ABSTRACT

SHAH, KUNAL DEEPAK. Image Processing for Cognitive Models in Dynamic Gaming Environments. (Under the direction of Dr. Robert St. Amant).

Cognitive models have typically dealt with environments that are either artificial or real but too simplistic. This stems from the fact that the process of describing the environment to the cognitive model is a complex vision problem. In order to realize the full potential of cognitive models, it is imperative that they be able to operate in natural domains. We attempt to overcome this limitation by providing a perceptual component to a cognitive model that interacts with more realistic environments. This perceptual component is an image processing substrate that has been customized for two different gaming environments. The substrate formerly worked only for the static environments we associate with conventional graphical user interfaces; the work we describe here extends its functionality to a more general class of interfaces, as represented by the driving game and Mars rover game. A cognitive model built on the ACT-R cognitive architecture has been developed that demonstrates the use of the image processing substrate in performing the driving task.

IMAGE PROCESSING FOR COGNITIVE MODELS IN DYNAMIC GAMING ENVIRONMENTS

by
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Biography

Kunal Shah was born on August 7, 1980 in Mumbai, India. He graduated with a Bachelor of Engineering degree in Information Technology from Nirma Institute of Technology (Gujarat University), Ahmedabad in June 2001. He worked as a Project Intern with Tata Consultancy Services, Mumbai as part of his final semester project. He then joined the Masters program in Computer Science at North Carolina State University. While working towards the Masters degree, he also spent summer and fall 2002 interning with Allied Telesyn Networks Inc., Raleigh, NC.

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1. Introduction

This thesis addresses the issue of developing image-processing algorithms that meet the needs of cognitive models, while adhering to the theory of human vision to a certain extent. The focus is on an image processing system that has been coupled with the ACT-R[1] cognitive modeling architecture. The system supports interaction with dynamically changing visual environments associated with an off-the-shelf computer game that runs independently of the model. The image processing techniques have been tailored to two different games and are intended to be extensible to others. This thesis discusses the image processing approach, its strengths and limitations, and its implications for cognitive modeling in more naturalistic environments. It also sheds light on the design issues to be considered for different gaming domains, the tradeoffs to be made in modeling human vision by computational means for efficiency in playing games and the changes necessitated by dynamic environments in a system such as SegMan[2] for its use in such environments.

1.1 Motivation

Cognitive models are systems that attempt to explain human cognition through the explicit representation of knowledge structures and processing. A cognitive model is a computational model of human information processing. Cognitive models commonly include components analogous to processes studied by psychologists, including working memory and long-term memory processing, perception and motor action. The earliest cognitive models were developed to reflect specific aspects of human problem solving,

such as being able to retrieve specific information from memory. Gradually, however, cognitive modelers have come to rely on unified modeling architectures that attempt to capture most or all of the phenomena that fall under the category of cognitive processing. Models created in these architectures simulate human behavior by committing errors and taking time to perform actions. For example, each covert step of cognition and overt action has latencies associated with them that are based on psychological theories and data. Some of the well-known cognitive architectures that have been used in practice are Soar, ACT-R and EPIC. It is possible to build any number of cognitive models within a given architecture, which can then be combined to model any complex processing activity.

These cognitive models have a number of uses. They help cognitive modelers validate predictions made by psychologists about human behavior and thereby better understand the human behavior, in the same way that ergonomics researches work with models of human physiology or civil engineers work with models of bridges before they build them. Cognitive models also provide a means of applying knowledge about human behavior to the design of user interfaces, thereby helping in improving their quality and usability [Citation]. Particularly, cognitive models have been used in three main ways. They have been used as surrogate users that show how different designs lead to different behaviors and why users have trouble with particular activities. Such cognitive models have been used to populate synthetic environments, for example fighter aircraft crews[32] and also as simulated users to test interfaces[33]. They have also been used as embedded assistants that guide the interaction in order to help users with their tasks. “Cognitive tutors” are

such models that have been used in school education[31]. They encapsulate the knowledge about the task that the student is attempting and provide specialized support based on that knowledge. Finally, they have been used for predicting some aspects of human performance such as time and errors with a given interface, thereby helping in creation of better designs. Keystroke Level Model and GOMS family of models are such models that have been deployed successfully[29].

A basic concern in cognitive modeling is the representation of problem-solving environments. Ideally, we want an environment that the model lives in to reflect all of the relevant details that humans are aware of and constrained by in carrying out a task. The most direct way of satisfying this goal is to build models that can interact with the real world. In most of the early cognitive models, the interaction was based on hooks provided by the interface, bypassing the complex visual processing that occurs in humans. For some cognitive modeling systems, visual input was generated via the look-up of properties in a hand-constructed interface specification. Other models interacted with dynamic simulations of interfaces, constructed to mimic the behavior of a real interface, but tailored to the input and output requirements of the model. The drawback of these approaches is that there are built-in biases when a model interacts with a simulation or hand-built environment. Interface simulations and specifications are abstractions; they do away with details of a real interface that may or may not be important. Real user interfaces exhibit variation in timing, predictability and reliability of actions, and the occurrence of events uninitiated by the user, which may or may not be relevant to

performance on a given task. Neglecting these subtleties can bring the validity of empirical cognitive modeling results into question.

A more general approach is to allow direct access to input and output devices, such as display screen and the mouse. Doing so provides a way for a model to manipulate all interfaces in an interactive system. Such a mechanism would be ecologically valid and save a lot of effort that goes into the development of simulated or hand-built interfaces. However, the cognitive model now needs to address a new set of complexities dealing with visual processing, object manipulation and so forth. Recent research efforts have adopted the modest goal of building cognitive models that can interact with software environments designed for human users. Everyday productivity applications contain text, numbers, and discrete objects and symbols in relatively simple arrangements; these environmental properties make it feasible, sometimes even straightforward, to accommodate the input requirements of a symbolic cognitive model. SegMan[2] is such a system designed to interact with Microsoft Windows graphical direct-manipulation interface. It is a perceptual substrate that uses computational vision to "see" the environment. SegMan enables other programs to be able to see the graphical interface screen as a human would see it. It takes pixel-level input from the display, runs the data through image processing algorithms, and builds a structured representation of visible interface objects. This enables programs to interact with Microsoft Windows as if it were a user sitting at the console instead of relying on low-level APIs. However, SegMan is limited in its applicability to a wider range of interfaces because it relies on the constraints on the complexity of the interface imposed by standard design conventions.

For example, Microsoft Windows graphical user interface is highly rectilinear and highly standardized. Even, the components such as buttons and other controls are rectangular, with lined borders and shadows.

Such environments are relatively simple in comparison with natural environments. They tend to be static, discrete, and predictable, properties that can be exploited by a model but that simultaneously limit the range of results that can be reached in experimenting with them. Hence, the image processing algorithms for such environments do not require sophisticated techniques. In order to realize the full potential of cognitive models, it is imperative that they be operable in natural environments. Our work attempts to overcome this limitation, by building models that can interact with computer based video games. Our system extends the functionality of SegMan to a more general class of interfaces, not merely static environments. Games are representative of such environments and we believe that if we are able to apply cognitive models in such dynamic games, then they can easily be applied to general interfaces as well. Games have played an important role in helping cognitive modelers gain insight into the process of human reasoning. Historically, strategy games such as tic-tac-toe and chess have led to an improved understanding of human cognition. More recently, dynamic games such as Unreal Tournament have attracted attention as testbeds in which dynamic real-time human decision-making can be observed and reproduced[28].

Visual processing and analysis are key to effective human behavior in these environments, which was earlier neglected in cognitive modeling research on computer

games. We believe that eventually, if we are to reach the goal of building models that interact with real environments, the issue of visual processing must be addressed. The work in this thesis describes early steps toward this goal. This research is aimed not at building specific models of human behavior, but rather to extend the infrastructural software that modelers have access to in carrying out their research. The work should by evaluated by what it allows modelers to do now that they could not do earlier.

Section 2 describes the properties of visual environments that are relevant to the development of an image-processing component for cognitive models. It gives a brief introduction to the games that we have considered. Section 3 explains in detail the process of object recognition and describes some of the image processing techniques that have been widely used for object recognition purposes. It explains the model of biological vision and tries to establish correlation between the image processing techniques and the theory of human vision. In section 4, we describe our image processing architecture, which has been adapted to two different game interfaces. We explain how the image processing system has been extended from a set of general-purpose techniques to include functions specific to the driving game, to support a realistic model of human driving. We evaluate our system and show the results obtained. Finally, section 5 concludes with a summarization of the goals achieved and describes the areas where more work needs to be done.

We believe that our work has implications for cognitive modeling in games[3], models for robot agents[4], and models for user interface evaluation[5].

2. Visual Envrironments for Cognitive Modeling

As mentioned before, our system intends to extend the functionality of SegMan to a more general class of interfaces, not merely static environments. One classic example of such an interface would be an Air Traffic Controller. Another example of this is a traffic-monitoring interface. These interfaces can be characterized by their dynamism and their richness in content and interactivity. Games typically exhibit the same characteristics. Hence, we believe that games are representative of the type of interfaces just described. We believe that if we are able to apply cognitive models in such dynamic games, then they can easily be applied to general interfaces as well. Moreover, three-dimensional interfaces are still a rarity. Hence, for the purposes of our thesis, we have considered only two-dimensional games and the image processing substrate is essentially a two-dimensional substrate.

