AI. But another level of AI memory performance would have the AI noticing that pattern, and making adjustments to how it would handle the situation in the future. This would be tantamount to learning about how the player is learning.

Another useful lesson from nature is that the rate of memory reinforcement and degradation in the human brain is not the same for all systems. Usually, memories are created only after repeated exposure to the information. Likewise, already existing memories tend to take a period of time before they either wither through misuse, or will require conscious counter-association in order to quell. Memories associated with pain aversion, however, may never fully extinguish, even if the person only experienced the relation once. This is a good example of nature using dynamic hard coding. The usually plastic changes in the brain can be "locked in" (by stopping the learning process or moving these changes into a more long-term memory) and thus not be allowed to degrade over time. But like the brain, too much hardcoding used in the wrong place can lead to odd behavior, turning people (or your game characters) into apparent phobics or amnesiacs.

Another concept to think about is long-term versus short-term memory. Short-term, or working memory, can be thought of as perception data that can only be held onto for a short time, in a small queue. The items sitting in short-term memory can be filtered for importance, and then stored away into longer-term memories, or simply forgotten about by sitting idle until a time duration is hit or additional data comes in and bumps it off the end of the queue. Varying the size of the queue and the rates of storage creates such concepts as attention span, as well as single-mindedness.

Many games have essentially digital memory. An enemy will see a player and pursue the character for a while. But if the player hides, the enemy eventually forgets about the player and goes back to what he was doing. This is classic state-based AI behavior, but it is also very unrealistic and unintelligent behavior. It's even more unrealistic when the enemy didn't just see the player, but was shot and injured during the exchange. By using a more analog memory model for our opponent, he could still go back to his post, but he'd be much more sensitive to future attacks, would most likely spend the time at his post bandaging his wounds, would probably make it a priority to call for backup, and so forth. For sure, some games do use these types of memory systems. But the vast majority does not.

The brain also makes use of modulators, chemicals that are released into the blood, affect some change in brain state, and take a while to degrade. These are things like adrenaline or oxytocin. These chemicals' main job is to inhibit or enhance the firing of neurons in specific brain areas. This leads to a more focused mind-set, as well as flavoring the memories of the particular situation in a contextual way. In a game AI system, a modulator could override the overall AI state, or just adjust the behavior exhibited within a certain state. In this way, conventional

state-based AI could be made more flexible by borrowing the concept of modulation. The earlier-mentioned enemy character that the player alarmed could transition to an entirely different Alerted state, which would slowly degrade and then transition back down to a Normal state. But using a state system with modifiers, the enemy could stay in his normal Guard state, with an aggressive or alerted modulator. Although keeping the state diagram of a character simpler, this would require a much more general approach to coding the Guard state. More on this in Chapter 15, under finite state machine extensions.

The human brain stores things in different memory centers. It does this in a few different ways: direct experience, imitation, or imaginative speculation. With the possible exception of speculation, which would require quite a sophisticated mental model, game characters may gather information in the same ways. Keeping statistics on the strategies that seem to work against the human and then biasing future AI behavior could be thought of as learning by direct experience. Imitation would involve recording the strategies that the human player is successfully using and employing them in return.

The problem that games have had with classical AI learning algorithms is that they usually take many iterations of exposure to induce learning. It is a slippery slope to do learning in the fast-paced, short-lived world of the AI opponent. Most games that use these techniques do all the learning before hand, during production, and then ship the games with the learning disabled, so that the behavior is stable. This will change as additional techniques, infused with both speed and accuracy, are found and made public.

But learning need not be "conscious." Influence maps (see Chapter 19) can be used by a variety of games to create much lower level, or "subconscious" learning, making AI enemies seem smarter without any of the iteration issues of normal learning. A simple measure of how many units from each side have died on each spot of the map could give an RTS game's pathfinding algorithm valuable information necessary to avoid kill zones where an opponent (human or otherwise) has set up a trap along some commonly traveled map location. This learning effect could even erode over time or be influenced by units relaying back that they have destroyed whatever was causing the kill zone in the first place. Influence maps are also being used successfully in some sports games. For example, by slightly perturbing the default positions of the players on a soccer field to be better positioned for the passes the human has made in the past. The same system can also be used by the defensive team to allow them to be better able to possibly block these passes. Influence map systems allow cumulative kinds of information to be readily stored in a quick and accessible way, while keeping the number of iterations that have to occur to see the fruition of this type of learning very low. Because the nature of the information stored is so specific, the problem of storing misleading information is also somewhat minimized.

