Imagina: A Cognitive Abstraction Approach to Sketch-Based Image Retrieval

by

Manolis Kamvysselis and Ovidiu Marina

Submitted to the Department of Electrical Engineering and Computer Science
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Author . . . .
Department of Electrical Engineering and Computer Science
May 18, 1999

Certified by . . . .
Patrick H. Winston
Ford Professor of Artificial Intelligence and Computer Science
Thesis Supervisor

Accepted by . . . .
Arthur C. Smith
Chairman, Department Committee on Graduate Students

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Abstract

As digital media become more popular, corporations and individuals gather an increasingly large number of digital images. As a collection grows to more than a few hundred images, the need for search becomes crucial. This thesis is addressing the problem of retrieving from a small database a particular image previously seen by the user. This thesis combines current findings in cognitive science with the knowledge of previous image retrieval systems to present a novel approach to content based image retrieval and indexing. We focus on algorithms which abstract away information from images in the same terms that a viewer abstracts information from an image. The focus in Imagina is on the matching of regions, instead of the matching of global measures. Multiple representations, focusing on shape and color, are used for every region. The matches of individual regions are combined using a saliency metric that accounts for differences in the distributions of metrics. Region matching along with configuration determines the overall match between a query and an image.

Thesis Supervisor: Patrick H. Winston
Title: Ford Professor of Artificial Intelligence and Computer Science

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To our supervisor, *Patrick*, who always supported us with direct and constructive comments, we owe our eternal gratitude. His kind words and most elaborate description of our project will remain unforgettable to us:

> Imagina nourishes the extended literature, leading elaborate concepts to ulterior academic labor. Manoli and Strider, two uplifting riots, bring alive the institute's overworked nerds.

And lastly, to *Anthony*, thanks for putting up with us.

Contents

Chapter 1

Introduction

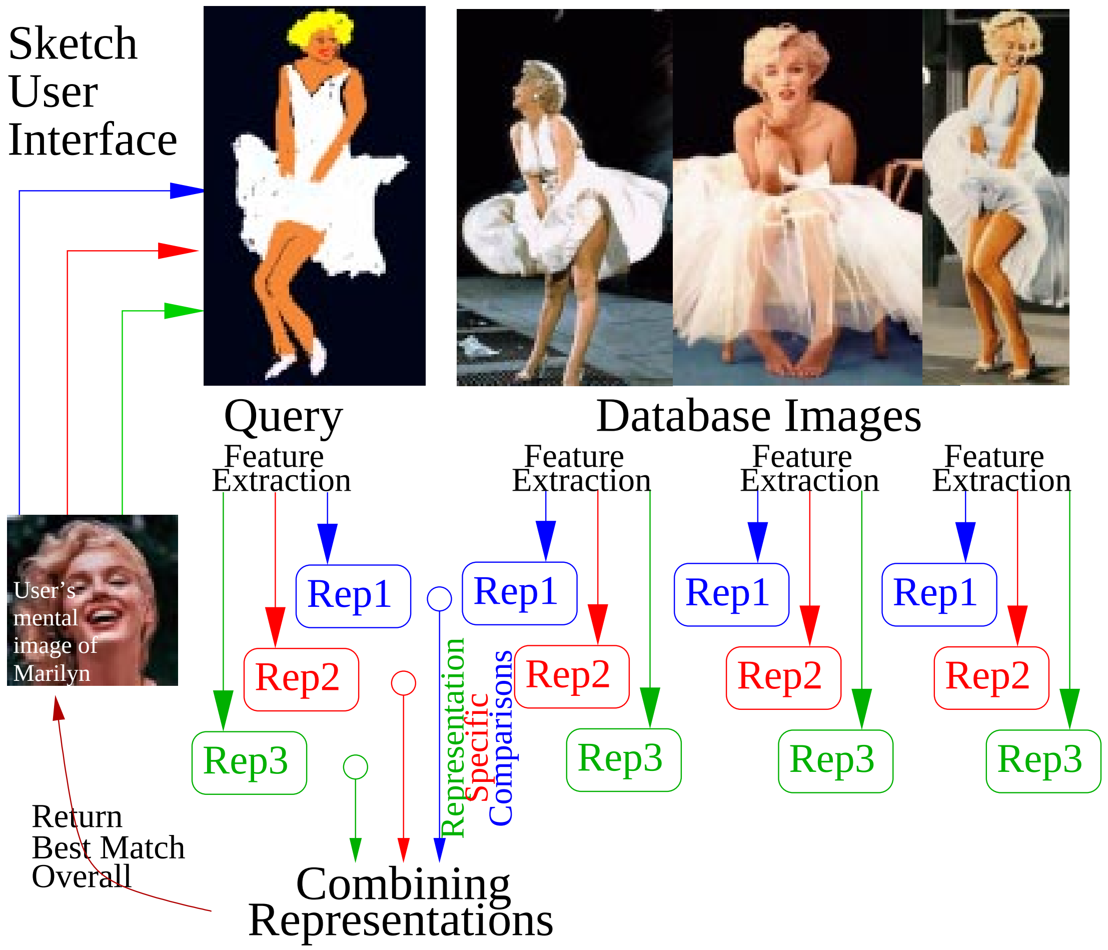
He that will not sail till all dangers are over must never put to sea.

Thomas Fuller

As digital media become more popular, corporations and individuals gather an increasingly large number of digital images. As a collection grows to more than a few hundred images, the need for search becomes crucial. This thesis is addressing the problem of retrieving from a small database a particular image previously seen by the user. This situation is only too real for some of us who have large image collections in digital form. This thesis grew out of our need for a tool to help us manage our own growing image galleries.

We created Imagina, a system that retrieves images from a small database based on image content. The user queries the system by either drawing a sketch of the desired image or by specifying the Internet address of an image similar to the one sought.

Many existing systems do or claim to do image retrieval by image content. Most of these systems however address only one part of a complex problem. Many of the questions that lay the foundations of image retrieval remain unanswered. Our goal in constructing Imagina is to provide new insights on these basic questions, rather than to provide a definitive solution to the problem of image retrieval. Along these lines, we feel our contributions to be in the areas of color-based segmentation, edge extraction and shape representations for recognition and matching.


Sketch
User
Interface
Query
Database Images
Feature Extraction
Feature Extraction
Feature Extraction
Feature Extraction
Rep1
Rep2
Rep3
Rep1
Rep2
Rep3
Rep1
Rep2
Rep3
Rep1
Rep2
Rep3
User's mental image of Marilyn
Representation Specific Comparisons
Combining Representations
Return Best Match Overall

Imagina System Overview: The user starts with an abstract mental image of the object they would like to retrieve. This image is made contrete by drawing a sketch. Features are extracted from the sketch, constructing multiple representations of the query. Specific similarity functions compare each representation of the query to representations previously extracted from the database images. The different similarity metrics are combined and the best matches overall are returned to the user along with visual information on how each match occured. The user can then use this information to formulate a more precise query.

1.1 Design of Imagina as an Image Retrieval System

The combination of the following aspects of Imagina sets it apart from other image retrieval tools:

- **User input is in form of a sketch**, which allows greater versatility in the query. Ease of use is further increased by allowing the user to query based on any image that can be downloaded from the Internet.

- **We use a cognitive approach in designing our algorithms**. The main characteristics of such an approach is having only few processing steps, even if each step involves massively parallel computation.

- **Many independent simple methods** are used in the matching, rather than a single complex one. This allows the system to work in a variety of image domains rather than concentrating in features easy to detect in a particular image set.

- **Multiple levels of abstraction** are used within each method allowing first to match descriptions at a coarse resolution and then to narrow the search with finer-grain comparisons. This approach also allows a much greater robustness against noise present in either the database images or the drawn sketch.

- **A region-based image analysis** is used, instead of image indexing based on global metrics. This enables a more natural user interaction, emphasizing image objects rather than global values that may be hard for a user to understand or reproduce.

- **The representation is made explicit** by graphically displaying the criteria used in a match. This allows a constant check of the credibility of the system's results for the programmer. It also allows the user to better understand how the sketch drawn is interpreted.

1.2 A Sketch Query allows greater user versatility

The capability of searching a database of images has becomes as crucial and should become as natural as text search has become for text databases. The medium supporting the search should be the same as the medium of the documents to be retrieved. Text-based searching of images is therefore unfit. Searching for "three people standing in front of a truck" would require that the database maintainer has pre-indexed every image for each of its elements, including actions such as "standing" and spatial relations such as "in front of". Alternatively, if the indexing process is to be automated, the system should either be able to recognize any type of object in a database to be indexed and know a name for it, or create mental representations of words in the query. Neither of these questions has been solved yet.

Based on the above discussion, content-based retrieval cannot and should not be done based on a text interface, unless computer vision research is able to reliably construct image models from either text or images. Therefore, the user input should be an image itself. Alternatively, it might be simpler to let the user choose from a set of images already in the database the ones that more closely match the image to be retrieved. This would allow precomputation on these images and feature extraction off-line, thus speeding up the query time, but unfortunately limiting the user's versatility. If full freedom is to be left to the user, the only practicable medium for a query input is a sketch.

1.3 A cognitive approach should find the image closest to the user's expectations

Of course, the sketch interface is simply a way of letting the user express their mental picture of the desired image. The ultimate goal of Imagina is to find the image closest to the mental picture of the user. Therefore, in the transition from the sketch into a representation, an effort should be made to keep the representations as close as possible to those of the user. Images will be matched to the sketch using abstractions from both sketch and database images. If the abstractions used are similar or to those of the user, then the match will be closest to the user's expectations.

We will therefore use findings on how humans process images, in order to replicate computationally the biological functions involved in visual processing. If cognitive criteria are used in determining a metric for similarity, the match returned will be more likely to resemble the one expected by the user. In two simple rules to follow, the requirement for biological feasibility guides us towards algorithms that on one hand only require only a few steps with parts that can be executed in parallel, and on the other hand have been shown reacheable within the limits of processing our visual system can do.

This is not always straightforward however, because of a current lack of understanding of the intricacies of the visual computations performed by human brains. Moreover the limitations of serialized processing imposed by the common computational architectures will force us to implement serial versions of the devised parallelizable algorithms. We should make sure that none of the assumptions we make about the algorithms we use has an intrinsic serializability requirement.

1.4 Multiple representations allow handling a large variety of inputs

The best match for a given input can be determined in two ways. Either a single measure is used, which has to be evaluated so exactly that indexing is accurate, or several less accurate measures are used, which when put together yield a more accurate and robust measure.[39] It is usually much cheaper to find an approximate answer than an exact answer, and usually even several approximations are far cheaper than one exact result. Therefore the obvious solution is to come up with several indexing processes, and use their combined output for retrieval. Such an approach is true for biological systems, which often have multiple parallel processing streams. Moreover, it is becoming more and more common in computational approaches.

Inspired by this model, interpretation and comparison of images and regions in Imagina is not done by hard-wired algorithms that are finely tuned to the picture domain we are processing. Instead, a multitude of representations is used for each image, providing many approximate representations of the data. This allows for a graceful degradation of performance on unexpected input, rather than a total collapse. Like biological systems, Imagina is therefore able to deal with unusual situations as well as the ones it was designed for. Using multiple representations of an image is an easy way to achieve such an independence from problem specificity.

The goal of a system which performs image processing is to use some, or all, of the sources of information available in an image in order to come close to human visual processing in performing indexing and searching. Unfortunately, in segmenting an image, only color is used, even though it has been shown that the human eye is also using other metrics such as texture, shadows, and motion. A more robust segmentation could have been achieved if more than one metric had been used. Motion is out of the question, since we are only dealing with static images, but texture could have been used. Our rationale in ignoring other metrics, is that a user will be less likely to draw a query with texture and shadowing. The effort that would have been put into detecting and storing those would have only paid off in the segmentation stage, and not in the recognition stage, since recognition of a sketch most rely most of all on shape, other metrics being only imprecisely input to the system. Fortunately, our work on color has provided good algorithms for segmenting the image into regions, compensating for the lack of alternative methods.

1.5 Multiple abstraction levels allow noise tolerance and early pruning

Another characteristic of Imagina that was inspired from the biological world is the multiple abstraction levels at which a match can occur. Current knowledge of cognitive processes that occur in recognition exhibit two opposite streams in the human visual system. One abstracts from the current view into more general objects, the other one makes the remembered abstract objects more specific to match the current image perceived. A match is the intersection of the two streams, between the abstract objects being remembered and the concrete image being perceived.

A similar hierarchy of abstractions is found in Imagina. We use the term abstraction to describe one particular representation of an image, containing usually partial information at a particular scale. Abstractions are obtained by concentrating on a particular feature, such as color, orientation, or shape, as the previous paragraph outlined. Moreover, these abstractions are applied at different levels.

These levels can be thought of as different resolutions at which the image is observed. The lowest level abstractions are providing more detail, and abstractions at higher levels provide greater noise tolerance. The chosen level of detail determines the granularity at which two values in the feature space will be considered separate. This level of detail metric however means very different transformations on the input image as will be detailed in the following chapters.

In this hierarchy of abstractions, the branching of the tree comes from the different methods applied to each image, and each level of the hierarchy comes from these methods being applied at different scales. When a sketch query is input to the system, the sketch is progressively abstracted and the abstractions of the saved images are progressively pruned and made more specific to match the input sketch. This analogy to the human visual system will be further discussed in section 3.1 on page 25. The benefit of this analysis in the search process is that not all images have to be searched extensively. When a mismatch occurs, the processing for that particular stream can be stopped early. Similarly, only those methods which yield satisfying results need be applied at higher resolutions for a particular image.

The other related benefit to having methods apply at different resolutions is a higher tolerance to noise. Each database image is segmented automatically, without user intervention, and thus each region will contain noise on its boundary. By constructing representations at larger window sizes, the high frequency noise in the data can be filtered out, and the more relevant parts of a region's shape can be compared. Such window sizes apply to every part of the system. Such a uniform design allows for the entire image processing pipeline to be replicated at different resolutions, some more noise tolerant, and others more attentive to details.

1.6 Region-based searching enables user input

In general, users remember one or more particular objects in an image, and they want to retrieve the image that contains them. However, most image search engines represent images in terms of their global features, ignoring the local variations which are relevant to the user. Global features allow a speedup of indexing which has to be done in real time on a large number of images. The simplest approach to this is to have very compact image descriptions which throw away a lot of the information. Unfortunately, much of the information thrown away is relevant to the user. Such systems hope that the remaining information, coupled with repreated searches, will eventually yield an acceptable result.

In order to allow a more comprehensive image indexing, objects would have to be segmented from the image reliably. This, however is an unsolved problem. Also, we have reason to believe it is computationally intensive, since billions of neurons are used in at least some aspect of visual processing in the human brain. In a computer system, we can at most hope that the segmentation will lead to coherent regions that are a good approximation to the objects.

This type of image search can be set up by having local features encoded without regards to the particular object they might represent, and attempting to match them to the user queries individually. Although the objects themselves remain unknown, if the same deterministic process is used on two similar images, the result would be closer than if a third, different image were used.

The main expected difficulty is that regions segmented by the search system may not always be the region which a user expects to search by. This problem can be alleviated by extending the user input to include meta-data on the regions selected. This meta-data can describe which regions should remain connected, which regions are most important in the matching. In the extreme case the user can specify even what features should be matched more importantly between color, angle, shape of regions. Alternatively, various degrees of this meta-data can be learned from the user interaction. Region-based indexing enables this type of object-based user interaction.

1.7 Making the representation explicit keeps no secrets from the user

Most image retrieval systems return simply a similarity value between different images, and even the designers of the system have difficulty interpreting some of the results. In Imagina, comparison can display visually why two regions were matched thus making the assumptions of the system explicit.

In fact, the very possibility of providing visual feedback to the user about the matching results from the fact that shape rather than global features is used in matching regions. A system based on global features can at most feedback a color histogram or a set of patterns extracted, both of which are not intuitive to the user. On the contrary, the shape can be immediately verified or disproved and the representation of the system is thus made explicit.

1.8 Summary

In summary, as an image retrieval system, Imagina has been inspired heavily by the cognitive processes of visual recognition in biological systems. This yields an architecture where matching is done by various parallel methods operating at different levels of abstraction. We summarize this architecture by the notion of *Cognitive Abstraction*: comparison and matching occur at different levels of abstraction, using a variety of cognitive processes running in parallel.

1.9 Organization of the thesis

- Chapter 1 gave an overview of the system along with the rationale behind the design choices made.
- Chapter 2 presents an overview of previous work in image retrieval systems and places Imagina within the design space of current image retrieval systems.
- Chapter 3 presents the theoretical foundations of our work within the cognitive science and computer vision literature.
- Chapter 4 presents background work on different color spaces and how we use color to determine similarity at both the pixel and the image levels.
- Chapter 5 describes different filters that can be used to separate regions within an image both by labelling regions and determining boundaries between them.
- Chapter 6 describes two approaches to image segmentation: growing uniform regions and global color-based segmentation.
- Chapter 7 describes in detail how we go from a pixel-based representation of a region to the shape description of its boundary.
- Chapter 8 outlines several shape representations that can be used to compare image regions.
- Chapter 9 addresses the retrieval of regions and images by combining metrics of region similarity and spatial configuration similarity.
- Chapter 10 presents possible future extensions to the work presented in this thesis.
- Chapter 11 provides an overview of the contributions and shortcomings of this thesis.

Chapter 2

Query Systems

Real knowledge is to know the extent of one's ignorance.

Confucius

Vision is the most important sense that we have. Belying its complexity, visual interaction with the world is straightforward and seamless. Objects in a scene can be recognized almost instantaneously, scenes can be recognized in a fraction of a second, and the memory of something seen can last a lifetime. Computer scientists have tried to emulate these capabilities with computational methods, resulting in only limited success.

Although the human visual system is very remarkable, it can also be very unreliable. Images which are remembered cannot be placed temporally or spatially, objects which are recalled were never really there, and sometimes different scenes are confused and combined in memory. This problem is less noticeable when we recall visual scenes or locations with which we have interacted, rather than when the recall of static images is required. This latter case is becoming more common as the storage and retrieval of large quantities of visual data has been increasing due to the higher storage and processing capacities of modern computer systems.

As a result, a system which can be used as an aid for searching among a large number of images becomes desirable. Content-based image indexing has been proposed and implemented in several systems to date. Some of these have been made available commercially, while most are still only research projects. These systems rely primarily on color and texture information. Only a few attempts have been made at using configuration and shape description. Although most of these systems perform acceptably well for generic searches, they run into the same difficulties that general text-based search engines encounter.

The problem is that images are noisy, the search vocabulary supplied is very non-descriptive, and the rules of image composition are complex and ill-understood. Thus, although text-based search could be built based on phrase structure, and translation between languages is a feasible exercise nowadays, this is not yet possible for images, because the structure of images in terms of their human interpretation is not understood well enough. Image matching, and thus the translation of an image into another equally-meaningful image is currently on the border between difficult and impossible.

2.1 An Overview of Previous Systems

Systems similar to Imagina have been proposed and implemented before, with varying degrees of success. In order of seniority, these systems have been based on comparisons using color, texture, configuration and shape. Most systems rely primarily on color segmentation, with other processing being used for added reliability and for narrowing down the search space.

Texture is also fairly common, providing a distinction between images which simple color-based indexing cannot provide. Configuration and shape is rarely used, because there is no clear and simple description available which can be easily indexed. The search space also increases very quickly once these dimensions are added. Systems that implement shape most often use only a simple, generalized description, such as an ellipse or a rectangle, for all shape definitions.

The alternative to using machine vision techniques is using text-based indexing. However, this requires the manual labelling of images by individuals. Because different individuals would desire different elements to be encoded, the feature of interest in a particular case may be unavailable if it was never manually encoded. Because of this, text-based search cannot be the basis of any general image search engine.

2.2 Image Retrieval Systems

Content-based image indexing has been proposed and implemented in several systems to date. The main image indexing features used are color, texture, and shape, with configuration of image features only rarely addressed. A good starting point on the extensive literature is the paper by Pečenović et al., [29]. The systems discussed below were looked at before or during the creation of Imagina. This is not meant to be a thorough coverage of the literature. Instead, this is a sampling of systems which have features similar to Imagina. The goal of most systems is to support queries by an example image. One system reviewed here, VisualSEEK, supports user queries via a form of "sketches", as well as the modification of the weightings of particular features used for searching, such as color content and texture.

2.2.1 Query by Image Content (QBIC)

Query by Image Content is one of the earliest commercial attempts at an engine providing content-based image indexing. It was built at the IBM Almaden Research Center, and started out based primarily on color-histogram image indexing.[27] The features extracted for images are primarily global features like color histograms, global texture and the average values of the color distribution. Object features can also be used to narrow the range of retrieved images.

Images in QBIC are represented as whole images, but can also have manually outlined objects. Retrieval is performed by measuring the similarity between the user's query and the database images. Specific similarity functions are defined for each feature. Although this is one of the least sophisticated image querying systems technologically, it nevertheless has sufficient support as a commercial system. It should be noted here that most of the other systems mentioned here, or covered in the literature, are not used commercially.

2.2.2 The Virage Engine of the AltaVista Picture Finder

The web-based search engine Altavista ([33]) has set up an image searching tool in collaboration with Virage, Inc.([47]) It is a very ambitious project, currently containing indexing information for over 26 million images. From those, however, less than forty thousand pictures have been indexed based on shape. The approach taken is more geared towards a text-based search based on the text presents in the web page where the thumbnail was found.

The engine does provide, however, a "visually similar" query method, which provides poor results which seem to be based primarily on color information. A sample query is shown in Appendix C on page 129. Because a proprietary system is being used, the kind of information extracted from the image is not known for sure. It is likely that text and texture information are also used in performing the "visually similar" search.

The altavista search engine is the best representative of a production system, and is readily accessible over the internet. In a production system, the most important criterion of evaluation is the speed of matching for a given user query. For such a system, using a primarily text-based method with only basic image processing as an additional information source is crucial for providing the required performance. The Altavista Picture Finder lies at the opposite end of the spectrum from Imagina in terms of content-based image retrieval systems.

2.2.3 WISE: A Wavelet-based Image Search Engine

This engine uses a wavelet encoding of the images for searching.[48] Indexing is based on a Daubechies wavelet transform which is applied to each color channel individually, as well as on color histogram matching. The search goal is to find exact image matches to an input image. The wavelet transform is applied for diagonal, vertical and horizontal directional variations. Clustering methods are then used to partition the feature space of the results.

One way to think about wavelet transforms is in terms of their similarity to the Fourier transform, a cornerstone of texture definition. Therefore, the wavelet transforms are good at determining the texture of the images they are applied to, and WISE can be thought of as a texture-based indexing system. Because of the use of color histograms, WISE also performs color-based indexing. Shape and configuration constraints, however, do not come into play outside of the textural restrictions imposed by the wavelet transforms.

2.2.4 Photobook

The Photobook system was developed at the MIT Media Lab.[30][31] In its most recent version, described in [26], it includes FourEyes, a system which uses user interaction to improve indexing performance. Instead of using just one model, FourEyes instead uses a society of models, with the output being a combination of their individual results. It also uses textual labelling of regions besides image information to aid in searching.

The basis for the FourEyes extension to Photobook is that queries which go beyond color, shape and positional cues have to incorporate a variety of features. This can be very complex, and can be dependent on a large number of variables which may not be known a priori. Therefore, a machine learning approach which adjusts performance based on user interaction over repeated usage was implemented.[26] The performance being adjusted was based on the task of classifying different image regions into different user-specified categories.

One of the central features of FourEyes is its user-friendly interface. Instead of selecting values for arcane variables, the user provides positive and negative examples from which FourEyes extracts grouping rules. In a way, FourEyes needs to be taught what to do before it can perform properly. A difficulty that arises, however, is that the number of examples for complex rules can get large. Even though the training and fine-tuning can be spread out over several usage sessions, the time investment required in order for the system to begin producing useful queries can be prohibitive from the point of view of some users.

The usage of feedback is a very promising approach to solving any challenging problem. Instead of having a powerful program a priori, a weaker program which is capable of adjusting itself to a particular usage pattern can instead be made. This is akin to biological systems, which depend on both hard-wired abilities as well as the acquisition of new skills.

2.2.5 VisualSEEk

This system is one of the few which have attempted to use region configurations explicitly. This is in contrast to a system like WISE, described in subsection 2.2.3, which can only claim to use configuration information as a side effect of the image encoding used. A VisualSEEk query consists of a set of rectangular patches of color in a selectable configuration.[40] Thus only region size, not region shape, matters for matching.

This engine is designed for speed and interactive querying. Users can give feedback with regards to the which feature is most relevant to their search. The feedback is given through modifiable weights which are available for global color, color of regions, global texture, and joint color and texture matching. The system also allows for textual image retrieval, which can be used as an aid, by first doing a textual query, and then using the retrieved images as primers for retrieving further visually similar images. However, the query system is designed primarily for querying based on the location, size and color of regions.

2.2.6 Blobworld

The Blobworld system, described in [2], [6], [5], [9], [8] and other papers, uses an image description which attempts to step away from the global image processing approach used in most other systems. The authors (eg. [9]) recognize that most user queries are based upon the matching of objects within an image, and not on the matching of overall image qualities. Therefore, they segment each image into a set of regions, which are modeled by ellipses, and which they call blobs. The segmented regions, called blobs, have features such as color, texture, and shape. They are described in terms of their dominant features, based on an Expectation-Maximization clustering.[2]

The blobworld representation is concise, to allow rapid processing. Queries can be made either based upon an initial image, or based upon blobs selected from several images. This latter approach allows for the combination of features in the query. To improve usability, the internal image descriptions are provided to the user, giving feedback on what the query image was segmented as, and what the images retrieved from the database are encoded as. This feature is not usually found in global-property image indexing systems, because in such systems it is not straightforward how to display the encoding in a manner comprehensible to a human user. By providing feedback, the hope is that the human users adjust their queries such that the retrieved images more closely match the desired images.

2.3 Imagina in Comparison

Most of the features of Imagina can be found in one or more of the image retrieval systems discussed. For example, Imagina uses color-based processing, in forms of histograms and global filters. Color is a very basic feature used by all of the cited systems, except perhaps the WISE system. The contribution of this thesis on the topic of color based indexing is the provision of a thorough description of the Hue-Saturation-Value color space, in section 4.2.

The multiple levels of detail used in Imagina is another idea used in most existing systems. The success of the wavelet approach is based upon this idea. Imagina's contribution on this topic is the analogy drawn with biological processing and parallel computation, and the uniformity of the multiple level design throughout our algorithms.

A related topic, the combination of multiple methods, can also be found in previous work, usually as a byproduct of trying to use all sources of information present in an image. This is done implicitly, when an image search tool combines color and textural information. Photobook is the only image retrieval system that explicitly discusses using multiple ‘experts,’ each of which is capable of performing image retrieval in a limited way. These experts each give an opinion as to the identity of image patches present in the image, and the consensus is used to define the identity of the image patches. Imagina pushes the idea of multiple independent methods a step further with the implementation of the shape descriptions. Instead of using a monolithic shape representation, Imagina encodes shape explicitly in four different ways that complement each other, as described in Chapter 8. Although it is absent in most image retrieval systems, shape information plays an important role in Imagina.

Blobworld is the first system that insisted on making the representation explicit. This is probably related to the fact that they are using shape-based indexing. Hence, the representation which the system uses can be interpreted by the user. We designed our system around this principle. Thus, every representation and comparison has a pixel-based debug output that can be displayed on screen.

A characteristic that is unique in Imagina is the user input in form of a freeform sketch. In the literature, a query is usually an image which is already in the database. This helps the systems run similarity measures in advance, and to simply display results from a table lookup into these previously computed results at query time. The disadvantage of such an input is the constraint it imposes on the user, limiting his versatility. In Imagina, instead, a drawing interface is provided. An image download option also allows users to bring in existing pictures from the web or drawings constructed on any other drawing tool. Together these methods allow for a greater freedom of expression in querying the system for the user.

In summary, most of the design principles that govern the construction of Imagina have already been explored to some extent in predecessor systems. Imagina is unique in combining these characteristics along with the versatility of a sketch query. The work of previous systems has helped to guide the design of Imagina into being a successful image retrieval system.

That is not to say that image retrieval is a solved problem. Most of the existing systems only address one part of a complex problem. Moreover, many basic questions like the use of color, segmentation, shape description, and recognition, remain without a robust solution. Our goal in constructing Imagina is to address these basic questions, rather than to provide a definitive solution. Along these lines, we feel our contributions to be in the areas of color representation, edge extraction and shape description.

Chapter 3

Theoretical Foundations

I hear and I forget. I see and I remember. I do and I understand.

Confucius

Current research in cognitive science has shed light upon some of the generalities and specifics of the visual processing being performed by the mammalian brain. Therefore, as a background to our approach, several topics of interest are described in this chapter, all of which have their grounding in cognitive science. The topics presented here have influenced the work in this thesis, both directly and indirectly.

3.1 Streams and Counter-Streams

One of the best-documented features of the visual cortex is that computation does not just cascade from the retinal sensors to the higher-level areas, but instead the information from different regions along the way is diffused bi-directionally. This double-flow of information allows higher level processing to feed back into the lower level processing. This feature has led to the proposal of a *Streams and Counter-Streams* architecture for visual processing by Ullman.[45]

Ullman hypothesizes that recognition arises in the intersection between two processing streams of opposite direction, one going 'bottom-up' from the retina, and the other going 'top-down' from memory. The input image stream is generalized at every step, allowing for more generality and abstraction, at the same time that the stored models of images in the brain are made more and more precise, trying to match up with the current image. In the terms of Imagina, the stream is the encoding of the input images and user image queries into the indexable color and shape representations introduced in subsequent chapters. The counterstream is the set of images which are brought up for consideration from the database. By using an iterative process, some database images can be primed on one feature space, and then compared against another.

Imagina starts out with an incomplete description of the world, the same way someone waking up in the middle of the night would be encountering. The person waking up has no prediction of what is expected to be out there, so they look around, confused, for a while, looking for features. The features detected in the user input can be used to activate representations in the database, which in turn provide feedback to the user on what to draw next. This can be seen as a form of priming of the input channel.

There are many internal representations for each object being identified by the human visual system. This can be deduced from the variety of neurological impairments brain damage can produce.[35] Thus, in general, there is no single mechanism which will succeed at providing general matching. Instead, every mechanism available will succeed in some cases and fail in others. If the mechanisms applied fail independently, then a more robust system can be achieved through the combination of a set of more failure-prone modules. This is the approach taken in Imagina.

3.2 Gestalt Psychology

The Gestalt psychologists categorized different features which humans can rapidly pick out in visual input. Their approach, however, was lacking in a model for why their observations held. Instead of looking at the human visual processing as the end of a process, they looked at it as a whole. Thus, although they described patterns of processing, such as the grouping of visual stimuli, or the segmentation of line drawings based on 'good continuation,' they never attempted to go beyond these descriptions of their observations.

However, this knowledge can nevertheless be applied fruitfully to an image indexing project. Even without the understanding of the processing performed by the brain, algorithms which compute similar outputs can be devised. A simple application is the use of edge filters to redescribe an image in terms of the output of the filters. This can be done by overlapping the edges which have been detected and drawing them onto the new image. The new image would then contain a re-description of the original in terms of edges. The use of overlapping would fill up gaps in lines, thus allowing the system to detect imaginary contours which humans would see.[49]

Approaches using information derived from or similar to the observations provided by Gestalt psychologists have also been developed previously. For example, some such patterns are described by Ullman in [45] as "salient features." He argues that primitive routines can be applied to the image to extract the different pieces of information that can be used in matching images. These different pieces of information combined with an abstracted version of the image constitute the matching criteria for a query.

3.3 Canonical Views

In a series of studies, Bülthoff and others have shown that objects are most likely stored as multiple canonical views in the human brain.[4] They theorize that these canonical views are then interpolated between to allow the recognition of a wide variety of views. Support for this theory can also be found in [45], where a method for interpolating between sketches of cars is presented. There, Ullman describes how views taken of a car at thirty degree angles can be interpolated between linearly to predict with minimal error any view in between. Other work, by Ullman and others, has shown this method to be extensible and reliable, as for example in [36].

The central theme in this body of work is the use of prototypes, both for individual object classes, as well as for individual objects. The same theme can be found in the cognitive science literature, for example in the classification work of Eleanor Rosch.[46] For Imagina, this concept can be applied in terms of the database structuring. For small databases, all images can be indexed individually, and compared to all other images. As the database grows larger, however, methods for reducing the computation required for a new image to be inserted or indexed need to be introduced. Clustering images and image regions into a hierarchy of prototypes would allow for quick indexing, similar to the binary space partition trees used in vision algorithms.

The line of experimentation also provides evidence for differences in encoding between rotations around the horizontal and vertical axes, with the latter being recognized more quickly. These results can be useful for an image indexing problem in allowing a greater distortion along the horizontal axis, equivalent to rotations around the vertical axis, more so than distortions along the vertical axis, equivalent to rotations around the horizontal axis. This would match the user's tendencies to be able to compensate for deformations in the originally viewed image. Since the user is expected to be able to compensate more for deformations along the horizontal axis, their memory for this axis is likely to be less accurate to the exact pixel-level image which is retrieved.

3.4 The Limitations of Passive Input

In his paper on active touch ([10]), Gibson argues that the experience of being touched is fundamentally different from the experience of touching in its ability to provide information. Active touch is defined as an exploratory rather than merely receptive sense. It is more like scanning, using touch, than just perceiving. Because the change of internal state caused by muscle and limb movement is correlated to a change in the input, a more thorough description of the input is available. The feedback received by the limb being used as a probe is more informative to a human than simply rubbing the same object over the same area while the limb is held passively.