The algorithms that make up this substrate are affected by the differences in the visual interfaces provided by the gaming environments as well as the task to be achieved. A classification of games helps in identifying the class of image processing algorithms that should be used for the domain in question.

2.1 Classification of Games

Though it is possible to classify games in various ways, the classification for the purpose of our research is based on the requirements imposed by the cognitive model that controls the game and the visual interface provided by the gaming environment. Designers must

consider the efficiency, robustness and accuracy of candidate image processing algorithms and tradeoffs with the requirements of the cognitive model. For example, if a cognitive model is operating in a dynamic environment, efficiency of the image-processing algorithm takes precedence over accuracy so that it is able to meet the real time requirements of the cognitive model.

Accordingly, based on the properties relevant for the design of an image processing component in a cognitive model, we can summarize environment properties (and to some extent task properties) as follows.

- *Static versus dynamic environments*

  In some environments, changes take place only in response to the actions of the model. In a gaming environment, monitoring and real-time responses in the image-processing component are necessary for the model to maintain an accurate representation of its properties.

  The key to image processing algorithms for the games which require fast response are the efficiency and speed of computation. These are the games that need to be continuously polled by the controller. On the other hands, there are games such as strategy games whose environments remain static or can be changed only by intervention of an external entity such as an agent. With such games, a real time response is not necessary and hence the requirement of a highly efficient image-processing algorithm can be relaxed.

- *Discrete versus continuous environments*

  An environment is effectively continuous if it is characterized by patterns that vary over a range of values much greater than can be individually accounted for symbolically (e.g., arbitrary numerical values, hues or auditory signals.) Digitized environments, such as the pixels of the screen image of a game, are effectively continuous if the individual pixel values and relationships are not meaningful to the cognitive model. The goal of image processing is to translate continuous attributes into discrete values that can be handled by the model.

- *"Simple" versus "complex" environments*

  The complexity of the objects constituting the environment is a dominant factor in choosing the image-processing algorithm. There are several dimensions to complexity.

  - Shape

    Shape is the most powerful cue for recognition. Humans can recognize objects based on their shapes even in absence of texture or color information. An important factor relating shapes that has to be considered while choosing the image processing algorithm is whether it needs to deal with a set of pre-defined shapes or any arbitrary shape. In the former case, matching techniques can be used. After a series of preprocessing steps, the

image is partitioned into distinct regions and these regions are then assembled combinatorially to form super regions, which are then matched against prototypes of the possible objects to actually recognize the super region[6]. These prototypes can be thought of as stored views of the different possible objects. Multiple views of the same object are stored. The problem of detecting objects in scenes, which do not have a limit on the number of different types of objects that need to be dealt with, becomes very complex.

- Color and texture

Intensity and texture are other important cues for object recognition. Techniques such as normalization and quantization combined with edge detection for contour analysis and texture analysis are used for segmenting out objects based on colors. Such techniques usually involve a preprocessing stage of multi orientation filtering[7], inspired by the model of biological vision.

- Motion

Often, the shape, color and texture information may not be sufficient to detect objects. The best example of this is in camouflaging[8], when it is not possible to distinguish the bounds of an object based on color or shape.

The methods used to deal with such environment exploit motion information. As a matter of fact, many image-analyzing techniques till date have used motion information as the basis for segmenting objects from background. In some games, attending to motion can be the most efficient way of focusing attention on properties of the environment that are relevant at the current time.

- Spatial Relationship

This indicates the amount of visual information that needs to be processed and it directly affects the processing time. Depending upon the type of environment that needs to be dealt with, appropriate algorithm has to be chosen, the tradeoff being efficiency and the accuracy.

- Spatial Positioning

In some environments, only a subset of the visible scene might need to be processed, while for other environments, the entire visible region has to be processed. Further simplification is possible if the subset occurs at a fixed position. Processing such games is relatively simple and less time consuming.

Most of the image-processing algorithms are based around a combination of these characteristics. They are explained in detail later.

- *Sparse versus crowded environments*

  This refers to the number of objects that need to be processed. The environment can consist of a large number of objects or it could just have a few objects. However, it is not this number that determines the image processing be used but, the number and the complexity of the objects of interest that hold the key.

  The complexity of those objects of interest, as discussed above, is more important, but if only a few objects need to be considered, then the burden on the image processing algorithm reduces dramatically and the requirements of fast computation and efficiency can be addressed easily.

- *Predictable versus unpredictable environments*

  In some environments, it is possible to predict the next state of the environment by knowing the current state. Static environments have high degree of predictability, though this may change when actions are initiated. The games we have considered in our research are also to some extent predictable. For example, if objects always move in straight or at least continuous trajectories, then once an object's visual representation has been processed it can be tracked instead of iteratively reprocessed. This can simplify the task of object recognition to a certain extent.

The above factors can be thought of as forming one dimension each of a multidimensional space. Different games then fall into this space, and they may lie either on a single dimension or many of these dimensions at the same time. This classification helps in resolving selection conflicts between algorithms differing in their properties such as efficiency, accuracy, robustness and so on and thereby helps in making a prudent choice in the selection of algorithm. Given a set of candidate algorithms with different properties (for example, some may be more accurate and robust but less efficient while others may be more efficient but less accurate), it is possible to zero in on an algorithm or at least reduce the available candidates by classifying the domain in question based on the above taxonomy[1].

Previous work on visual processing for cognitive models has dealt with environments that are static, predictable, simple, and relatively sparse. The focus was on translating effectively continuous patterns, represented on the screen at pixel level, into symbolic representations of characters, widgets and other standard visual objects in the Windows environment[2]. The games that have been addressed in this thesis are dynamic, less predictable and more complex in a variety of ways. They are still relatively sparse and do not differ qualitatively from standard productivity applications with respect to discreteness and continuity.

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[1] For this, we need to have available a near-complete set of image processing algorithms, which can then be sorted out based on the environments in which they operate effectively.

2.2 Games We Considered

We have worked with two different games, whose interfaces are shown in Figure 1 and Figure 2. All of these games were developed by others and have not been modified by us. Figure 1 shows a first person driving game, in which the model controls the speed and steering of the car. Figure 2 shows a Mars rover simulation. The goal is to direct the rover over the planet surface, collecting as many specimens as possible. When the rover collides with rocks, these disappear and release a small swarm of creatures to be chased and captured. Although we have developed image-processing functions that can parse both these environments, the only environment for which we have constructed complete cognitive models is the driving game[9]. This game will thus be the focus of our discussion.

Figure 1: 3D-Driver

Figure 2: Mars Rover

As mentioned earlier, one of the targeted applications of this research is to provide a means for evaluating the ease of use of a user interface. A human-robot interface is one such interface that assumes much significance largely due to that fact that in the current setting, robots are not fully autonomous and hence require supervision. The 3D-driver game resembles a human-robot interface in several ways. On the surface level, it uses a first-person view as task perspective and the environment changes dynamically in response to the actions of the user and task environment, which is also the case for many human-robot systems. On a deeper level, driving behavior is a prototypical example of real-time, interactive decision making in an interactive environment. The simulation we are using is comparable to many robot applications in that it relies heavily on perceptual-motor skills, and involves decision-making under time pressure and interacting with a dynamically changing environment. Furthermore, the driving game represents a simplified driving environment, which corresponds sufficiently to real-life driving but is nevertheless a controlled setting. Because its source code is extensible, we can manipulate aspects of the environment (e.g., slow or fast driving) and add an interface whose features can be varied (e.g., bigger or smaller buttons), essentially allowing for controlled experimental manipulations.

3. Related Work

Our approach has been influenced by the work done in computer vision and image processing systems dealing with object recognition. Object recognition is the process by which the image-processing algorithm generates a symbolic representation of the environment as required by the cognitive model. This process has been extensively researched under the fields of computer vision and image processing. These are two distinct but closely related fields falling under the umbrella of computer imaging. This distinction is based upon who is the ultimate receiver of the visual information. Image processing algorithms process images and the generated visual information is directly used by human beings, whereas computer vision application processed images are used by a computer[10]. Image analysis is an important topic in computer vision. Image analysis combined with feature extraction and pattern classification is the key to a computer vision system, the end product of which is the extraction of high level information (such as objects) from an image. Most of the techniques used for image processing are also used in computer vision systems.

In this section, we discuss the biological vision process and the three stages through which it proceeds. Then, we describe the object recognition process in detail and its correlation with human vision. We also explain some of the well-known algorithms/techniques used for object recognition.

3.1 Visual Recognition in Humans

Because we are building cognitive models, the visual processing involved should ideally be based on the model of biological vision. Another overriding objective of modeling a vision system on human vision is that if the system is built the way the human vision system works, then the vision system can be extended far more generally to different domains than a system designed to work with specific image types. However, in practice, even the most general-purpose systems have application specificity[11]. Below we briefly describe the way biological vision works. Note that the terms biological vision and human vision have been used interchangeably here.

Biological Vision

Vision is the process by which humans get an understanding of the world they live in. Study of vision involves not only the way visual information is processed to produce a description that is useful to the viewer, but also the way information is represented at various stages of visual processing[12]. We are concerned with the former. Biological vision proceeds in 3 main stages, which are

- Low Level Vision
- Intermediate Vision
- High Level Vision

During each of these stages, the visual image undergoes transformation from one representation to another with each representation having more useful information than the one in the preceding stage. It should however be noted that as we proceed from one level to a higher level, some amount of information loss occurs. The boundary between these 3 stages is a blurred one.