Cognition

The flood of data coming from our senses bombards us at all times. How does the brain know which bits of information to deal with first? Which pieces to throw away? When to override the processing it is currently doing for a more life-threatening situation? It does this by using the brain's various systems to quickly categorize and prioritize incoming data. Cognition can be thought of as taking all your incoming sense data, also called perceptions, and filtering them through your innate knowledge (both instinctual and intuitive) as well as your reasoning centers (which includes your stored memories), to come up with some understanding of what those perceptions mean to you. Logic, reason, culture, and all of your personally stored rules can be thought as merely ways of sorting out the important perceptions from the background noise.

Think of the sheer volume of input coursing into the mind of a person living in a big city. He must contend with the sights, sounds, and smells of millions of people and cars, the constant pathfinding through the crowd, the hawkers, and homeless vying for his attention, and countless other distractions. Perceptions are also not all external. The pressures of the modern world cause stress and anxiety that split your attention and fragment your thoughts. Your mind also needs to try to distill the important thoughts inside your own head from the sea of transient, flighty ideas that everyone is constantly engaged in. If your brain tried to keep all this in mind, it would never be able to concentrate sufficiently to perform any task at all. Only by boiling all this information down to the most critical half-dozen perceptions or so at any given time can you hope to accomplish anything.

In game AI, we don't suffer as much from the flood of data because we can pick and choose our perceptions at any level in the process, and this makes the whole procedure a bit less mystical. In Figure 1.3, you can see a mock-up of a sports game using different perceptions for the various decisions being made by the AI player in the foreground. Make sure, when coding any particular AI subsystem that you only use those perceptions you truly need. Be careful not to oversimplify, or you may make the output behaviors from this subsystem too predictable. An auditory subsystem that only causes an enemy character to hear a sound when its location is within some range to the enemy would seem strange when a player sets off a particularly loud noise just outside of that range. A game design should take into account distance and starting volume, so that sounds would naturally trail off as they travel. You might also want to take into account the acoustics of the environment because sounds will travel much longer distances in a canyon than in an office building (or underwater versus open air). These are very simple examples, but you see the notion involved. Perceptions are much more than a single value, because there are usually many ways to interpret the data that each perception represents.

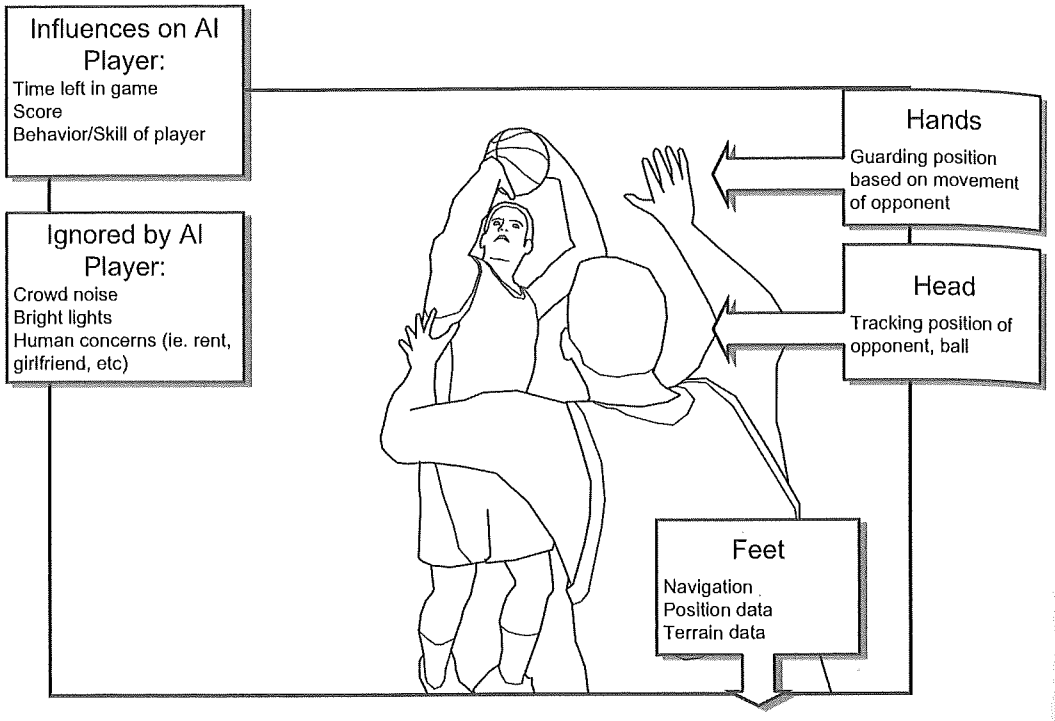
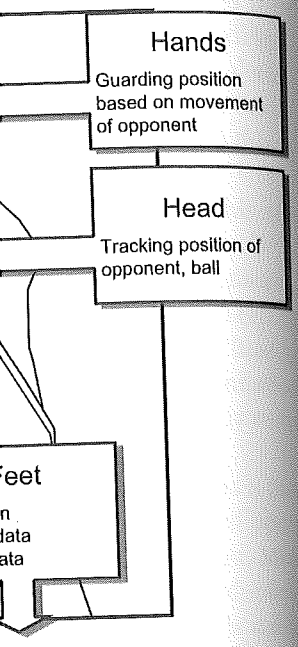