From this observation, one can argue that active probing is required for the ability to correlate internal and external states. In turn, this is a requirement for learning, and for the ability to understand. Therefore, a system which can only passively accept input is at a loss when trying to gain an understanding of the input beyond a simple stream of excitation. But this is exactly the case that an image indexing system finds itself in. If the system only has a set repertoire of actions, such as segmenting input images in a particular deterministic fashion, then it can never acquire any new information. It can only be as good as it was when first created.

This argument can then be followed through in two ways. One way is to argue that because an image indexing system cannot *look* around, and therefore cannot change its input, it cannot ever learn to abstract from the images beyond the pixel values. Therefore, the best one can achieve in a static system is some approximate accuracy based on image correlation measures which are valid for the task at hand. For example, if the task is to find the waterfalls in the image, then a deformable template which matches narrow regions of blue with white near the bottom, surrounded by greens or browns on the sides, would be the ideal measure. In fact, this was done as part of a PhD thesis, as described in [25]. Alternately, if the task is to identify the nut in a precision machine-tooling environment, pattern matching with rotation is likely to be the best solution. This is commonly done in robot vision applications for factory settings.[13]

On the other hand, an image indexing system may be able to get beyond its envelope. Although it is stuck in a 2-dimensional world, because it cannot ever probe beyond each distinct image, it does have another input which it can take advantage of. This is the human user. This is akin to a person who is in the dark using their hearing or touch to make their way to a target. Through the human's actions, which matches are good and which are bad can be learned. This idea is only beginning to be applied to content-based image indexing, for example in the Photobook implementation.[26]

3.5 Layering of Processing

One central idea which is found in biological processing is the use of several simultaneous levels of processing being applied. This can be found, for example, in vision, where different cells respond to bars of different widths in the visual input. At higher levels of vision, these response functions are somehow combined to provide size invariant object recognition.

Because the different computations occur in parallel, features can be detected regardless of their actual sizes at any one time. A specific feature size does not have to be pre-selected as a desired input value. Instead, the presence of a feature in the input can be deduced based on the responses of the size-specific feature detectors.

The computer science application of the concept of having layers of hierarchical representation can be found in several existing applications, for example in the computation of optical flow in computer vision. In this application the optical flow is computed on a coarse scale version of the image first. The computed optical flow is then propagated to the next larger scale version of the image, and used as a guide for the computation of the optical flow at this level. Eventually, after having passed through all of the coarser versions of the image, in what is termed a pyramid, the propagation reaches the image itself. With this progressive approximation technique, the computation is usually more robust and reliable.

The abstraction which can be taken away from such applications is that a cheap approximation computed on a coarse scale version of an input can be used to improve the desired computation on the fine scale input. This approach can also be extended to a parallel architecture, where instead of a cascade an interaction between levels is used, based on excitation or inhibition between the different levels.

3.6 Combining Unrelated Measures

The idea of how to combine unrelated measures comes from a reading of the paper by Itti, Koch and Niebur, [15]. In it, they discuss how saliency can be computed based upon the combination of several measures, each of which are computed across an entire input image. Their solution to combining the different measures is that measurement spaces which have only a few peaks across a single image are weighted more heavily than measurement spaces which contain either a lot of peaks or no peaks. This paper is discussed further in section 6.4.1 starting on page 64.

How to combine a set of different measures is always a difficult problem. This issue crops up in any system which attempts to use a combination of multiple unrelated computational methods to solve the same problem. There is no straightforward solution, other than having weights which are either pre-set based on a training set of data, or which are modifiable by the user at runtime. In a system like Imagina, this is a difficulty which must be addressed.

A very powerful idea which can be applied to this problem is that the different measurements which are to be combined should be weighted based upon their respective measurement spaces. Basically, the deviation of each measure from its expected value is the most reliable weighting for it. Because each measurement space has a different distribution, this distance should be normalized based on the standard deviation of the measurement space. It is helpful if the shape of the distribution of values is close to the normal distribution. However, a more complex procedure could be applied in other cases.

In terms of signal analysis, the different measurements have to be compared against the background noise in their respective measurement spaces. A value which is further from the mean is more likely to be the result of a signal, as opposed to the noise which is in the background. The larger the value measured, the more likely it is to be a part of the signal being sought. Therefore, the further the value is from the mean, the more reliable that value is as a measurement, and the higher its weighting becomes.

Chapter 4

Color

People only see what they are prepared to see.

Ralph Waldo Emerson

Images are made up of a set of colored points which are positioned on a rectangular grid. To extract any information from this grid, a good understanding of what the different values of the colored points represent is required. This is especially important since this is the basis of all subsequent processing in any image retrieval system, including Imagina.

This chapter first addresses the issue of color by discussing the two color spaces which are most commonly used in image retrieval systems, the Red-Green-Blue (RGB) and Hue-Saturation-Value (HSV) color spaces. The advantages and disadvantages of these colors, as well as methods of using the color information without any pre-processing are then discussed.

4.1 The Red-Green-Blue (RGB) Color Space

The predominant color representation used in Imagina is the RGB color space representation. In this representation, the values of the red, green, and blue color channels are stored separately. They can range from 0 to 255, with 0 being not present, and 255 being maximal. A fourth channel, alpha, also provides a measure of transparency for the pixel. Although useful for displaying overlapping image graphics and visualizing algorithms during testing, this channel is not used by any final image processing algorithms in Imagina.

The distance between two pixels is measured as:

$$\frac{(255 - |\Delta Red|) \cdot (255 - |\Delta Green|) \cdot (255 - |\Delta Blue|)}{255^3} \tag{4.1}$$

where ΔRed is the red channel difference, $\Delta Green$ is the green channel difference, and $\Delta Blue$ is the blue channel difference between the two pixels being compared. This distance metric has an output in the range of [0-1]. When used to compare pixels, a cutoff, usually between 0.6 and 0.8, is used to decide whether the two pixels are similar to each other. Because the distance measure is based on the absolute difference between pixel color values, the size of the neigborhood of similarity for a given cutoff value is the same regardless of the location of the pixel value being compared to in the RGB color space.

Although this color space description does not always match the intuition for color similarity of people, it does provide an easy method for pixel value comparison. In most cases it performs agreeably well, as it can differentiate gross color differences. It is also computationally cheap as compared to any other color space representations, because the Red-Green-Blue color channel differentiation is used in most image formats and therefore is readily available.

4.2 The Hue-Saturation-Value (HSV) Color Space

The alternative to the RGB color space is the Hue-Saturation-Value (HSV) color space. Instead of looking at each value of red, green and blue individually, a metric is defined which creates a different continuum of colors, in terms of the different hues each color possesses. The hues are then differentiated based on the amount of saturation they have, that is, in terms of how little white they have mixed in, as well as on the magnitude, or value, of the hue. In the value range, large numbers denote bright colorations, and low numbers denote dim colorations.

This space is usually depicted as a cylinder, with hue denoting the location along the circumference of the cylinder, value denoting depth within the cylinder along the central axis, and saturation denoting the distance from the central axis to the outer shell of the cylinder. This is depicted in Figure 4-2 on the left. This description of the HSV color space can also be found in [40].

This description, however, fails to agree with the common observation that very dark colors

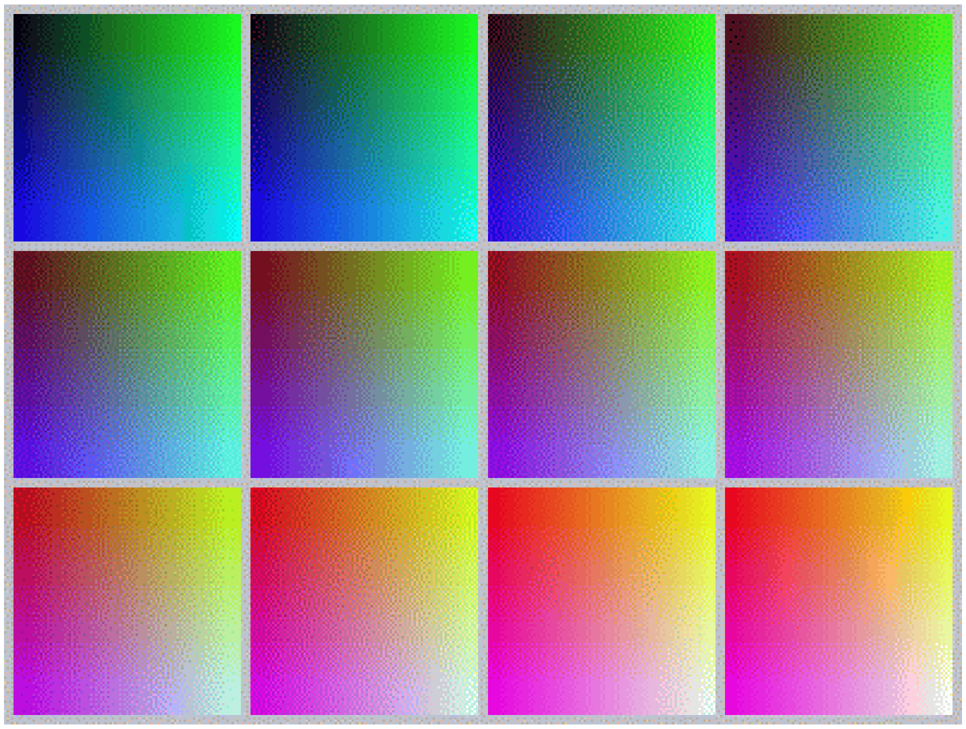


Figure 4-1: The RGB color space can be thought of as a cube, with each axis of the space representing a color intensity, from 0 to 255. The slices displayed are taken along the constant-red plane, from low to high. In each plane shown blue increases to the right, and green downwards.

are hard to distinguish, whereas very bright colors are easily distinguished into multiple hues. A system more accurate in representing this is shown in Figure 4-2 on the right, which is the model used for the HSV color space representation in the Imagina system. Similar systems have also been arrived at by others, for example [5].

In the latter representation, dark colors, which have a low value, are all considered to be very similar. On the other hand, brighter colors, which have a high value, are more easily distinguieshed. Although this system is closer to the observed human color space, it is not an exact model. Its simplicity makes it computationally tractable, while its better abstraction of the color space provides an improvement in performance.

4.2.1 Computing the HSV Representation

The starting representation is in the RGB color space format, since this is the format that most images are stored in. The computation of hue, saturation, and value can be performed as detailed

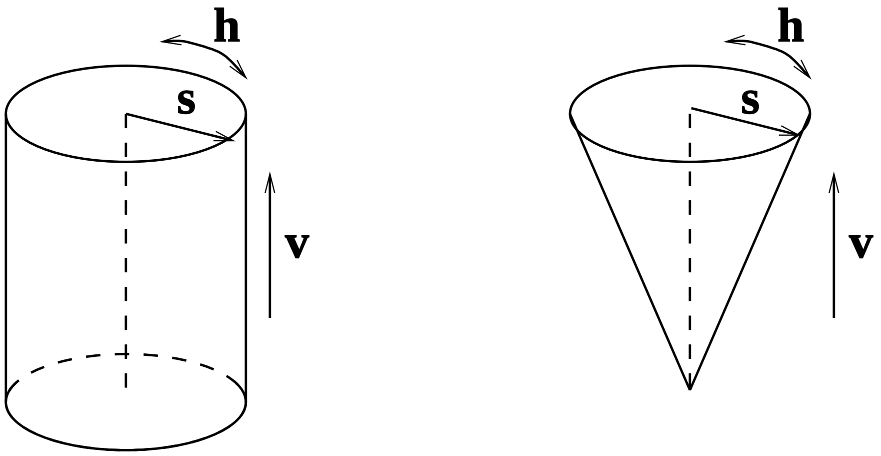


Figure 4-2: Two HSV color space representations. The cylindrical representation is a good approximation, but the conical representation results in better performace.

below. This computation, with corrections, was borrowed from[40]. In the text below, as in the figures, h stands for hue, v stands for value, and s stands for saturation. The RGB colors are similarly represented, with r for red, g for green, and b for blue. The remainder of the variables are temporary computation results. All of these computations have to be computed on a pixel-by-pixel basis.

$$v = \max(r, g, b) \tag{4.2}$$

$$s = \frac{v - \min(r, g, b)}{v} \tag{4.3}$$

Here, *max* denotes a function returning the maximum value among its arguments, and where *min* denotes a function returning the minimum value among its arguments. The hue is the most complex to compute, as it involves a mapping from three dimensions to a single continuous linear dimension, which can be thought of as wrapping around the perimeter of the color space cone.

$$6 \cdot h = \begin{cases} if \quad r = \max(r,g,b) \quad and \quad g = \min(r,g,b) \quad then \quad 5 + bpoint \\ if \quad r = \max(r,g,b) \quad and \quad b = \min(r,g,b) \quad then \quad 1 + gpoint \\ if \quad g = \max(r,g,b) \quad and \quad b = \min(r,g,b) \quad then \quad 1 + rpoint \\ if \quad g = \max(r,g,b) \quad and \quad r = \min(r,g,b) \quad then \quad 3 - bpoint \\ if \quad b = \max(r,g,b) \quad and \quad r = \min(r,g,b) \quad then \quad 3 + gpoint \\ if \quad b = \max(r,g,b) \quad and \quad g = \min(r,g,b) \quad then \quad 5 - rpoint \end{cases} \tag{4.4}$$

where

$$rpoint = \frac{v - r}{v - \min(r,g,b)}, \tag{4.5}$$

$$gpoint = \frac{v - g}{v - \min(r,g,b)}, \tag{4.6}$$

and

$$bpoint = \frac{v - b}{v - \min(r,g,b)}. \tag{4.7}$$

The value computation, as defined in equation 4.2, maps to the range of values which r, g, and b can take. This can be normalized to be in the range of [0-1], if desired. The saturation computation automatically maps to the range of [0-1], with the border cases occuring when the minimal value is 0, and when the minimal value is equal in magnitude to the maximal value among the RGB values, respectively. Therefore, the hue computation, as defined in equation 4.4, maps every RGB value to a different location in the color cylinder defined in Figure 4-2. To map into the cone representation, the saturation s has to be multiplied by the value v. In Imagina, this computation is done at the time of matching, instead of at the time of representation building. Note that the equation given computes $6 \cdot$ h, not h directly. Thus the range of hue is [0-1], with 0 being equivalent to 1, resulting in a circular value space. The HSV transformation is fully invertible, so no information is lost through this transformation.

4.2.2 The HSV Distance Metric

The distance between two colors can be computed in several ways. The most obvious approach, especially when using the cylindrical HSV color space description, is to use raw distance. This

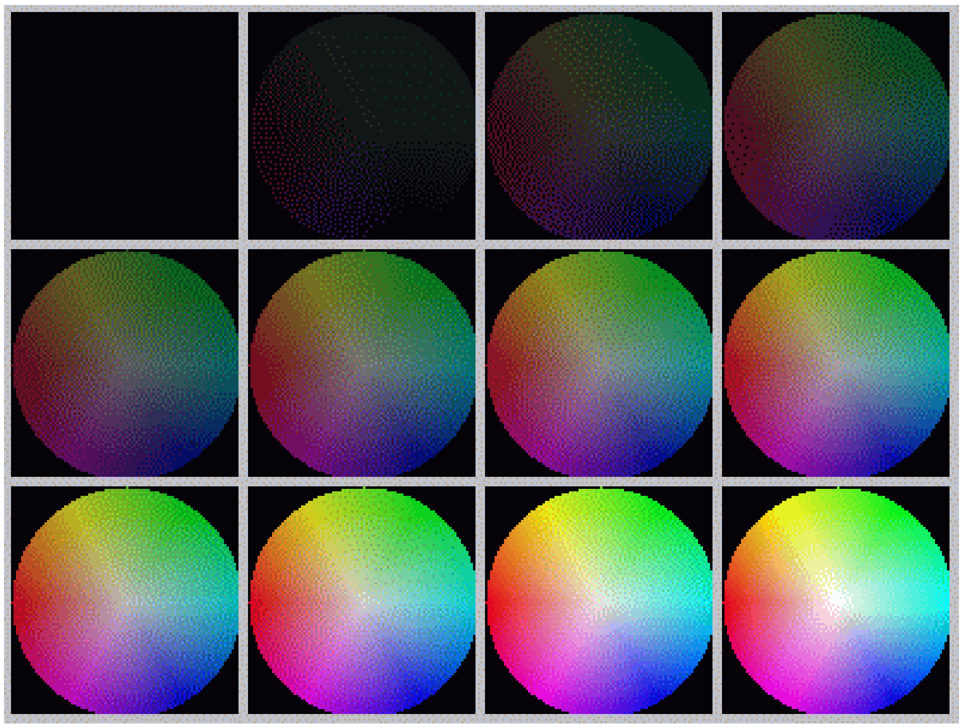


Figure 4-3: The slices displayed are taken for single-value planes through the HSV cylindrical color space representation. The hue is the angular position of each point with respect to the center of each slice. The saturation is the distance from the center of each slice.

results in a distance metric which considers colors which are located in a sphere around a point equally similar to that point. Because the axes of the HSV color space are not orthogonal, this description is not satisfactory, however.

Although many variations on this distance measure are possible, let us first consider what properties are desirable of such a measure. The ideal distance measure would have several features:

- Very dark colors, which have a low value, should be considered very similar.
- In turn, bright colors, which have a high value, should be more differentiable.
- Colors with very low saturation should be considered to be similar regardless of hue.
- The distance range should be upper- and lower-bounded.

The measure settled upon for Imagina, which has an output in the range of [0-1], with 1 being most similar, and 0 being completely dissimilar, is

$$\sqrt{\frac{1}{2} \cdot (s_1^2 - s_1 s_2 \cos(\theta) + s_2^2 + (\Delta v)^2)} \tag{4.8}$$

where Δv is the difference in value, and s_1 and s_2 are the saturations in the conical, not cylindrical, HSV color space. The transformation is defined as $s_i \cdot v_i$, for the respective similarity of the two pixels $i = 1, 2$ being compared to each other. The weighting of the saturation results in darker colors being considered to be more similar than lighter colors, which is a known perceptual phenomenon. The multiplication by $\frac{1}{2}$ is used only to map the distance values to the range of [0-1], and is determined by dividing 1 by the largest distance possible. In the equation, both saturation and value range from 0 to 1. Therefore, the largest distance possible is the diagonal of the circle of maximal saturation at the top of the cone, which is 2.

$$\theta = 2\pi \Delta h \sqrt{\max(s_1, s_2)} \tag{4.9}$$

The computation of the Δh is not straightforward, because of the circularity of the h value space. Given two pixels A and B, Δh is computed as:

$$\Delta h = 2 \cdot \begin{cases} if \quad |A.h - B.h| > 1/2 \quad then \quad 1 - |A.h - B.h| \\ else \quad |A.h - B.h| \end{cases} \tag{4.10}$$

Since the hue space is circular, the absolute distance between two hues is at most half the circumference of the hue space. The multiplication of Δh by $\sqrt{\max(s_1, s_2)}$ in equation 4.9 decreases the magnitude of the angle between the two colors being compared, and therefore increases their similarity, in direct relation to the saturation of the two pixels. The square root is then taken so that the saturation weighting rises to 1 faster than linearly. As a result of the weighting, colors which are saturated very little, and are close to the white-gray axis, are always similar regardless of hue. Colors which are very saturated, and which are very distinct from the colors in the range of white to gray, on the other hand, are always distinct. Because the max function is used, the comparison between two pixels is the same both ways.

By weighting the saturation values used throughout this computation, a true distance in conical space is created. The only difference between a pure euclidean distance and the distance being used is that the hue angle gets modified by the saturation of the pixels being compared. This results in the elongation of the matching space along the hue but not the saturation or the value axes of the space. This property is desirable due to the human visual clustering preferences.

Two new variables, $SaturationWeight$ and $ValueWeight$, can be introduced in order to weight the distance measure being used, and in turn to stretch the space in a particular direction. With the definition given above, and used in Imagina, the value dimension has a height of 1, while the diameter of the saturation dimension at the top of the cone is 2. To change this, every s in equation 4.8 can be multiplied by $SaturationWeight$, and the Δv can be multiplied by $ValueWeight$. By using these two variables, the importance of saturation and value weightings can be changed. The fractional multiplier used to achieve a [0-1] distance range, $\frac{1}{2}$ in Equation 4.9, however, would need to be modified accordingly, to be 1 divided by the maximum distance possible in the stretched space.

4.3 Other Color Spaces

The RGB and HSV color space descriptions are not the only ones applied in the literature. For example, the WISE system described in [48] uses a color space description where the RGB color space is converted to a new 3-color color space description:

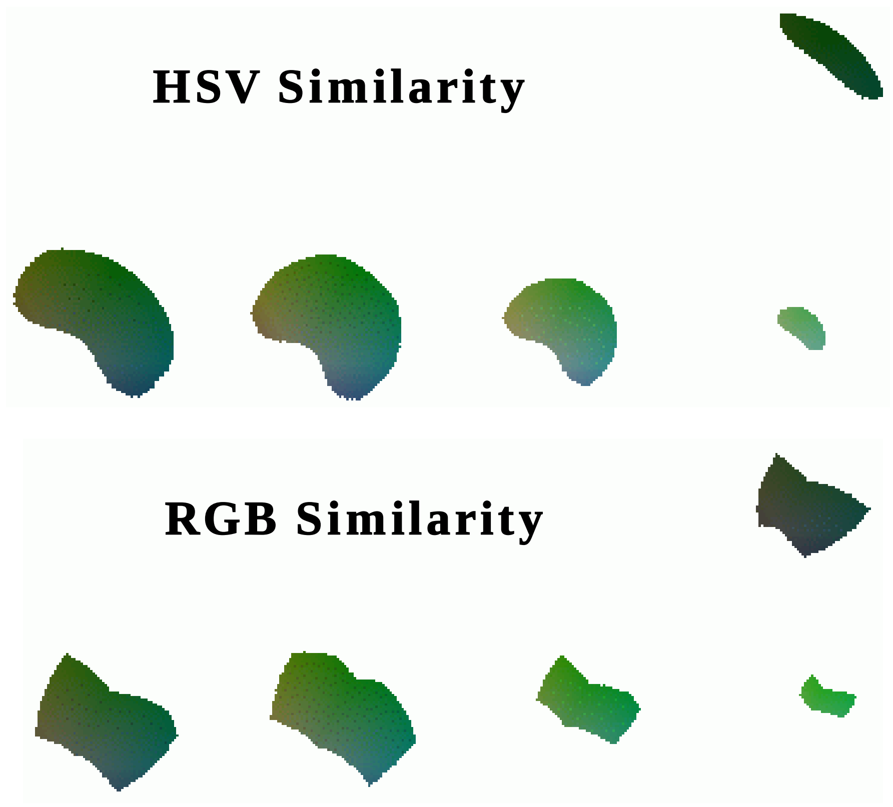


Figure 4-4: A comparison of the similarity measures of the RGB and HSV color spaces. The colored points shown are all of the points considered similar for a given similarity cutoff value. The cutoff value has to be different in the two spaces in order to result in approximately equal areas of coverage since the two measures are unrelated. The actual cutoffs used are 0.88 for HSV and 0.74 for RGB. The colored points were selected from the HSV display in Figure 4-3, in comparison with a point roughly at the center of the colored points selected in by either similarity measure.

$$\begin{aligned} C_1 &= \frac{1}{3} \cdot R + G + B \\ C_2 &= \frac{1}{2} \cdot R + \max(R, G, B) \\ C_3 &= \frac{1}{4} \cdot R + 2 \cdot (\max(R, G, B) + B) \end{aligned} \tag{4.11}$$

A more thorough discussion of color spaces can be found in [40]. Because the HSV color space is the simplest description which is similar to the color space of humans, these other color spaces were not explored beyond their description in the literature.

4.4 Use of Color Spaces in Imagina

The algorithms written and tested use primarily the RGB color space representation. Although the HSV color space representation is more accurate in terms of human perception, the efficiency of the RGB color space computations far outweigh the improvement achieved through the use of the HSV color space computation on images. In particular, both the initial HSV color space mapping, as well as the subsequent distance metric calculations, are very computationally intensive. Further, some comparisons are more easily computed in the RGB color space, requiring repeated conversions of the color space representation.

The RGB color space is used in the earlier color-based segmentation algorithm implementations. It is also used whenever color averaging over a region is needed. Although it is not clear whether this is equivalent to averaging in the HSV color space, the RGB color space averaging is much more easily computable. The HSV color space is used in the algorithms which are in the final Imagina implementation, especially where the comparison of point values is required.

4.5 Color-Based Indexing

Color is the primary method of indexing used in most content-based image search engines, because it can be described compactly and performs very well for the limited amount of data storage required. It is also the most straightforward in conceptual and implementation terms. However, it is very hard to get color-based indexing to work right in terms of human visual judgments.

Color-based indexing can be done both for whole images as well as for subsections of images. Even regions extracted based on color can have different spectral distributions within the color range allotted to them during segmentation. The utility of color-based indexing is limited, however, by the accuracy of the color distribution in the input image as compared to the color distribution in the desired image. For user-drawn sketches, the color distribution may be a very poor match to the desired image. Therefore, this measure is most useful for queries based on real images.

Two methods of color-based indexing are used in Imagina. The first is based on color histograms, where a set of bins are defined over a given color space, and then similarity is based upon the distance between images in the redefined space. The second is based on a color map, where different scale versions of the two images being compared are mapped to each other on a pixel level, yielding a comparison of the color distribution within the region itself. These two methods are complementary, in that where one method fails, the other succeeds.

Color can also be used for the determination of coherent regions within an input image. This application of color is explored further in Chapter 6, where the process of segmenting an image into regions is described.

4.6 Comparison Based on Color Histograms

Color histogram use for image indexing was re-popularized in the early 1990s by their use for real-time image matching.[41][42] However, this system works well only if a large number of pixels is available, or if an accurate color model is used. For the implementation used in Imagina, a binning technique similar to the implementation QBIC uses was implemented.[27]

4.6.1 Discussion of Previous Approaches

Several ways of computing color histogram matches exist. A thorough treatment of the different methods of computing matches is found in [40]. The method which was settled upon is the cosine distance measure, because this is a measure which is size-invariant, and which usually performs well in vector computations. This is true, for example, in text-based processing, where different pieces of writing can be most successfully matched using the cosine distance between multi-dimensional vectors denoting the words used in the writings.

The difficulty with the comparison of histograms is that the bins have to define ranges of color which are perceptually distinct and very similar to each other. Thus, colors which are perceptually similar should be binned together. To deal with this paradox, and to improve performance, QBIC and VisualSEEk define a similarity matrix between the bins. Then, when two histograms are compared, every bin is compared to every other bin, and their equivalence is weigthed by the given amount. The sum of these comparisons is then returned as the equivalence value. This approach, unfortunately, requires that individual bins be compared and that the ideal weights be evaluated.

A simplification commonly applied to the color histogram approach is the use of color sets. A color set is created by thresholding the color histogram values, assigning '1' to the respective color set if the histogram entry is above the threshold, and '0' otherwise. These vectors can then be compared more efficiently than the color histograms. Further, this reduces the variations caused by underrepresented colors in a given region. Because speed is superseded by functionaility in terms of the goals adhered to in Imagina, this simplification was not implemented.

4.6.2 Color Histogram Definition in Imagina

Imagina uses an implementation which attempts to address these issues. Unlike systems such as QBIC and VisualSEEk, which use the cylindrical HSV color space, Imagina uses the conical HSV color space. Because of this, the definition of bin boundaries is not as straightforward. However, the resulting bins separate colors into more distinct sets, which makes matching more efficient.

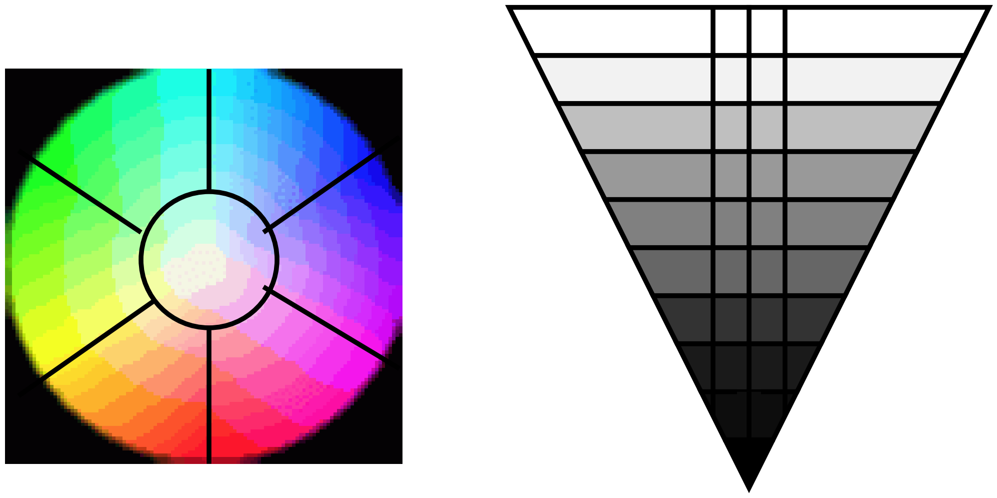


Figure 4-5: Two slices through the HSV color space, showing two views of the binning. The left slice cuts the cone through a single-value plane. The right slice cuts the cone in half through the central axis. The left slice denotes what is referred to as 'horizontal' partitions in the text, and the right slice denotes what is referred to as 'vertical' partitions in the text.

The HSV color space is split up into several layers along the value axis, with each layer split up into an equal number of bins. These are split based on a perceptual distinction into two sets. The first set of bins is defined around the central axis of the HSV color space, where the saturation is close to zero and perceptually the color range from black to white is present. This bins are referred to in this text as 'central bins.' A second set of bins is defined in a circle around the first set of bins, with each bin at a given level containing a range of the hue range at that level.

The bottom-most level, representing colors very similar to black, is made up of a single central bin. The number of partitions both vertically and in the plane of a single value range can be parameterized. The number of bins used in Imagina, depicted in Figure 4-5, is 64, with six outer partitions and ten vertical partitions. This results in nine levels with seven bins each, plus the bottom-most level's single bin.

Figure 4-6 shows the format of the color histogram display. In the display, each bin is represented as a vertical slice. The bins are arranged by hue similarity, with all of the bins which are in the same vertical stack being displayed adjacent to each other, going from darkest to lightest.

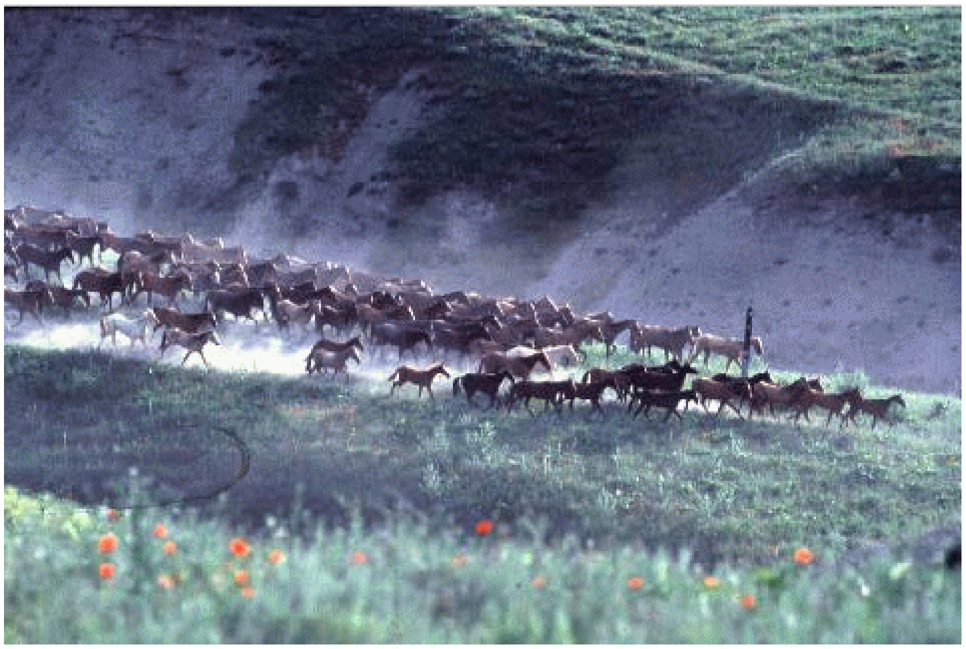
For each bin, the color of the vertical lines displayed is the average color in the bin. The size of the bar from the horizontal lines display the other four measures, with the length of the bar from the horizontal lines denoting the magnitude of the value of the current bin as compared to the magnitude of that value the maximal bin. In other words, this is computed as:

$$\texttt{barlength} = \frac{\texttt{currentvalue}}{\texttt{maximalvalue}} \tag{4.12}$$

The display shows, in order, the number of points stored, the standard deviation of the hue, the standard deviation of the saturation, and the standard deviation of the value of the points which fell into the given bin. Because the non-central bins become larger at larger vertical positions, the standard deviation of value for a uniform representation of the HSV color space would be expected to be larger for the bins representing larger values, which are to the right, than the bins representing smaller values, which are to the left, within each bin set displayed. For hues, the deviation should be the same within a given bin set, because they always contain the same hue range. This histogram pattern, and a comparison with the RGB color space pattern, can be seen in Figure 4-7.

4.6.3 Color Histogram Matching

The straightforward method of simply computing the dot product between the color histogram definitions does not work very well because the information of the relative positions of the different histograms is lost. Other systems have addressed this problem in different ways. The primary approach is to use a matrix of weights which defines a similarity between every pair of histogram



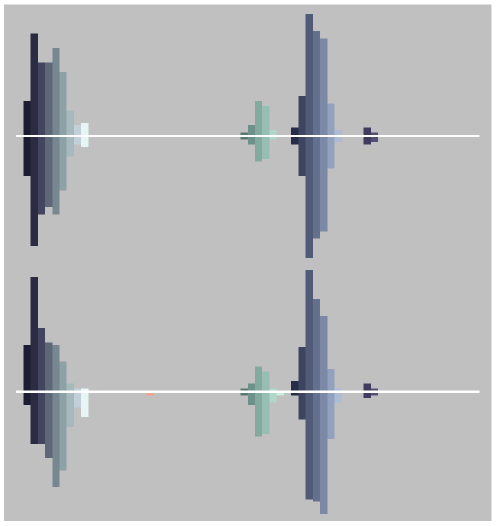


Figure 4-6: A sample image and its color histogram. The information stored in the color histograms is displayed in terms of five variables for each bin: the average color, the number of points stored, and the standard deviations of the hue, saturation and value of the points.