3.1.1 Low Level Vision

Low level vision refers to the visual processes responsible for generating representations that give information about the properties of the surrounding environment. These processes do not need knowledge about the domain in which they operate and do not need to recall memories about the objects already seen and known. They operate directly on the visual stimulus regardless of the task being performed. They rely on the physical properties of objects such as continuity and rigidity. Different parts of this visual field can be processed at the same time, and hence low level vision processes are bottom up and parallel (spatially uniform). Some such processes are those that analyze movement, surface shading, texture and color.

A dominant visual process during low-level vision is edge detection. An image, as captured by the photoreceptors of the eyes, can be thought of as forming a very large 2D array of light intensities. Experiments in animals have revealed that images are usually treated as equivalent to a sketch of their outlines. Even in humans, perception of an image is more affected by significant intensity changes than the light intensity values per se[13].

Binocular stereo and analysis of visual motion[13] are other dominant visual processes occurring during this stage of vision.

Marr, in his analysis of vision, describes a representational framework for the early visual processes that constitute low level vision[14]. He points out an important characteristic of human vision that it tells about shape and space and spatial arrangement. This implies that even in absence of information about objects, it is possible to correctly perceive the geometry of objects.

The suggested framework consists of three representational stages.

- Representation of properties of the two dimensional image, such as significant intensity changes and local 2D geometry. This involves operations such as edge detection, peak finding and zero crossings.
- Representation of properties of the visible surfaces in a viewer-centered coordinate system, such as surface orientation, distance from the viewer and some coarse description of prevailing illumination. This involves operations such as binocular stereo.
- Representation of the 3D structure from an object-centered coordinate system and its organization.

3.1.2 Intermediate Level Vision

Intermediate level vision refers to the visual processes that are concerned with grouping entities together. There is a thin line between intermediate and high level vision. The difference lies in the fact that processing that falls under the realm of intermediate vision does not require knowledge of the properties of specific objects in the world. However, it is still dependent on the task being performed[15]. The term intermediate vision does not necessarily imply the order in which the processing phases itself; it is possible that high level processes are executed without relying on intermediate level processes.

Processes that extract shapes and analyze their spatial relationship usually constitute intermediate vision. Which shapes to extract is a task dependent problem. In order to examine the spatial relationship, the visual processes cannot operate on separate parts of the visual field independently. Hence, intermediate level vision has properties of non-uniformity and open-endedness[13].

3.1.3 High Level Vision

High level vision refers to the visual processes that help in carrying out tasks such as visual object recognition, visually guided manipulation, locomotion and navigation through the environment. These processes are heavily dependent on the task being performed, and rely on knowledge about the properties of objects such as their shape, color, texture, transformations they undergo and so on. This involves looking up the

catalog of objects in the long-term memory and comparing the representation of various objects within this catalog with the representations of objects that have been generated during the preceding stages[13]. Thus, it is more a problem of memory organization, retrieval and reasoning.

3.2 Image Processing for Object Recognition

As will be seen, the object recognition process exhibits a moderate level of similarity with the human visual recognition process. The object recognition process (as a part of image analysis) can be viewed as a sequence of the following steps[10].

- Preprocessing the image
- Data Reduction and Morphological filtering
- Feature extraction and analysis

Any image processing or computer vision algorithm that deals with automatic object recognition, in order to be robust, should consider the effects of

- Non-uniform lighting
- Occlusion (of one object by another)
- RST (rotation, scalability and translation) characteristics of an object
- Object deformities (i.e. partial defects in object)
- Presence of noise in the image

The design itself should be such that the problems caused by these factors do not have a telling effect on the ultimate performance of the algorithm[16].

3.2.1 Preprocessing

During this stage, the image may be quantized (reducing the number of color levels or spatially) or it may be enhanced to prepare it for the subsequent processing steps. Some other image geometry operations such as crop, zoom, shrink, enlarge, translate and rotate may be performed on the entire image or parts of image (called regions of interest). Much of the work done during this phase of object recognition process constitutes part of what is done during the early vision phase in humans[11].

Another important and widely used preprocessing operation is edge detection. Edge detection is a procedure that finds the borders of objects in an image and thereby, indirectly extracts them. It is a group operation since it looks at the values of the neighboring pixels. It is often used as an intermediary step in more sophisticated segmentation algorithms and frequently as the preliminary step to the line detection process. The most common edge detection method is a gradient-based procedure that calculates the gradient and uses a gradient threshold to determine the presence of edge. These methods are basically discrete approximations to the differential methods, which identify an edge as a large change in color/texture over a small spatial distance. Typically, a mathematical process called convolution is used for this purpose. A convolution mask a.k.a. kernel is slid across the image, which has been padded with

additional rows and columns. The mask is overlaid on the image and the coincident values are multiplied and the results are summed up to get the new pixel value at the image location corresponding to the center of mask. Different types of kernels may be used for edge detection. These kernels can be directional or non-directional. Once the edges have been detected, it may be necessary to find out lines. A line may be defined as a collection of edge points that are adjacent and have the same direction. Hough transform[17] is often used for this purpose and is described later.

3.2.2 Data Reduction & Morphological Filtering

The data reduction algorithms take the preprocessed image and reduce the image data such that it can be analyzed by feature analyzing algorithms. This is a crucial step to the object recognition problem and involves image segmentation as the key to it. Morphological filtering refers to changing the structure/form of the image. This phase also contributes to the processing occurring during the early vision stage.

Segmentation is the process of delineating regions that constitute an object and separating them from the background in an image. It is directly influenced by the category to which the game belongs. The goal of image segmentation is to divide the image into regions, which may represent an object in its entirety or may be part of a larger object. Various methods exist to segment an image into regions with varying levels of complexity and the accuracy with which the image is segmented. The basic idea underlying these methods is that the objects can be distinguished by either considering them to be a lump of pixels

with some measure of homogeneity in terms of features such as color, brightness, texture or perceiving them as having contrast with other objects on their borders. Another important issue is related to connectivity between segments i.e. deciding the segments that should be combined so that they represent an object. For this purpose, neighboring pixels are examined. A pixel has a maximum of 8 neighbors. The connectivity can be determined by examining either of the following.

- 8 neighboring pixels (eight connectivity)
- 4 neighboring pixels: north, east, west and south (four connectivity)
- 6 neighboring pixels: north, east, west, south, northwest and southeast (six connectivity NW/SE) or north, east, west, south, northeast and southwest (six connectivity NE/SW)

Most of the image segmentation algorithms make use of one or more of the below mentioned techniques.

- Region growing and shrinking
- Clustering
- Boundary detection

3.2.2.1 Image Segmentation techniques

Region growing and shrinking

This refers to the class of methods that process the image in essentially the spatial domain. Initially, the image is split up into a fixed number of regions. This region can be the entire region itself or it may be a single pixel (making the number of regions equal to the image resolution) or this initial number can be chosen based on some other criterion. Once the initial partition is done, these regions are then merged or split. Three important notions taken into account during this merge/split are merge order, merge criterion and region model[18]. Merge order defines the order in which the regions should be merged. Given two regions, merge criterion is used in determining whether they should be merged or not. This merge criterion is usually some kind of homogeneity test and it is largely application dependent. Region model defines the representation of the resulting merged region.

This technique of image segmentation gives rise to a hierarchically segmented image, where, at different levels in the hierarchy, the image is segmented at different levels in terms of the fineness of segmentation. The merge/split is recursively performed until a specified criterion is met (for example, all the regions pass the homogeneity test or the image is factored into a pre-defined number of regions). There are many variations of this algorithm. Algorithms that employ splitting only are called multiresolution algorithms.

Clustering

This refers to the class of methods that use domains other than the spatial domain as the primary domain for clustering. Some such domains include color space, histogram space and feature spaces. Histogram thresholding[19], which is explained later, is one such method.

Boundary Detection

This refers to the class of methods that detect objects by finding boundaries between objects. These boundaries indirectly segment the image into objects. The normal procedure followed here is to edge detect the image, and then combine these edges into line segments, which, then are merged into object boundaries.

3.2.2.2 Segmentation Algorithms used in practice

Some of the segmentation methods that have been used in practice are explained below in non-decreasing order of their complexity.

Thresholding

This is one of the simplest segmentation techniques[19] and belongs to the class of algorithms based on the clustering technique described earlier. A threshold (θ) is chosen and all the pixel values above (or below) that threshold are set to 0. This implies that those pixels that are set to zero comprise the background. This can be stated in mathematical notation as below.

For bright object on dark background,

if brightness (pixel(x,y)) >= θ

brightness (pixel(x,y)) = 1

else brightness (pixel(x,y)) = 0

For dark object on light background,

if brightness (pixel(x,y)) < θ

brightness (pixel(x,y)) = 1

else brightness(pixel(x,y)) = 0

The thresholding parameter can also be something other than the brightness. For example, in a RGB image, each of the R, G and B bands may be checked against different thresholds. The important decision in thresholding is choosing the threshold value. Some of the common techniques for determining this value are described below.

Fixed threshold

This is the simplest of all methods of choosing the threshold. Here, the threshold value is chosen independently of the image data. This method is useful for those images in which the background is homogenous and in contrast with the foreground. Consider Figure 3 below, which is a snapshot from the Mars Rover game introduced earlier. Figure 4 and

Figure 5 show the histogram (color intensity on X-axis and number of pixels on Y-axis) and the thresholding operation on it with a threshold value of 94 respectively.