FIGURE 1.3 A visual depiction of various perceptions being taken into account by a game character.

We can think of the systems used in the AI world as filters as well. Whatever technique we are using as our primary decision-making system, to determine the right action to perform, is really just a method of filtering the current game state through all the possible things that the AI can do (or some subset of these possibilities, as defined by some rule or game state). Thus, we see the primary observation many people make about AI in general—that it all boils down to focused searching, in some way or another. This is true to some degree. Most AI systems are just different ways of searching through the variety of possibilities, and as such, the topography of your game's possibilities can be used to conceptually consider the best AI technique to use. This topography is generally called the "state space" of the game. If your game's possible outcomes to different perceptions are mostly isolated islands of response, with no real gray conditions, a state-based system might be the way to go. You're dealing with a set of exclusive possible responses, an almost enumerated state space. However, if the full range of possible responses is more continuous, and would graph out more like a rolling hillside with occasional dips (or another metaphor with more than three dimensions, but you get the idea), a fuzzy system or one using neural nets might be a better fit, as they tend to work



a game character.

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ions, but you get the idea), a
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better at identifying local minima and maxima in continuous fields of response. We will cover these and the other AI systems in Part III and Part IV of the book; this was merely for illustration.

Theory of Mind

One psychological construct that is again being embraced as a major field of investigation by both behavioralists and cognitive scientists is that of the so-called Theory of Mind (ToM). This concept has a good deal of merit in the field of game AI because our primary job is creating systems that seem intelligent. A ToM is actually more of a cognitive capacity of human beings, rather than a theory. It fundamentally means that one person has the ability to understand others as having minds and a worldview that are separate from his own. In a slightly more technical fashion, ToM is defined as knowing that others are intentional agents, and to interpret their minds through theoretical concepts of intentional states such as beliefs and desires [Premack 78]. This isn't as complicated as it sounds. Think of this as having the ability to see intent, rather than just strict recognition of action. We do it all the time as adults, and humanize even the most nonhuman of environmental elements. Listing 1.1 shows a bit of code from a Java version (written by Robert C. Goerlich, 1997) of the early AI program Eliza, which, in its time, did a remarkable job of making people believe it was much more than it really was. The idea of attributing agency to objects in our environment is almost innate in humans, especially objects that move. In simple experiments in which subjects were asked to explain what they saw when shown a scene consisting of a colored spot on a computer screen moving from left to right, closely followed by a different-colored dot, a large portion of people described it as "the first dot was being chased by the second." People give their cars personalities, and even think (at some superstitious level) that if you talk bad about it, or suggest getting rid of it, it will perform poorly.

In human terms, the ability to form a ToM about others usually develops at about the age of three. A commonly used test to determine if the child has developed this cognitive trait is to question the child about the classic "False Belief Task" [Wimmer 83]. In this problem, the child is presented with a scene in which a character named Bobby puts a personal belonging, such as a book, into his closet. He then leaves, and while he's away, his little brother comes and takes out the book and puts it in a cupboard. The child is then asked where Bobby will look for his book when he comes back. If the child indicates the cupboard, he reveals that he has yet to develop the understanding that Bobby wouldn't have the same information in his mind that the child does. He, therefore, does not have an abstract frame of reference, or theory, about Bobby's mind, hence no ToM about Bobby. If the child gives the correct answer, it shows that he can not only determine facts about

the world but can also form a theoretical, simplified model of others' minds that includes the facts, desires, and beliefs that they might have; thus providing a theory of this other's mind.