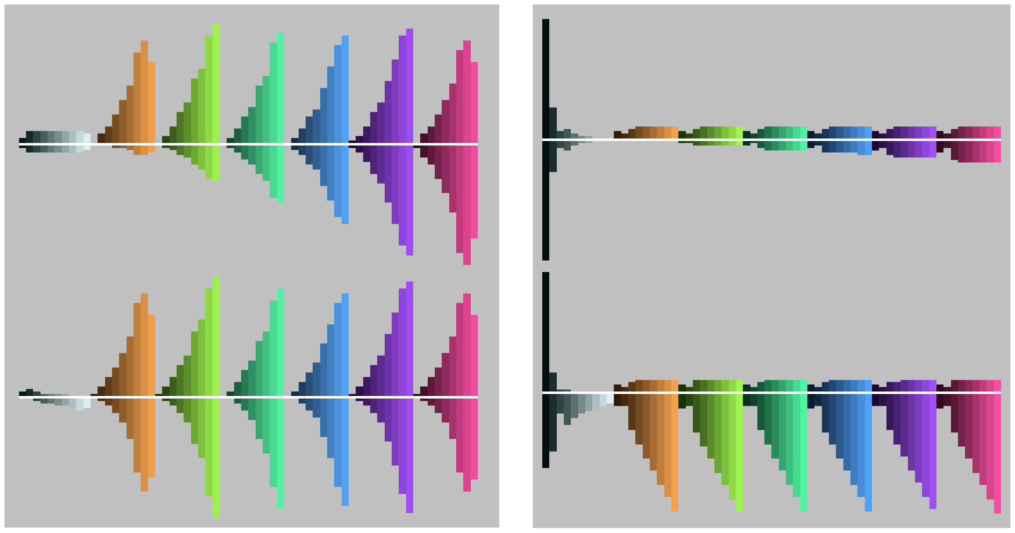


Figure 4-7: The color histograms of the displays of the RGB and HSV color spaces, shown on the left and on the right, respectively. The slight variation in the distributions of the different vertical bin sets in the RGB display is caused by the sampling error introduced by the RGB color space display. The HSV space histogram shows that the displayed values are unnormalized hue and saturations. Thus, except for value, the variation shown takes place primarily in the central black-to-white bin set.

bins. This matrix has to be pre-determined based on psychophysical or experimental data, or can be approximated as the similarity between every pair of bins based on a given measuring method.

An alternate approach is to take advantage of what is already known about the color space being used. Perceptually, bins which contain points in the same hue range, but which have different value ranges, look very similar to human viewers. The only noticeable distinction, over a large range of values, is that one range is darker than the other. This is perceptually a smaller difference than a change in color.

Bins which have different hues but the same value ranges, however, are very different. Therefore, matching can allow different value ranges of a given hue range to interact, while different hue ranges are kept separate. This is achieved by grouping together all of the bins of a given hue for matching. The bins representing the black-to-white range also make up a distinct group.

In performing this computation it is assumed that the distribution of color is more relevant than the actual lightness of the colors. Using this approach, a lighter and a darker image of the same scene or object will be considered more similar than if this assumption were not made. As an extension, hue ranges which are adjacent may also be allowed to interact, as an improvement to

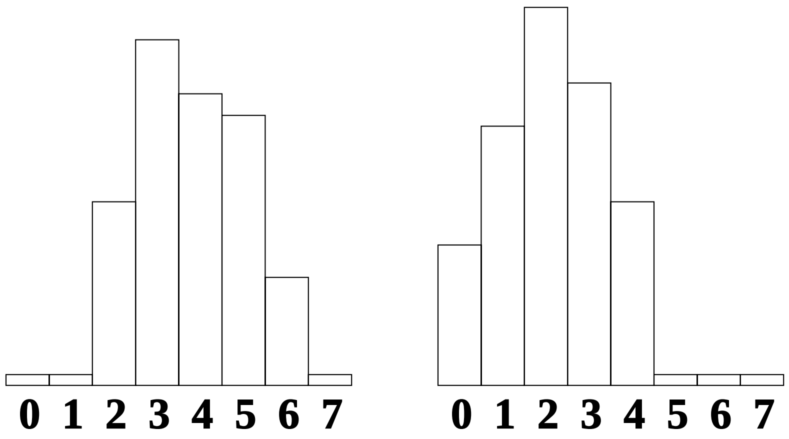


Figure 4-8: A sample color representation of two different regions, showing only the bins in a single hue range. Although the two color distributions are about the same, the shift in the bins represents a darker image on the right. In this figure the bin numbering goes from darkest on the left to lightest on the right.

this approach. This was not explored in depth as the scheme as described here works sufficiently well for color matching.

The advantage of this approach is also its weakness. Sometimes the distinction between lighter and darker views is important, as for example when comparing a white and a black background. However, the next color representation described in this chapter, based on color mappings, does not have this difficulty. Since both are applied when matching is performed, the potential misjudgment of one color representation are mitigated by the judgment of the other color representation.

4.7 Comparison Based on Color Mappings

A color mapping is a very simple and straightforward representation based on color. The intention of the color mapping representation is to measure not only the color ranges represented in an image, but also the their distribution. This is in contrast to the former representation, where the location of the color values did not matter.

The representation is built by taking the input image or region and resizing it into a square. Images are always subsampled to fit into a square whose sides are a power of two. This square is then iteratively subsampled into a square whose sides are half of the previous square's sides. The subsampling performed is equivalent to a RGB color space averaging filter. The iterative halving of the image stops at a square with a side length of two.

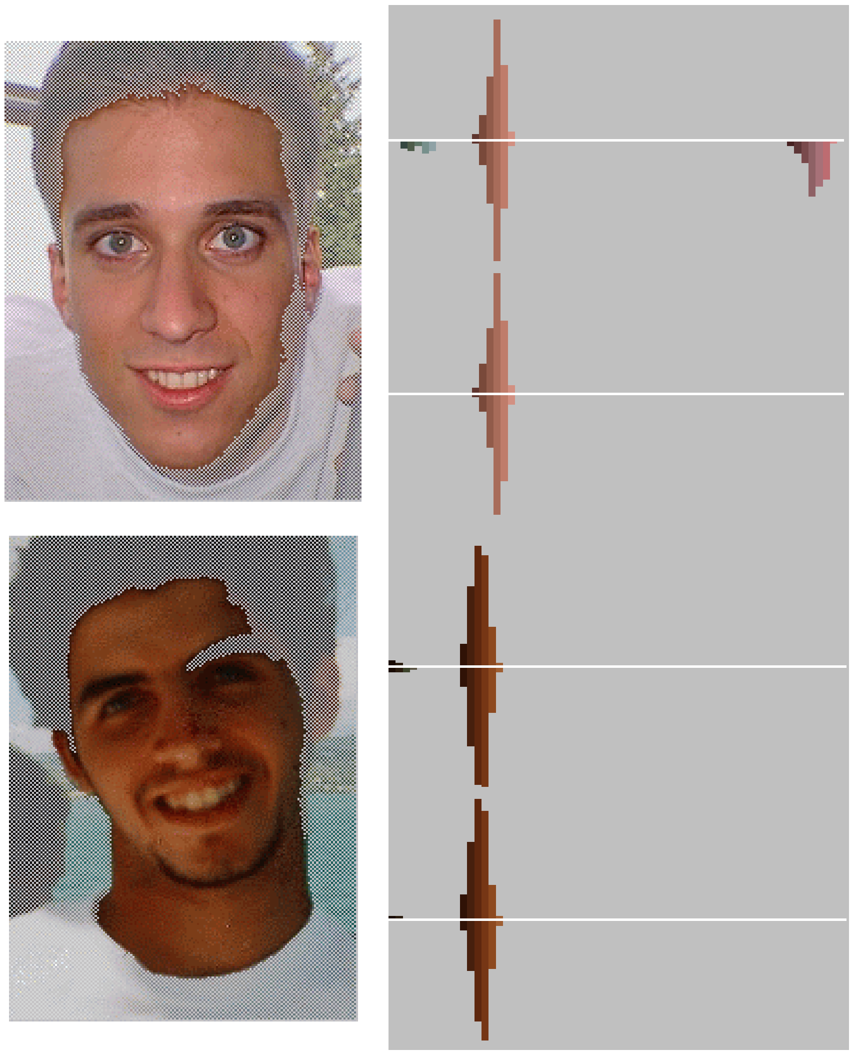


Figure 4-9: An actual color histogram match. Although the two faces are very different in lightness, both of them have a similarly shaped distribution of color in the pink hue color range, resulting in a high match value, of 0.97. This is in contrast to the figure following.

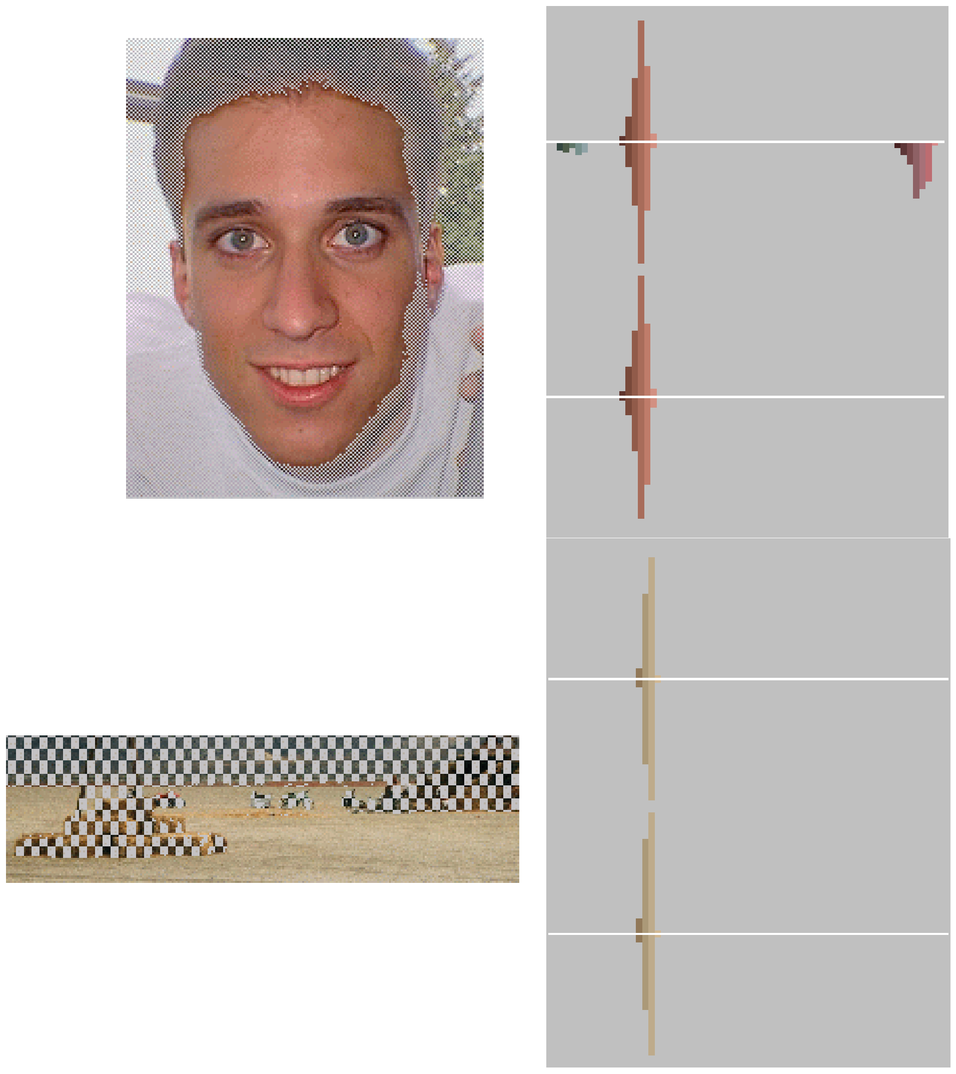


Figure 4-10: The comparison of one of the faces with a third region, which also has colors primarily in the same bin range, but whose distribution is different. The match result, 0.86, is lower because of the difference in the distribution shapes. A comparison with a region which has little of the pink hue color range would result in a value close to 0.

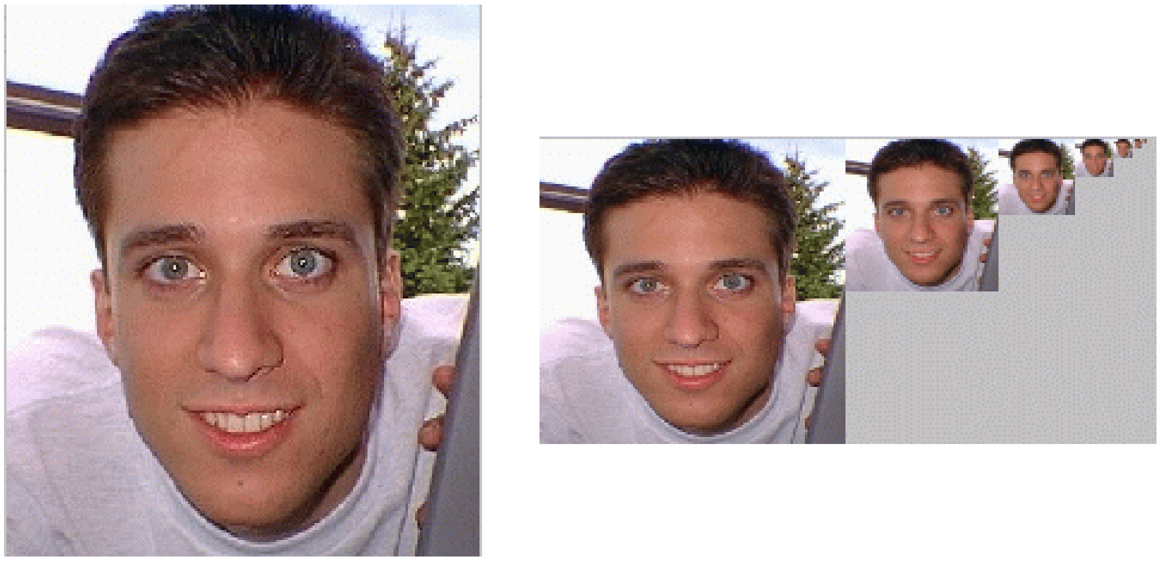


Figure 4-11: An image and its color mapping. The color mapping representation takes its input and downsamples it into a sequence of squares. Matching between images can then be performed by comparing the square representations of the two images being compared.

The color mapping is a representation which does not account for the actual shape of the regions being matched. All of the inputs are stretched into the same shape. Matching is then performed from the smallest level upwards, with the weighting of the match at each level being a weighted sum of the match at the previous level, and the match at the current level. The match at a single level is computed to be the average of the similarity measures of the overlapping pixels in the two color mappings being compared.

Although this representation might seem inefficient, an efficient implementation can be achieved in one of two ways. Either the entire representation is built as described above, and matching is performed by averaging a random sample of the pixels in the two representations, or the maximum square side size is limited to 16. Even at very low resolutions, on the order of 256 pixels per map, the matches between the single levels of the color mappings are within 10-15computed when comparing the entire color mapping levels. Thus, only a small amount of accuracy is lost when limiting the matching to a small color mapping size. Although the computational efficiency is not a key issue in the design of the current system, for a larger production level system this becomes important.

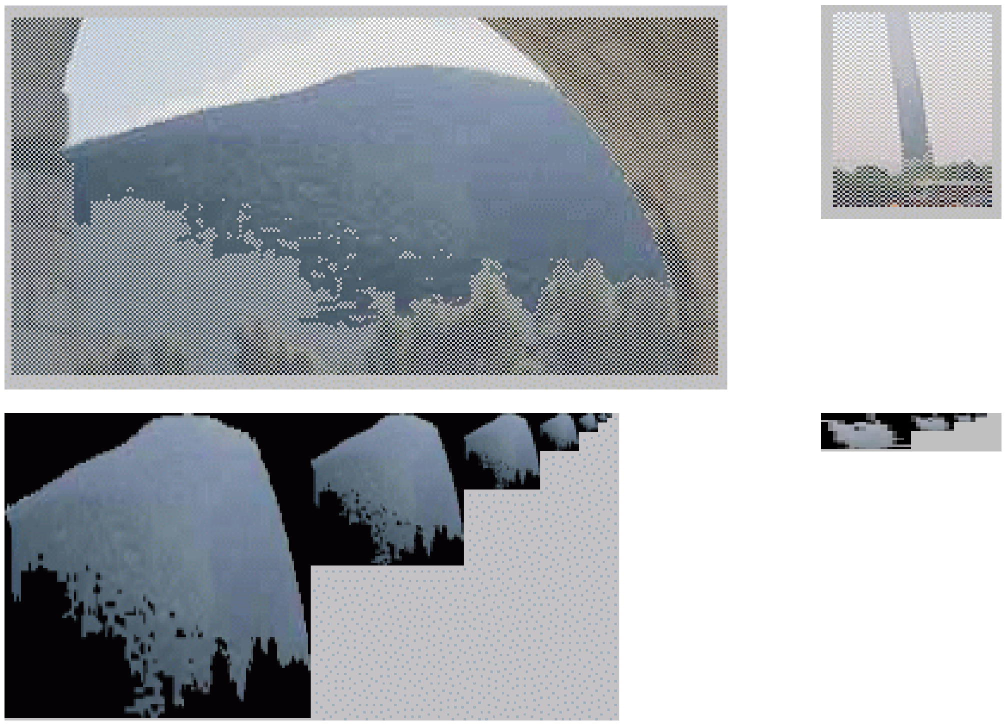


Figure 4-12: A color mapping comparison. Even though the shapes of the two regions are very different, and the original regions started out at different scales, the overall match is considered to be very good because the colors of the two regions match so well. Numerically, the match is 0.825.

4.8 Uses of Color-Based Comparisons

Color-based comparison is most useful when the input is most true to the color of the desired image. For drawn user queries, this is rarely the case. Although color can be specified, it is often more distant from the desired color than a real image input would be. It is also usually very evenly distrbuted, with each region having only one shade. Thus, the color comparison based on the distribution shape would not be very helpful in this case.

The only aid that the color comparison can provide is to distance the space of really bad matches from the space of good matches. By selecting a color, the user emphasizes all of the regions in the database which have a similar color, while regions of very different colors are de-emphasized. Therefore, color can be used as an aid in pruning the search space. However, color cannot be depended upon to perform the search when a user query is used in the stead of an actual image.

If a real image is used as a query, then color is clearly one of the best ways to perform matching. The color distribution would then matter much more.

The central utility of color, however, is in its aid to further processing of the image. Color is the basis of filtering, which is described next, and segmentation, which is following. All of the higher level representations of image regions which are developed in Imagina depend upon a good way of separating colors in an image.

Chapter 5

Filters

Hither the heroes and nymphs resort,

To taste awhile the pleasures of a court;

In various talk th'instuctive hours they past,

Who gave the ball, or paid the visit last;

One speaks the glory of the British Queen,

And one describes a charming Indian screen;

A third interprets motions, looks and eyes;

At every word a reputation dies.

Alexander Pope, The Rape of the Lock

The central problem with retrieving information out of an image is that it is very hard to distinguish relevant information from noise. This is especially true for extracting meaningful and coherent regions from an image, which is the central problem that needs to be solved in order to allow for region-based image indexing. Although the general approach settled upon is to use color, there are many ways to use this information to achieve segmentation.

In this chapter we explore methods of extracting information which have a biological basis. Because of this, concepts from cognitive science will be discussed. To facilitate this, a basic understanding of the workings of the retina and of the human visual system in general is assumed throughout this chapter. Readers who desire background information can look up any introductory neuroscience textbook, for example [35].

The approach to filtering presented here is based on the definition of a general filter object which can be applied to an image at every image position. This idea is similar to the use of wavelets, except that the filters defined and used are much simpler in form. The concept, however, is derived from work in cognitive science. The human brain is known to continuously compute a variety of local comparisons in parallel across the entire visual input. The most commonly known comparison are the red-green and the blue-yellow color-opponent filterings, which are known to take place as early as at the retina. Luminance-based filtering is also known to take place, but it is not clear whether this is performed at the retinal or cortical levels.

5.1 Opponency of Values as a System of Measurement

As used here, color opponency is defined as the weighting of a value positively for the presence of one measure and negatively for the presence of another. When computing a given filter over a particular area, the result is the sum of the filter values times the subtraction of the negatively weighted measure from the positively weighted measure. Thus, the two measures being considered can be thought of as opposites.

Opponency is used in filtering for several reasons. The main reason is that this is a known feature of the visual system. It is also a more robust measure, since information is used for each local computation. If a region of color is encountered which has the excitatory color strongly represented but the inhibitory color not represented, then the filters will measure high values throughout, for any kind of feature shape. This is not the desired performance. Another reason is that this method is better computationally, as one computational pass can be used to measure two variables. The additional information present also decreases the effect of noise.

Very early on in the visual pathway, color opponency, of red-green and blue-yellow, is computed in a roughly circular center-surround manner. This is depicted in figure 5-1. The central region is preferentially excited by one input type, and inhibited by another input type, while the surround reacts in the opposite manner. Thus, flat regions of either input type have no effect. Instead, the locations of change in either type are selected. By having color opponency, changes between the two colors are made more significant than either color alone.

5.2 Types of Measurement

Several types of opponency are explored here. The simplest methods are the red-green and the blue-yellow color opponencies. A second method uses only hue value, in the HSV space, or the sum of all of the color channels, in the RGB space, as the measure being weighted. A third method considers the distance of the color from a given color, either by using the RGB or the HSV color comparisons.

For red-green color opponency, the input types are the red and green color values in the RGB color space. For blue-yellow color opponency, the input types are blue and the average of the red and green color values in the RGB color space. This is because when additively combining colors, which is done for example by television sets and computer monitors, red and green combined result in yellow.

5.3 Types of Filters

Several filter types can be deduced from the current knowledge of the response patterns of neurons throughout the visual processing stream. At the lowest level, response patterns which are maximal for spot stimuli are found. As early as the visual cortex elongated stimuli of a particular orientation begin to be the inputs resulting in a maximal neural response. Farther on, more complex features such as corners, stars, hand outlines, or particular faces are the maximal stimuli.

The current understanding of these response patterns is that at the lowest level neurons with small circular receptive fields compute the center-surround response at each location on the visual input. At the next level, these responses are then combined into elongated receptive fields, yielding neurons which respond maximally to lines which have a given orientation and are located at a given location in the visual field.

These edge detectors can then be combined into more complex stimuli. How a corner detector could be built seems fairly straightforward. How more complex detectors are set up in the brain is still unknown. A feature of the visual processing stream which may aid in creating more complex detectors is that every filtering is performed at several levels of resolution. Thin edges are detected at one level, wide edges are detected at another, and so on. By having multiple parallel levels of filtering, approximators which are more noisefree can be combined with approximators which have more noise but provide greater detail.

The computation required to perform this filtering can become large. Therefore, only the simplest filters were considered in this exploration. These filters are of two kinds: filters to detect spots, and filters to detect edges.

5.3.1 Spot Filters

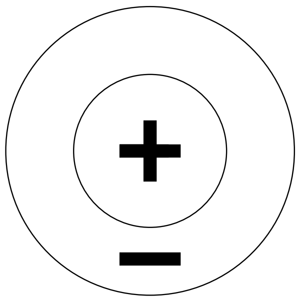


Figure 5-1: The simplest center-surround filter, a spot filter, has an excitatory center and an inhibitory surround.

Spot filters are fairly straightforward. The central region is excitatory and the surround is inhibitory. Spot filters emphasize local changes without providing information as to the directionality of the gradient.

In their implementation, spot filters were approximated by square arrays whose center contained positive values and whose surrounding area contained negative values. As the central region becomes larger, the measurement made becomes more robust.

5.3.2 Edge Filters

In the visual system, edges are described in terms of the combination of the outputs of the primitive circular center-surround sensors. This can be achieved by combining several center-surround sensors in a manner similar to that shown in Figure 5-3, by, for example, summing the outputs of these sensors. In the implementation used, edges were computed using a separate filter which has an elongated positive field buttressed by two negative fields.

Edge filtering can be performed in two different ways. Either localized or step-wise changes of a given directionality can be searched for. Localized changes can be searched for by using edge filters. Step filters, a variation on this theme, allow the emphasis of stepwise changes without focusing on a given line width. A step filter is equivalent to an edge filter which is cut lengthwise and then

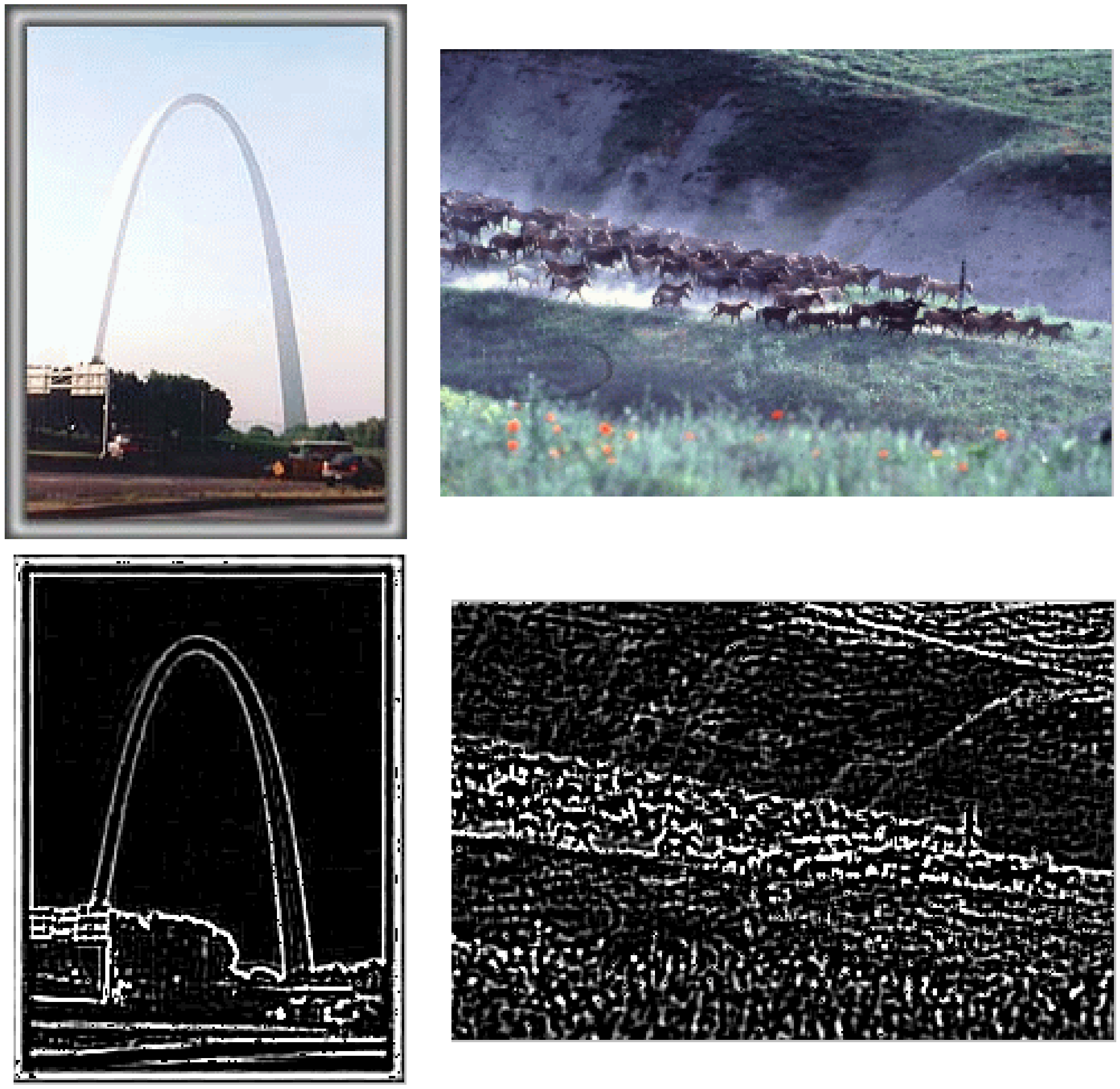


Figure 5-2: The result of the application of a spot filter over two images. For some images the results are very good, while for others the results are very noisy.

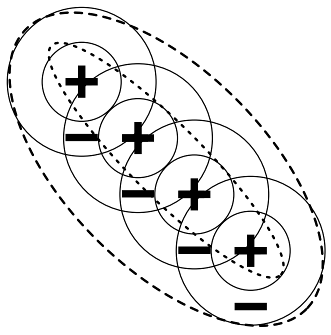


Figure 5-3: A center-surround edge filter can be created from the combination of a set of center-surround spot filters.

stretched to the original width.

5.3.3 Excitatory and Inhibitory Filtering Field Shapes

A modification to the simple filtering paradigm is the enhancement of the sought-for change through the emphasis of this change. This can be done by having the outer, inhibitory field have a very negative value next to the border with the excitatory field, and then increasing in value, thus becoming smaller in magnitude, as the distance increases. This results in an emphasis on abrupt local change as opposed to the smoother change which is emphasized by flat value fields.

The excitatory region, however, is always flat, as it is contained within the filter. If a similar shape were used, then a circular shape filter would result, where the true center of the filter would matter little in the shape being detected.

5.4 Output Modifications

The output of the application of any given filter at any given position in an input image is a single value. This value does not have a direct correlate to a visual representation. It is only a measure of the belief which can be placed in the existence of a given feature at this location in the image.

To make this output usable, several things can be done. First of all, the location itself can be tagged. Secondly, the entire filter image can be painted onto the locations where the filter is applicable. When using non-binary outputs, the filter, weighted by its local output, can be painted at each image location. Third, instead of painting the entire filter, only the feature which is being detected can be painted onto the image.

Tagging each location individually this is useful in determining where each filter is applicable in a given image. However, it does not aid in any image processing step, because at best this results in a series of pixels which are tagged with different values. Alternately, the filter itself can be painted onto that location. This results in the emphasis of continuous features as well as the inhibition of neighboring filters. Lastly, the entire area which the given filter overlaps when it computes a positive value can be tagged. This would result in the given area being labelled as being similar to the pattern being searched for. For more complex filters, this method could be used to locate areas of texture in the image. These areas can then be segmented away, either disjointly or conjointly with color information.

5.5 Difficulty of Filter Application

Although the displays of filter outputs provides information which is useful for human viewers, the extraction of information from them is nevertheless difficult. Due to constraints on time this topic was not studied further. However, the approach presented here, used in combination with the methods presented in Chapter 7, which describes the extraction of edge descriptions, may prove successful in providing a robust approach to shape extraction.

The other extension to the topic of filters is the computation of texture. For example, information could be gathered by edge filtering the different levels of the color mapping representation presented in section 4.7. This would provide an estimate of the Fourier transform of the image. This, in turn, is equivalent ot the approaches most commonly used for textural descriptions.

Chapter 6

Image Segmentation

Time extracts various values from a painter's work. When these values are exhausted the pictures are forgotten, and the more a picture has to give, the greater it is.

Henri Matisse

The complexity of generalized image understanding lies in that several objects have to be recognized and segmented simultaneously during most interactions with the visual world. The difficulty lies in selecting which stored image to match with which part of the visual input, and to what extent the different views have to be combined in order to yield a match for an input. The issue of image segmentation has baffled scientists for decades, and no clear-cut solution has been proposed. Such a solution may never be found, since in humans there is an apparent overwhelming devotion of cortex in the brain to image processing, denoting a concentration of resources upon this task.

When dealing with static images, the lack of motion information exacerbates this problem. How to do this well is still an area of active research. Many solutions have been proposed, some of which make assumptions about the image, and others which feed parameters, such as the number of regions expected, to the segmentation algorithm being used. One commonly used approach in image retrieval systems is the use of Expectation-Maximization to determine the segmentation of the image based on color.

The approach described in this chapter develops a different methodology to achieve the goal of image segmentation. A novel approach was developed in order to explore the possibility for a parallelizable approach to image segmentation. More traditional methods are usually serial algorithms which perform well on a serial architecture but are not biologically feasible.

Toward this goal, first, the growing of a coherent image region from a single point in an image is developed. Then, a related algorithm is presented which provides a full image segmentation. Both of these algorithms rely solely upon color information for segmentation, because textural information is not implemented in Imagina. The base assumption made in all of these algorithms is that an image can be segmented into coherent regions based on the similarity of the color which makes up those regions.

6.1 The *Grow* Algorithm

The first algorithm developed for region segmentation is the growing of regions from a selected point outwards. From the starting point, each neighbor is considered in turn, and all neighbors which are sufficiently close to the value of the selected point are added to the region being grown. The region growth is performed in an outwards-moving fashion, such that all current neighbors are added to the region before any of their neighbors are considered. This is shown in figure 6-1.

The region being segmented is expected to result in contiguous points on an image plane. Although there are point-by-point variations due to noise in any image, this is not a problem. Once a region has grown beyond a few pixels, multiple paths will exist from the current region's boundary to a similarly colored point, unless another colored region is in its path. When starting, however, the local values affect performance significantly.

All of the points which are labelled as part of the region at the end of this algorithm are similar to the starting point by some measure. Whether to include a given point is based upon its similarity to the point where the *Grow* algorithm is initiated at or to a pre-computed value which is fed to the algorithm.