Figure 3. Original Image

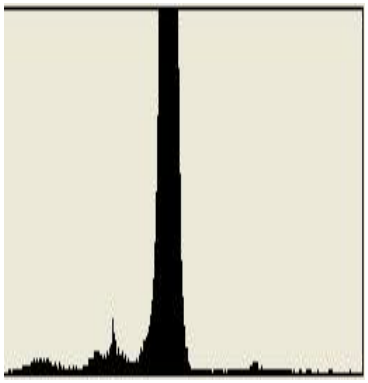


Figure 4. Histogram

Figure 5. Thresholding (θ = 94)

Histogram derived threshold

Other techniques for determining the threshold make use of the histogram of the image pixel values. The histogram may be smoothed to reduce the effect of small fluctuations. Some of the algorithms that use the histogram to find the threshold value are listed below.

- Isodata algorithm

This is an iterative method to determine the threshold. Initially, the threshold is chosen as the mid-value of the range of pixel values. Then, mean values of the pixels on both sides of that threshold are computed and their mean is found. This procedure is repeated until the mean value obtained remains constant.

This can be represented as

$\theta(i) = (\theta(f,k-1) + \theta(b,k-1))/2$ *until*

$\theta(i) = \theta(i-1)$

- Triangle algorithm

This method is useful when the histogram doesn't have a distinct peak. A line connecting the peak in the histogram and the least pixel value in the image is drawn, and the distance of this line from the histogram is computed at each pixel value. The threshold is the pixel value where this distance is maximum.

- Background symmetry algorithm

This method is useful when the histogram has a strong and distinct peak. The peak value in the histogram is found, and a p% value is computed on the non-object side of the histogram. The threshold is then chosen as below.

$\theta = peak\_pixel\_value - (p\%\ value - peak\_pixel\_value)$

The p% value indicates that only (1-p) percent of pixels have a value greater than the p% value.

Region Growing Using Recursive Shortest Spanning Tree and Binary Partition Tree

This technique of image segmentation falls under the genre of region growing algorithms. It is a bottom-up method that starts out by viewing the image as a graph and each pixel in the image as the node of the graph. The nodes in the graph represent the regions found so far. Thus, the initial number of regions is equal to the number of pixels in the image. Each region in the initial graph is connected to its four adjacent regions via a link. The cost of this link is calculated as a function of luminance, chrominance and area values between the two adjacent regions. This cost represents the distance between the two regions. The lower this cost, the more likely that these two regions belong to the same segment (and hence the object). The area of region here indicates the number of pixels in that region. Thus, the distance is calculated as

$$d(R_i, Rj) = \left\{ [Y(R_i) - Y(Rj)]^2 + [U(R_i) - U(Rj)]^2 + [V(R_i) - V(Rj)]^2 \right\} \times \frac{N(R_i) \times N(Rj)}{N(R_i) + N(Rj)},$$

where Y, U and V indicate the three different streams in YCbCr color space and N indicates the number of pixels belonging to that region[18].

The two regions that have the minimum distance between these are merged together into a single region and the mean value of the chrominance and luminance is calculated that now represent the chrominance and luminance of the merged region. The new area is also calculated and the link between the two regions is removed, thereby forming a spanning tree of the graph. This process is repeated over and over again until the image is segmented into a pre-defined number of regions. Thus, the method effectively creates a

hierarchically segmented image, where the image coarseness increases down the hierarchy.

Often, the segmented image obtained using the above method is subjected to some further processing to extract the object. One such technique is called the Binary Partition Tree method. It starts with a given initial partition and the regions in this initial partition form the leaves of the tree. These regions are then merged in the order specified by merged order (defined earlier) according to a merge criterion. The merging continues until one single region is obtained. The resulting binary tree represents the image at different scales of resolution.

3.2.3 Feature Extraction and Analysis

This phase is comparable to the intermediate level and the high level processing stages in human visual processing system. Feature extraction phase corresponds to the intermediate level processing (though there are some distinctions between the two in that feature extraction is often driven by information about specific objects). Shape detection is an important part of the feature extraction process.

Care should be taken while selecting the features, so as to ensure that the features chosen are robust. A feature if RST invariant (rotation, scaling and translation invariant) will remain the same despite the object being subjected to rotation, scaling or translation.

In order to extract features, the image that results from data reduction and morphological filtering is analyzed and labels are then assigned to the objects. The labeled object now can be thought of as a binary image having a value of 1 and the rest of the image is having a value of zero. This image is then used to extract features of interest such as area, center of area, axis of least second moment, perimeter, Euler number (defined as the number of objects minus the number of holes) , projections, thinness ration and aspect ratio[10]. While the first four are used more commonly and help identifying the location of the object, the latter four are used under specific conditions and tell something about the shape of the object. The way they are obtained is explained below.

Let I_i at a given location (x,y) be defined as

if (x,y) belongs to i^{th} object,

$$I_i(x,y) = 1,$$

else

$$I_i = 0$$

So, the area is now defined as

$$A_i = \sum_{y=0}^{N-1} \sum_{x=0}^{N-1} I_i(x,y)$$

And the center of this area is given by

$$\bar{x}_i = \frac{1}{A_i} \sum_{y=0}^{N-1} \sum_{x=0}^{N-1} x I_i(x,y),$$

$$\bar{y}_i = \frac{1}{A_i} \sum_{y=0}^{N-1} \sum_{x=0}^{N-1} y I_i(x,y)$$

The axis of least second moment gives information about object's orientation. This axis is the axis about which it takes the least amount of energy to rotate the object. It is calculated as

$$tan(2\theta_i) = 2 \frac{\sum_{y=0}^{N-1} \sum_{x=0}^{N-1} xy I_i(x,y)}{\sum_{y=0}^{N-1} \sum_{x=0}^{N-1} y^2 I_i(x,y) - \sum_{y=0}^{N-1} \sum_{x=0}^{N-1} x^2 I_i(x,y)}$$

The perimeter P is calculated by adding up all the '1' pixels that have a '0' pixel as neighbor. The other method is to find the edge of the object and then calculate the number of '1' pixels.

The thinness ratio T is calculated as

$$T = 4n\left(\frac{A}{P^2}\right)$$

$T = 1$ indicates that the object is a circle. As the value of T decreases, the object increases in thinness. The inverse of thinness ratio is called the irregularity or compactness ratio.

The Euler number is used for optical character recognition and it is defined as the number of objects minus the number of holes (for example, the Euler number of the character 'o' is zero, 'i' is 2 and that of 'v' is 1).

Projections are also used in applications like character recognition. Moreover, for optical character recognition, a method that takes projections on horizontal and vertical planes can also be used.

The horizontal projection is calculated as

$$h_i(y) = \sum_{x=0}^{N-1} I_i(x, y)$$

The vertical projection is calculated as

$$v_i(x) = \sum_{y=0}^{N-1} I_i(x, y)$$

Often, it is necessary to derive information about the shapes present in the image. Hough transform is the ideal candidate for this purpose.

3.2.3.1 Hough Transform

Hough Transform is a proven tool for detecting simple shape primitives such as line, circle, ellipse, parabola and the like. It can also be used to detect general shapes. The characteristic of Hough Transform that makes it an attractive choice for shape detection is its ability to work well on images that have been distorted by noise. It also works well for locating objects that have been occluded by some other objects or when the preprocessing stages (usually some type of edge detection) yield an under detected image.

However, Hough Transform per se is computationally prohibitively expensive and this has been the major stumbling block retarding its wide spread use. Another factor working to its disadvantage is the storage requirement as imposed by this algorithm. Techniques have been devised that have made this algorithm practically possible to implement, though under some constraints[16].

The classical Hough transform can identify those shapes that can be described in terms of parameters. Generalized Hough transform can be used to detect those shapes that do not have a parametric description. Hough Transform usually takes as input an image that has been edge detected and works on the resulting set of edge points.

The principal idea underlying Hough Transform is that each shape that is required to be detected from a given set of edge points in spatial domain can be described in terms of parametric equation and that each of the edge points contributes to a subset of the entire parameter space with the property that the target shape's parameters will correspond to the intersection of the subsets formed by the edge points. If a shape is described by 3 parameters, then the parameter space will be 3 dimensional. An accumulator array is defined over the parameter space that keeps a track of the number of points in spatial domain that contribute to this point in the parameter space. The bin in this accumulator array that contains the highest number of edge points identifies the parameters, which best fit, the shape in question. A threshold can also be used so that all the bins in the accumulator array which have value greater than this threshold are chosen for further examination. With the above method, the size of the accumulator array increases sharply

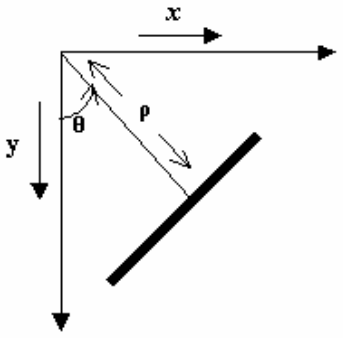
with an increase in the dimensionality of the parameter space. Also, the time required in looking at each bin in the accumulator array will increase. This makes this method very expensive in terms of computational time and storage requirements.

One of the variations of Hough transform that tries to address this problem divides the parameter space into regions (i.e. the parameter space is quantized). The accuracy of Hough Transform algorithm is however compromised (for example, 2 lines lying close to each other, would be mapped to the same block in parameter space). Nevertheless, it is effective in reducing the storage space requirements as well as the computation time. The quantization blocks themselves can vary in size and the advantage of having large such blocks is that the search time and storage requirements decrease.