LISTING 1.1 Some sample code from a Java version of Eliza.

```
public class Eliza extends Applet
      {

    ElizaChat       cq[];
    ElizaRespLdr    ChatLdr;
    static ElizaConjugate  ChatConj;
    boolean         _started=false;
    Font            _font;
    String          _s;

    public void init()
         {

        super.init();
        ChatLdr = new ElizaRespLdr();
        ChatConj = new ElizaConjugate();

        //{{INIT_CONTROLS
        setLayout(null);
        addNotify();
        resize(425,313);
        setBackground(new Color(16776960));
        list1 = new java.awt.List(0,false);
        list1.addItem("Hi! I'm Eliza.  Let's talk.");
        add(list1);
        list1.reshape(12,12,395,193);
        list1.setFont(new Font("TimesRoman", Font.BOLD, 14));
        list1.setBackground(new Color(16777215));
        button1 = new java.awt.Button
             ("Depress the Button or depress <Enter> to send to Eliza");
        button1.reshape(48,264,324,26);
        button1.setFont(new Font("Helvetica", Font.PLAIN, 12));
        button1.setForeground(new Color(0));
        add(button1);
        textField1 = new java.awt.TextField();
        textField1.reshape(36,228,348,24);
```

```
        textField1.setFont(new Font("TimesRoman", Font.BOLD, 14));
        textField1.setBackground(new Color(16777215));
        add(textField1);
        //}}
        textField1.requestFocus();
    }

    public boolean action(Event event, Object arg)
        {
        if (event.id == Event.ACTION_EVENT && event.target ==
                                                        button1)
            {
                clickedButton1();
                textField1.requestFocus();
                return true;
        }
        if (event.id == Event.ACTION_EVENT && event.target ==
                                                        textField1)
            {
                clickedButton1();
                textField1.requestFocus();
                return true;
        }
        return super.handleEvent(event);
    }

    public void clickedButton1()
        {
        parseWords(textField1.getText());
        textField1.setText("");
        textField1.setEditable(true);
        textField1.requestFocus();

    }
    public void parseWords(String s_)
        {
        int idx=0, idxSpace=0;
        int _length=0;      // actual no of elements in set
        int _maxLength=200;  // capacity of set
        int _w;

        list1.addItem(s_);
        list1.makeVisible(list1.getVisibleIndex()+1);
        s_=s_.toLowerCase()+" ";
```

```
            while(s_.indexOf("'")>=0)
                s_=s_.substring(0,s_.indexOf("'"))+
                        s_.substring(s_.indexOf("'")+1,s_.length());

            bigloop: for(_length=0; _length<_maxLength  &&
                             idx < s_.length(); _length++)
                 {
                // find end of the first token
                idxSpace=s_.indexOf(" ",idx);
                if(idxSpace == -1) idxSpace=s_.length();

               String _resp=null;
               for(int i=0;i<ElizaChat.num_chats && _resp == null;i++)
                    {
                   _resp=ChatLdr.cq[i].converse
                                              (s_.substring(idx,s_.length()));
                   if(_resp != null)
                        {
                       list1.addItem(_resp);
                       list1.makeVisible(list1.getVisibleIndex()+1);
                       break bigloop;
                   }
               }
               // eat blanks
               while(s_.length() > ++idxSpace &&
                         Character.isSpace(s_.charAt(idxSpace)));
               idx=idxSpace;

               if(idx >= s_.length())
                    {
                    _resp=ChatLdr.cq[ElizaChat.num_chats-1]
                                               .converse("nokeyfound");
                    list1.addItem(_resp);
                    list1.makeVisible(list1.getVisibleIndex()+1);
               }
           }
       }
//{{DECLARE_CONTROLS
java.awt.List list1;
java.awt.Button button1;
java.awt.TextField textField1;
//}}
}
//---------------------
```

```
class ElizaChat
    {

    static int          num_chats=0;
    private String      _keyWordList[];
    private String      _responseList[];
    private int         _idx=0;
    private int         _rIdx=0;
    private boolean     _started=false;
    private boolean     _kw=true;
    public String       _response;
    private String      _dbKeyWord;
    public int          _widx = 0;
    public int          _w = 0;
    public int          _x;
    private char        _space;
    private char        _plus;

    public ElizaChat()
        {
        num_chats++;
        _keyWordList= new String[20];
        _responseList=new String[20];
        _rIdx=0;
        _idx=0;
        _keyWordList[_idx]=" ";

        _space=" ".charAt(0);
        _plus="+".charAt(0);
    }

    public String converse(String kw_)
        {
        _response = null;
        for(int i=0; i <= _idx - 1;i++){
            _dbKeyWord = _keyWordList[i];

            if(kw_.length()>=_dbKeyWord.length()&&
                    _keyWordList[i].equals
                        (kw_.substring(0,_dbKeyWord.length())))
                {

                _widx = (int) Math.round(Math.random()*_rIdx-.5);
                _response = _responseList[_widx];
```

```
                    _x=_response.indexOf("*");
                    if(_x>0)
                         {
                        _response=_response.substring(0,_x)+
                                        kw_.substring(_dbKeyWord.length(),
                                                      kw_.length());
                        if(_x<_responseList[_widx].length()-1)
                            _response=_response+"?";
                        _response=Eliza.ChatConj
                                              .conjugate(_response,_x);
                        _response=_response.replace(_plus,_space);
                    }
                    break;
                }
            }

            return _response;
        }

        public void loadresponse(String rw_)
             {
            _responseList[_rIdx]=rw_;
            _rIdx++;
        }

        public void loadkeyword(String kw_)
             {
            _keyWordList[_idx]=kw_;
            _idx++;
        }
    }
```