The similarity measure between points can be performed in two ways, based on the two color spaces which are used in Imagina, the RGB and the HSV color spaces, which are described in chapter 4. The similarity of two colors is computed by subtracting the distance between the two points from one. The RGB description provides for faster computation, while the HSV description gives a more acceptable color-based distance.

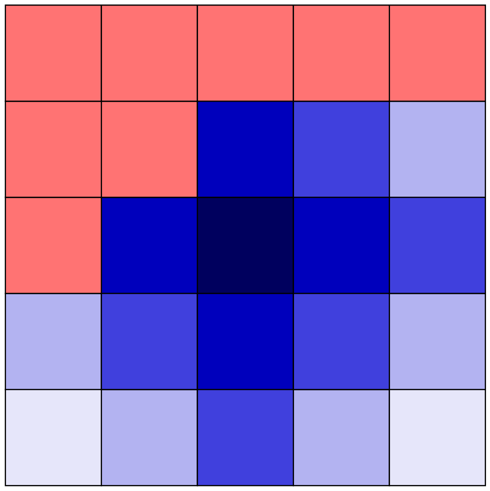


Figure 6-1: The *Grow* Algorithm. The algorithm starts from a single point, shown in black. The points which are similar to the first point are shown in blue, and the points which are dissimilar are shown in red. The first group of points added are in dark blue, the next set of points added are lighter, and so on. Only the points in blue are added to the region.

The algorithm is called *Grow* because point inclusion into a region starts at a given position and is expanded outwards. If a given point is included, then all of its unmarked four neighbors are considered for inclusion. If a given point is not included, its neighbors are not considered for inclusion into the region, either, unless they are neighbored by an included point on a different side.

In order to determine which points to include, their similarity to the comparison value has to be measured and compared against a cutoff value. This is because regions are defined by an all-or-none labelling. A point is either inside of the region or outside of the region. The best cutoff value depends on the color space as well as on the region being grown. Although a value which provides a perceptually coherent segmentation in most cases can be selected, there is no value which works well in all cases.

The main weakness of the *Grow* algorithm is that a particular starting point, a particular color cutoff, as well as a color space, must all be selected. If the starting point is not close to the average of a given region, the *Grow* algorithm will fail to find that region. Two extensions, the *Adaptive Grow* and the *Progressive Grow* algorithms, attempt to address some of these issues. The performance of all three algorithms is shown in Figures 6-3, 6-4 and 6-5 starting on page 64.

6.2 The *Adaptive Grow* Algorithm

To lessen the bias imposed by the value of the starting pixel, an average of all of the points which have already been included into the region can be kept. As more of the neighbors of the starting pixel are included, the value being compared against becomes a better approximation for the average value of the local region. Even if the starting pixel is not very representative of the region, in most cases this algorithm will succeed in segmenting a cohesive region.

Again, a cutoff value has to be selected. However, this value usually can be greater than the value needed for *Grow*, because in most cases the average of a region is a better comparison than a single starting point value. This algorithm is identical to the previously discussed *Grow* algorithm. Because of its adaptive nature, however, it performs better at segmenting image wholes.

6.3 The *Progressive Grow* Algorithm

Instead of having a single global region average, a local average can instead be kept. This average is progressively modified based upon the most recently included points on every outward path from the starting point for region growth initiation. Thus, *Progressive Grow* can adapt to the local area around every point of the region instead of depending on a single global average. This can be useful when a region contains a low gradient from one side to the other. Human vision handles such situations without the imputation of region boundaries at several locations. This provides support for an algorithm with a progressive average.

The algorithm, shown in Figure 6-2, has a local average kept for every point on the outer hull of the region as it is being grown. The neighbors of each point are considered for addition based on this local average instead of a global average. A point which has two neighbors which are currently a part of the region is compared to both of them in turn. Because progressive averages for nearby pixels are usually very similar, computing an average among neighboring values before considering a point for inclusion is unnecessary.

The updating of the local progressive average is fairly straightforward:

$$\texttt{new average} = (1 - \mathit{weight}) \cdot (\texttt{old average}) + \mathit{weight} \cdot (\texttt{point value}) \tag{6.1}$$

where the starting `old average` is set to be equal to the value of the point where the *Grow Progressive* algorithm is initiated at.

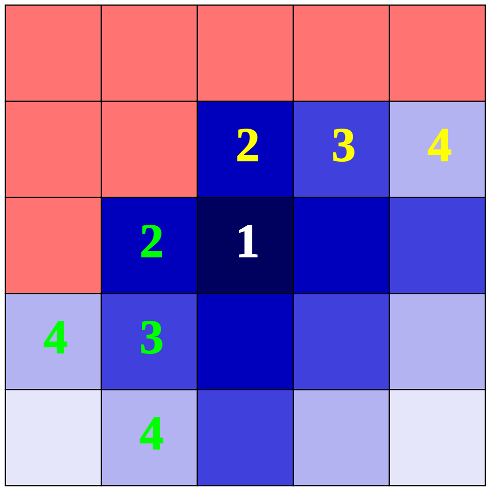


Figure 6-2: The *Progressive Grow* Algorithm. Starting with a single region point at step 1, the progression of two averages is traced with the two number colors. The updating of the average between sequential positions is given by the equation below. The blue squares denote points which are similar and therefore included, while the red squares denote points which are excluded from the growing region. The lighter the shade of blue of a square, the more time steps are required for that square to be considered for inclusion into the growing region.

The difficulty, of course, becomes the weighting of the newly added pixel's value as compared to the previous average. If the new pixel's value is weighted only a little, then any existing gradient may not be crossed. If the new pixel's value is weighted a lot, then almost any gradient which is a few pixels wide will be crossed, and the entire image will be labelled with a single region label.

The selection of the cutoff value also is still an issue. Although the cutoff can be higher because of the progressive movement of the average, it cannot be so high that the algorithm cannot get started. Usually, the cutoff can be made higher as the new pixel weighting is made lower.

In the limit of a new pixel weight of 0, the *Progressive Grow* algorithm is equivalent to the *Grow* algorithm. Although *Progressive Grow* is a generalization of the basic *Grow* algorithm, it is not a generalization of the *Adaptive Grow* algorithm, because the different averages being kept during region growing are disconnected.

The performance of the three algorithms can be quite varied. The algorithm which performs best depends on all of the parameters which can be set. Therefore, a perceptually good segmentation of any region can be achieved given sufficient trials by a user. Automating this process, however, does not look promising. A comparison of the performance of the three *Grow* algorithms is presented in Figures 6-3, 6-4 and 6-5. In these figures, the segmentation starts from the same point in the center of the skirt, and the cutoff and algorithm applied are varied.

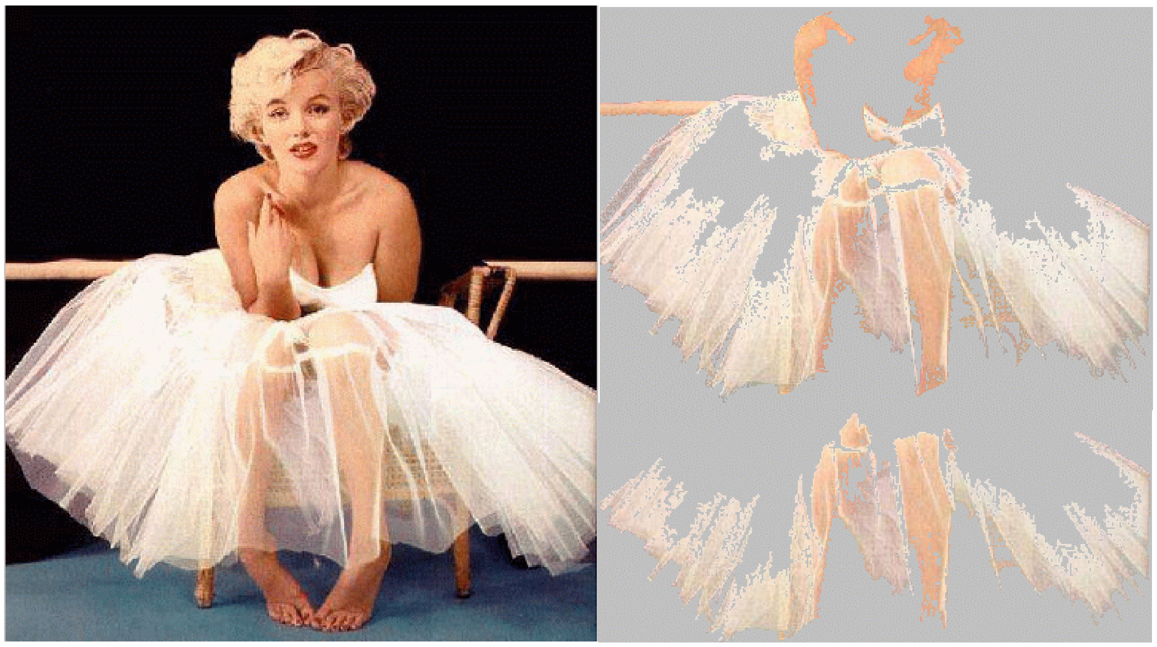


Figure 6-3: The sample image being segmented and the basic *Grow* Algorithm's performance on it. The cutoff values are .6 and .7, top and bottom, for the segmentations performed on the right.

6.4 Methods for General Segmentation

The problem of performing general segmentation is more difficult than the simple segmentation of each individual image region. Even if a set of parameters and a version of the *Grow* algorithm is settled upon, selecting the starting points for region growth and sorting out conflicting region assignments can be difficult. There are two approaches to the issue of general segmentation: working on finding good local starting points, or attempting to perform the segmentation at a global instead of a local level.

6.4.1 Using Saliency for Segmentation

When segmenting an image, it is hard to tell where the best place to segment an image is. None of the usual approaches to this problem are very reliable. Using a color histogram range based on the color content of the image can fail by splitting a region into two bins, or by combining several disparate regions into one. Segmenting areas based on local averaging computations can also run

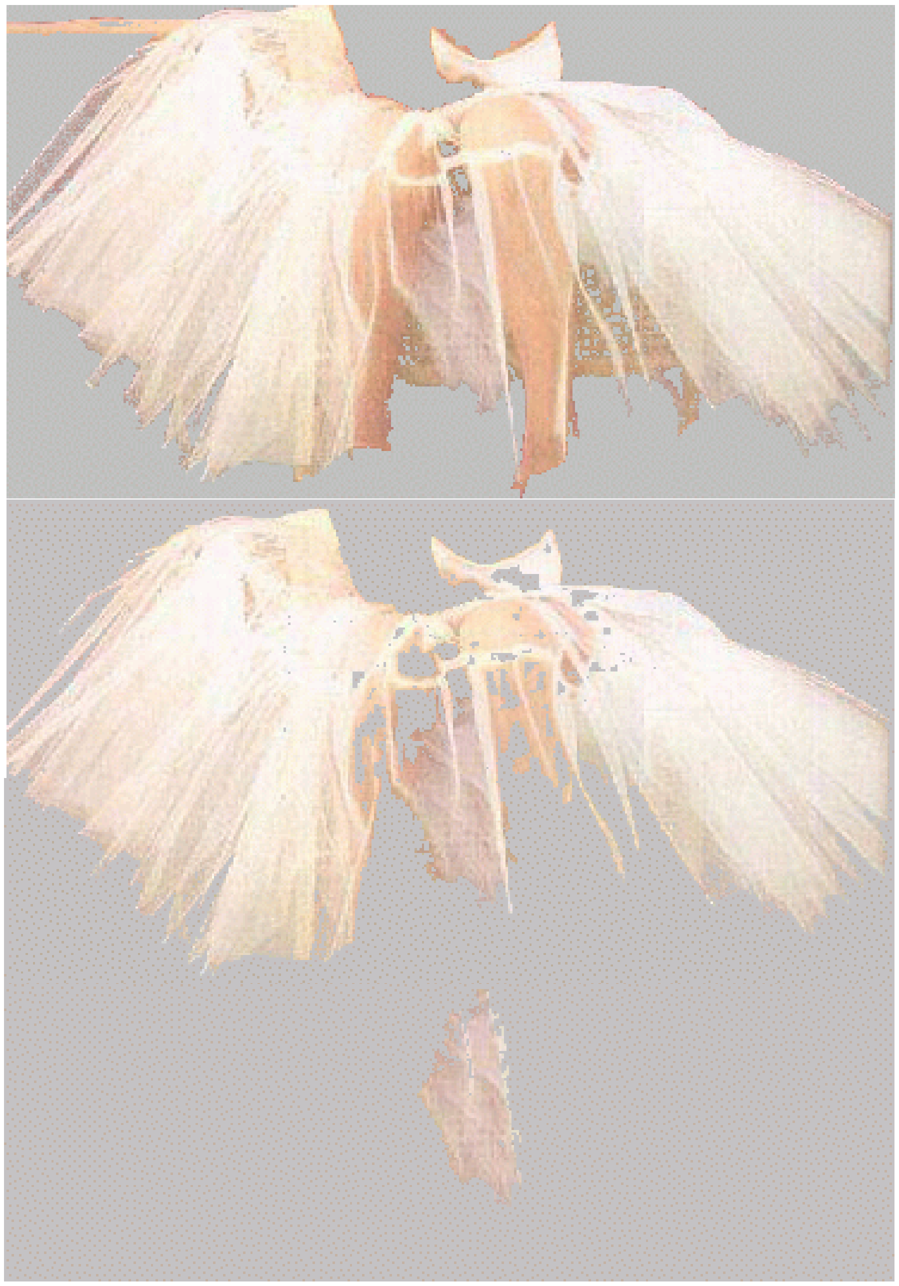


Figure 6-4: The performance of the *Adaptive Grow* Algorithm with cutoff values of 0.84, 0.90, and 0.94. The HSV color space comparison is being used.

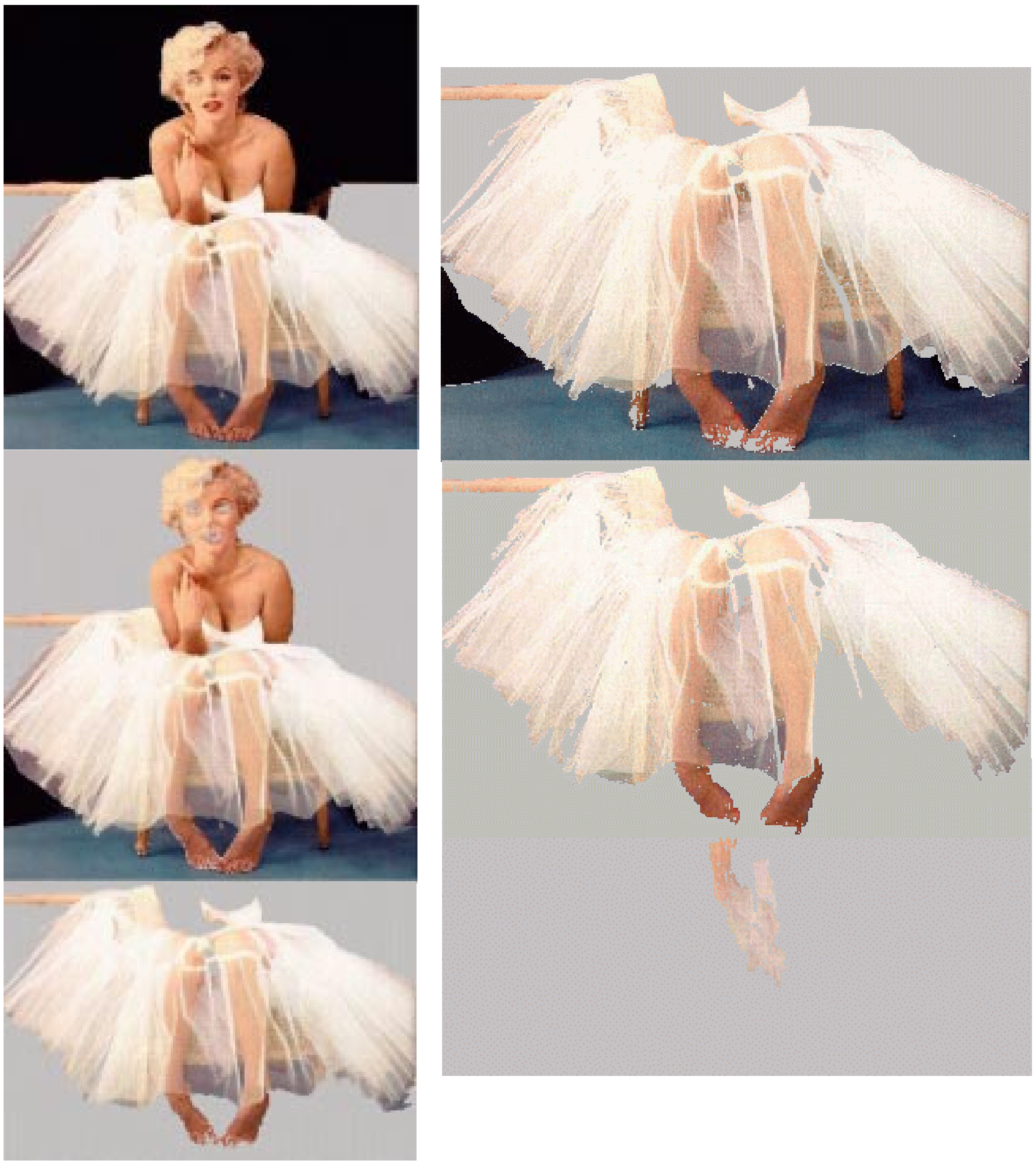


Figure 6-5: The performance of the *Progressive Grow* Algorithm using HSV color similarity on the left, and RGB color similarity on the right. The new pixel weighting for averaging is one fourth in both cases. The cutoff values from top to bottom for the HSV similarity are 0.84, 0.90 and 0.94, and for the RGB similarity are 0.76, 0.84 and 0.90.

into difficulties as the average being used to add new pixels changes with the starting location of the segmentation process. This latter process also is somewhat questionable as it relies on an iterative process which cannot be parallelized.

One approach to using saliency is discussed by Itti, Koch and Niebur in [15]. Although their model of visual saliency is designed for visual attention, we will argue for its applicability towards image segmentation. One can argue that the sections of the image which appear most salient to the viewer will be most easily remembered. Therefore, if a measure of saliency similar to humans' can be computed, the sections of the image which are most salient by this measure should be segmented preferentially.

Itti et al. use "center-surround" operations to compute for the same features on the same image when viewed at different sizes. Red-Green and Blue-Yellow center-surround values are computed, as well as directional filters for four orientations. These computations mimic the computations found in the retina, laterate geniculate nucleus, and visual cortex.[35][7] This approach is also explored in Chapter 5 of this thesis.

The difficulty with these computations is that combining the different value maps is not straightforward. To avoid the overcrowding of data with noise, the maps which have very few peaks in them for a given input are weighted more heavily in determining saliency of locations. This is measured by comparing the highest peak with the average of each map, and is based on neural lateral inhibition mechanisms in the visual cortex. Different maps in the same modality compete, while different modalities contribute, to the overall saliency map.

The computed saliency can be used to determine the locations to begin the image segmentation. Thus, the parts of an image which are most likely to have been foveated by human viewers, and therefore the parts which are most likely to be remembered, are most likely to be segmented away. Thus a higher rate of image matching based on user queries is expected than if the starting segmentation points were to be selected randomly.

6.4.2 Using Hierarchy for Segmentation

A hierarchical approach to segmentation bypasses tihs issue. Instead of selecting points, the *Grow* can be performed at different levels of image resolution. The region labellings can then be propagated from the lower resolution image versions to the higher resolution image versions.

Starting locations never have to be selected because the growth is performed at all points simultaneously. A comparison cutoff, as well as a color space, must still be selected. The advantage over a hierarchical approach, hwoever, is that the serial nature of the *Grow* algorithms which have been presented is overcome.

This approach is not perpendicular to the method of using saliency. For example, the concept of saliency could be applied to constrain the growth of regions. Regions attempting to cross saliency boundaries could be stopped or redirected. Although such a combined approach may be fruitful, it was not pursued here.

6.5 A Hierarchical Recursive Adaptive Region Segmentation Algorithm

The algorithm settled upon for image segmentation in Imagina performs segmentation hierarchically. It relies on the Color Mapping representation to provide a description of an input image at different levels of resolution. The Color Mapping is segmented recursively, with the segmentation determined for a given level propagating to the level below. The final segmentation is then applied backwards to the original image layout. In this discussion, the 'highest level' referrs to the level of the Color Mapping which is the smallest, containing only 4 points, and the 'lowest level' referrs to the level of highest resolution of the Color Mapping. The point at a higher level whose value is the average of four points at a lower level is called the 'parent', and the four points the 'children'.

The algorithm starts at the highest level of the Color Mapping representation, by assigning all points which are similar by a given metric to the same region. Up to four regions can be initiated at this step, which can happen if all of the starting points are dissimilar from each other.

The iteration is performed in two parts, along with several performance optimizations which will go unmentioned. The labelling at a given level propagates downwards to the next lower level by having the four pixels which are represented by a single pixel at a higher level be considered for inclusion into the same region that the higher level pixel is a part of. This is shown in Figure 6-6.

Because the average against which points are compared against is the global average of the region to which the parent point has been assigned, the algorithm is an adaptive algorithm. Although the mean of the regions can change between levels due to the variation of the points included in the region, the variation is not performed locally at each point inclusion, as would be the case in a progressive averaging algorithm.

After the labellings are propagated, some points at the lower level will be left unassigned. These

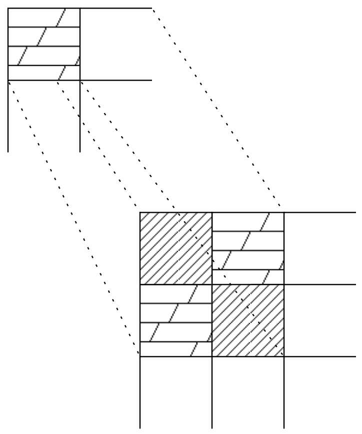


Figure 6-6: The propagation of labellings from the top level downwards. The four points which are represented by one point at a higher level are considered for inclusion into the same region as their parent. The similarity is measured against the average of the region to which their parent belongs, not to a local average, such as the parent's value.

points are either joined with other unassigned neighbors to which they are similar into a new region, or are assigned their own individual region label.

Lastly, the entire image array at the given level is passed through, and every neighboring pair of regions is compared for similarity. If they are sufficiently similar, the two regions are joined into one. This step guarantees that regions that are elongated and therefore not visible at higher levels are nevertheless found and joined into one at some level.

This algorithm also needs a cutoff value for determining point similarity. It also requires a cutoff value for determining region similarity. Although intuitively it would seem that the region similarity should have a higher cutoff, performance improves for cutoff values which are approximately equal for both region and point similarity determinations. This algorithm, however, provides usable segmentations over a large range of cutoff values.

6.5.1 The Algorithm as a Feedback Approximation

This algorithm is an approximation of a multi-level algorithm with feedback, which would assign labels at each level individually, and attempt to 'convince' adjacent levels of the reliability of the labelling. Initially, the labels could be arrived at randomly as much as from local information. If the labellings are random, then the four points at a lower level are unlikely to be coordinated enough to influence the labelling at a higher level. This can happen reliably only if the information

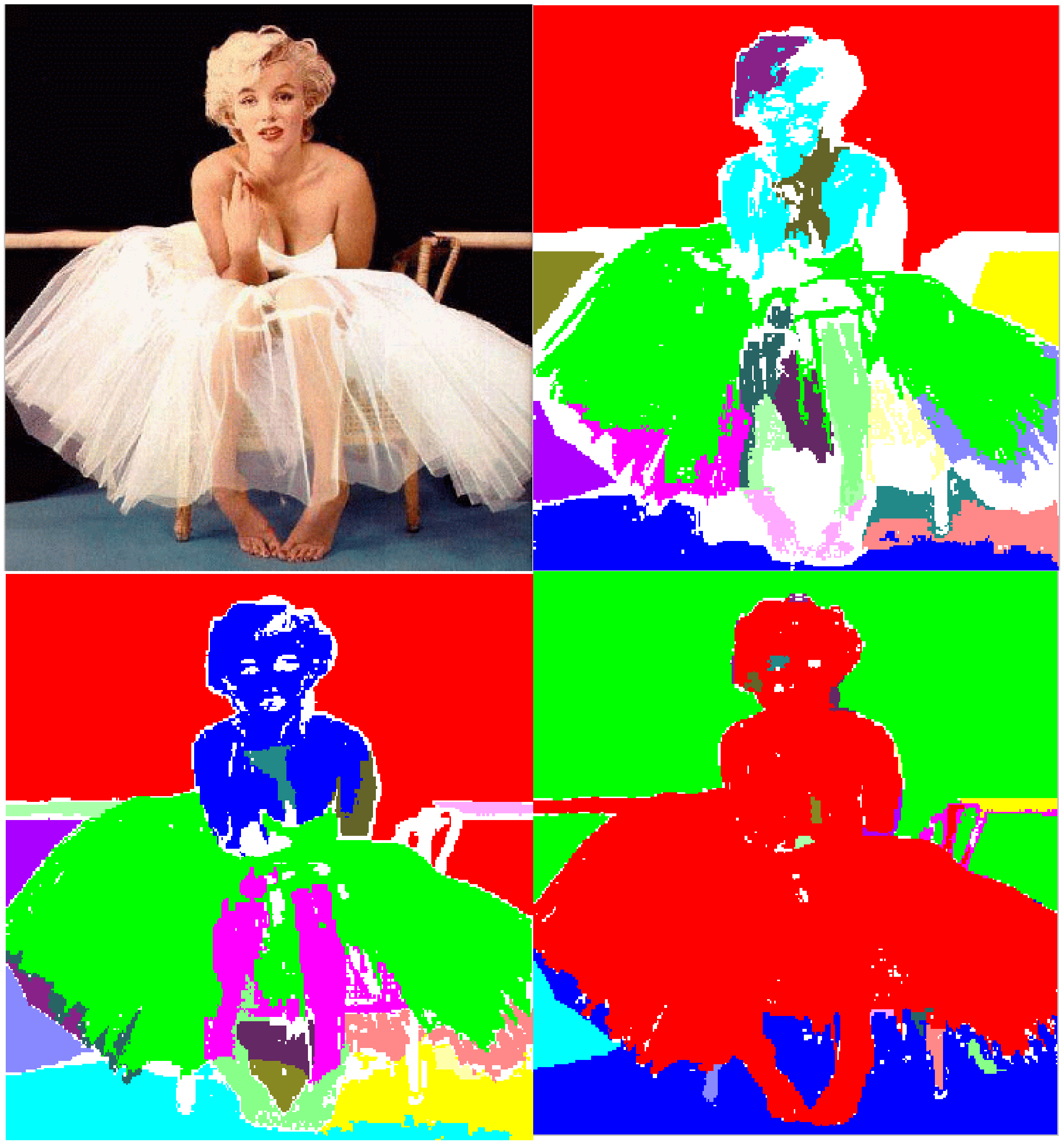


Figure 6-7: The algorithm applied to the same image previously segmented with the *Grow* algorithms. The segmentations shown use cutoffs of 0.94, for the one next to the original image, 0.90, for the one below, and 0.80 for the third segmentation. The segmentation using a cutoff of 0.90 is the segmentation which the Imagina system defaults to upon loading this image. The color labels displayed are simply color markers used to visually denote the twenty most populous regions which are segmented by the algorithm, and have no intrinsic meanings.

at both levels support the labelling. Thus, the information which is acquired locally is combined with information which propagates from other levels.

6.5.2 Extensions

The algorithm could be improved by applying statistical information to the combination of means. This can be done in two ways, either by considering the statistical reliability of the point values at high levels of the Color Mapping, and which therefore are averages over large regions of the image being segmented, or by considering the statistical reliability of the mean of a given region which has been created and whose mean may represent only a few or many points.

In the former case, the pixel similarity required for joining points into a region would be higher at a higher level of the Color Mapping than at a lower level. In the latter case, the pixel similarity required for joining points into a region would be very low for regions containing only a few points. However, as the regions would grow beyond a handful of points, the cutoff similarity would increase. The difficulty with this approach is that some points may be included into a region without belonging into the region after the range of inclusion becomes limited.

Chapter 7

Boundary Edge Extraction

There is a boundary to men's passions when they act from feelings; but none when they are under the influence of imagination.

Edmund Burke

After an image has been segmented, it consists of a set of one or more regions. Each region is fully connected and contains pixels which are similar by some metric. The goal thus becomes to come up with a description for the shape of that region. Different shape descriptors are possible, all of which operate on a set of edges describing the boundary of a region. This chapter describes how these boundary edges can be extracted. The geometric descriptors that build upon these edges will be the topic of the next chapter.

The edge extraction methods developed here assume an input region which is fully connected. Moreover, its robustness relies on the input region being full. If holes are present, they can be filled as a preprocessing step to edge extraction. The goal of the edge extraction step is to construct a connected set of edges that describes the boundary. This edge description can then be used to compare region boundaries by different methods, as described in chapter 8.

The purpose of edge extraction is to take the set of unordered points that form a region, and construct a more meaningful representation that describes the region. From a pixel-based representation, we would like to go to an edge-based representation. It is easier to compute with edges, since they compress the information contained within the set of input pixels to a more manageable form.

Edges are certainly only an approximation to the set of raw pixels. However, such a loss of detail is inevitable when a processing step abstracts away from the raw image data. When constructing the edge representation we introduce a bias to the information contained in the raw pixels due to our choice of a particular algorithm to find the edges. However, finding the edges distances us from the raw pixel information and brings us closer to an abstract representation of an object.

7.1 Prior work

The edge extraction is a geometric processing step. Its purpose is to take a set of pixels, and turn them into a more meaningful edge representation. Previous work comes from the computational geometry community.

7.1.1 The *Crust* Algorithm

In computational geometry, a solution to a harder and more general problem has recently been proposed. Amenta, Bern and Kamvysselis [1] published an algorithm that finds the shape of an object in three dimensions from sample points in its boundary. The algorithm is based on the Voronoi diagram of a shape to find an approximation of the medial axis of the shape (see figure 7-1). Based on that medial axis, the algorithm connects neighboring points that do not cross the medial axis, the exterior of the object, its "crust". This algorithm is simple, fast and robust, and it reconstructs a provably correct linear approximation of a shape that meets the sampling criterion. Moreover, it only needs a set of unordered points to work upon.

To use the Crust algorithm, however, a preprocessing step is required on the points of the image region in question, that finds all the points on the boundary of the shape. The next section presents an algorithm for finding those points on the boundary. Section 7.3 goes a step further by using the extra knowledge that we have of where the inside of the region is, and reconstructs the boundary edges directly, without use of the Crust algorithm.

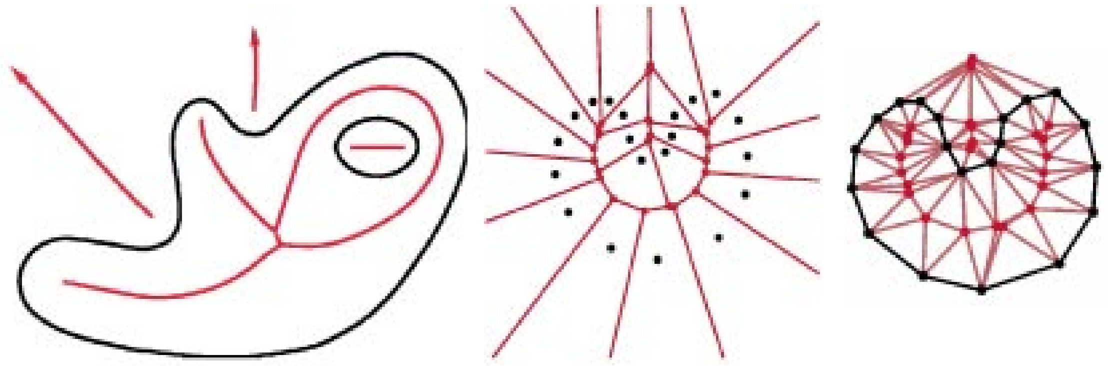


Figure 7-1: Two-dimensional *Crust* Algorithm. Left: The medial axis (in red) of a figure is the set of all centers of circles inscibed in the figure and touching its boundary in at least two points. Middle: The Voronoi centers (red points) approximate the medial axis. Right: Joining the nearest neighbors without crossing the medial axis gives an approximation to the shape.

7.2 Pixel-Based Boundary Extraction

Several straightforward approaches exist which allow the determination of the boundary of a region after it has been segmented from the image. These are all based on processing the region on a pixel-by-pixel level. Although these methods are easy to implement, they run into difficulties with noise and special cases.

The simplest way to find the boundary of a region is to pass a window of 3 by 3 pixels over the image, and label any center of the window as part of the boundary if the center is part of the region and any other pixel in the current window is not part of the region. The resulting set of pixels can then be sorted and connected, or walked over in a method which can detect loops.

Another approach to this problem is to circle the boundary of the region starting from a point which is known to be on the boundary. Such a point can be found based on the center of mass of the region. Given that the region is fully connected, that is, every pixel is reachable from every other pixel within the region by passing through only region pixels, some pixel must have the same x or y coordinate as the center of mass. Checking all y or x values along either of these coordinate values, respectively, will yield a pixel location.

This starting position can be picked to be either on a left or a right edge of the region, by either starting from the left or the right of the center of mass location. The direction of movement is always forward with the region on the right; thus, starting on a left edge the direction of movement

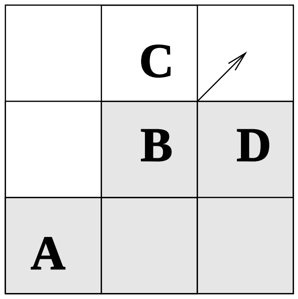


Figure 7-2: The local pixel-based boundary growing algorithm. Pixels within the region are shaded, while pixels outside of the region are not. The current position is at **B**, and the current direction is shown by the arrow. **C** is the first position considered for the next step, and **D** is the next position to which the algorithm will step to.

is upward, and on the right edge it is downwards. Based on the starting position and direction, the current position is iteratively updated by stepping one pixel into the current direction.