Line Detection using Hough Transform

Line is a collection of adjacent edge points having same direction. The parametric equation of a line that Hough Transform makes use of is

$$x\cos\theta + y\sin\theta = \rho,$$



where ρ is the distance of the foot of perpendicular from the origin. Thus, the parameter space is 2 dimensional, ρ and θ being the parameters. For each edge point in spatial domain, the value of ρ is calculated for all values of θ and this point (in spatial domain) is recorded in the proper block in the

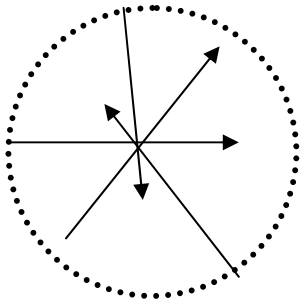
parameter space. At the end of this process, the number of hits in each block indicates the number of edge points that lie on the line(s) described by this block. Depending upon the threshold, a decision is made as to which lines exist in the image.

Circle Detection using Hough Transform

The parametric equation of circle used by this method is

$(x-a)^2 + (y-b)^2 = R^2$, where (a,b) is the center of the circle and R is its radius.

Given as set of edge points, the objective is to find the center of the circle on which the points lie. This assumes that the radius of the circle is known in advance and that each edge point is on the boundary of the circle. For each edge point in the edge-detected image, a candidate center point is obtained which lies at a distance R in the direction of normal to the local edge. This produces a set of candidate center points in the parameter space. The points are accumulated in the accumulator array and the center of circle is the block in this array that has the peak value. As it can be seen from this method, even in the case of partially occluded objects, the peak point found in the parameter space still will be the actual center of the circular object and hence this method works well. However, a lot of storage space is required for the accumulator array.



Extensions of the gradient vectors tend to intersect at center of the circle.

In addition, relaxing the constraint that the radius is known in advance, the method will have to compute the values for accumulator array for every different possible radius value and this can be seen as employing different planes in the parameter space, one for each radius value. However, prior knowledge of gradient (obtained using a directional edge detection filter) can help in speeding up this process. Extending the gradient vectors at each edge point within the image space can achieve this. All gradient vectors will intersect at the point that marks the center of the circle. The following figures show the output of Hough transform applied to a sample circle.

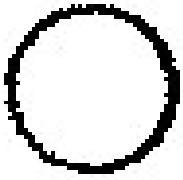


Figure 6. Original Image

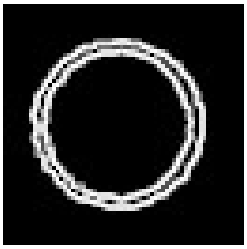


Figure 7. Edge Detected Image

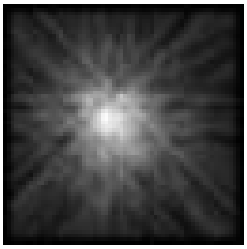


Figure 8. Hough Space

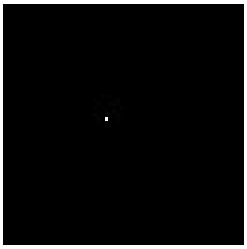


Figure 9. Center of circle

Hough Transform for General Shapes

The Hough Transform is computationally very expensive when used to locate general shapes whose orientation is unknown[20]. When it is known, however, it is possible to get away with a single plane in the parametric space. To improve the efficiency when dealing with special cases like ellipse and polygons, separate solutions have been devised.

Once the features have been extracted, the next step is to classify them to identify objects. This requires application level knowledge and hence, application specific knowledge is used in this final phase. This corresponds to the high level vision processing occurring in human visual system. One way to classify objects is to define a feature space and then compare the object's feature vector against the actual object's feature vector. A feature vector is an n-dimensional vector such that each dimension represents exactly one feature of the object. Thus, for example, if three separate features characterize an object, then the corresponding feature space is three-dimensional. Different methods are used to compare the similarity (or the difference) between two feature vectors. The most common metric used to measure the distance between two vectors is the *Euclidean distance* between them. For two vectors X = [$x1$,$x2$,…,xn] and Y = [$y1$,$y2$,….,yn], the Euclidean distance between X and Y is defined as

$$\sqrt{(x1-y1)^2+(x2-y2)^2+.....+(xn-yn)^2}$$

A variation of this basic Euclidean distance called range-normalized Euclidean distance is sometimes used to account for large differences between the corresponding components of the two vectors being compared.

Another metric used for comparing two feature vectors that uses the similarity measure is the *vector inner product*. For two vectors X and Y as defined above, it is defined as

($x1.y1 + x2.y2 + …..+ x$n.yn)

This measure too can be normalized to achieve greater accuracy.

4. The System

We have made an attempt to design our image processing algorithms based on the model of biological vision. At the same time, we have considered other efficient means of solving the same problem, and described the tradeoffs of using these two different approaches. The efficient approach is an engineering approach to the visual image analysis problem. Our approach to image processing reflects a combination of these two approaches.

In this section, we describe the overall system architecture and its components. We first describe the core vision system and all the operations it provides with a pseudo code of their procedure. Then, we describe image-processing approach taken for the two games. For each game, we discuss the cognitive model requirements, the image-processing operations, the underlying assumptions, the rationale behind the approach and its limitations.

4.1 System Design

Figure 10 shows the generic architecture of the system that involves a cognitive model interacting with image processing substrate to get information (in symbolic form) about the environment.

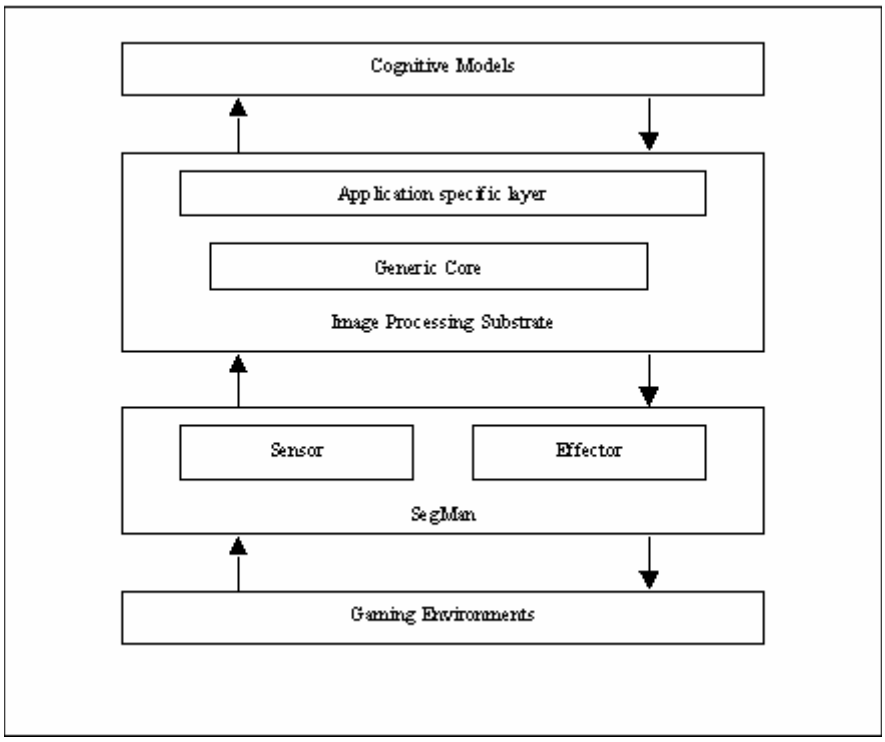


Figure 10. Architectural Diagram of the System

We have developed a cognitive model only for the driving game. This model is based on the ACT-R architecture. It gets information about the environment from the image processing substrate and takes action using the mouse and keyboard input functionality provided by SegMan. The image processing substrate takes pixel-level input from the screen (i.e., the screen bitmap) by capturing snapshots of it at regular intervals. For this, it makes use of APIs provided by the SegMan system. Thus, SegMan provides sensor and effector services to the system.

As can be seen, the image processing substrate consists of a generic core vision subsystem and an application specific sublayer on top of it. The generic core provides functionality that can be used independently of the game in question.

The application specific sublayer consists of functions that provide a general level of information about the image. Because tasks inevitably have domain-specific properties, we must tailor the image-processing component by adding functions for specific games. For the driving game, the extensions are based on studies of human driving as will be explained later. These additional functions are built on the generic core.

4.1.2 Generic Core

The generic core is intended to provide much of the functionality that is seen during the early stages of vision. The functions that it provides can be used directly on the captured image to preprocess it. They could also be called from within the application specific layer for application specific processing.

Figure 11 shows the control flow within the generic core. The operations such as edge detection could either work directly on the captured image or the normalized and quantized image. Normalization and quantization is always performed on the captured image. Histogram is computed from the normalized and quantized image. This histogram is subsequently used by the segmentation algorithm to determine the threshold based on which it segments the normalized and quantized image. For locating moving objects, either the edge detected image or the normalized and quantized image is used.