It has been routine in philosophy, and the mind sciences in general, to see this ability as somewhat dependent upon our linguistic abilities. After all, language provides us a representational medium for meaning and intentionality; thanks to language, we are able to describe people's actions in an intentional way. This is also probably why Alan Turing gave us his famous test as to a true measure of intelligence exhibited by a computer program. If the program could communicate successfully to another entity (that being a human), and the human could not tell it was a computer, it must be intelligent. Turing's argument is thus that anything we can successfully develop a ToM toward must be intelligent—great news for our games, if we can get them to trigger this response within the people who play them.

Interestingly, further studies in chimpanzees and even some lower primates have shown that they have remarkable abilities toward determining intention and prediction toward each other and us without verbal communication at the human level. So, the ability to form ideas about another's mindset is either biologically innate, can be determined with visual cues, or is possibly something else entirely. Whatever the source of this ability, the notion is that we do not require our AI-controlled agents to require full verbal communication skills to instill the player with a ToM about our AI.

If we can get the people playing our games to not see a creature in front of them with X amount of health and Y amount of strength, but rather a being with beliefs, desires, and intent, then we will have really won a major battle. This superb suspension of disbelief by the human player can be achieved if the AI system in question is making the kinds of decisions that a human would make, in such a way as to portray these higher traits and rise above the simple gameplay mechanic involved. In effect, we must model minds, not behavior. Behavior should come out of the minds that we give our AI creations, not from the programmers' minds. Note that this does not mean we need to give our creations perfect problem-solving abilities to achieve this state. Nor does this mean that every creature in the game must have this level of player interaction and nuance. The main bad guys that will be around for a while or other long-term characters (including the protagonist) would be helped by making them more "rich" in terms of personal connection to the player. One of the primary things a lot of people attribute great movies to is a "great bad guy." Usually it's because the bad guy has been written in such a way that people can really sense his personality and get into his thinking to a certain extent.

What does a realization of this human tendency give us as game producers? It means that as long as we follow some rules, people's brains actually want to believe in our creations. In effect, knowledge of this fundamental, low-level goal (that of brains constantly working to create a ToM about each other) can help give the programmers and designers guidelines about what types of information to show the player directly, what types to specifically not show, and what types to leave ambiguous. As the illusionist says, "The audience sees what I want it to see."

Take for example, an AI-controlled behavior from a squad combat game. In Figure 1.4, we see the layout of a simple battlefield, with the human player at the bottom of the map, and four CPU enemies closing in on him, moving between many cover points. The simple behavioral rules for these enemies are the following:

- If nobody is shooting at the player, and I'm (as the enemy) fully loaded and ready, I will start shooting. Note that only one player can shoot at a time in this system.
- If I'm out in the open, I will head for the nearest unoccupied cover position, and randomly shout something like "Cover me!" or "On your left!" or even just grunt.

- If I'm at a cover position, I'll reload, and then wait for the guy shooting to be finished, maybe by playing some kind of scanning animation to make it look like he's trying to snipe the player.