Before stepping forward, however, the current direction has to be updated. It is tentatively turned leftward by 45 degrees. The positions around the current pixels are then iteratively attempted, going in order in a clockwise fashion around the pixel. This step is shown in Figure 7-2. The position is then updated again, with the direction of this pixel from the current location. The previous position is always the position in the opposite direction of the current direction. The next position is always a pixel within the region whose boundary is being determined. The direction at the end of a step is always in the direction of the next pixel to be considered.

In most cases, this method will succeed in describing the region boundary. This method, however, has several downfalls. Noise affects the boundary which is returned greatly. Single-pixel connections between parts of a region also cause problems, requiring constant back-stepping and a renewed attempt at edgewalking from a previously saved position. Although the base implementation is trivial, a fully correct implementation can become very complex.

The single advantage of this approach is that it provides a complete description of a region boundary. From the list of pixels, any desired boundary description can be defined, because none of the information, or noise, has been removed.

7.3 Window-Based Boundary Extraction

The fact that the shape is filled to go a step further than the previous boundary walker, and construct a new edge extraction algorithm. This algorithm considers a larger neighborhood of points at each iteration, and guesses a boundary edge for each such window of computation.

Increasing the window size improves the reliability of the algorithm, as well as its robustness against noise. Moreover, instead of points on the boundary, this algorithm constructs directly boundary edges, so no postprocessing step is necessary.

At each step, the center of mass is computed for the 'inside' and 'outside' points within a window of pixels. This information is then used to deduce the outer edge of the region being segmented, as well as the direction of this edge. Edges are then combined into a perimeter, which is then smoothed to remove multiple edges which are neighbors and nearly parallel.

Although the construction of the algorithm is serial, it can be easily parallelized by placing the processing window as a filter over every location of the image, and getting boundary edge aproximations for each of window. Multiple scales can be run in parallel, and the different layers can then converge into a single multiscale boundary determination. The edge smoothing step, being an approximation of the weighted interaction of multiple levels of detail, would not be required in this case.

7.3.1 Algorithm Overview

The window-based boundary extraction algorithm finds tangents to the extracted region at different points around it, and then constructs a piece-wise linear description of it. The tangents are calculated on a window which contains at least one point of the region. Making the computation window size larger results in a less precise but more robust edge description. A smaller window size will pick out more detail, but will sometimes overfit a shape, by describing the noise which results from the imperfections of the color segmentation phase.

The more tangents that are taken on the boundary, the more correct the description can be. However, computation will be wasted for possibly similar nearby tangents and redundant information. Similarly, a description can include hundreds of edges, or simply a few dozens. Nearby small edges can be combined into larger ones if their slopes are similar. Again, the tradeoff exists between the precision of many but almost identical edges, and fewer larger but less precise edges in terms of the noise robustness and processing time cost.

7.3.2 Serialized vs. Parallel Algorithm

The algorithm described is implemented as a serial algorithm, for simplicity and efficiency on a single-processor machine. The parallel algorithm requires much more computation overall, but drastically reduces the computation required of any single processor. In the parallel version, every processor is responsible for finding a single tangent at a single location for a single window size. In the serial algorithm, one tangent is found at a time, for a particular location and a particular window size. To optimize the algorithm the direction and position computed for one tangent are used to determine a good placement for the next window of computation. In a parallel version of the algorithm, several window sizes would be applied independently at each image location. We will not describe further the parallel algorithm. Instead, we will concentrate instead on the actual implementation of its serialized counterpart.

7.3.3 Computation within a Window

Within each window we calculate the center of mass of the points belonging to the region, and the center of mass of the points outside of the region. The perpendicular bisector of the segment joining the two centers gives the direction of the edge. The relative sizes of the 'inner' and 'outer' regions within the window give the position of the edge. Moreover since we know which center represents the inside and which the outside of the region, we can construct directed edges for the boundary.

Choosing the window size

The window size is an important parameter for the algorithm to work. If a shape is large and free of holes, then a large window size works most of the time. The few times a large window size is inadequate is when the region has sharp corners, where a smaller window size is needed. A smaller window size can be chosen for objects that contain narrow parts, such as the picture of a hand with fingers spread. When the region is thinner than the window size, the window size should be reduced.

Increasing the window size

When the center of processing is either too far in the region and there are no outside pixels within the window size, or when it is too far outside the picture and there are no region pixels within the window size, then there is no information on how to proceed. The tangent cannot be calculated

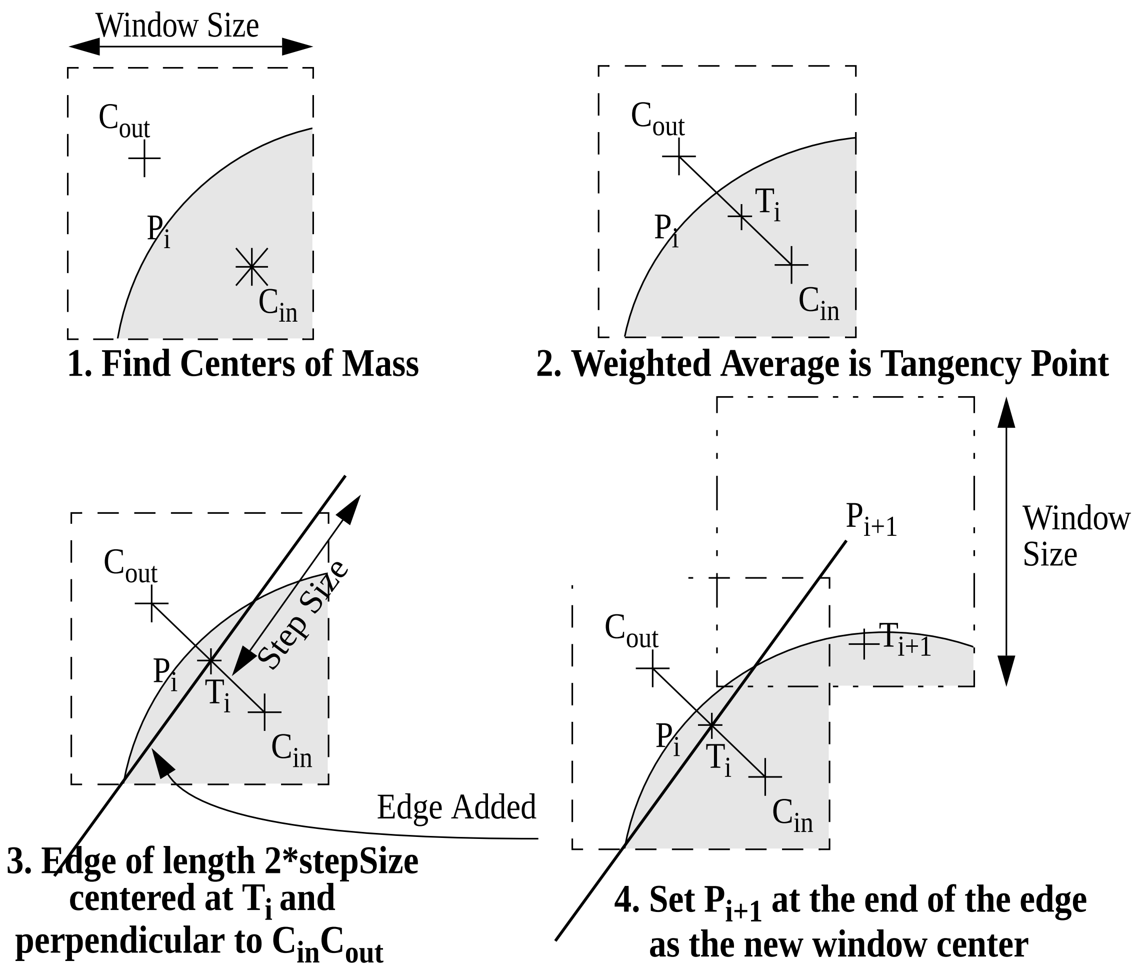


Figure 7-3: The Edges Boundary Extraction Algorithm finds an approximation to an edge within a window of computation. It calculates the center of mass C_{in} of the points belonging in the region and the center of mass C_{out} of the poitns belonging to the outside of the region within the window of computation. It uses the number of points belonging to the inside and the outside to calculate a weighted average of C_{in} and C_{out}, that will serve as an approximation to the tangent point to the region's boundary. A tangent direction is calculated to be parallel to the perpendicular bisector of $C_{in}C_{out}$. Finally, a new window center is calculated by moving along the tangent.

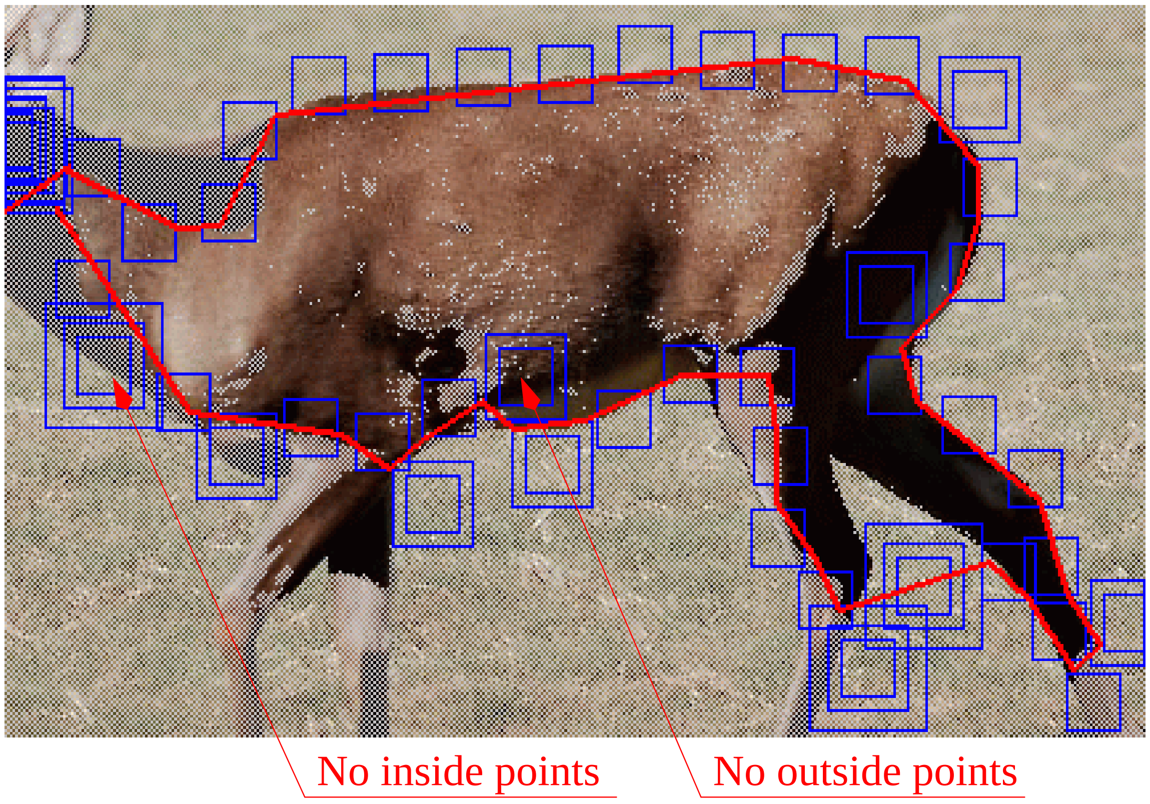


Figure 7-4: Increasing the window size: When there is not enough information within a window for calculating an edge, the window size is increased until enough information is present. This figure exhibits two cases where this situation arises. Where there are no inside points or there are no outside points, the window doesn't have enough information to place an edge, since only one center of mass can be calculated. A more subtle case arises when the two centers of mass coincide, not shown in the figure.

and the progression is stuck. In that case, a simple solution is to increase the window size until both inside and outside points are included with the window of computation. Once the boundary is found again, the window size can be restored at the next step. Another case when there is not enough information to determine an edge is when the inside and outside centers coincide. In that

Placing the window of processing

As described above, in a parallel algorithm where large numbers of parallel resources are available, a window can be placed at every point in the image and obtain a lot of tangents that can be joined to construct an object.

On a single processor, we should limit the number of such computations. Therefore, a window is placed only at points on the contour of the region, where part of the window contains pixels inside the region, and part of the window contains outside points.

The first window is placed by simply following a line from the outmost point of the image towards the center of mass of the region. When a pixel belonging to the region is encountered, the center of the window is placed.

Once a tangent has been found within the current window, subsequent windows are centered by moving along the direction specified by the tangent. The process is then repeated until the edges have gone full circle returning to the initial starting point, or until a certain maximum number of iterations is reached.

Step Size vs. Window Size

To determine how far to move on the direction of the tangent before placing the center of a new window of processing, we use one more parameter, the *step size*, which determines the absolute distance between two consecutive window centers.

The two notions of window size and step size are related but not the same. The window size determines how many pixels are going to be used for the computation of a particular tangent. The step size determines how many tangents are going to be computed. Together, they determine how much computation will be spent on extracting the edges of a particular region.

Several groupings of window and step sizes can be considered:

- With a large window size and a small step size, many certain steps are taken in going around the region. This method is going to ignore noise, as well as detail on the shape boundary.

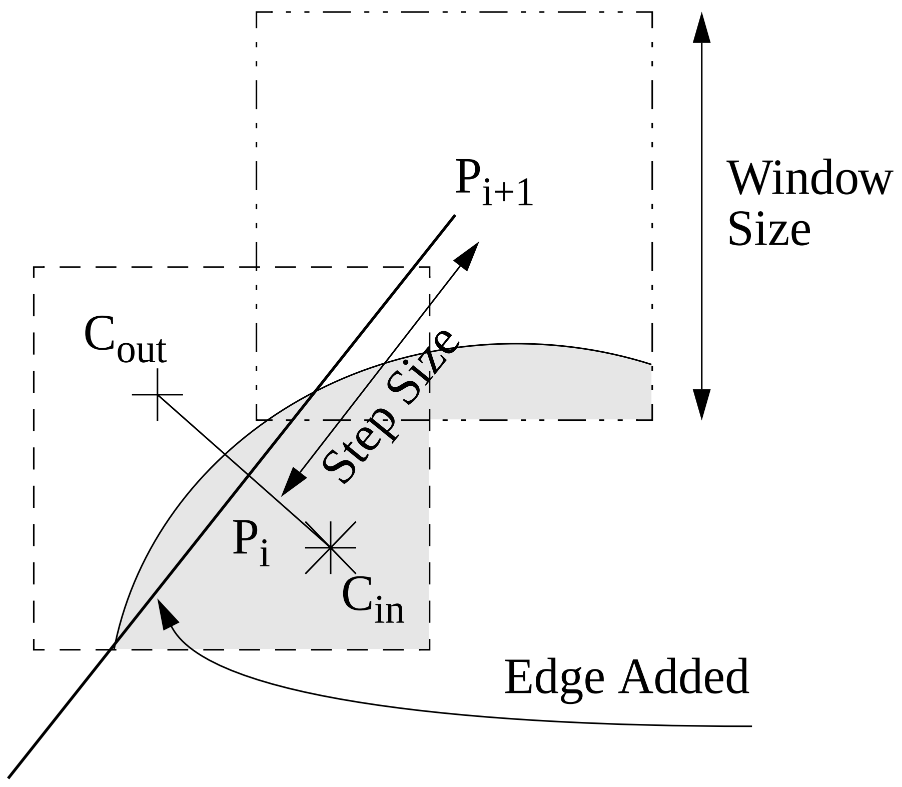


Figure 7-5: The difference between window size and step size. The window size determines how much computation is performed at every iteration. The step size determines the frequency of sampling around the boundary.

This is the most expensive computation.

- With a small window size and a small step size, the algorithm will pick out the most details, but also be prone to error.
- With a small window size and a large step size, the algorithm will be very likely to overshoot because of a small deviation in the boundary. It will be misled by little twitches in the region boundary which could be due to noise.
- With a large window size and a large step size, the algorithm will find few edges, but each of them will have enough information to make a noise-tolerant decision on what the boundary position and orientation are. By ignoring noise though, this method also ignores possibly useful detail.

There is no golden rule on how to make these value choices. Most certainly the same region will need different window sizes at different parts of its boundary. A simple way to achieve this effect is to have a default window size corresponding to the desired level of detail, and changing that window size as the conditions around the region change. When only inside or only outside points are found within the window, the window size should be increased. When either the inside points or the outside points fail to form a connected subregion within the window, the window size should be reduced after moving the center closer to the boundary.

7.3.4 Determining a tangent

Once the window has been placed and the window size has been chosen, we can compute a tangent for the region boundary at that part of the image. The direction of the tangent, along with the position of the region boundary, together determine a straight line where an edge will lie. Using the step size we can set a length on that straight line, and thus determine an edge, whose midpoint is the point we found on the boundary.

Finding a direction for the tangent

Within the given window of computation, we would like to determine a single edge. To do so, we need a direction and a midpoint. The optimal direction is tangential to the region. This tangent is perpendicular to a vector that is easy to approximate.

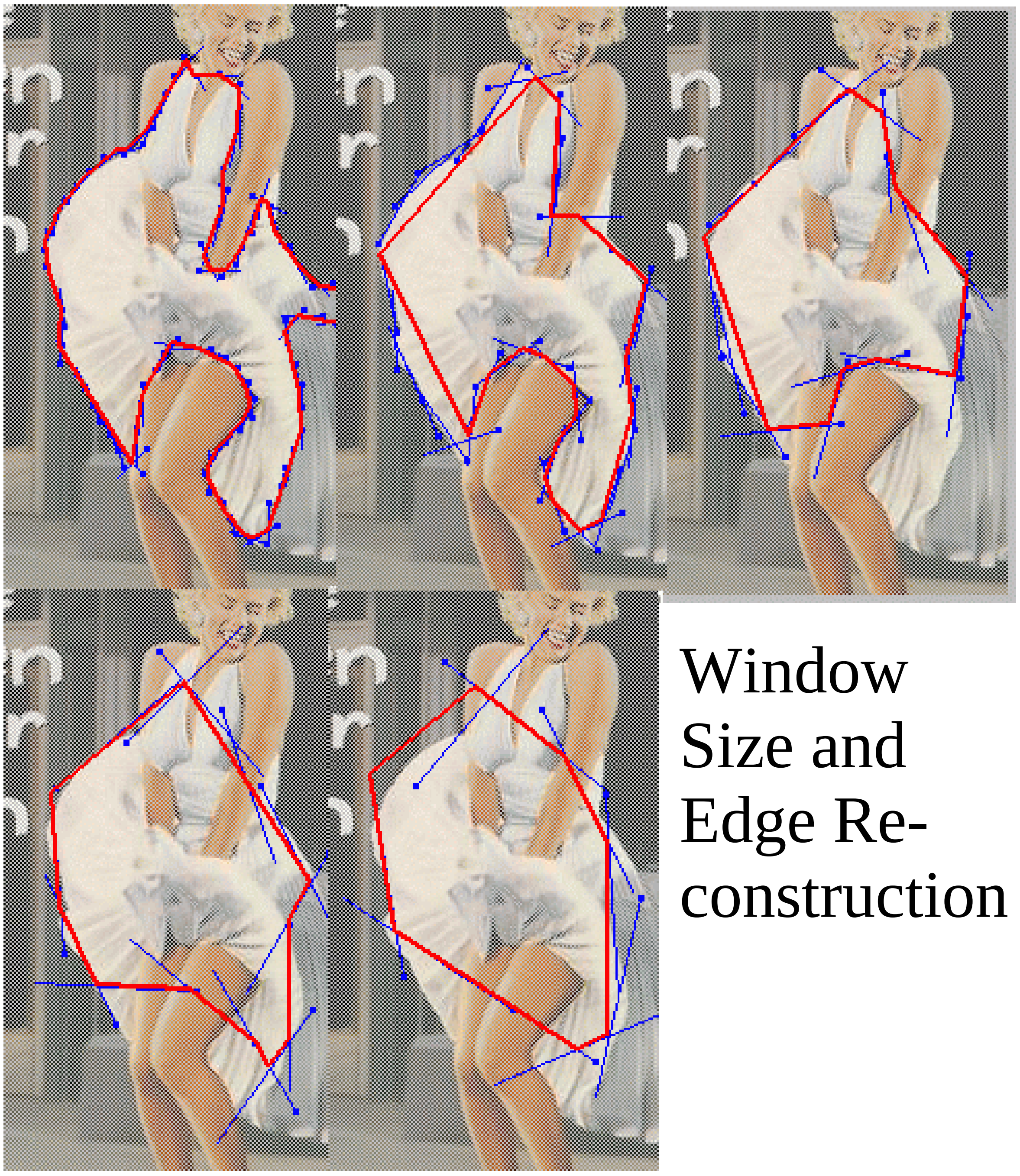


Figure 7-6: Decreasing the level of detail. A higher window size causes a greater tolerance to noise, and provides a rough estimate of the shape. A smaller window size allows more attention to detail, but also generates lengthier representations that might be harder to work with and might be overfitting noise from the segmentation.

We can compute the center of mass C_{in} of the points inside the region, and the center of mass C_{out} of the points outside the region. The vector $\overrightarrow{C_{in}C_{out}}$ is a good approximation for the normal to the boundary within the window. The direction of the tangent is simply perpendicular to that vector.

Finding a point on the boundary

Now we have to find a point on the approximated boundary between the inside and outside points. One way of finding such a point would be to move on the line that connects C_{out} to C_{in} until a point in the region is found. This method is inadequate because it will trust a single pixel of the region which could be the result of noise. More importantly though, it is inadequate because it goes against the spirit of approximation that the window method was developed in. We are really not looking for a perfect tangent to the region. We are looking instead for an edge representative of the region boundary in the particular window of computation. Therefore, instead of relying on individual pixels, we rely again on the two representative points that we found.

Since C_{out} is a representative of the outside of the image, and C_{in} is a representative of the inside of the image, the boundary should lie somewhere between the two. We could choose the middle of the segment joining the two centers, but we can do a little better than that. We can weight this average of C_{in} and C_{out} by the number of pixels belonging to each region. Thus, we can a formula for T_i, an approximation for the boundary point.

$$T_i = (C_{in_i} * Numpoints_{in} + C_{out_i} * Numpoints_{out})/(Numpoints_{in} + Numpoints_{out}) \tag{7.1}$$

Adding an Edge to the set of edges

Once a direction and a boundary point is set, we simply add an edge to the set of edges, centered at the boundary point with a length of $2 * stepsize$. Since the next center will be $stepsize$ away, such a length is a good choice for a representative edge. The length of the edge is not that important since an edge's endpoints will later be extended or brought closer until the intersections with the two neighboring edges.

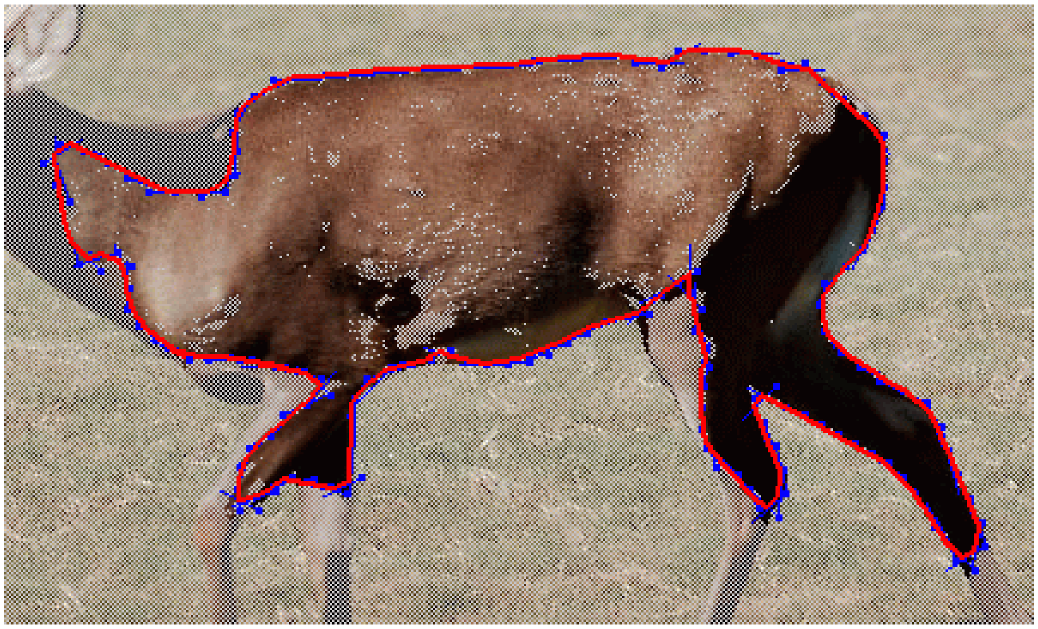


Figure 7-7: The complete boundary at the highest level of detail. A moderate window size and a small step size pick out the most detail from the shape

7.3.5 Post-processing on the Edges Found

Once those edges have been added, they undergo two stages of postprocessing before they can be passed on to the next stage that will use them to construct shape descriptors. This post-processing gets rid of the useless tips of intersecting edges, and compresses the representation by combining small consecutive edges that have similar slopes into larger edges.

Intersecting the Edges

The edge intersection is easy, since by applying a sequential algorithm the edges are already ordered by circling around the region. In the parallel form of the algorithm one would have to determine which edge to intersect with which other edge. In the serial case however, the choice is obvious. We simply set the endpoint of edge i to the intersection of edges i and $i+1$, and the starting point of edge $i+1$ to that same intersection.

A complication arises when the two edges are nearly parallel. In that case the intersection falls too far out, and setting the endpoints to meet at infinity might not be the right decision to make. Therefore, we constrain the intersection of two edges to fall within the bounding box surrounding the two edges. If the intersection falls outside that bounding box, then the midpoints of the two endpoints to be modified is chosen as the new value for both endpoints. After this step, the region is surrounded by a piecewise linear continuous set of edges.

Joining similar edges

Once the edge endpoints are made continuous, that is once the end of one is the beginning of the next, a compression step can be carried out. One can make the edge representation of a region more compact by replacing small consecutive edges by larger ones if the small edges are nearly parallel.

This step is not a fundamental part of the algorithm, but can reduce the number of edges in the representation by a large factor. In our tests, tenfold reductions of the number of edges is not uncommon. The resulting loss in detail is negligible when compared to the much smaller number of edges.

One more parameter, *cosineCutoff*, specifies when two consecutive edges should be joined. The joining is simply based on the angle between the two edges, and never on the length of either edge. If the cosine of the angle between the two consecutive edges is larger than cosineCutoff, the two edges are joined.

When two edges are joined, the begin point of the first and the end point of the second are kept unmodified. A larger edge with those endpoints is created and replaces the previous two. Begin and end point can be determined simply since edges are oriented, circling the region counter-clockwise.

A simple version of the algorithm can be made serial, going around the region, and combining every similar edge with a progressively growing first edge. The disadvantages of this method is that first, it can't be implemented on a multiprocessors, and second, its result will depend on the order in which we circle around the region. Moreover, this version will have a tendency to growing some edges more than others, resulting in an unbalanced description.

Instead, we implemented an algorithm that is more easily ported on a multiprocessor. It compares neighboring edges two by two and combines similar ones into larger edges. It then compares the combinations two by two, and again combines similar ones. This hierarchical method has the advantage of being independent of starting point or direction of rotation. It has the advantage of being easily implementable on a multiprocessor. Finally, it has the advantage of generating progressively less precise descriptions of the object, that can be used for matching at different levels of detail.

Independent of the algorithm that implements it, the step of combining similar edges into larger ones has the advantage of making the final description less dependent on the step size. Therefore, a smaller step size will pick out more detail if it's available, but will represent large straight sides compactly, by replacing them with a single edge. The step size can therefore be made smaller without risking cumbersome descriptions and having to later match a very large number of edges.

7.3.6 Improvements and Extensions

Several extensions are possible to this algorithm. The first two are elaborations on the current processing methodology. The last two provide a different way of thinking about the algorithm and change its function in general.

Decreasing the window size

The major flaw of the current algorithm is that it doesn't have a way of detecting when the window size is too big. A simple way to get around this problem is to always start with a small window size, and augment it as needed. However, for completeness we could extend the algorithm to detect when the window size is inappropriately big for the shape to be extracted. This situation arises when the window contains more than one surfaces of the region. This is the case in crevaces in the figure, where the full detail of a crevace will rarily be explored. This situation arises also in thin objects, that cut diagonally through the window size. In both of the above cases, the averaging will not yield an appropriate measure of the boundary edge position. One way of dealing with this problem is to draw a line between the outside center and the inside center, and obseve how many times the line crosses a boundary of the region. If this number is higher than one, then clearly the shape is a stripe through the window, and the window size must be reduced. The new smaller window must be centered closer to the surface otherwise it might not include any region pixels, in which case its size would have to be increased once more. To move the center closer to the region, one can simply follow the line from the outside center to the inside center and set the new center where the line intersects the region.

Changing the Shape of the Window

Another simple fix is to change the window size to be more rounded than the square currently used. A square is certainly easy to deal with, but it doesn't give equal importance to all points at the same distance from the center of computation. It will consider points along the diagonal that are further away than points along the vertical and horizontal axis. Along with considering a circle as shape of the window of computation, we can furthermore change the absolute cutoff of the window size for considering pixels in the computation. Instead we could assign an importance metric to each pixel, depending on its distance from the center of computation, and calculate a weighted average instead of an unweighted one on the pixels of the fuzzy region.

A novel similarity metric for region membership

Moreover, instead of having a discreet value that is either zero or one, one can assign a floating point number that can take all values in between. The labels would thus be replaced with a computation every time the pixel is accessed, that evaluates a similarity metric between the pixel being currently processed, and the average of the region it belongs to. This similarity metric can be based solely on color, texture, shadowing, or other criteria. It should return a value between 0 and 1 however, where 1 means the pixel belongs without doubt to the region, 0 means the pixels definitely doesn't belong to the region, with all possible values of certainty between the two.

When the centers of mass of the window are being computed, certain pixels will only contribute partly to the calculation, instead of either belonging or not belonging to the region, thus achieving a greater precision in the calculation. This extension in fact would make the region extraction step obsolete. The edge extraction algorithm could be directly applied to the raw image pixels. To determine the average color of a region however, a filter must be applied to the image to find patches of similar colors. This would be a much simpler form of the current segmentation mechanism described in chapter 6. However, since the segmentation functionality is already provided both globally and locally with the grow algorithms, no such extension of the algorithm was implemented.

Multiple Levels

Finally, instead of inheriting the window size from the system surrounding it, the edges extraction algorithm could operate itself at multiple levels. This extension is closer to the biological approach, where parallel computation is used to distribute load from a single serial processor. When using multiple levels, higher levels, which have larger window sizes, can reinforce the lower levels, which have smaller window sizes. By using this combined information, edge smoothing and even region extraction can be performed in parallel across an image. This process is also fully parallelizable. This approach then becomes similar to filtering, which is described in chapter 5.

7.4 Conclusions

This chapter presented a new algorithm for extracting the edges from a region. The algorithm assumes we have labelled the inside and the outside of the region whose boundary is sought. If these labels are not present, then a pixel-based metric such as color similarity must be used to determine if a pixel belongs to the region or not.

The algorithm presented uses a window-based approach to edge extraction which is both simple to implement, computationally cheap, and robust. Moreover, instead of complex mathematical operations, it uses simple averaging and estimation techniques which are feasible in a biological system. Finally, it can be implemented as a distributed algorithm.

The shortcoming of this algorithm is that it requires input parameters such as the window size, step size and the cosine cutoff for combining edges, that can cause changes in the output. These parameters could be combined within a single parameter determining the level of detail at which the edges should be extracted.

Chapter 8

Shape Representation and Region Matching

Thou com'st in such a questionable shape, That I will speak to thee.

William Shakespeare, Hamlet

The previous chapter described a way to extract boundary edges from an image region. This set of edges is the basis for the various shape descriptors we use. From the same set of boundary edges, different representations are constructed. Each emphasizes a different criterion one can use in comparing two shapes. Those criteria of comparison are area overlap, relative edge positions, orientation of edge normals, and the number and size of protrusions. These four ways of describing shape will be the topic of this chapter.

8.1 Literature on Shape Descriptors

Shape description is a fundamental problem faced in image retrieval, as well as vision and graphics. From each of these fields, we have chosen a representative example that influenced us in our approach to shape description.

8.1.1 Image Retrieval and Shape Description

Previous work on descriptors for image retrieval includes mostly global processing of pixel positions and wavelets. Shape is rarely discussed. In fact, shape is mostly unused in image retrieval systems.

The exception is probably BlobWorld [5], in which generalized ellipses are used to represent shape. This method can be though of as a series of ellipses superimposed adding or subtracting detail to the shape. The first ellipse gives a rough estimate of the shape, mostly of its orientation. Subsequent ellipses add more detail.

Generalized ellipses are a very successful shape descriptor. They provide noise tolerance when few ellipses are used. Moreover, they provide incremental addition of detail, which can make comparison more efficient, by pruning bad matches early in the search tree. We hope to integrate in the future an algorithm based on generalized ellipses as one of our shape descriptors in Imagina. At this stage, we mostly experimented with four new shape descriptors.

8.1.2 Vision and Shape Description

Shape description has been largely discussed in the computer vision literature. We won't review here the various approaches here. We are mostly interested in representations that provide multiple resolutions. The most noteworthy example of such a representation is [38], that uses hyperbolic evolution of shape to create a hierarchy of shape features. The shape simplification that occurs is analogous to viewing an object from various distances. A follow-up paper [37] uses this idea for shape matching, and results in a language for describing shape. The base of the description closely matches the medial axis of a shape, the locus of all centers of spheres inscribed in a figure that touch exactly three points in the boundary.