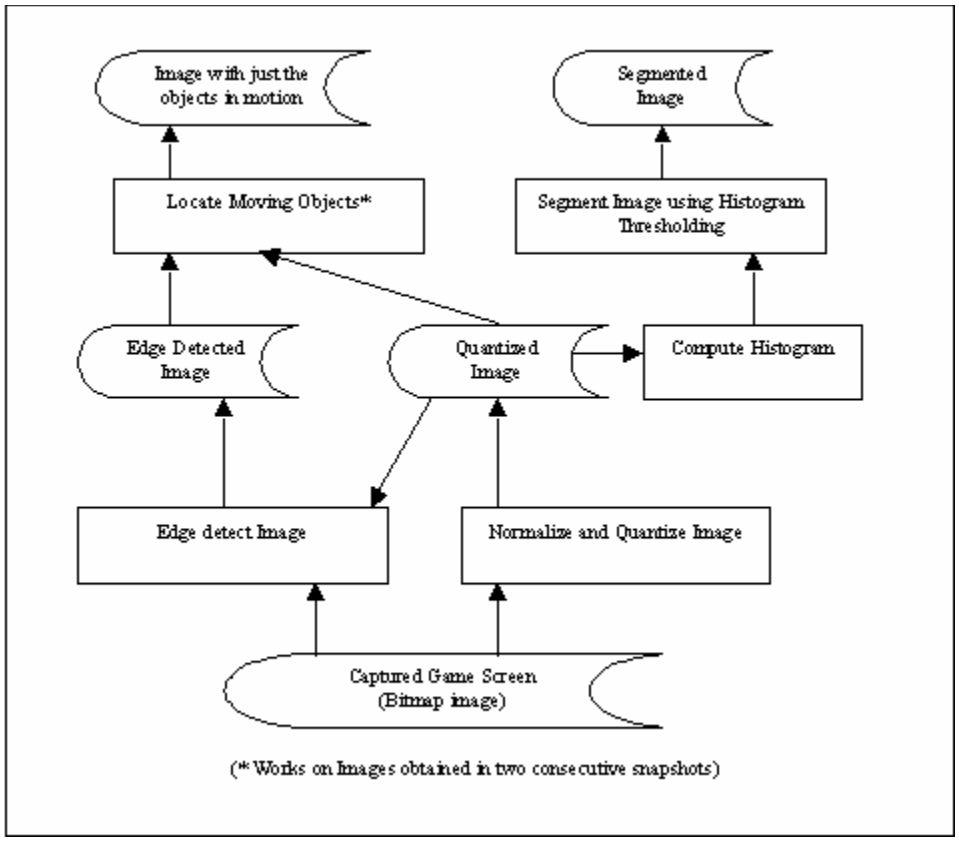


Figure 11. Control flow Diagram of Generic Core

The following operations are currently supported in our core vision system.

- *Normalize and Quantize Image.*

  Usually the captured image contains a level of detail (in terms of number of values in the R, G and B streams in the image) not needed to serve the model's purpose of controlling the game effectively. This function normalizes the number of color levels per stream used in the image to a value appropriate to serve the model's needs.

Quantization is specified in terms of the number of levels desired in each stream. A value of x for each level means x Red levels, x Green levels and x Blue levels, resulting in a total of x^3 colors. It has been found that with three quantization levels, most of the necessary information is maintained.

It should be noted that knowledge of the domain influences the choosing of certain parameters (such as number of quantization levels or the shape of object to look for) used during the first two phases. Figure 13 shows the effect of applying this operation to a snapshot of the 3D-Driver game.

- For each pixel in the image
  - Read the pixel color value
  - Get the R, G and B components of the color value
- Split the range 0-1 into a number of intervals equal to the number of levels desired minus one
- For each interval, find the mid-value of that interval. Thus, a level will represent all the values that lie between the mid-value belonging to the previous interval and the mid-value belonging to the next interval
- Accordingly, determine which level in 0-1 do normalized R, G and B values computed earlier belong.
- Scale the normalized value back to the desired level in range 0-1
- Determine the value of resultant R, G and B values in the range 0-maximum value that R, G and B can have
- Combine the quantized R, G and B values to get the resultant pixel value

Procedure 1. Normalization and Quantization

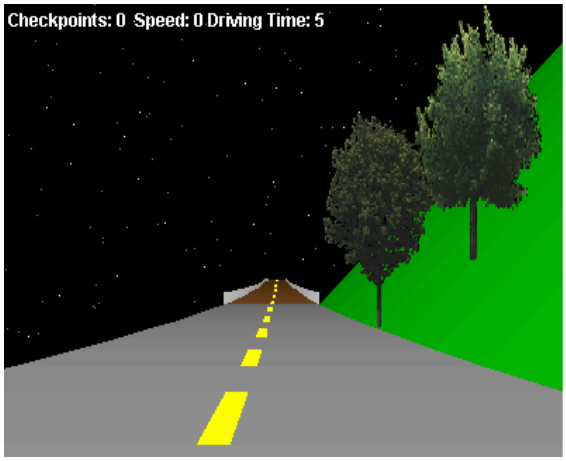


Figure 12. Driving environment without any image processing

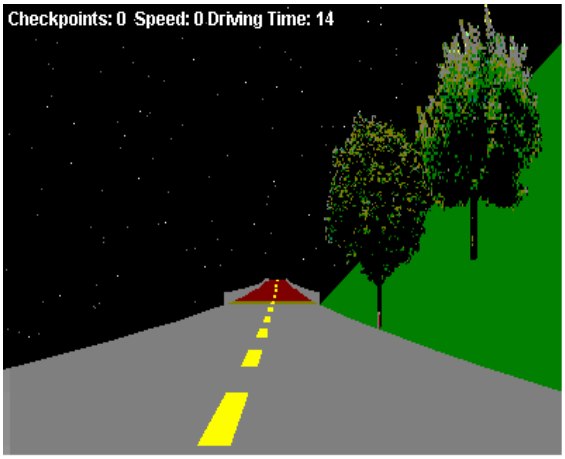


Figure 13. Driving environment after normalization and quantization

- *Edge Detect Image.*

  This function highlights changes in color intensity values in the image. Laplacian 3x3 edge detection kernel is used for convolution. This kernel, shown below is non-directional.

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

  A convolution operation of the image pixel values is performed with the kernel. Figure 15 shows the effect of applying this operation to a snapshot of the 3D-Driver game.

- Prepare the edge detect filter (In our case: 3x3 – {-1,-1,-1,-1,8,-1,and -1, -1,-1})
- For each pixel in the image
  - Convolute the pixel value and its surrounding pixel values (depending upon the size of the kernel) with the filter kernel
  - Assign the result to the pixel

Procedure 2. Edge Detection

Figure 14. Driving environment without any image processing

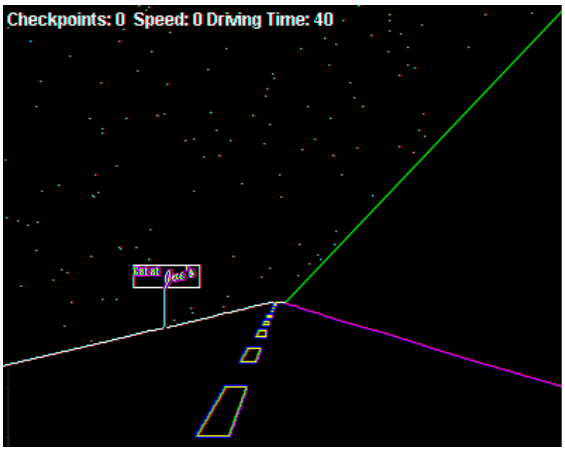


Figure 15. Driving environment after edge detection

- *Compute Histogram.*

  This function computers the histogram of the normalized and quantized image. The histogram is used for the selection of a threshold in the subsequent segmentation procedure.

- Create a hash table which uses color intensity value as the key
- Scan the image from left to right and top to bottom
- At each location, get pixel color value
  - If pixel value already a key in hash table
    - Increment the count associated with that key
  - Else
    - Create a new entry in hash table with the pixel value as the key
    - Initialize count to 1
- Find the key with the maximum count in the hash table. This key represents the peak in the histogram and corresponds to the color intensity occurring most frequently in the image.

Procedure 3. Compute Histogram

- *Segment Image using Histogram Thresholding.*

  This function segments the image using the threshold value computed using the histogram. It basically separates the foreground objects from the background.

- Use the computed histogram and determine the peak pixel value corresponding to the background intensity using the peak finding test. Put thresholds on either side of this peak.
- Scan the image from left to right and top to bottom
- At each location, get pixel color value
  - If pixel value within the two thresholds, it represents a background pixel
    - Mark this value zero

Procedure 4. Image Segmentation using Histogram Thresholding

- *Locate Moving Objects.*

  This function detects moving objects in successive game screen snapshots. It assumes that the background remains static and the only change in the environment is due to moving objects. The two edge detected images (say image1 and image2) obtained during the earlier processing step are ORed with each other which yields an image that shows the new position of the object superimposed on the image1. The rationale behind using OR operation is that except for the moving objects, everything else in the two consecutive images would remain same. Subtracting image1 from this ORed image will give the object that is moving.

▪ Capture two snaps of the environment. Call them image 1 and image 2
▪ Edge detect image1 and image2 using Procedure 2
▪ OR image1 and image2
▪ Subtract image 1 from the resultant image[2]

Procedure 5. Locate Moving Objects

4.2 Mars Rover

Figure 17 shows one snapshot of the environment in Mars Rover game. The game environment is relatively static, predictable, simple (classification of objects based on color and motion) and crowded. Usually, the environment changes only upon the some action from the model. However, for some time after that, the environment keeps on

[2] All non-zero pixels in the resulting image belong to objects that have been moving

changing by itself, after which it again becomes static. The number of objects (here rover and rocks) can be large and hence it is crowded.