Now imagine how this battle will look to the human player. Four enemy soldiers come into view. One starts firing immediately, while the other three dive for cover. Then, the one that was firing stops, shouts "Cover me!," and runs forward for cover as a different soldier pops up and starts firing. Here we have a system in which the soldiers are completely unaware of each other (save for the small detail that "someone is shooting"), the player's intentions, or the fact that they're performing a basic leapfrogging advance-and-cover military maneuver. But because the human player is naturally trying to form a ToM about the enemy, the human player is going to see this as very tightly-coordinated, intelligent behavior. Therefore, the ruse has worked. We have created an intelligent system, at least for the entertainment world.

Bounded Optimality

When rationality is a goal of your AI system, the *degree* of rationality you are striving for can be the prime determiner of the overall system design. If your goal is

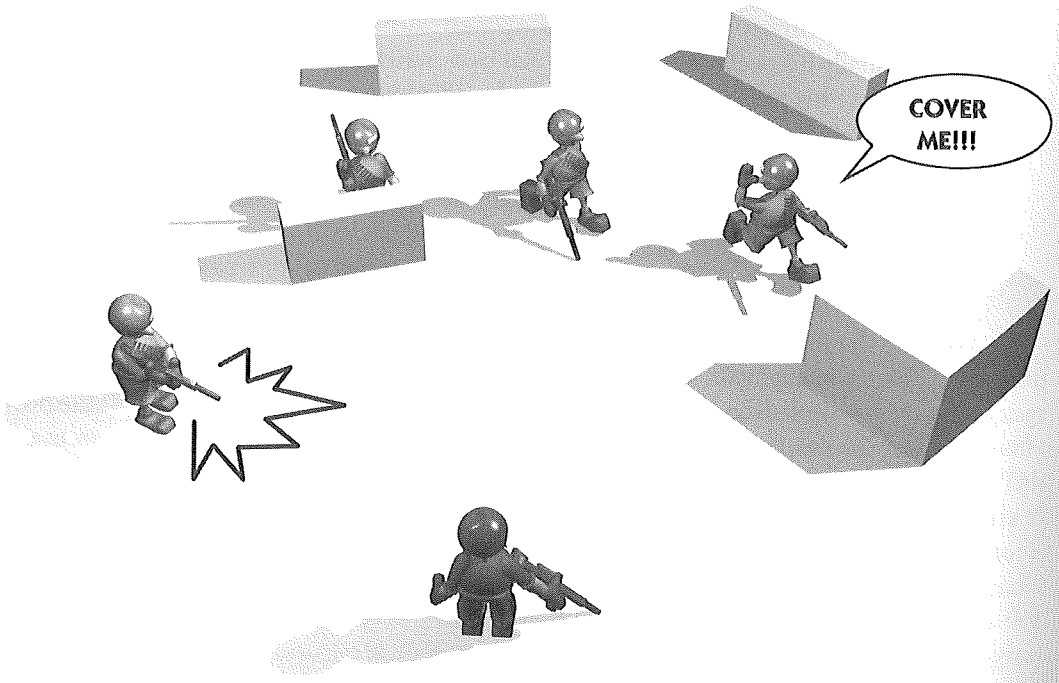

FIGURE 1.4 Emergent Theory of Mind in a loosely coordinated enemy squad.

near-perfect rationality, you might have to accept that your program is going to need a huge amount of time to run to completion, unless the decision state space you are working with is very small indeed. For most entertainment games, perfect rationality is not only unnecessary, but actually unwanted. As discussed earlier, the goal of game AI is usually to emulate a more human performance level, including all the foibles, falls, and outright screwups.

One of the reasons that humans make all these mistakes is the near certainty of *limited resources.* In the real world, it's practically impossible to get everything you need to come up with the perfect solution. There's always some bottleneck: too few details, not enough time, insufficient money, or just plain limited ability. We try to overcome these hurdles by using what is called *bounded optimality* (or BO), which just means that we make the best decisions we can in the face of resource restrictions. The chances of getting the best possible solution are directly linked to the number and amount of limitations. In other words, you get what you pay for.

BO techniques are prevalent in most academic AI circles (as well as in game theory and even philosophy) because "optimal" solutions to real-life problems are usually computationally intractable. Another reason is that very few real-life problems have no limitations. Given the realities of our world, we need a method of measuring success without requiring absolute rationality.