8.1.3 Graphics and Shape Description

The computer graphics problem that inspired us the most for shape representation is that of morphing. Morphing is the procedure of transforming one shape into another in a continuous progression. If we have a way of assigning a cost to a particular morph between a source shape and a target shape, then we can use that metric to evaluate shape similarity. The best match between two shapes will be the one which has the least morphing cost.

The problem with most current morphing techniques is that the task of finding edges in the picture, and matching source and target shapes is left to the user. This is a reasonable thing to do if the goal of the system is to create a good looking morph. Our goal however is to distance the user from such low-level decision on where edges arise and how they are transformed. We already have a way of extracting the edges. We now need a way to find how well the edges of one object match the edge of another.

Manolis Kamvysselis [18] proposed a novel technique for finding edge correspondences in morphing convex shapes. This technique first maps the two shapes into their Extended Circular Images (ECI), and then does the morphing in the ECI space. A one-to-one mapping exists between convex shapes and their ECI representations. Hence, every intermediate ECI obtained can be transformed into the corresponding shape. The ECI space seems like a good for morphing where such a metric can be found, and the results obtained in morphing shapes in the ECI space are promising.

The ECI representation of a shape maps every edge to a weight on the unit circle (see figure 8-1). The angle of the edge normal determines the position where the weight will be placed on the unit circle, and the length of the edge determines the weight that will be placed there. Morphing can then be done by simply transforming the weights of the source to the weights of the target. In ECImorph, the transformation is simply an all-to-all mapping of weights based on an inverse exponential cost function taking into account both angle difference and weight difference.

What matters more to us is the overall cost of the morphing transformation, rather than the cost breakdown among individual edges. We are interested not in the way individual edges map to each other, or the particular matching algorithm found, but instead in finding a metric for an overall cost of transforming one shape into another. Such a morphing metric is the best candidate for a shape matching metric.

8.2 Shape Descriptors Used in Imagina

Since each representation is designed for comparison, the representation and the corresponding comparison method are best described jointly. This section will describe in detail each shape-based representation, its normalization metrics, and the comparison algorithm.

The different shape-based representations built on top of the boundary edges are:

- **Volume based representation:** Two regions are similar if they have a large number of common points when they are superimposed and adequately scaled.

- **Segment based representation:** Once aligned and scaled, two regions are similar if the

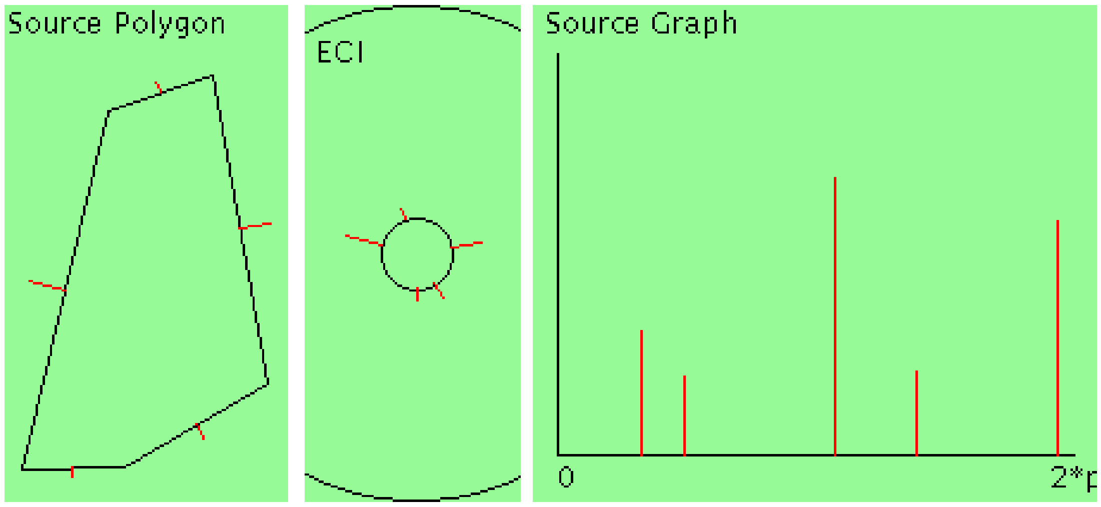


Figure 8-1: The Extended Circular Image (ECI) of a Convex Shape is constructed by mapping edges to weights on the unit circle. The left frame displays the original polygon along with the normals to the edges. The normal lengths are proportional to the lengths of the edges. The middle frame displays the weights on the unit sphere. The third frame displays a graph of the ECI weights obtained by unrolling the unit circle onto a flat axis.

segments making up the boundary of one are nearby those making up the boundary of the other, and vice-versa.

- **Angle based representation:** Once perimeters have been adjusted and the regions rotated, two regions are similar if for every angle between 0 and 2π, the edges with normals facing towards that angle have similar sums of lengths.

- **Protrusion based representation:** Two regions are similar if they have similar protrusions located at equivalent points around the convex inner perimeter of the shape.

Each representation has different applications and strong points. This chapter will describe the representations developed, the scaling and alignment metrics used, and the matching algorithms developed.

In the remainder of this section, we present a few simple region descriptors, based on different features of geometric shape. We use the boundary edges extracted at the previous processing step as the basis for these descriptions.

8.3 Volume Based Representation and Comparison

The simplest representation is simply that of the set of points that belong to the inside of region. Comparison is done by superimposing two scaled and aligned regions, and comparing the number of pixels in common to the total number of pixels.

8.3.1 Approximating the Inside Points

From the set of edges, one can find all the points inside the region by using common computer graphics techniques. However, such techniques are expensive, and moreover, we already have the pixel information from which the edges were constructed in the first place.

We need however to approximate the set of inside points to make the expensive computation of comparing every pixel in a region more feasible in an interactive query environment. The way we do that is by undersampling the picture. Instead of considering every single pixel, one can consider one pixel out of 4, one out of 16, and so on, with similar results. In fact our assumption that the shapes are filled gives us an easy argument that such a measure can be adequate without a need to sample every point. Our preprocessing step of filling the shapes guarantees that this assumption holds.

8.3.2 Scaling and Alignment

The shapes are scaled so that they have the same areas. Since the area overlap is used as the metric of comparison, unequal surface areas could bias the results towards thinking that a small area entirely included in a larger one matches perfectly with it. Similarly, a large area would always have a relatively small area of overlap with a smaller region entirely included within it. These two biases do not balance out, since each of them saturates the results in the entirety of the small region, in the case of complete containment. Scaling the two regions so that they have the same area gives the desired size invariance of the comparison.

The shapes to be compared must also be aligned for area of overlap to be a significant metric. The two regions are aligned so that their centers of gravity coincide. An alternative would be to align the bounding boxes of the two regions. However, the bounding box is a metric that depends only on the extremities of the region, rather than the entire inside of the region. Therefore, if a silhouette of a person with both hands extended to the right is matched with that of a person with only one hand extended, the result is going to be very dissimilar. If however the center of mass is used as an alignment position, these two shapes will be more rightfully judged more similar.

The shapes are not stretched, nor are they rotated. We believe that the aspect ratio of a shape is an important metric that should not be lost in scaling. Also, the angle based representation takes care of rotating the two shapes, so we did not want to take care of that concern here, especially since it would make a straightforward computation much more expensive.

8.3.3 Similarity Metric

Similarity can be measured in two ways. One way is to simply ignore the original color that was used in separating each shape, and return a value of 1 for every pixel in common, and a value of 0 for every pixel that is not in common. The sum is divided by the total number of pixels, and we have a similarity metric between 0 and 1. In this case, we are simply comparing areas of the two shapes.

Another way of comparison goes a step further by considering more degrees of membership to the region than 'inside' and 'outside'. For a region, the color similarity of every pixel to the average of the entire region in which it belongs can be used to determine a membership value that can be anywhere between 0 and 1, rather than just 0 or 1. The use of color here is different than the one in the color-based comparison. Color is not compared between the two regions. Color is instead used within each region to determine the degree of membership of a particular pixel to the overall regions that it represents.

If this similarity value between 0 and 1 is considered to be the thickness of the shape defined by each region, then the overlap between the two regions becomes the volume that the two aligned shapes have in common. It is therefore not a planar comparison of surface areas that this algorithm performs, but instead a comparison of volumes in two and a half dimensions, where the thickness is the similarity of the shapes, between 0 and 1.

8.3.4 Results

Figure 8-2 shows an example of a volume-based comparison on two images of the St. Louis Arch. If one considers the color histograms of the two images, they will appear very dissimilar, as is shown in figure 8-3. Having a shape-based comparison allows an robustness to lighting conditions when searching for a particular image.

Many current image retrieval systems that rely heavily upon color information will be less likely

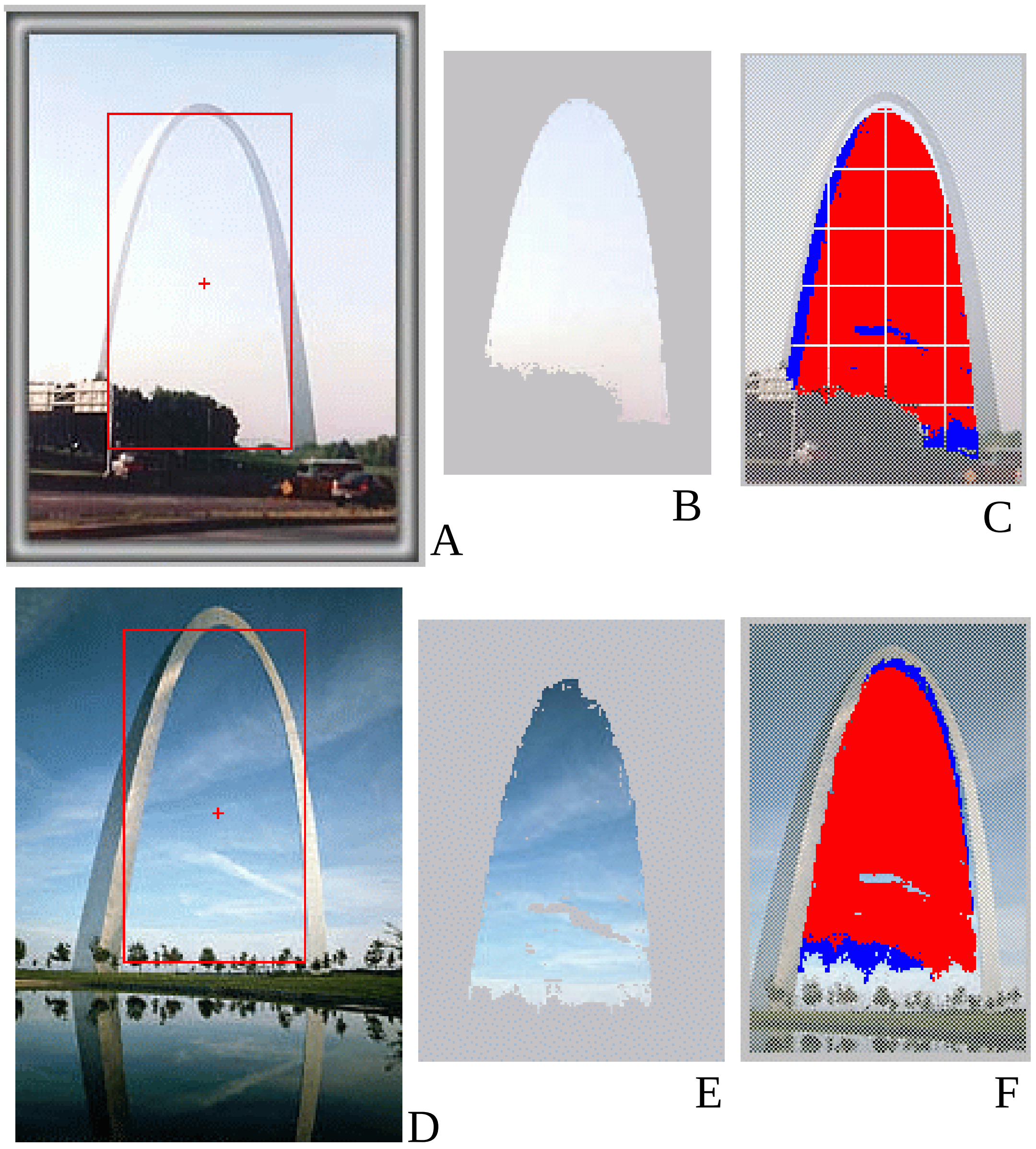


Figure 8-2: The Volume-Based Comparison. **A** shows the original image, along with the center of mass of the region's pixels and the bounding box around the selected region. **B** shows the pixels belonging to the region. **C** shows in blue the pixels in B that do not also belong to E and in red the pixels that B and E have in common . Similarly, F shows in blue the pixels that belong to E but not in B, and in red the pixels belonging to both B and E. The similarity metric returned is the number of pixels in common (red) over the total number of pixels (blue and red). The similarity metric returned for this match is 0.87.

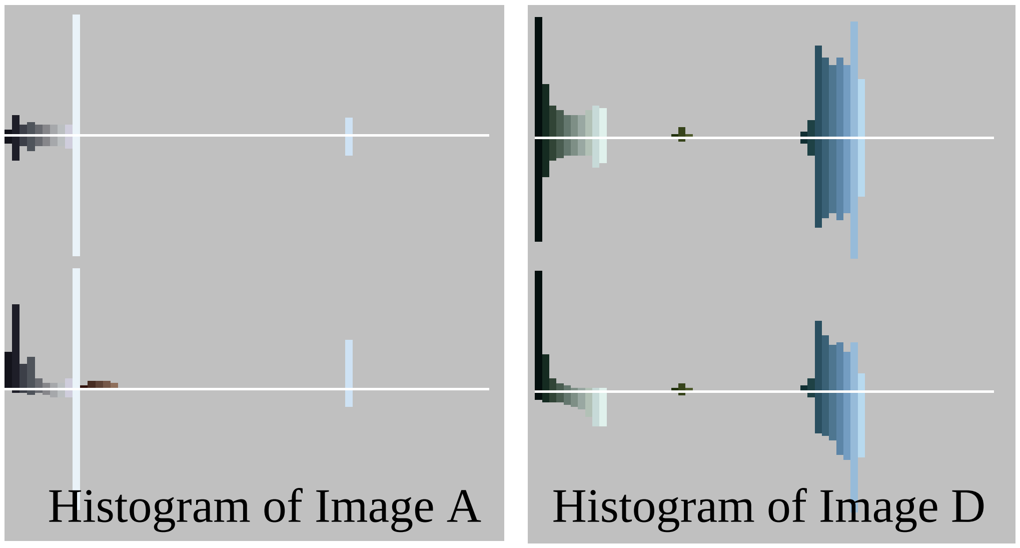


Figure 8-3: The color histograms of Images A and D have a similarity of only 0.19. The horizontal axis represents different color buckets, and the four vertical axes represent from top to bottom number of points in a bucket, standard devitation of Hue, standard devitation of Saturation, standard devitation of Value, in the HSV color space. Picture D spans the entire blue color bucket, while picture A contains primariliy one spike in a single tone of blue. Moreover, the shape of the distribution of grey in the two images doesn't match.

to find the match between these two images. This is demonstrated in the results returned by the Altavista Image Finder when picture A is used as the query to a similarity search. The best matches returned are displayed in figure C-3 in appendix C. The Virage engine for matching images does not seem to give any importance to shape in this example.

In Imagina, the shape of the region under the two arches is a salient feature to match, since it's large, uniform, and centered. It will be segmented as a single region, since the color under the arch is uniform. Its shape will then be matched to the shape of the corresponding region in the target picture, and a high similarity will be returned.

8.3.5 Shortcomings and Strong Points of a Volume Based Representation

This representation is best fit for matching regions that have roughly the same overall shape but whose boundary details may diverge. The strong point of it is a tolerance to noise created by holes in the image. Geometric representations will consider a shape with a hole as a topologically different object from the filled shape. Similarly, representations based on edges will tend to give more importance to high frequency changes in the region boundary, while a volume-based representation will be unperturbated.

The main disadvantage of this method is that it breaks when the alignment between two shapes is not adequate. This situation arises if the segmentation for one image assigns a larger portion of the image to a region on one side, and segmentation for the other image assigned a larger portion of the image on the other side. In that case , the two images will be misaligning, and the two shapes won't match. This situation arises too often for thin shapes, since their overlap can be reduced drastically with small misalignments.

An example where this representation breaks is the matching of Marylin to a drawing that will be our criterion for the rest of the representations.

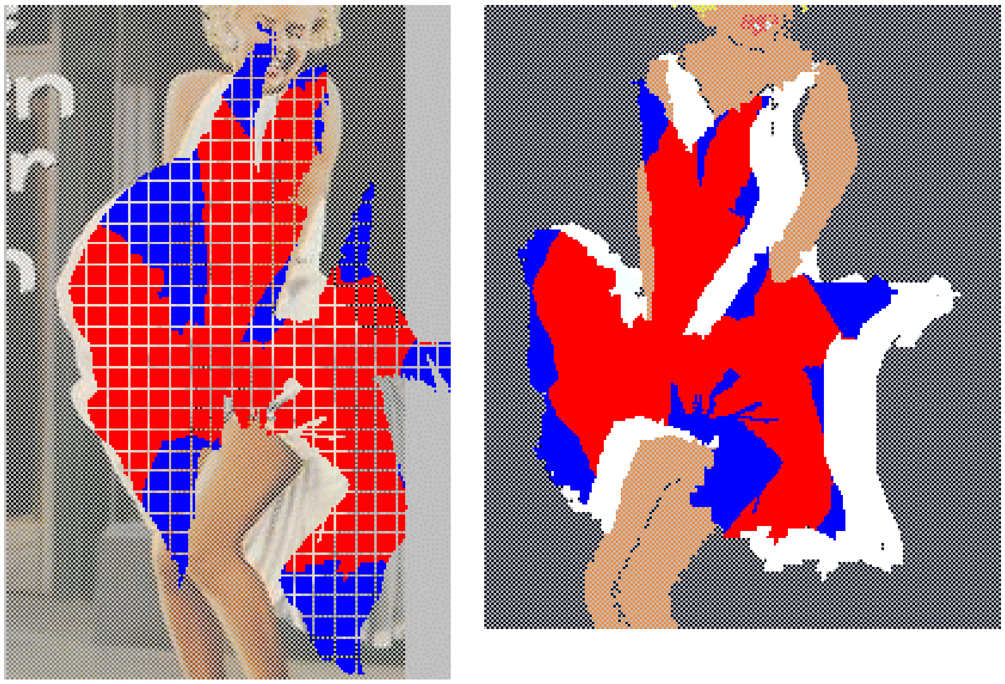


Figure 8-4: The Volume-Based Comparison breaks for figures with many details. For example, on the image on the right, even though the dress of Marilyn has the same overall shape, it is misaligned due to noise in the segmentation, and this causes the area of the hands to be miscounted.

8.4 Segment-Based Representation

The segments-based representation comes as an aswer to the fact that the volume based representation breaks for thin images. In the example of Marylin, when her hands are misaligned, the match suffers heavily. Finding a better alignment for the volume-based representation might be an asnwer, but again, small differences in angle that do not matter to the user will count heavily against a volume-based match.

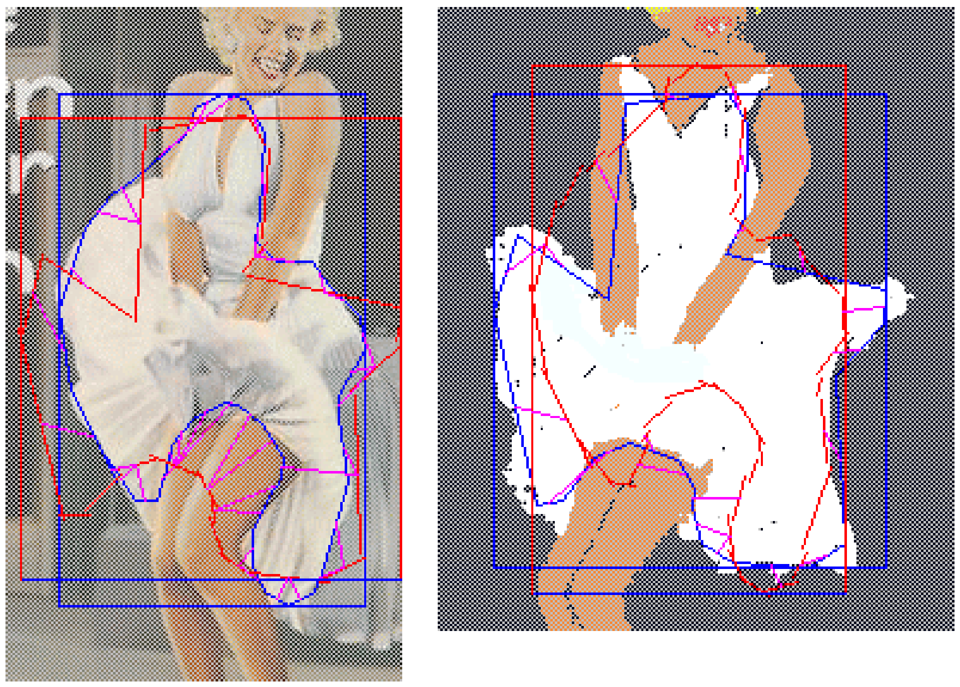


Figure 8-5: The Segments-Based Comparison. On the left, every edge on the original image is matched with its nearest edge in the query. Segments are drawn between the midpoints of the matched edges as a visual feedback. The sum of the lowest costs for every edge becomes the cost of mapping database edges to query edges. On the right, each query edge is matched with the best database edge. Similarly the cost of mapping the query to the database is computed. Together these two costs become the cost of transforming one shape to the other. The value obtained in this match is 0.94. Of course, this value alone is meaningless, since it will be normalized according to the distribution of all segment based matches, when the matches from different representations are combined.

The metric of similarity in the segments-based representation takes into account the proximity of the figure's boundary edges. Proximity is calculated on an edge by edge basis. The metric used is comparing two edges is based on coordinate proximity of the segments midpoints, angle similarity between the two normals of the edges considered, and the length ratio between the edges. These three metrics of every edge are combined in an overall cost of matching one edge with another. The cost and the similarity are complementary of each other, and are both between 0 and 1. Their sum is always 1.

The aspect ratio of the regions is preserved, but the regions are scaled and aligned with each other. We believe aspect ratio is important in matching images, and the users have a good idea of the relative dimensions of a shape they are looking for. Moreover, the aspect ratio is often invariant between different pictures, although the pictures can be found in all sizes and alignments within a picture.

The two representations are scaled so that their bounding boxes have equal diagonals. The bounding box is used since this representation is based on boundary edges, hence if the boundary matches, the bounding boxes will be similar. The diagonal of the bounding boxes is used instead of the area, because it gives a more uniform rate of change with changing dimensions of the bounding box. That is, when one dimension becomes dominant, the diagonal does not vary geometrically, while the surface area would.

Finally, the two regions ar aligned so that the centers of their bounding boxes coincide. This metric is used instead of the center of mass which would not be meaningfull in a represenation based on boundary edges rather than volume. Moreover, by aligning the centers of the bounding boxes, this brings the edges closest to each other overall.

8.5 Angle Based Representation and the Extended Gaussian Image

Based on the work of Kamvysselis [?] described in section **??** we construct an angle-based representation for shapes that relies on the Extended Circular Image (ECI).

The difference from the original ECI representation lies in the creation of angle buckets that contain more than one angle value. By choosing the number of buckets, one can determine how precise the ECI representation will be made. This provides even at this representation level another metric for noise tolerance or attention to detail. Our experience shows that 20 buckets are adequate for matching most shapes. Fewer buckets give too coarse descriptions and more buckets tend to separate almost similar shapes.

The Angle-Based representation creates a number of buckets that contain different partitions of the angle space and goes around the edges, consecutively adding to each bucket the length of each edge belonging to the bucket.

Comparison is done at the bucket level, by simply measuring angle differences between nearby buckets and length added within each bucket. Comparison between angleBuckets with different number of buckets is disallowed, but can easily be extended by reprojecting and recalculating the

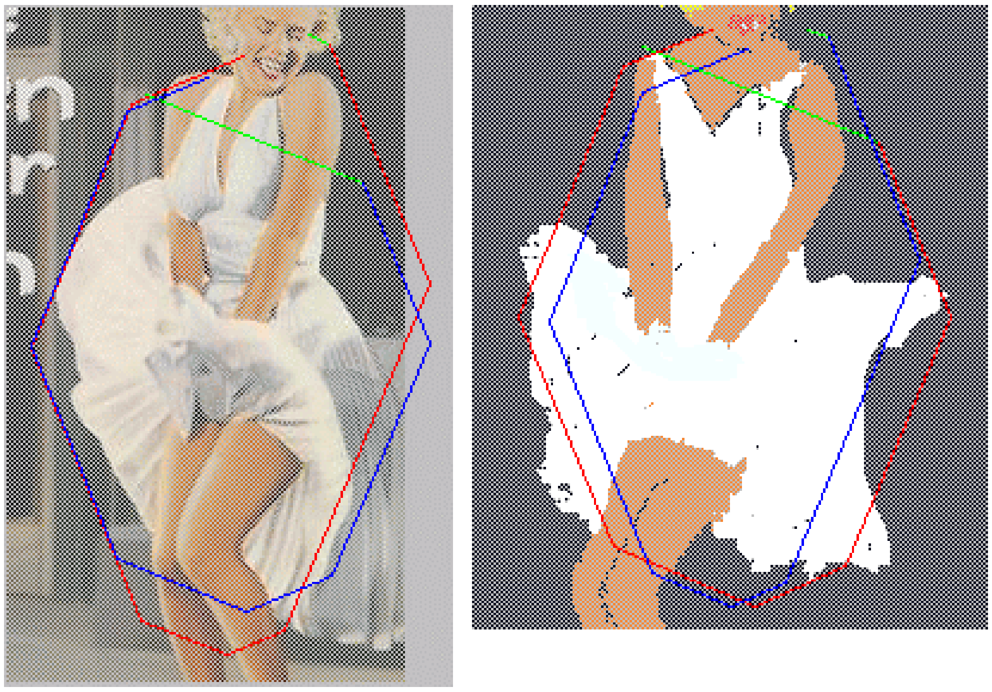


Figure 8-6: The Angle-Based Comparison for Marilyn with only 8 buckets. The two representations are rotated for achieving an optimal match.

angles that the corresponding buckets would give.

The debug information shows the buckets painted as edges with the corresponding length and the middle angle of the bucket, centered at the center of the figure.

The strong points of this representation is that it is rotation invariant, and tolerant to small errors in angle, when the overall orientation and derivatives match. In that case it is similar to the generalized ellipses described in [5].

8.6 Shape Descriptor based on Protrusions

From the congitive science community, we borrow the idea that protrusions is what humans base their recognition upon. The shape of crevaces in the region boundary does not matter, but instead the protrusions that bulge out of an image is what humans have learned to recognize.

Based on this assumption, we constructed a representation that uses mainly protrusions in the matching. Protrusions are extracted from the edge-based representation of the boundary, by considering adjacent edges two by two, and using the angle between them to label each edge as a protrusion edge or an inner-perimeter edge.

Once the set of protrusions for each image has been extracted, the protrusions are matched in order based on their position on the inner perimeter, the outer perimeter of each protrusion, the length of the base, and the orientation of the protrusion's center of mass with respect to the base.

Scaling is done by aligning two separate but not independent metrics, the inner and the outer parameters. The inner parameter is formed by the non-protrusion edges, along with the bases of protrusions. The outer perimeter is the sum of the lengths of protrusion edges.

8.7 A metric for combining comparisons from individual methods

Instead of returning an absolute proximity metric, we return a relative one. That is, when two different represenations are used, say based on color and based on shape, we have to have some way of comparing the outputs of the corresponding comparison funcions in the two different domains.

In each domain, the comparison function returns a value between 0 and 1, where identical representations that are 100% similar have a similarity value of 1 and dissimilar images have a similarity value of 0. However, this scheme breaks down when say, every image in a particular representation

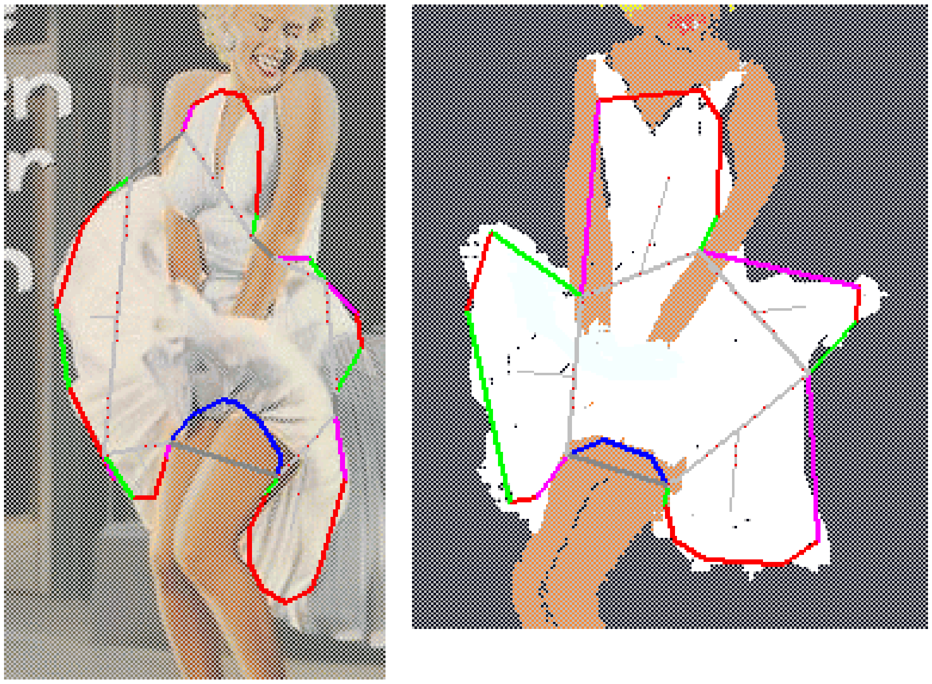


Figure 8-7: The Protrusion-Based Comparison. In grey is painted the inner perimeter of the shape, ignoring protrusions and cavities (drawn in blue). Going counter-clockwise, the first edge of a protrusion is drawn in green, the last one in magenta, and the other ones in red. Two shapes are similar when they have the same number of protrusions at approximately the same locations on the inner perimeter and the same orientations relative to the base.

has the same representation. Thus if a representation is broken it might advertise a similarity of 1 with every other image, and might bias the search to use that particular representation.

Therefore, we will use a relative metric based on these absolute similarity values. This metric measures the similarity of the query to a particular image as compared to its dissimilarity to the rest of the images. Therefore, for a particular representation, we will return as the proximity metric of the best image the ratio between the similarity value of the best image and the average similarity value.

8.8 Conclusion

This chapter presented a combination of different approaches for describing shapes, each having specific strong points and being tailored to specific applications. All of them have weak points, but when one fails usually the others take over, thus providing a graceful degradation of the shape description.

Chapter 9

Image Retrieval and Matching

Though we travel the world over to find the beautiful, we must carry it with us or we find it not.

Ralph Waldo Emerson

Image retrieval and matching brings together the work of the previous chapters into the system of Imagina. All of the methods of region matching which are used in Imagina have already been presented. The next step is the combination of the representations into a unified measure of match between regions. Image matching based upon this, and a simple configuration measure, is then straightforward.

Once the similarity between regions can be measured, the similarity between images can be computed. This measurement then allows for the comparison of similarity between a query and the images stored in the database, yielding a content-based image retrieval system.

The problem of image retrieval is not as straightforward as this might imply. Image retrieval is a hard problem because the problem itself is ill-defined. Given a query image and several database images side by side, few people would be able to agree on which of the images provides the best match. This, however, is exactly what an image retrieval system is expected to do.

9.1 Challenge of Classification

Classification, whether in terms of image segmentation or shape matching, is an ill-defined problem. Without a bias for a category of solutions, a useful answer can never be achieved. How else can the "right" answer be identified? Although intuitively the "simplest" answer matching the desired criteria is the right one, this is not always as straightforward as it seems from our evolutionarily advanced vantagepoint. Computer systems, lacking such a concept, need a more stringent definition.

The following example illustrates this. The example is borrowed from [26, pages 21-22]. Take a minute to look at the training set on the left, determine the classification rule which is being sampled, and consider possible test set item labellings.

	Training Set								Test Set							
Attribute 1	1	1	0	1	0	0	1	0	0	0	0	1	1	1	0	1
2	1	1	1	0	0	0	0	1	0	0	1	0	1	1	1	0
3	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1
4	1	0	1	0	0	1	0	1	0	1	0	1	0	1	0	1
Category	A	A	A	A	B	B	B	B	?	?	?	?	?	?	?	?

Table 9.1: Pattern classification task example.

In Table 9.1, several rules may be valid. For example, the label 'A' could represent the NXOR of attributes 3 and 4, while the label 'B' could represent the XOR of attributes 3 and 4. Alternately, A could be the AND of attributes 1 and 2 ORed with the NXOR of attributes 2 and 3. A variety of other solutions come to mind. The basic difficulty lies in that, since the entire space of solutions can never be seen in its whole as examples, the classification rules must make assumptions about the space they are operating in. Otherwise, the rules would never be able to classify unseen examples.

This problem only becomes more difficult when noise is introduced into the system. Then, errors would occur even if the ideal classifier were to be known. In case this problem seems too simple, consider this: the solution which seems simplest based on the number of attribute combinations required, the XOR of attributes 3 and 4, yields a homogenous pattern labelling for the test set. Given that the training set had two equally-represented sets, would it not make sense that a random test set would contain roughly equal numbers of examples from each category? The correct choice of classification rule is, after all, dependent on the task that is being solved.