Figure 16. Screen capture of Mars Rover

4.2.1 Cognitive Model Requirements

To achieve the objective of this game, the information that a cognitive model needs is information about the current position of the rover (relative to some axes), position of the rocks and the position of the creatures that are released upon collision with a rock.

4.2.2 Approach

A two-stage segmentation approach has been used. The first stage performs a coarse segmentation based on histogram thresholding as described in section 3.2.2.2. The threshold selected is based on the pixel value corresponding to the highest peak in the

histogram. This pixel value represents the background color intensity. All the remaining pixels either represent the rock or the rover.

The next level of segmentation is based on the region-growing algorithm. Since rocks are irregular in shape, it is not possible to identify them using any standard shape detection algorithm. A region growing technique is used where a region with more than a fixed number of pixels represents a rock. The homogeneity test for the region is based on the color intensity, along with consideration for possible holes/cracks in the rock surface. The rover is identified using some of its characteristic properties described later.

At the end of segmentation, this system has a list of all the rocks and the rover represented by their bounding pixels. The following sequence of operations outlines the procedure.

4.2.2.1 Preprocessing the Image

The generic core described in section 4.1.2 provides these functions. These prepare the image for feature extraction and analysis phase.

- *Normalize and quantize the image. (4 color levels were found to be useful).*

  This operation merges the background with the patches that appear with a fairly high level of accuracy; thereby, the image just consists of rocks, rover and background.

- *Remove the background.*

  This can be achieved using edge detection, which will yield an image that just has the boundaries of rocks and rover. The other method that we used computes histogram of

the image. In this histogram, the color intensity having the peak value indicates the background intensity. All pixels with this intensity are set to zero value.

- Capture screen into a buffered image
- Normalize and quantize the image using Procedure 1
- Compute the histogram and determine the peak pixel value corresponding to the background intensity using Procedure 3. Put thresholds on either side of this peak
- Segment the image into two regions based on this peak using Procedure 4

Procedure 6. Preprocessing for Mars Rover using Core Vision system

4.2.2.2 Application Specific Processing

Identification of creatures, rover and rocks are part of the feature extraction and analysis phase.

- *Identify the rover.*

  The rover was identified based on the strip length, strip width and the strip color

- Scan the image from left to right and top to bottom
- At each location, get pixel color value
- If pixel color matches that of the strip identifying the motor
  - check if this pixel is part of the strip by examining the surrounding pixels
  - find the orientation of car by determining the direction of the strip using its width and length

Procedure 7. Identify Rover

- *Identify the rocks.*

  The rocks display a characteristic of having homogeneity in their color intensities. This is especially true after the normalization and quantization phase, which prepares the image for segmentation. Thus, a non-black pixel having neighbors with the same color intensity values belongs to a rock. The neighborhood is taken to be at least 5 pixels in each compass direction.

/* Image is scanned from left to right and top to bottom */

Step 1

- Get the next pixel value
- If(came across a rock pixel[3])
  - go to step 2
- else
  - go to step 1

Step 2

- if(rock pixel a part of rock already found)
  - assign the rock number of the rock to which it belongs
  - go to step 3
- else
  - create a rock with a new rock number and assign this rock number to the pixel
  - go to step 3

Step 3

- Continue scanning left to right until came across a non-rock pixel or reached extreme right of the

[3] A rock pixel is identified if it fulfils the following condition: a non-rover and a non-background color intensity.

game screen

- If (reached extreme right of the screen)
  - mark the end of rock[4].
  - go to step 1
- if (came across a non-rock pixel)
  - check if really a non-rock pixel by examining a few more (approx. 15) pixels on the right[5].
  - If(any of this pixels is a rock pixel)[6]
    - go to step 3
  - else
    - mark the end of the rock.
    - go to step 1

Procedure 8. Identify Rocks

- *Locate creatures.*

  Taking the difference of two consecutive snapshots does this. This assumes that all objects other than creatures remain static in the two snapshots. For the purpose of driving the rover, this is a fairly reasonable assumption. This functionality is part of the core vision system that we use here. Refer to *procedure 3* for the details.

The software prepared for identifying rocks in the "Mars Rover" game was based on the following assumptions.

---

[4] Rock is not seen full.

[5] It is possible that a rock may have some patch of the same intensity as that of the background.

[6] This indicates that there is a crack/dent in the rock.

4.2.2.3 Assumptions

- The terrain on which the motor operates is such that it is not cluttered up with many rocks (for ensuring that the pixels having the background color are highest in number). This seems to be realistic, as in most of the natural scenes, the background would be predominant.
- There are no such dents in the rocks that the shadow of a rock can fall within a rock itself. (since in cases of rocks lying very near to each other, they are differentiated by means of shadow of the next rock). Regardless of this, the basic aim of identifying the rocks would be fulfilled, though the boundaries detected may be distorted.

Why this approach?

- Every real life object has certain features, based upon which the human eye can recognize it. In addition, unless the light incident on the object is parallel to the orientation at which the human eye sees the object, a shadow of that object would always be there. The approach adopted for the identification of rocks and motor is based on these two notions.
- This approach works fast, as the game area needs to be scanned just once, once the background and the patch color intensities have been identified. This alleviates the need for edge detecting the image, which would be computationally more expensive than the approach used. The alternative approach based on the model of biological vision would have entailed using edge detection operators for identifying the rocks. This too would have worked, but convoluting the entire image with the kernel is an

expensive operation. Subtracting background and patches works in this game as it achieves the same objective of separating out rocks from the image.

Limitations

- The software fails to accurately identify the boundaries of two overlapping rocks. However, it can differentiate them as two different entities.
- The software fails to recognize the motor when it is just half seen and the yellow part of it is on the other side.

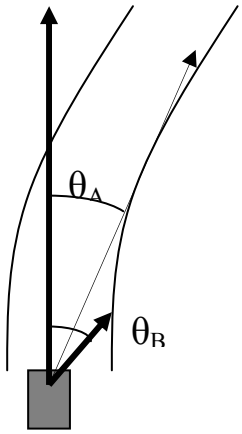
4.3 3D-Driver

Figure 17 shows a first person driving game, in which the model controls the speed and steering of the car. The game environment is dynamic, predictable to some extent, complex and sparse.

Figure 17. Screen Capture of 3D-Driver

4.3.1 Cognitive Model Requirements

To safely drive a car, it is necessary to know the future course of road, however, this does not require a complete 3D reconstruction of the scene. To know exactly what information is needed to drive the car, it is useful to understand where do the drivers look, the visual processing that occurs, what information is extracted from the road ahead and the steering process.



The steering model proposed by Donges[21] remains the most influential model. This model described the driving activity as consisting of two components, one responsible for an anticipatory (feed-forward) signal and the other responsible for visual feedback. The feed-forward signal gives the curvature of road about 1 second later from the current position. It translates to the angle between the current direction (θ_A) and that of some point of road further ahead. This angle corresponds to the angle of steering. This visual feedback (θ_B) is used to fine-tune the steering angle so that the car remains in lane, even if it started out of lane.

Later, studies of driving behavior by Land and Lee[22] and Land and Horwood[23] also led them to describe a "double model" of steering, in which a region of the visual field relatively far away from the driver (about 4 degrees below the horizon) provides information about road curvature, while a closer region (7 degrees below the horizon)

provides position-in-lane information. Attention to the visual field at an intermediate distance, 5.5 degrees below the horizon, provides a balance of this information, resulting in the best performance. Thus the image processing substrate needs to provide information about the following positions.

- horizon.
- left and right edges of road at about 5.5 degrees below horizon.
- slope of the edges at about 5.5 degrees below horizon.
- left and right positions where the road starts curving inwards.

4.3.2 Approach

A variant of the region growing technique described in section 3.2.2.1 has been used to perform segmentation. The image specific information used here is the knowledge about the presence of strip that serves to identify the road and knowledge about the color intensity of that strip. Once the strip is identified, the road is automatically identified as the region surrounding the strip. The road and strip are represented by the bounding pixel locations. Also, the entire image is not processed, but only a subset of it is processed when required. Another approach based on the 3 stages of vision would have segmented the image in its entirety as part of the early vision using segmentation routines (to be added to the generic core) and then left the work of detecting the strip and road to the application specific layer. However, considering the real time requirements of the cognitive model, we choose the former approach as a tradeoff for efficiency purposes.

The following sequence of operations outlines the procedure.

4.3.2.1 Preprocessing the image

The generic core described in section 4.1.2 provides these functions. These prepare the image for feature extraction and analysis phase. The only preprocessing operation we perform here is normalization and quantization.

- *Normalize and quantize the image (4 color levels were found to be useful).*

  This operation removes the texturing effect visible on the road and hence makes it suitable for analysis using color information.

▪ Capture screen into a buffered image
▪ Normalize and quantize the image using Procedure 1

Procedure 9. Preprocessing for 3D-Driver using Core Vision system

4.3.2.2 Application specific Processing

This sublayer performs functions that fall in the feature extraction and analysis stage of the object recognition process.

- *Draw Strip.*

  This function constructs a continuous strip by interpolating the slopes of the missing parts of the strips from the slopes of the existing ones. It takes as input an image that

contains a road with discontinuous strips and returns an image with a continuous strip. This can then be used to get the midpoint of the road at any scanline.