Like computers, the decision-making ability of people is limited by a number of factors, including the quality and depth of relevant knowledge, cognitive speed, and overall problem-solving skill. But that only covers the hardware and software. We also suffer from environmental limitations that might make it impossible to fully exploit our brains. We live in a "real-time" world, and must make decisions that could save our lives (or merely save our careers) in very short time frames. All these factors come together to flavor our decisions with a healthy dose of incorrectness. So, instead of trying to brute force our programs into finding the ideal solution, we should merely guide our decision making in the right direction and work in that direction for as much time as we have (of course, computing power will eventually get to the level that any time restriction will vanish to the point of nothing, but for now we must still grapple with what we have). The decisions that come out will then, we hope, be somewhat more human and work well with the limiting constraints of the platform and genre of game we are working on. In effect, we create optimal programs rather than achieve optimal actions.

A problem with trying to use BO methods on many types of systems is that they require incremental solutions; that is, solutions that get better by degrees as they are given more resources. Incremental solutions are definitely not universal to all problems, but the types of computationally challenging hurdles that require BO thinking can often be reduced in some way to an incremental level. Pathfinding, for example, can be given several levels of complexity. You might start by pathfinding between very large map sectors, then *within* those sectors, then locally, and then around dynamic objects. Each

successive level solves the problem slightly better than the last, but even the earliest level gets the player going in the right direction, at least in a primitive sense.

Lessons from Robotics

Robotics is one of the few academic fields with a good deal of similar tasking to the world of game AI. Unlike other academic endeavors which can deal with large-scale problems and can use exhaustive searches to find optimal results, robots usually have to deal with many real-time constraints like physics, computation speed problems (because of limited on-board computer space), and physical perception of the environment. Robots usually have to deal with the computational issues of solving problems intelligently and must house this technology into a physical construct that must deal with the real world directly. This is truly an ambitious task. As such, academic theories are taken and ground against the stone of reality until finely honed. Many techniques crafted by robotics end up in games because of the inherent optimizing and real-world use that robotics adds to the theoretical AI work done in research labs. The lion's share of the successful pathfinding methods we use in games, including the invaluable A* algorithm, came out of robotics research. Some of the prime lessons that robotics has given us include the following:

Simplicity of Design and Solution

Many robotics methodologies, like games, use the "whatever works" model. Robotics in general is a very hard problem, with an ambitious variety of challenges such as navigating undefined terrains, or recognizing general environmental objects. Every true perceptual sense that a researcher bestows on his or her robot translates into a tremendous amount of technology and study necessary to break down the system into workable parts. If the system can be made to work without the sense, then the solution is just as good, if not better, considering that the expense in both time and money was saved by not having to involve a complex perception subsystem. Some of Rodney Brooks's robots illustrate this perfectly: instead of trying to navigate areas by recognizing obstacles and either circumventing or calculating how to surmount them, some of his robot designs are largely mindless; insectile creations that blindly use general-purpose methods (like multiple simple flailing arms) to force their way over obstacles. The lesson here is that while others spend years trying tech-heavy methods for cleverly getting around obstacles and failing, Brooks's designs are being incorporated into robots that are headed to Mars.

Theory of Mind

ToM concepts have also been advanced by robotics. Researchers have discovered that people deal better with robots if they can in some way associate human attributes

(if not human thought processes) with the robot. Incorporating features into your robot that improve this humanization is a good thing for robotics researchers in that it actually makes the robot seem more intelligent to people, and more agreeable in the eyes of the public. Imagine a robot built to simply move toward any bright light. Humans, when asked to describe this simple behavior, will usually report that the robot "likes lights," or "is afraid of the dark." Neuroscientists usually call this human behavior "attributing agency." This is a fancy way of saying that humans have a tendency to think of moving objects as doing so because of some intentional reason, in most cases by a thinking agent. Think of it this way: you're on a trail in Africa, and you see the bushes rustling. Your brain thinks: "Yikes, there must be a lion over there!" and you head for the nearest tree. You're much more likely to survive (on average) with this response rather than if you were thinking: "Huh, that bush is moving. I wonder why?" It could just be the breeze, but statistically, it is less likely that you'll die if you don't take the chance. The other notion at work here is simple anthropomorphizing. Humans love to think of non-human things as if they were human. How many times have you seen someone at the park pleading with their Golden Retriever to "stop making this so hard, you know I've had a bad week, and I could really use your help with the other dog." It's all complete silliness. Spot isn't making things hard; he's reacting to the smells of the park with mostly predescribed instinctual behaviors. He has no knowledge whatsoever that you've been having a bad week, and for that matter really can't understand English. I've heard practically this same speech given to a computer, a car, and a 12-week-old baby.