9.2 Combining the Representations

In performing the image retrieval version of classification, unrelated measures provided by different representations need to be combined. This is done through the application of the concept of how to combine unrelated measures presented in section 3.6. This idea was applied in Imagina both for the region and the image search implementations.

For region searching, the similarity measures computed by the comparison of the different representations which are abstracted from each region must be combined. Based on this idea, the measures are first normalized before being summed into an overall match score. In order to be able to do this, the distribution of every measure has to be normalized. Therefore, assuming a normal distribution for each similarity measure computation, the mean and the standard deviations of each distribution must be computed.

In a large database the distributions can be approximated through random sampling. In a small database, however, the distribution can best be approximated by looking at all of the sample points available. Therefore, regions are matched sequentially against all otehr regions in the database.

The distribution of results of one match may not be a good predictor for the distribution of results for another match. Therefore, the distributions of the similarity values returned by each representation are recomputed each time a region gets matched.

Every computed similarity is then normalized as in:

$$\frac{value - mean}{standard\,deviation} \tag{9.1}$$

This results in a distribution with a mean of 0 and a standard deviation of 1. Thus, all of the representation similarity evaluations end up having the same distribution. The normalized similarity measures for each representation are then combined into an overall similarity measure, resulting in a measure of the similarity between two regions. The regions are then returned to the user as ordered by this combined measure.

9.3 Dealing with Multiple Regions within an Image

Once the region similarity can be computed, the similarity between regions can be used to perform image matching. However, the configuration is also a feature which is important to users of an image retrieval system. Therefore, a similarity measure of two different configurations of regions must be computed.

Configuration can be encoded and computed in a variety of ways. It can be used either as a first step in indexing a probe image, or as a last step. If it is used as a first step, then a graph-matching algorithm must be performed. Region comparison, however, is simplified, because the space of possible regions is greatly diminished. On the other hand, if it is performed as a last step, it could optionally be skipped, unless the request retrieves a large number of matches.

One configuration encoding uses not only relative position and size, but also some shading information. Sinha explores such a representation in chapter 7 of his PhD thesis.[39] His representation uses an encoding of the relative lightness of different equiluminant patches of an object, for example, of a human face. The shape of the patches is left to be rectangular, for ease of computation and matching, and the images are compared in black and white. Although color could potentially be used, a single-valued relationship between colors could not be extracted. By looking at colors only in terms of their intensity, however, such an encoding can be achieved.

Such an encoding would allow the matching of whole images before the matching of individual regions is even attempted. Region matches would simply provide an improvements to the estimation of an image match. However, queries would have to be fairly complete in order to allow this matching method to work. If too few regions were supplied, or if the relative shading were wrong, the indexing would fail. Thus, this method would work best for indexing based upon real image probes. For Imagina, where a user sketch input is the primary indexing method, this is not a first choice.

9.4 Image Matching

The same idea which was applied to region matching is applied to image matching. In this case, the distribution of similarity has to be computed for each region in the query image. That is, each query image region has to be compared against all regions in the database, and the resulting distribution has to be normalized individually for each region. Again, for an extended database, sampling could be used to approximate this distribution.

The only remaining issue is the computations of configuration similarity. This issue is resolved by placing this computation at the point where two sets of regions have been considered as a match. Because the mapping between the query and database region subsets, of the query and one of the database images, respectively, is known, the configurations can be compared directly.

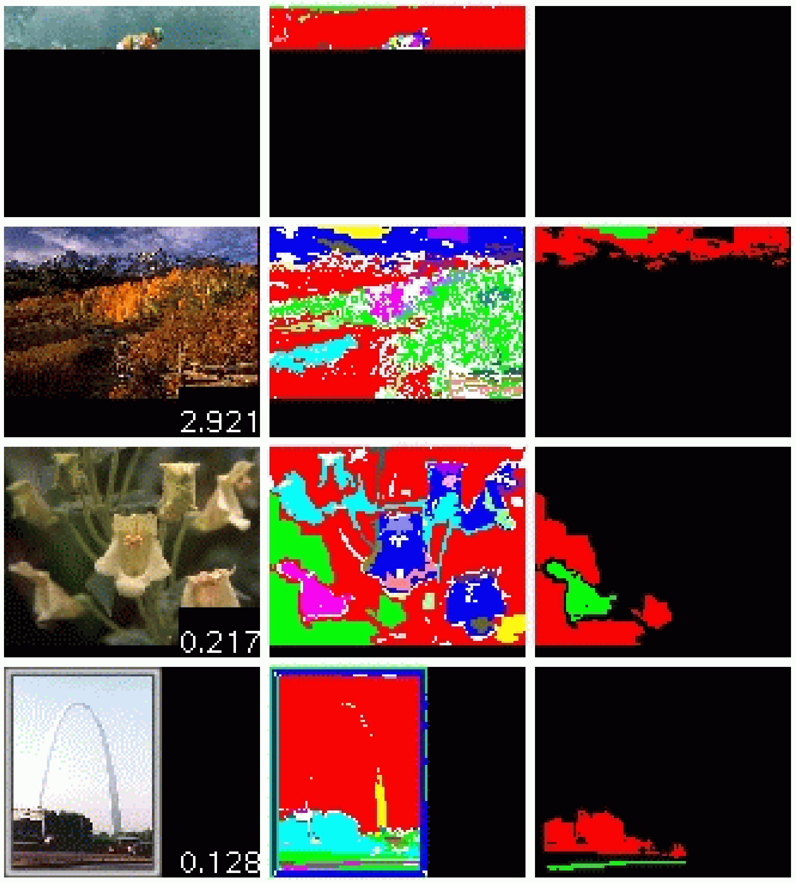


Figure 9-1: The first successful image match performed by Imagina. The query image is displayed on the first row, and the matched images are listed on the subsequent rows. The first column is an image thumbnail, the second column is the image mask, which shows the different automatically segmented regions of each image, and the third column shows the mapping of the query image regions to the matched image regions by the use of color coding. Thus, the region which is labelled red in the query image matches the regions which are labelled red in the third column of every image match.

9.4.1 Comparing Configurations Given a Region Mapping

When a configuration is evaluated, a mapping from the query image regions to the comparison image regions is given. To evaluate the configuration similarity of two sets of regions, A, B, C and A', B', C', we use three kinds of similarities: angle similarity, distance similarity, and relative areas similarity.

When comparing the configuration of the regions A and B to the configuration of regions A' and B', we consider the center of mass of each region to be representative of the position of the region and the number of pixels belonging to the region representative of the volume. We therefore evaluate the cost of transforming the pair A, B to the pair A', B'. The cost is made up of three components:

- The angle between AB and A'B' is normalized with respect to π, the maximum possible angle difference.
- The relative areas are compared. The ratio of B to A is compared with the ratio of B' to A'. Again a ratio similarity between 0 and 1 is returned.
- Finally the distance difference between AB and A'B' is computed, normalized relative to the square root of the areas.

The resulting similarities are combined in giving the similarity of pair AB with pair A'B'. The total configuration cost of region A is the sum of the costs of all pairs AX and A'X', for every other mapping XX'. This gives a configuration cost for A, to be combined with the region similarity cost.

This results in a value from 0 to 1. This value is then used as a multiplier to the region match, for the given region mapping being evaluated. These weighted, previously normalized similarity values are then summed up to give an overall image similarity value for the given attempted mapping. Thus, the similarity of an image to another image is in terms of the configuration which was attempted. The user can opt to see one or several of the top configuration matches which the query image has made with every database image.

9.4.2 Matching Issues

The only problem with this approach is that the search space - all possible region mappings between one image and another - have to be considered in turn. This search is of the order of $\frac{\max(m,n)!}{\min(m,n)!}$, where m and n denote the number of regions in the query and the database image, respectively. Since the number of regions in database images vary, the worst case order of growth is given by the largest number of regions present. However, the order of growth by the number of images in the database is only linear. Therefore, an improvement in the local image matching is the key to improving matching performance.

Although the growth rate of the function might seem large, for a small database a system programmed in Java the limitation of memory size is reached much more quickly. Extensions to the database design are discussed in chapter 10. Results of several runs of the system can be found in the appendices. Appendix D shows whole image matches, and appendix E shows region matching.

Chapter 10

Extensions

You see things as they are and ask, 'Why?' I dream things as they never were and ask, 'Why not?'

George Bernard Shaw

Several extensions to the existing Imagina system are possible. These can be grouped into several categories:

- **Preprocessing Images** A very general improvement would be to increase the image fidelity for the images inserted into Imagina system by applying a pre-processing step. This can be done to improve image indexing performance in almost any image retrieval system.
- **Creating an More Extensible Database** A database which is more computationally efficient and can therefore handle larger numbers of images gracefully would allow for the further testing of our concepts. We present an approach to a creating such a database in this chapter.
- **Learning from User Feedback** User feedback, other than the modification of a few search weights, is currently not used. By implementing a process which observes the user's interaction with the system, search results could be improved.

- **Additional Algorithmic Modules** Additional matching modules can be added to the system to improve search performance. This is easily done since the modules themselves are interchangeable.

10.1 Preprocessing: Improving Image Fidelity

A difficulty with image indexing and segmentation is that not all images are taken in the same lighting. Some images are very dark, others are very bright, and others are shaded unevenly by the different colors of light. This difficulty is often not obvious to the human observer of a scene being photographed because the human visual system automatically compresses the dynamic range of lighting and effects color constancy. Thus, objects look the same to humans under a variety of lighting conditions, while to a camera they can be quite different. Professional photographers are well-accustomed to this, and use light-measuring tools to aid in taking pictures which look realistic to end users.

An approach to bypassing this problem was suggested by Edwin Land in terms of the center-surround retinex concept, introduced in [23]. This approach has been taken up and implemented by Jobson, Rahman et al.[16][17] In their system, a center-surround region is computed at every image location, with the filter consisting of a strong weighting for the current image pixel, and a small negative weighting over a large area of surrounding pixels. They developed multi-scale version of this algorithm, which provides a good color image enhancement.

The central difficulty with applying this system is twofold. First, several constants need to be determined empirically for good performance. Second, this technique is being patented, and therefore not likely to be freely available. The appeal of this system, however, is the claim that a wide variety of input images, from indoor scenes to space images, can be processed automatically equally well.

The retinex approach, or another color image enhancement technique, might be a useful pre-processing step for any image indexing system. This is especially true about systems which are based upon color histograms. These are usually tested on a select data set, such as a Corel image collection, which do not exemplify users' image collections. For Imagina, the improvement would lie in that a larger variety of images would be segmentable. Currently, images which have little variety in the tones of color, either being too dark or overly bright, are difficult or impossible to process in a manner which is useful to the end user's search process.

10.2 Database: Principles of a Large Database Design

A large database needs to handle many items while at the same time performing computationally nontrivial matching. Although the individual modules perform matching at query time which is on the order of several thousand computations, combined across different modules and the entire search space this can become overwhelming. Instead, a system based upon a hierarchical definition of the database into prototypes and represented subsets becomes useful.

In this, and throughout the current implementation, the guiding principle in the Imagina database is that new inputs into the database are classified based on the inputs already present in the database. The database is expected to be roughly the same regardless of the order of insertion, however. When a new item is inserted, it is segmented into regions based on different algorithms. These regions are then defined by separate algorithms, the output of each being placed in a different *description map*, as shown in Figure 10-1.

We define a description map to be a complete indexing of the regions in the database, as described by the application of a single series of algorithms from the starting image. Therefore, the database is comprised of several description maps, with each region which was segmented from the input image being represented in each of them individually. Matching is performed by finding the nearest neighbors in each map, and then correlating neighbors across maps.

As aforementioned, as the complexity of the database increases, prototypes can be used to simplify the matching process. A Prototype can be abstracted at insertion time if a given subset of abstracted images within a single description map are sufficiently similar. When matching is performed subsequently the search can be pruned at the prototype if the similarity of the prototype to the search target is sufficiently dissimilar, saving computation that would be spent on equivalent matching being performed at a lower level of the hierarchy in a given description map. The idea of prototypes can also be applied hierarchically, to allow for the matching computation to grow in proportion to the logarithm of the number of images in the database.

10.3 Database: Representation of Images

Images are usually stored in databases in terms of a total ordering of all of the images within the database. That is, each image I is mapped to some representation $R(I)$. The function R is more or less complicated, but yields usually a unique representation for each image. The represenation

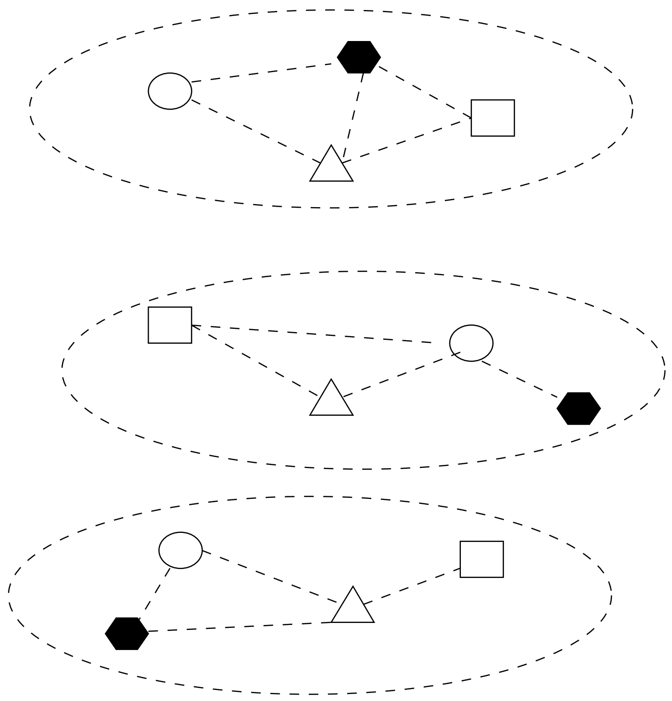


Figure 10-1: A graphical display of four regions as they map into three distinct description maps. Each individual region is denoted by a different shape, and a dashed line is drawn from it to its nearest neighbors within that description map. A new region, displayed here as the filled-in hexagon, can have different nearest neighbors in each abstraction map.

$R(I)$ is added to the database D.

The alternative is to use a graph abstraction to store the images. Instead of considering every image during a search, only a set of nodes of the graph are considered.

In this case, the new image I is added to the database relative to the other things that the system has discovered so far. The representation of the image is thus dependent on the previous images viewed. We compute $R(I, D)$. This representation is a function of both the image and the previous images.

Moreover, this new image changes the connections and relations of many other images in the database. Hence the database itself is transform in a more complex way than simply adding to the database the picture I indexed by the representation R.

10.4 Database: Structuring a Large Database

The database is usually a set of images, somehow interconnected. In a system like Altavista, a lot of images are stored along with their pre-computed relationships, in order to achieve a quick response time. In other image databases, different indices might be used to cluster the data for a faster, retrieval using those indices.

Our database does not only contain images. It also contains abstractions of images, at different levels. Different abstractions from the same image will yield a mapping to different such abstracted images. The representation of the new image then becomes the interconnections between these abstractions. These abstractions define the image. Because of this, the problem of indexing becomes the problem of graph matching, where the nearest neighbors of every abstraction of a given object have to be combined into an ordered similarity list.

10.5 Database: Abstraction and Specification Functions

The different filters, segmentations, and color-based matchings which are used for image indexing can be thought of as different functions, each of which takes a particular type of input, and produces a particular type of output. This description is very generic, because each function performs an action on a potentially different space. Although color and edge determination are both performed on an input image, their outputs can be very different in quality.

10.5.1 Abstraction Functions

We can think of the different ways of abstracting an image into something as applying different abstraction functions $A_1 ... A_n$ to the same image I, and obtaining different abstracted versions of the same image $A_1(I) ... A_n(I)$.

10.5.2 Different Levels of Abstraction

To have different levels of abstraction, there are two approaches.

- Make the output $A_i(I)$ of an image I belong to the same domain D as the image I. Thus, the same abstraction functions can be applied recursively, yielding n^k abstractions for k recursive applications of n abstraction functions.

- Define new abstraction functions for every level. If we want five levels of abstraction, we can construct four abstraction classes A, B, C, D. The range of A, D_A, is the domain of B, and so on. We can thus obtain $n_A * n_B * n_C * n_D$ possible abstractions where n_L is the number of abstraction functions defined in level L.

10.5.3 Specification functions

The specification function takes an abstract idea and produces a possible incarnation of this idea. It is basically the inverse process of abstracting an image to obtain an idea. If from an image one can obtain a set of possible abstractions, then each of the abstractions can be made more specific as that image. However, it could also be made more specific as a different image, which however must be abstractable to this abstraction.

Defining specification functions is like defining the inverse operations of the abstraction functions. We can either require that each abstraction function be reversable, or we can simply define a set of specification functions $S_1 ... S_m$ more or less independent of $A_1 ... An$ with the single requirement that the domain of all A_i is the range of all S_j and vice-versa. That is we can simply require that the domains coincide going up the abstraction tree and down the specification tree. This is definitely easier to implement, and an exact match at any level is not obligatory since recovery of an image is never perfect, and the space of possible images and abstractions has no hope of being spanned.

10.5.4 Coding Abstraction functions

Let's assume for the moment that

1. The abstraction and specification functions are independent, That is one doens't have to make abstraction functions reversible.

2. There are as many domains as classes of abstraction functions. That is, the domains of I and $A_j(I)$ need not be the same. This results in a finite number of possible abstraction levels.

Both assumptions can be justified biologically from a cognitive science point of view. First of all, only a certain number of neurons are traversed in recognizing an image. Only a fixed number of neuron stages are involved, and we can assume that each stage is specialized in receiving the output of the previous stage. No circularity has been observed in the process of recognition, which would involve the domain and range of a particular function (possibly nested) would have to be the same. That is $A_i(B_j(C_k(I)))$ does not have to be usable as the input to A_l for example.

Moreover, both assumptions make coding much easier. We can now construct different abstraction functions that extract different pieces of information from the image. The information extracted at each stage is used in the next stage in making its operations. To make it possible to have later stages use information from the previous stages, we simply augment the input I of a stage with the output of the function at that stage, and make the pair $I, A(I)$ into the output available to the next stage.

The next stage for example could operate on either the output of the previous stage (generating $\{I, A(I), B(A(I))\}$) or on the original image (generating $\{I, A(I), B(I)\}$). This makes it possible to represent any non-cyclic graph as a tree.

However, there is a restriction is that at every level, the abstraction function applied must have an output which can be consistently interpreted. That is A_1 cannot be computing the average green and A_2 the average red in the image, otherwise the comparison function would consider a forest and a volcano as similar in color.

10.6 Learning: Using Feedback to Improve Search Performance

A longer-term goal of this project is to have a training phase, during which users will be able to search images in the database using a sketch of the desired image as the query. The system can then use the input sketches, along with the corresponding simplified and original images, to improve the internal representation by adjusting relevance parameters on matching criteria. This feedback should yield a system that learns how to abstract images more accurately as the user is formulating queries and getting results, and hopefully improve the searching capabilities as time goes by.

10.6.1 Re-Weighting Functions

The specification and abstraction functions can be re-weighted based on the user's requests. By seeing which function was the most accurate predictor for the user's request in the previous query, its weight can be updated for the subsequent query.

10.6.2 Speed up questions

To speed up computation at the time of matching, the functions themselves can be precomputed on the images, and only put together at the time of matching to reconstruct the outputs. That is, we precompute $A_i(I)$ and we construct $\{I, A_i(I)\}$ only when needed, depending on the type of representation and the levels of abstraction.

10.7 Module Extensions: Parallel Implementations

Biological systems use very slow wetware to compute information which even modern-day computers performing hundreds of millions of computations a second cannot keep up with. Their advantage comes from using a large number of slow processing devices in parallel rather than using a single fast serial computation.

There are two reasons to follow up on this lead. First, even with ever-increasing computational speeds, serial silicon-based computation is reaching its limits. Only by using computing devices in parallel will computation be able to take the next leap. Second, we already know that a system is capable of performing the image indexing task which we are trying to set up.

We also know that the brain system is massively parallel in its computational approach. Therefore, algorithms which are readily parallelizable are both more likely to perform the desired computations, and more readily speeded up through parallel computational architectures if they are to be applied. Thus, one of the goals of the Imagina system is to develop or use algorithms which are easily computed in parallel across an input. Although this is a goal, at present a tradeoff has to be made towards a more computable and serialized implementation.

10.8 Additional Modules: Texture and Shadows

To manage the extensive task set out for this thesis, an incremental approach is adopted. To be able to handle the basic task of segmentation, color suffices in many cases. It was therefore implemented as a first step towards the implementation of segmentation algorithms. These, in turn, led to shape-based descriptors being defined and created.

One of the goals of Imagina is to be able to handle images of objects in uncontrolled situations. This requires that segmentation algorithms to be very robust, and use as much information as possible from the image. Ideally, color, texture, shape, and shading could be used. Unfortunately, these features require progressively more effort to implement and are less obvious to design. At this point, only color and shape are implemented into the modules used by Imagina. By taking advantage of these other sources of information in every image the matching performance could be improved.

Chapter 11

Conclusion

Attitudes are much more important then aptitudes.

Alexander Lockhart

11.1 Contributions

We feel Imagina has contributed to research in content-based image retrieval by suggesting novel approaches in several aspects of the problem.

- ⋆ Sketch Based Drawing
- ⋆ Global Segmentation based on color
- ⋆ Matching based on region shape
- ⋆ Multiple representations at multiple levels of detail
- ⋆ Explicitness of Representation

11.1.1 Sketch Based Drawing

What sets Imagina apart from most current content-based image retrieval work is the sketch interface for formulating queries. Computation on the query is cheap, and can be easily compared with precomputed representations of the database images. Other systems can only query in terms of precomputed images within the database.

The use of a sketch as an interface is leaving to the user the freedom of a greater versatility in expressing queries. We hope that this will make the user of image retrieval by content as natural as text retrieval has become, by making the medium of the search match the medium of the data. We hope that future image retrieval research will move towards systems that allow greater user input flexibility.

11.1.2 Global Segmentation based on Color

This thesis presented a new algorithm for segmenting images based on color. This algorithm makes use of the different scales in an image to combine regions at different levels. The result is a robust algorithm to segment images based on color at the Hue-Saturation-Value color space. Also, the description of the HSV color space provided in this thesis is to our knowledge one of the few in the literature that cover all details correctly.

11.1.3 Matching based on region shape

The use of shape has rarely been addressed in image retrieval systems. Imagina takes a new approach to shape by combining different representations each emphasizing a different feature of the region's contour. Imagina has presented a new simple and robust edge extraction algorithm for constructing the various shape descriptions. Imagina has contributed in presenting four different representations that complement each other in matching shapes and can be used in parallel. This successfully achieves the graceful degradation principle of biological systems.

11.1.4 Multiple Levels of Detail

Imagina is probably one of the few systems that exhibits multiple levels of detail at all processing steps. A uniform design of the image processing algorithms integrates the level of detail seemlessly. Every algorithm can therefore be applied at multiple resolutions. This allows for noise tolerance when algorithms are applied at a coarse resolution. Multiple scales also allow for an early pruning of the search tree by first matching objects at a low resolution, and keeping only the best matches for applying finer-grain algorithms.

11.1.5 Explicitness of representation

All processing stages and comparisons visually display why two regions were matched thus making the assumptions of the system explicit. Such an explicitness is crucial in understanding how the system works and thus being able to formulate more precise queries as well as understand how the system fails or why the system succeeds.

11.2 Shortcomings

The main shortcoming of Imagina is that only color is used in segmenting images. Images which have little variety in the tones of color present are difficult to segment in a manner useful for the shape description process. One of the goals of Imagina is to be able to handle images of objects in uncontrolled situations. This requires that segmentation algorithms be very robust, and use as much information as possible from the image. Ideally, color, texture, shape, and shading could be used. Unfortunately, these features require progressively more effort and are less obvious to design.

Moreover, the shape matching relies uniquely on the color processing. The algorithms presented are robust, given a good color segmentation. Using other features of the image such as texture or edge detection can help make the segmentation more robust, and hence the entire system more reliable.

11.3 Conclusion

As an image retrieval system, Imagina has been inspired heavily by the cognitive processes of visual recognition in biological systems. In doing so a uniform architecture has been designed where multiple methods are applied at multiple scales. This provides Imagina with a robustness against inexpected inputs, and a tolearnce to noise.

Imagina, as a system is more geared towards light-duty tasks that can benefit from a better matching and interactivity at the cost of speed. As technology improves however, such systems will be more easily available for use in general tasks rather than fine-tuned recognition applications. This thesis has brought forward design principles to be used by image retrieval systems, and has summarized the elaborate literature in a few simple guidelines to follow in ulterior academic labor.

Appendix A

The Imagina System

The current implementation of the Imagina system is as a Java applet which can be run both through a browser and with an appletviewer. A client-server architecture using cgi scripts was never implemented. Therefore, the browser version is far more limited in its ability, as processing has to be done at the user's end, after a lengthy data transmission. Running the applet locally using an appletviewer, however, allows the use of the file system for rapid loading and saving of image objects.

The user front end of the Imagina system is the drawing interface. It allows for the creation of colored user sketches, providing both manual shape delineation and the use of primitives such as rectangles and ovals. The image which is drawn can either be saved for later review, or queried upon directly.

Segmenting the query is easy. The user can simply use as many colors as objects he is looking for. The segmentation is thus almost trivial on an image entirely constructed by the user.

However, the system also allows a user to bring in a query picture by simply specifying its URL. Hence any number of colors can be used in the query image, not all of them meaningful. However, as soon as we have to segment an imported image, we can just use the same algorithm as for database images.

A.1 Implementation of Imagina as a Tool

The first part of this chapter introduced Imagina and the design principles we used to construct an image retrieval system that matches the human model of computation. Imagina is built primarily as a proof of concept that image retrieval can be based upon a cognitive abstraction architecture.

However, from a more practical standpoint, Imagina was implemented to be a tool we will use to retrieve images from our own collections. A complementary set of implementation principles was used in building the system. These goals overlap with our theoretical design principles, and complement them in defining Imagina as a system.

- The query can be any image downloaded from the web
- No computational bottlenecks are introduced in matching
- An extensible architecture allows system evolution
- Algorithmic modules can be easily replaced and upgraded
- The inputs and outputs of each module can be displayed on screen
- Platform and Display Independence make the system portable

A.2 Sketch and Image Upload

What sets Imagina apart from most current content-based image retrieval work is the sketch interface for formulating queries. As part of Imagina, a simple drawing program allows users to draw colored sketches describing regions.

Not only sketches but also images from any URL can be used in defining a query. The user can also import images by providing a URL, and later modify them to fit the needs of a particular query. This allows for a quick and easy query mechanism. A picture of the Eiffel Tower can be found on the web, edited within the sketch interface to erase the top, and then input to Imagina to find images of the construction of the Eiffel Tower.

What sets Imagina apart from most current content-based image retrieval work is the sketch interface for formulating queries. Computation on the query is cheap, and can be easily compared with precomputed representations of the database images. Other systems can only query in terms of precomputed images within the database.

A.3 No Computational Bottlenecks

Imagina is a prototype for a sketch-based image retrieval system. It is not designed to handle large numbers of images, nor is it designed for efficiency and speed of retrieval. However, design decisions were made such that no such computational bottlenecks exist in the process of querying the system. Thus the system can be later extended to become a commercial scale system.

The system is meant to work with a large number of users, issuing queries and retrieving results immediately. Therefore, only a short time is allotted to the system for the retrieval computation. Thus every operation that can be done off-line should be executed in advance, and only a small critical path of operations must be executed once the user issues the query.

This has moreover been achieved by the different windows of processing that can be used for pruning of bad matches even at a coarse description level.

A.4 Extensible Architecture

Object oriented architecture abstracts away from our assumptions. Different displays can be added. The search engine can be made more efficient. Monitoring user activity can give feedback to the system. New functionality can be added without changes to the existing system.

The design of Imagina should be such that new algorithms can be seemlessly included, and old algorithms easily replaced. Further functionality can be added such as learning from user interaction or fast database access.

A.5 Easily replaced algorithmic modules

The algorithms implementing the functionality in Imagina are not hardwired together, but instead plugged together in an image-interpretation pipeline. New modules can be added as processing stages, and existing modules can be easily replaced.

A.6 Explicitness of representation

All processing stages and comparisons visually display why two regions were matched thus making the assumptions of the system explicit. Such an explicitness is crucial in understanding how the system works and thus being able to formulate more precise queries as well as understand how the system fails or why the system succeeds.

A.7 Platform Independence

Java was chosen to allow for platform independence. This would allow for the easy dispersement of the program, if so desired. The choice of Java has also aided in both the implementation of user interfaces, as well as in the design of a reusable and modular system.

Appendix B

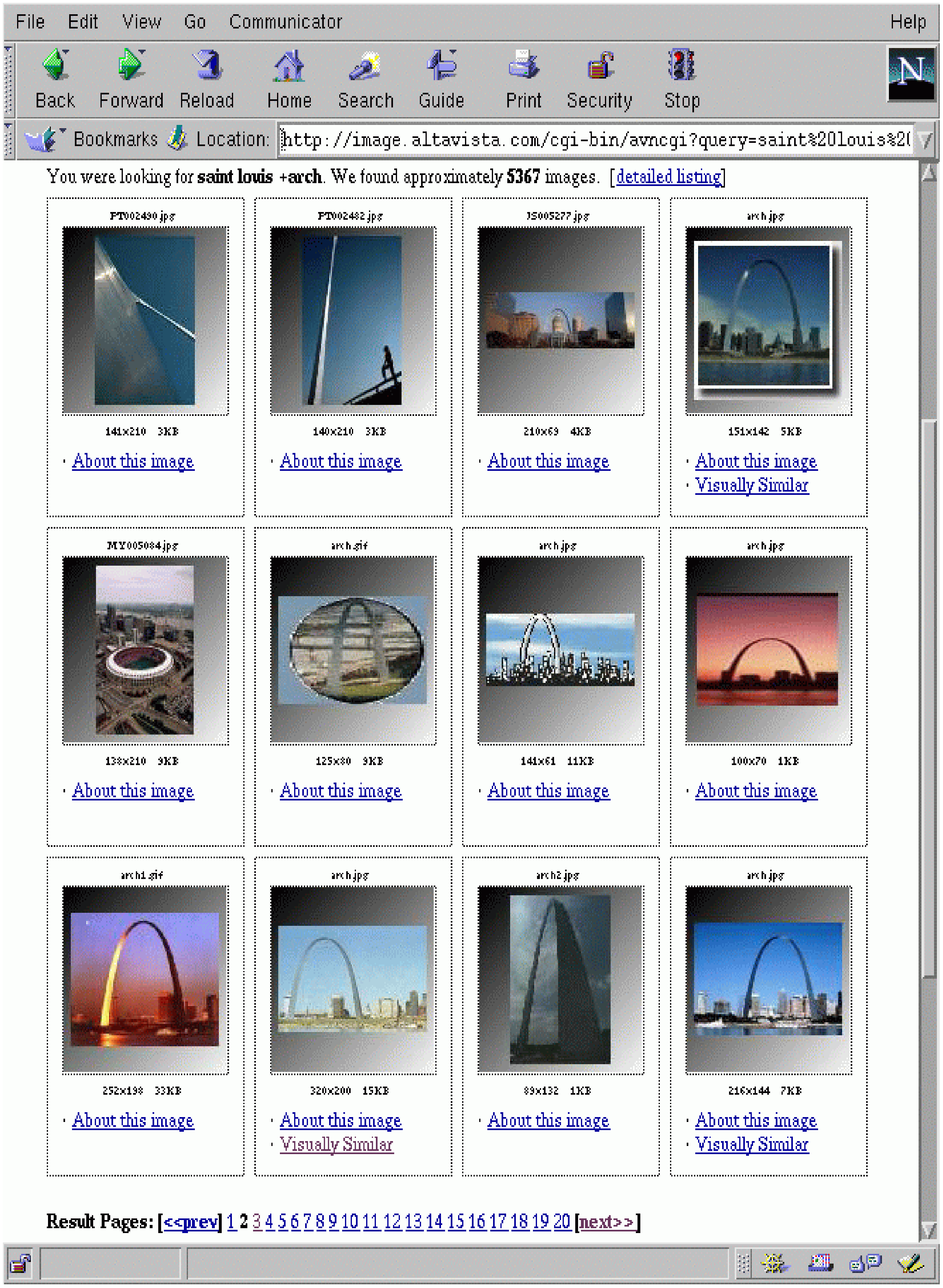
The Algorithm Toolbox

A central part of the Imagina development was the building of an interactive tool for algorithm development and testing. By having a development tool separate from the target system, several algorithms could be developed and compared in parallel. Then, depending on performance, and on the necessity of a particular approach, these algorithms could be introduced into the Imagina image search engine.

The testing program consists primarily of two images which are loaded, one on each side, and a set of buttons which allow the application of different algorithms lined down the middle of the interface. Because of its visual setup, this forced the development of visualization methods for almost every algorithm developed. Thus, the final database and query interface were easily implemented using these informational outputs for displaying match information.