- Search for and store the start and end points of each discontinuous strip
- Interpolate the slope of the connecting strips by averaging the slope of the two strips the new strip connects
- Draw the new strip based on the interpolated slope value at each scanline (y value) with the required width

Procedure 10. Draw Strip

- *Get Strip.*

  This function gives the location of the center of the road to assist the model in maintaining its location in the desired lane. It takes as input the scan line position.

- *Get Horizon.*

  This function gives the point beyond which the road cannot be seen, obtained by a linear bottom-to-top traversal of scan lines.

- *Get Left (Right) Road Edge End.*

  This function returns the points on either side of the road at which the road disappears at the horizon or disappears in a curve around a mountain.

- Starting from the left edge of the game screen search for the first point with color value equal to that of the strip (yellow with some allowed variance). This point marks the beginning of the strip. Note this value.

- Go back left to find the first non-strip pixel. This point belongs to the road; note its value. Continue searching backwards to find the pixel whose intensity is different from that of the road. This is the left road edge point.
- To find the center point along the width of the strip, search forward beginning from the point where the strip starts (this point was saved in step 1), and continue till the strip ends (indicated by a change in the pixel value). The center of the strip lies at a distance equal to half the value of the width of strip.
- To find the right road edge, scan the image from the right edge of the screen moving leftwards. Search for the first point with color value equal to the road color intensity found in the second step. This point marks the right road edge.

Procedure 11. Find left and right road edges and center of strip for a given value of scanline

- *Get Left (Right) Road Edge Start.*

  The road image begins at the bottom of the screen, in a perspective view, bounded on both sides by the edges of the game window. This function returns the points on either side at which the edge of the road is visible and not clipped by the window.

- Scan the image from bottom to top.
- At each scan line, search for the left (right) road edge using the method outlined in Procedure 11
- If this point does not equal the left (right) bound of the game (indicates that the road is curving inwards), then return this point.

Procedure 12. Find left and right road edge start points

- *Get Left (Right) Slope.*

Provides a mechanism for the model to estimate the extent of turn the road is taking.

- Check whether the given scanline falls within the upper and lower road bounds. If so, find the left and right road edges for two separate scan lines (one just above the input scanline and the other just below the input scanline) using the method outlined in Procedure 11. Given these points, compute the slope using the standard formula.
- If the given scanline falls outside the visible road region, the slope is computed at the road horizon. The same procedure mentioned above is followed, with input scanline taken to be the location of horizon.

Procedure 13. Find slopes on either sides of road at a given scan line

- *Detect Obstacle.*

Provides a mechanism for the model to determine if the road ahead is clear or has some other object in front.

- For each scanline in the visible portion of road, repeat the following steps until an obstacle is found.
  - Find the strip point and the right (left) road edge.
  - Scanning from the right (left) road edge, scan left (right) until a non-road intensity pixel is found.
  - If this point is the point where road adjoins the strip, then the road is clear of any objects. Otherwise, there is an obstacle ahead and return the y value.

Procedure 14. Detect obstacle

Assumptions

- The strip on the road always appears in any snapshot and is always of yellow color (or its variant as defined by a range of intensities). This assumption is realistic because even in a real environment, it can be safely assumed that there is a strip dissecting the road into lanes.
- The strip, as it appears in the game, is always surrounded by pixels of road i.e. a strip cannot have as neighbor any pixel other than that belonging to road. This might not be true at every instance and this will lead the model to think wrong. For example, when oncoming traffic partially covers the strip, the algorithm will falsely identify that traffic as the road (as the region immediately surrounding the strip is believed to belong to the road). However, this aberration will be not have a considerable effect on the performance of the model as the image processing algorithm will generate correct information in the subsequent runs.
- The road at a given scan line has the same intensity value at different positions from left to right. This is taken care of by the preprocessing stage that normalizes and quantizes the image, thereby smoothing out the image.

Limitations

- The current approach relies on the color intensity of objects. It doesn't take the shapes of objects into account. So, it cannot be extended for games that require shape matching for object recognition.

- Perceptual processing is not entirely robust; Determining the center of the lane can break down if the road is curving off too fast in one direction or another.

Why this approach?

- The only distinguishing characteristic of the road is the strip dissecting it into two lanes. So, by identifying the strip, it was possible to identify the road and get the points of interest to the cognitive model.
- A continuation representation of this strip is derived from the discrete strips that appear in the game screen. This is in accordance with the internal representation of the strip in human visual processing system.
- As long as the strip has color intensities falling within the predefined range, the approach will work for any other driving game that may have different objects appearing in the environment.
- This approach fits well into the model of biological vision. It proceeds by normalizing and quantizing the image and then edge detecting[7] it to locate the moving objects. It responds to the needs of the cognitive model based on the visual behavior as observed in drivers when they steer. We have however taken some liberties in maintaining a clean separation between the three stages of vision.

[7] For the purpose of demonstration, this was not done explicitly. Intensity changes are accounted for during the initial scanning as they are encountered rather than explicitly carrying out edge detection

4.4 Results and Evaluation

The system was implemented in Java as well as C++ using already existing APIs for interfacing with the windowing environment. Excluding the code for SegMan, the system approximately contains 2400 lines of C++ code. To illustrate the performance of the system developed in C++, a set of 20 runs was performed on a Dell P4 (1,700 MHz, 512 MB RAM) running Windows 2000. Mean processing times over a representative set of images in the driving task and standard deviation observed are reported below.

Table 1. Mean times and standard deviation in various function calls

Function Name	Mean time (in ms)	Standard Deviation (in ms)
Get Field Bounds (left, right)	**1155**	**31**
Get Road Edge (left, right)	**1155**	**31**
Get Slope (left, right)	**1170**	**34**
Get Horizon	**1211**	**35**

These numbers constrain the minimum cycle time. A good deal of the computation for these values is shared between the functions and can be cached across function calls, however, making the average cycle time somewhere between one and two seconds.

Note that for each function call listed above, the time indicated includes the time taken to capture the environment, and hence in reality, the time taken for processing this image is lower than what has been indicated above. These times do not accurately reflect human

visual processing speeds; nevertheless they are fast enough to allow interactive control of the driving game, to support modeling at a level of abstraction higher than the perceptual.

The image processing approach we have used differs in some ways from more cognitively plausible accounts of vision. The entire process is serial as opposed to the parallel processing that happens during the early vision stage. We do not perform stereo processing required to get depth information that happens during early vision and thus 3D processing has been neglected. Our approach does not consider texture differences that often plays an important role in early vision. Moreover, the processing that determines rocks in Mars rover and road and strip in 3D-Driver game is quite elementary and does not compare with the more sophisticated memory retrieval and pattern matching processing occurring during high level vision.

5. Conclusions and future work

Commonly a cognitive model will interact with a gaming environment through an API, by integrating the model with the environment[24], or by working with a simulation rather than with the actual environment[25]. Taking each of these approaches, researchers have produced valid and significant results, but there is a fourth approach that has some appeal of its own: to build a perceptual and motor extension to a cognitive model such that it can interact with the game using only the information and the controls that are available to the user. An early system, SegMan, is based on this approach[2]. However, SegMan is very limited in its functionality in that it can handle only static environments based on conventional graphical interfaces. To realize the full potential of cognitive models, it is essential that they be operable in real environments. We have addressed this problem and built an image processing substrate to provide symbolic and numerical information to a cognitive model. This image processing substrate essentially extends SegMan and thereby retains all of the functionality of SegMan.

Using off-the-shelf application demonstrates the wide applicability of this approach and opens up a lot of other domains where a similar image processing approach can be used for perceptual processing. Not only can it be used for automatic navigation, but also for undertaking studies for improvement of user interfaces in mixed initiative environments[26]. [9] describes a possible application of our vision system for suggesting improvements in human-robot interfaces in urban search and rescue environment.

This system also demonstrates a way of providing cognitive modelers with a wider range of environments against which their theories can be tested. This work is preliminary in the sense that our system has played a part in the evaluation of only one such environment, which means that its generality remains an open issue. However, it should be noted that a single visual-processing algorithm couldn't be made to work in different types of environments. Even in human vision, domain specific knowledge is used during the 'high level vision' phase, which essentially means that it may not be possible to develop a vision system independent of the domain in which it is meant to be operational. The other aspect that can be observed is that a significantly different approach needs to be adopted for dynamic systems. The cognitive model in the game described above interacts with the image processing substrate every few milliseconds and hence it is asynchronous. This is in contrast to SegMan in which the cognitive model tries to get the state of environment only upon some external event, making it synchronous with user inputs.

This work can be extended for building vision systems for much more demanding environments, such as that of a Mars Base Explorer as shown in Figure 18, that will exercise all of the capabilities of a cognitive model, from motor actions and perception to reasoning and learning.

Figure 18. Mars Base Explorer

This game is an excellent example of an environment in which objects can be identified on the basis of their geometric shape. Hough Transform described in Section 3.2.3.1 is a good candidate algorithm for object recognition here.

The generic core can be made much more robust by adding functionality for segmenting images based on the various segmentation techniques described in section 3. This will allow the system to be used in a wider variety of environments. Also, the current approach works well with computer generated images, which is free from noise. Edges are crisp, color and shapes are not ambiguous and there are a limited number of object types. However, in real world images, noise will inevitably be present due to improper lighting conditions, camera movement and so on. The noise effects may make the vision problem harder. Our approach does not take into consideration this aspect and hence, some work is required in that direction.

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