By working with people's natural inclination to attribute desires and intentions, instead of raw behaviors, to just about anything, researchers hope to make robots that people will not just tolerate but enjoy working with in the real world. Robotic projects like Cog and Kismet [Brooks 98] continue to push the realm of human-robot interaction, mostly through social cues that deepen and build upon people's ToM about the robot to enliven the interaction itself and the learning that the robot is engaging in. People *want* to believe that your creation has a mind and intentions. We just have to push a little, and give the right signals.

Multiple Layered Decision Architectures

Many modern robotics platforms use a system whereupon the decision-making structure of the robot is broken down into layers which represents high-level to low-level decisions about the world [Brooks 91]. This bottom-up behavior design (sometimes called subsumption) allows robots to achieve a level of autonomy in an environment by always having some fail-safe behavior to fall back on. So, a robot might have a very low-level layer whose only goal is to avoid obstacles or other nearby dangers. This "avoidance" layer would get fresh information from the world quite frequently. It would also override or modify behaviors coming from further

up the decision structure, as it represents the highest priority of decision making. As you climb the layers, the priority lessens, the amount of interaction with the world lessens, and the overall goal complexity goes up. So, at the highest level, the robot could formulate the high-level plan: "I need to leave the room." In contrast, the bottommost layer might have as its plan "Turn 10 degrees clockwise, I'm going to run into something." The layers within this system know nothing about each other (or as little as possible), they simply build on one another in such a way that the various tasks normally associated with the goal at large are specialized and concentrated into distinct layers. This layer independence also creates a much higher robustness to the system since it means that a layer getting confused (or receiving bad data) will not corrupt the entirety of the structure, and thus, the robot may still be able to perform while the rest of the system returns to normalcy.

A structure of this kind is very applicable to game genres that have to make decisions at many levels of complexity concurrently, like RTS games. By sticking to the formal conventions expressed (as well as experimentally tested) by robotics teams using subsumption techniques, we can also gain from the considerable benefits these systems have been found to exhibit, including automatic fault tolerance (between layers of the system), as well as the robustness to deal with any number of unknown or partially known pieces of information at each level. Subsumption architectures do not require an explicit, start-to-finish action plan, and a well-designed system will automatically perform the various parts of its intelligent plan in an order that represents the best way the environment will allow. This book will cover a general way of breaking down AI engine issues using a method something like this approach in Chapter 23.

Summary

This chapter covered some basic AI terminology that we will use in later chapters, some general psychological theory, and some concepts from other fields that are applicable to AI system design.

- This book will use the term *game AI* to mean character-based behavioral decision making, further refined by concentrating on tasks that require choosing among multiple good decisions, rather than finding the best possible decision.
- Older games used patterns or let the computer opponent cheat by giving it clandestine knowledge that the human player didn't have; both methods are being abandoned because of the increasing power of AI systems being used in games.
- AI is becoming more important in today's games, as players demand better opponents to more complex games. This is true even though many games are going online because most people still play single-player modes exclusively.

- Game AI needs to be smart and fun because this is primarily a form of entertainment. Thus, game AI needs to exhibit human error and personality, be able to employ different difficulty levels, and make the human feel adequately challenged.
- Brain organization shows us the use of object-oriented systems that build upon each other, in complexity order.
- Like the brain, our AI systems can employ long- and short-term memories, which will lead us toward more realistic AI behaviors.
- Learning in a game, like in real brains, can be conscious or unconscious. By using both types, we can model more realistic behavior modification over time, while still focusing our learning on things we deem important.
- Cognition studies lead us to think of AI reasoning systems as filters that take our inputs and lead us toward sensible outputs. Thinking of the nature of the state space that a given game has, and contrasting that with the types of AI techniques available, the right filter can be found for your game.
- By striving to feed into the natural human tendency to build a Theory of Mind about the AI-controlled agents within our game, we can extend the attributes of the agent to basic needs and desires, and therefore extend the realism of his decision making to the player.
- Bounded rationality is a formal concept that we can use to visualize our game AI goals. We are not searching for optimal actions, but optimal incremental programs that give good solutions while working under many constraints.
- Robotics gives us the notion of design and implementation simplicity, extends our desire for cultivating a ToM towards our creations, and provides us with a generic subsumption architecture for designing and implementing autonomous agents from the bottom up.