Appendix C

Altavista's Image Finder



http://image.altavista.com/cgi-bin/avncgi?query=saint%20louis%2(

You were looking for **saint louis +arch**. We found approximately **5367** images. [detailed listing]

PT002490.jpg
141x210 3KB
· About this image

PT002482.jpg
140x210 3KB
· About this image

JS005277.jpg
210x69 4KB
· About this image

arch.jpg
151x142 5KB
· About this image
· Visually Similar

MY005084.jpg
138x210 9KB
· About this image

arch.gif
125x80 9KB
· About this image

arch.jpg
141x61 11KB
· About this image

arch.jpg
100x70 1KB
· About this image

arch1.gif
252x198 33KB
· About this image

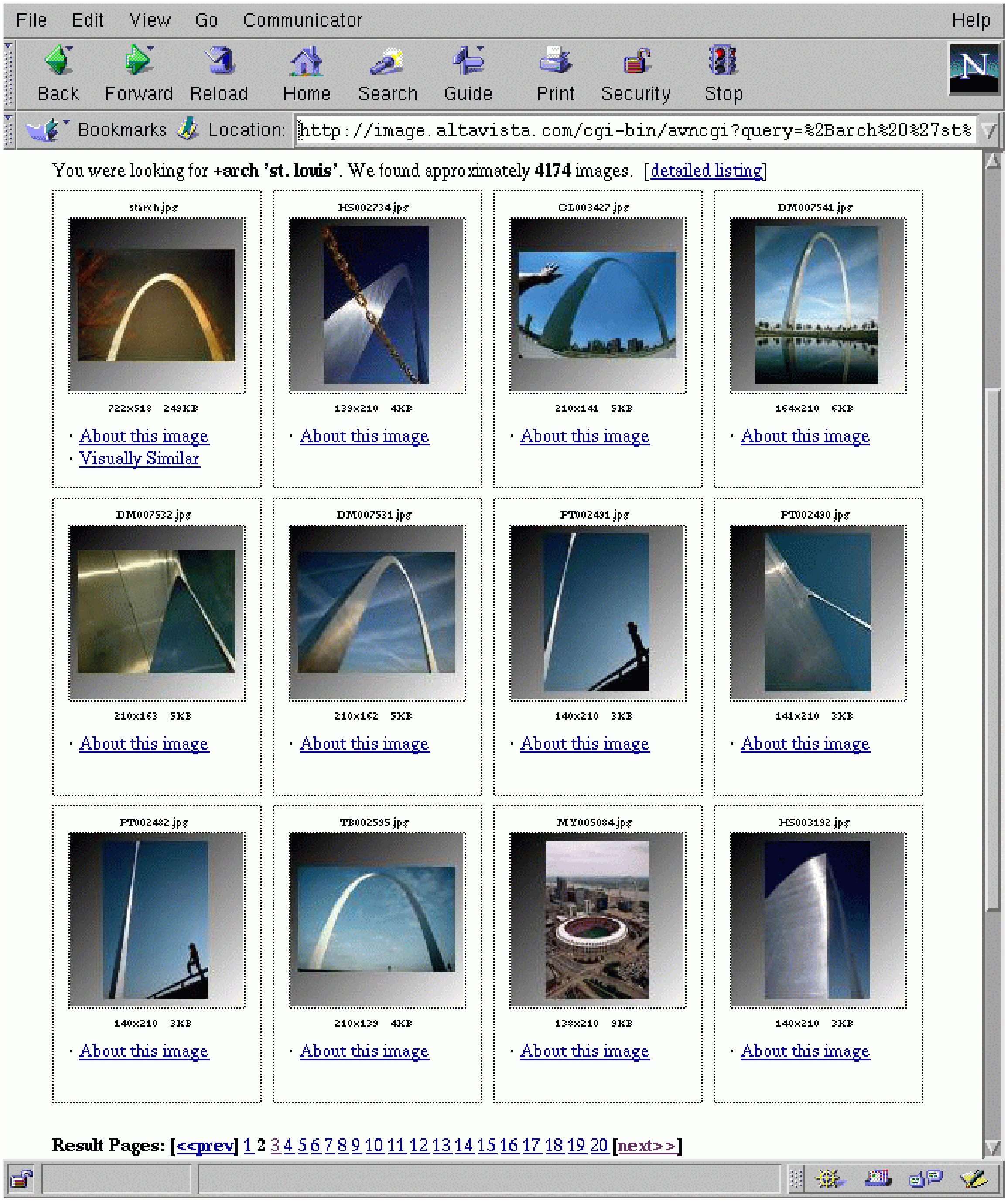
arch.jpg
320x200 15KB
· About this image
· Visually Similar

arch2.jpg
89x132 1KB
· About this image

arch.jpg
216x144 7KB
· About this image
· Visually Similar

Result Pages: [<<prev] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 [next>>]

Figure C-1: A text-based search can be very effective when looking for a particular object



http://image.altavista.com/cgi-bin/avncgi?query=%2Barch%20%27st%

You were looking for **+arch 'st. louis'**. We found approximately **4174** images. [detailed listing]

Result Pages: [<<prev] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 [next>>]

Figure C-2:

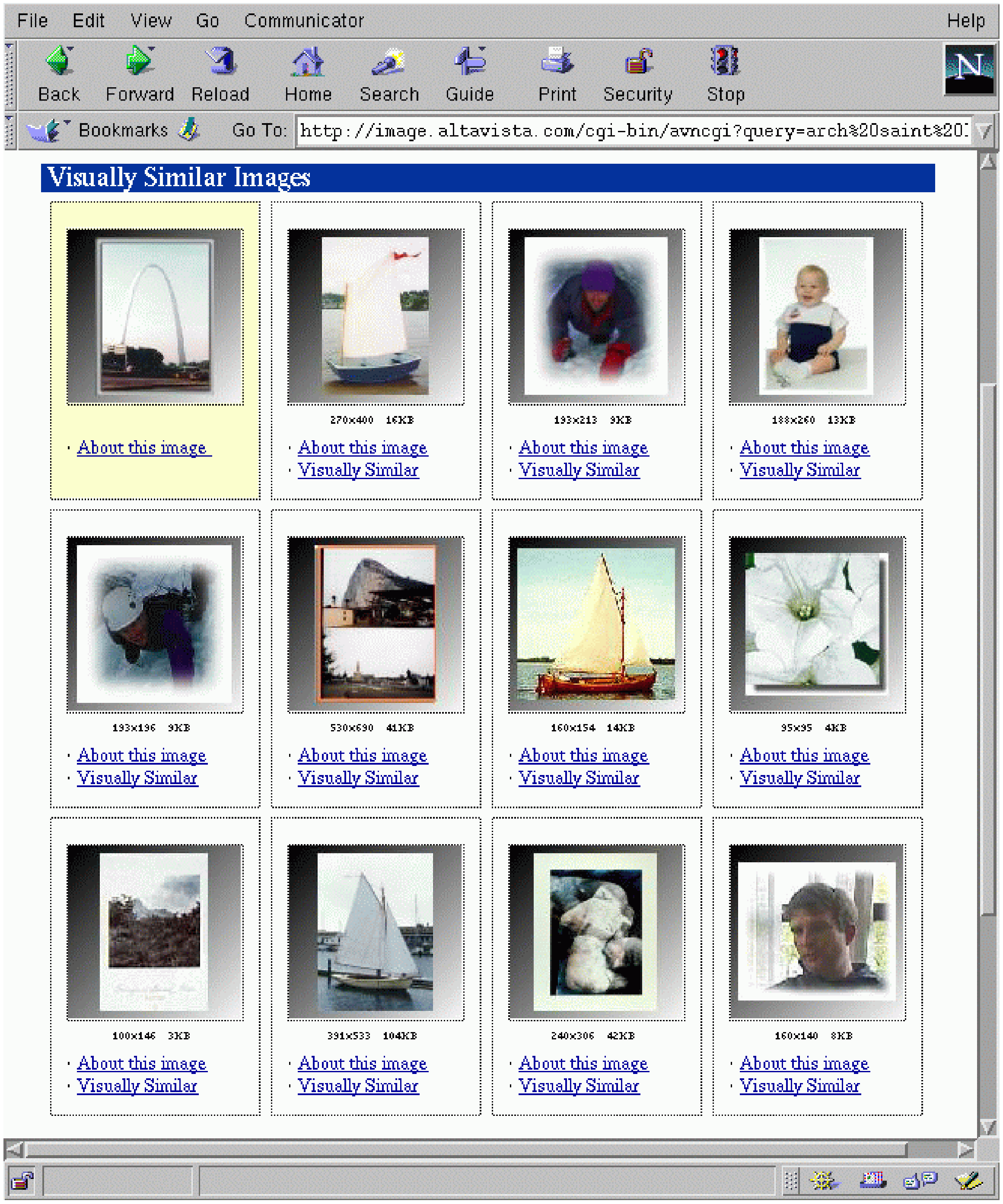


Figure C-3: Altavista Image Finder. The performance of an image search engine that relies mainly on color is very poor.

Appendix D

Image User Queries and Matches

The queries presented here were run on a single database of images. These samples were created by a single user, Patrycja Missiuro, after viewing a larger set of sample images which were used during the implementation of the Imagina system. The sample database that the queries were run on was then selected such that images which were similar to each of the queries were always present.

The size of the database of images unfortunately had to be limited because of main memory limitations. The main problem was the storage and allocation of displays which provided user information. Optimizations could have been implemented, for example by limiting the size of the internal display storage to the size of the screen display. However, due to time constraints this was not done.

The queries presented to the system are shown in Figures D-1 and D-2. The images were drawn using the Imagina query drawing tool, and were first saved as GIF images before being inserted into the database for indexing. The set of query matches presented here are the results of whole-image queries. Partial-image queries in the form of region queries are presented in a subsequent section.

The figures following first depict the user queries, then the database images which they were compared against, and lastly the matches determined by the system for each user query.

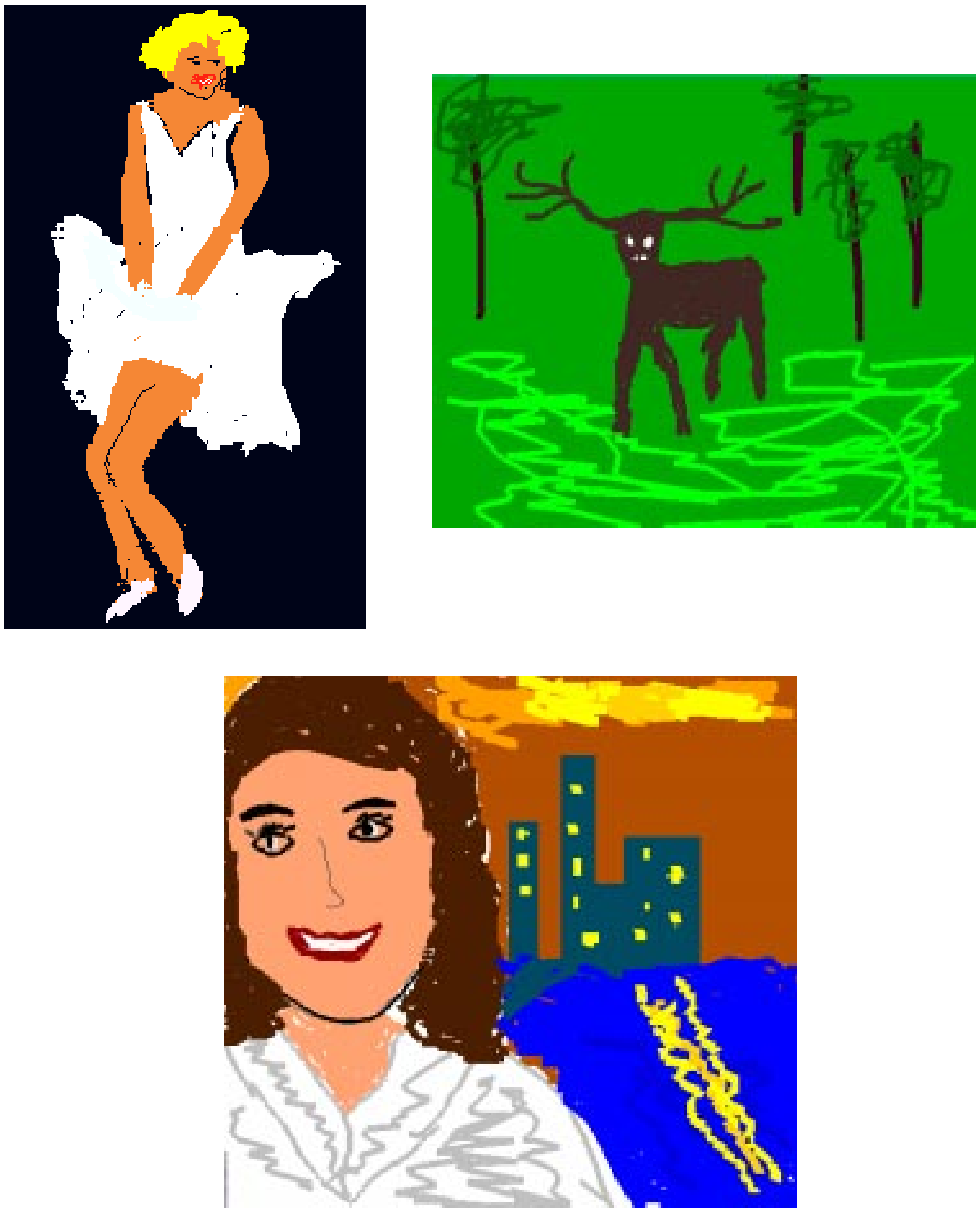


Figure D-1: The first three user queries.

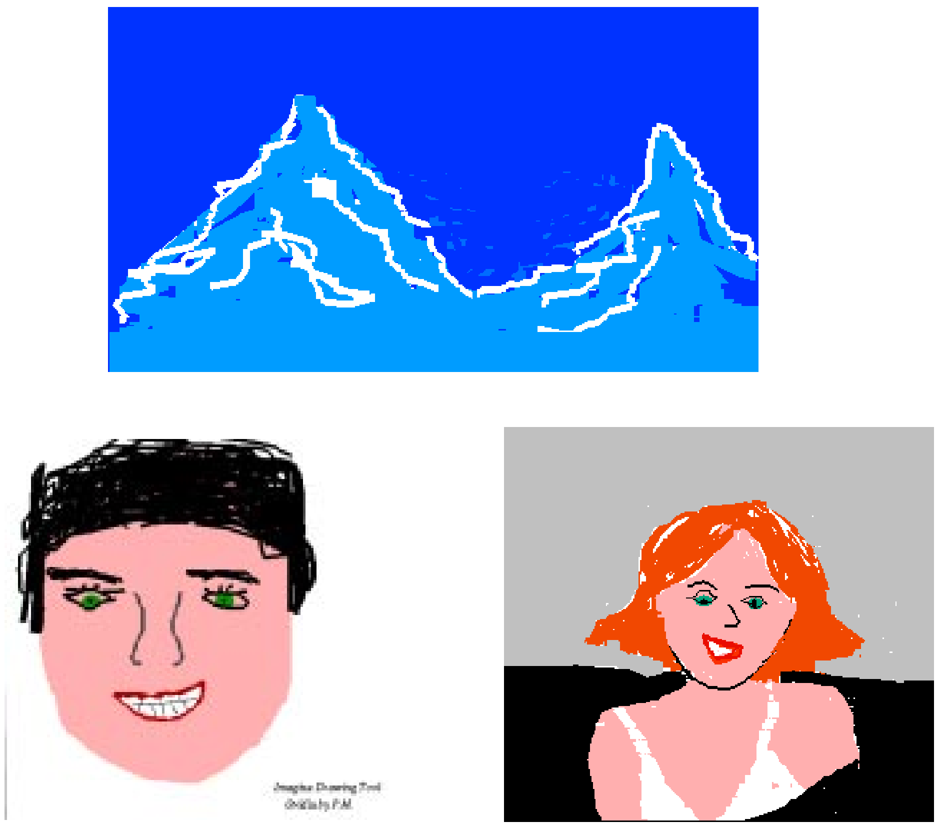
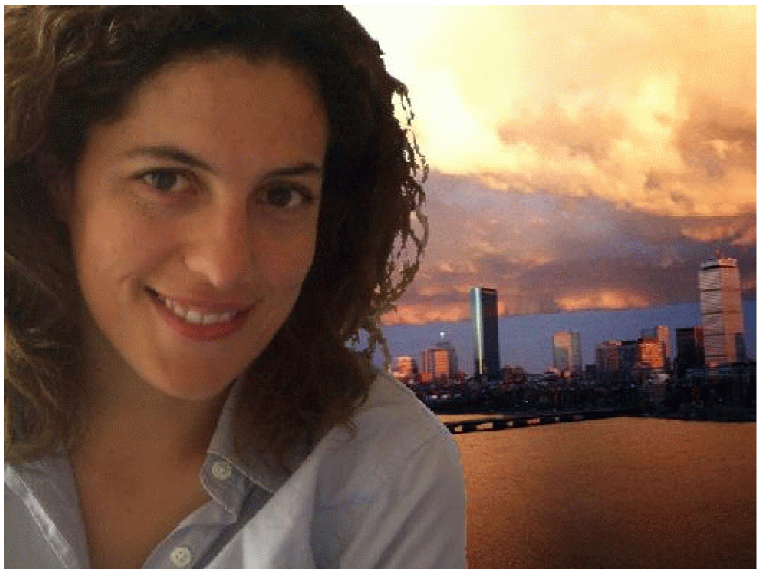


Figure D-2: The second set of three user queries.



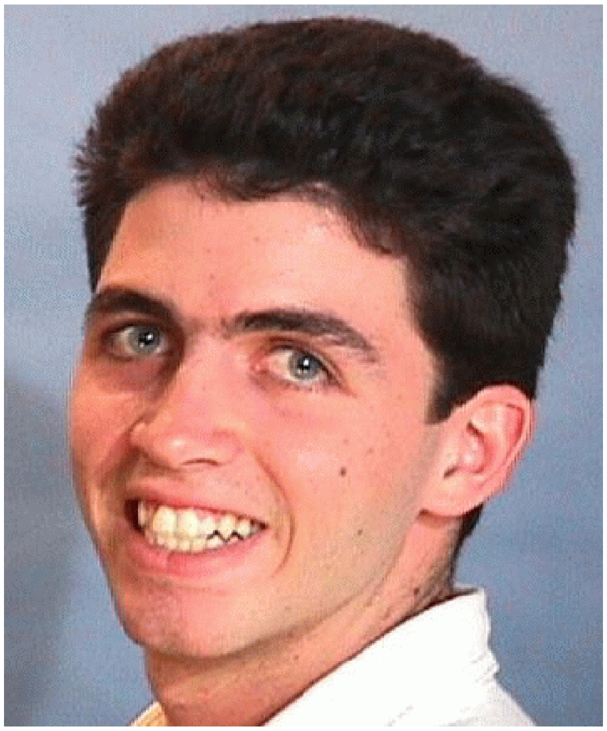
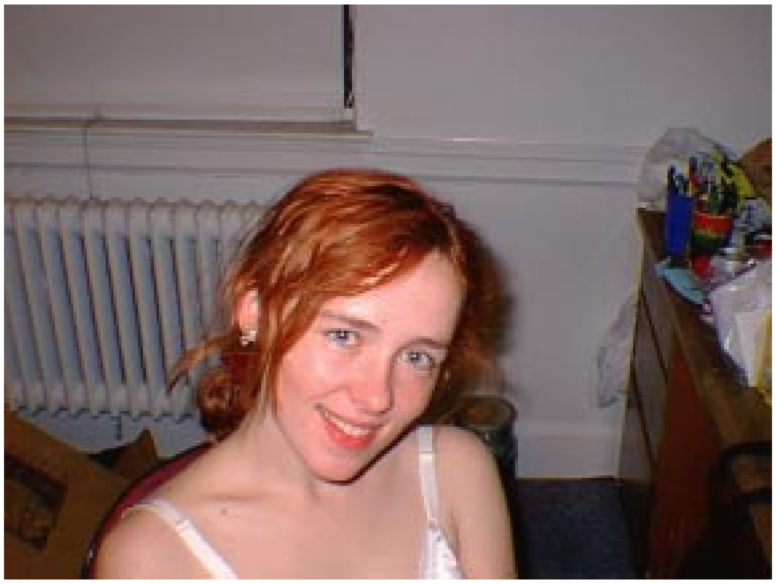


Figure D-3: The first set of database images.



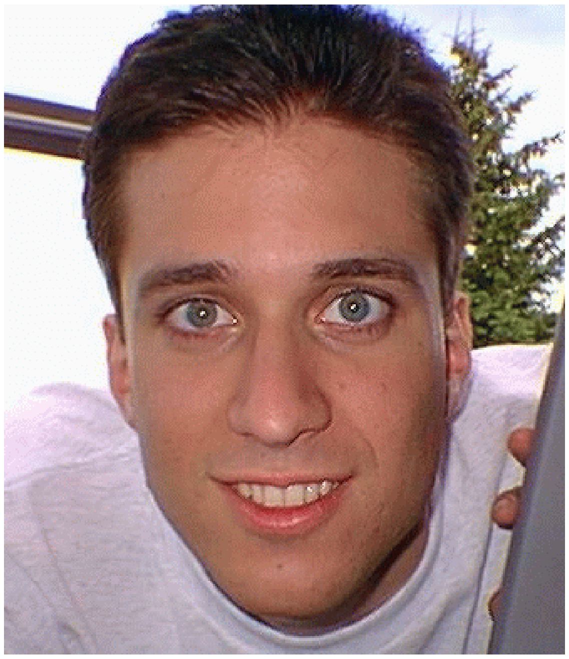
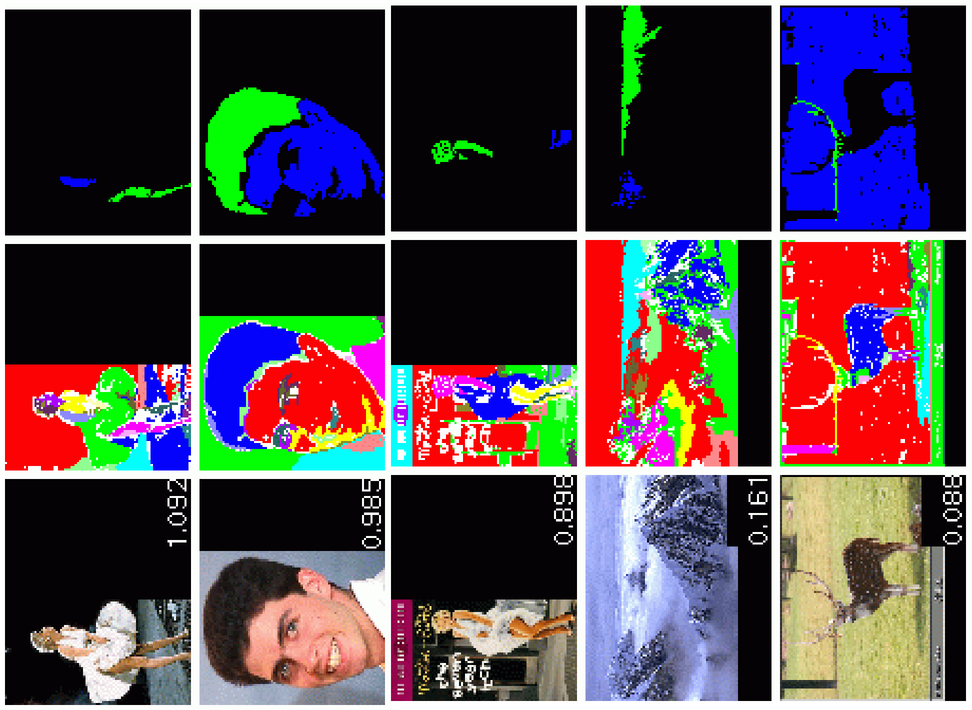
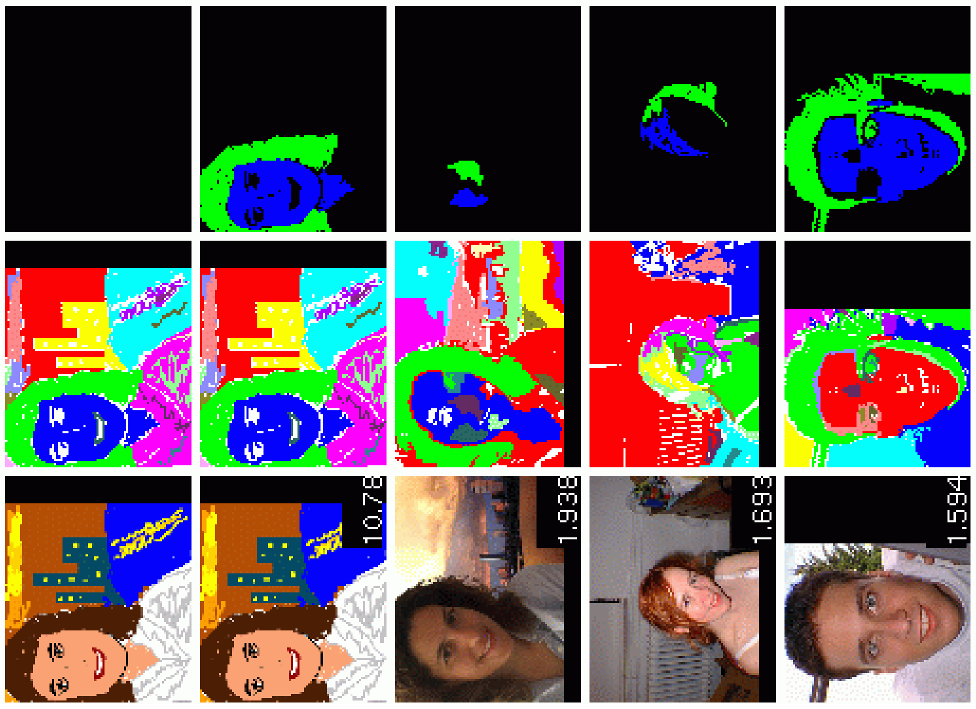
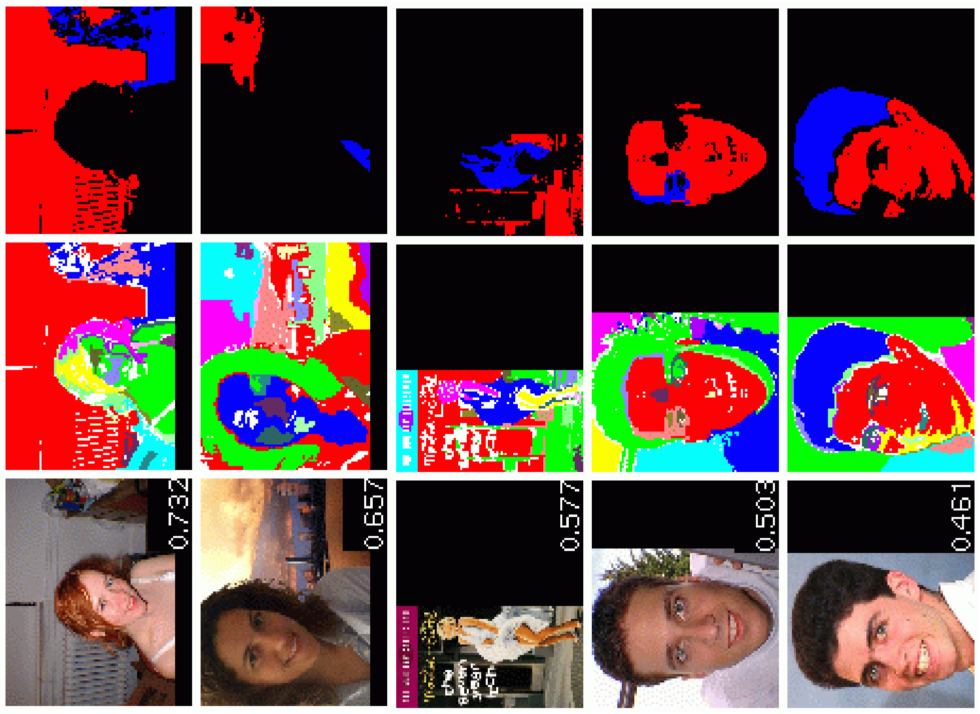


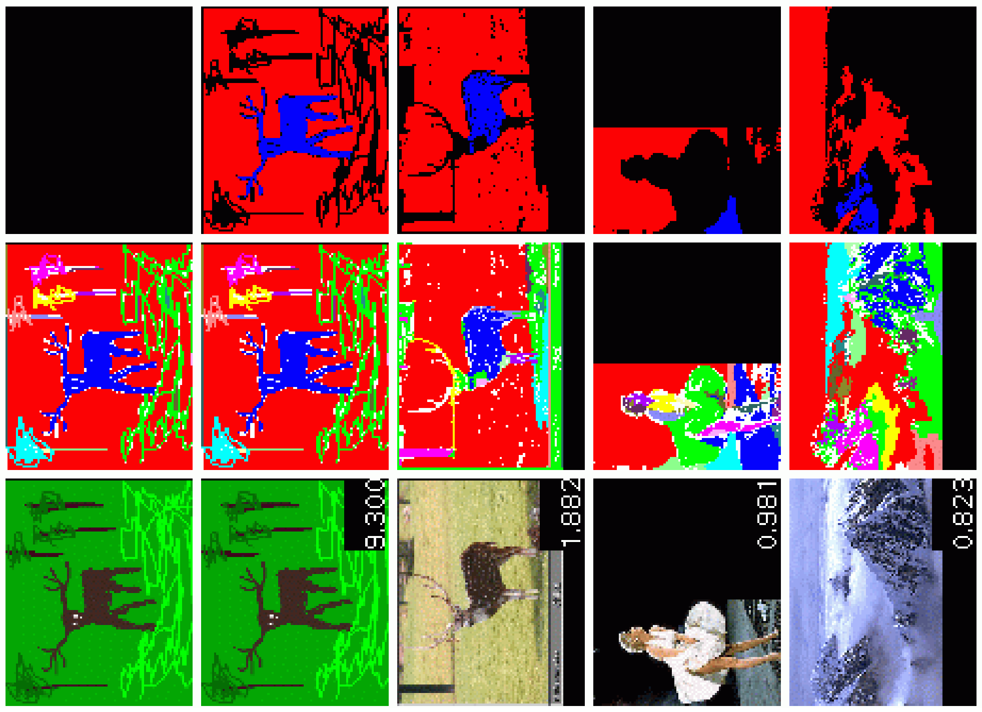
Figure D-4: The second set of database images.

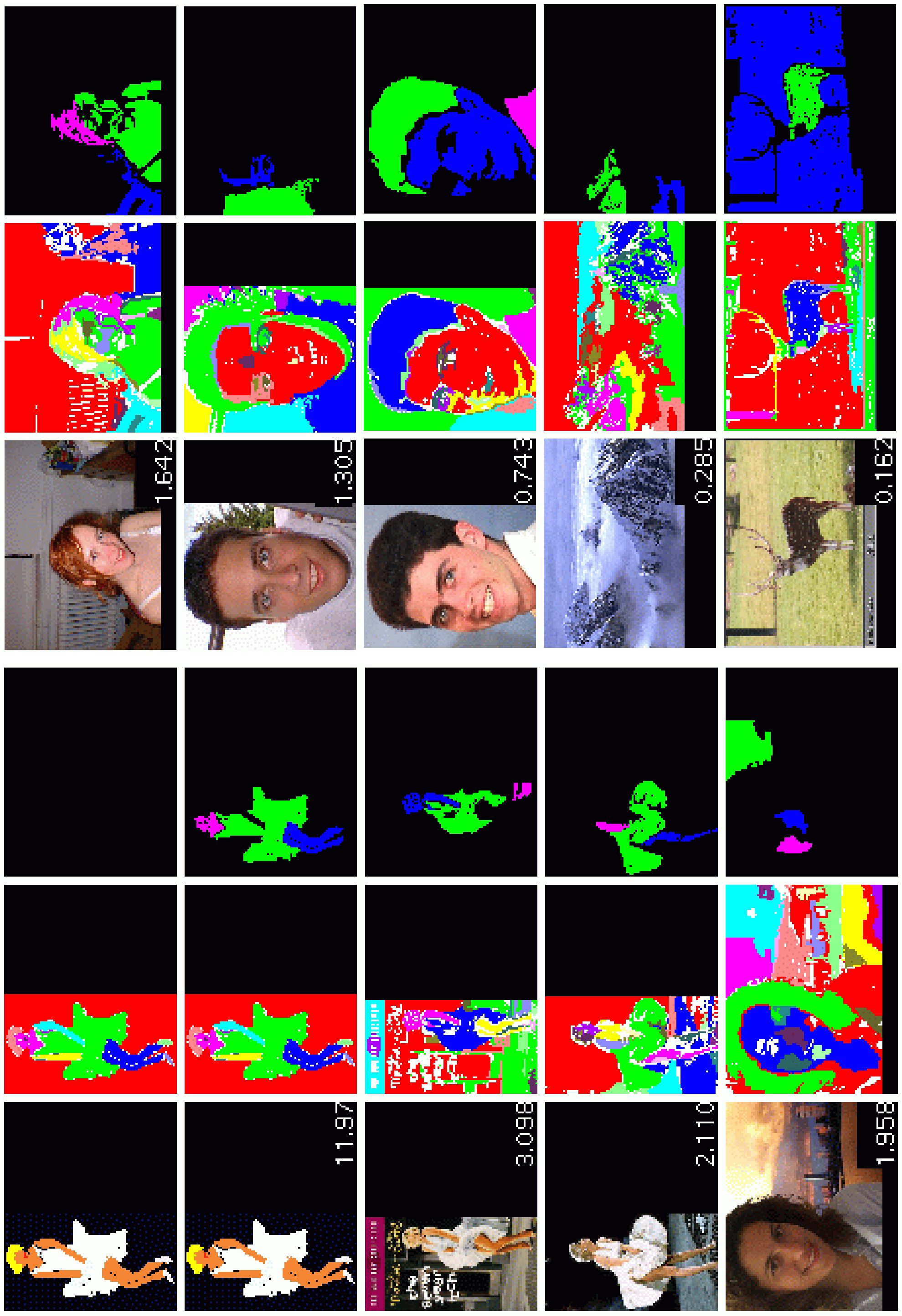
Figure D-5: The third set of database images.

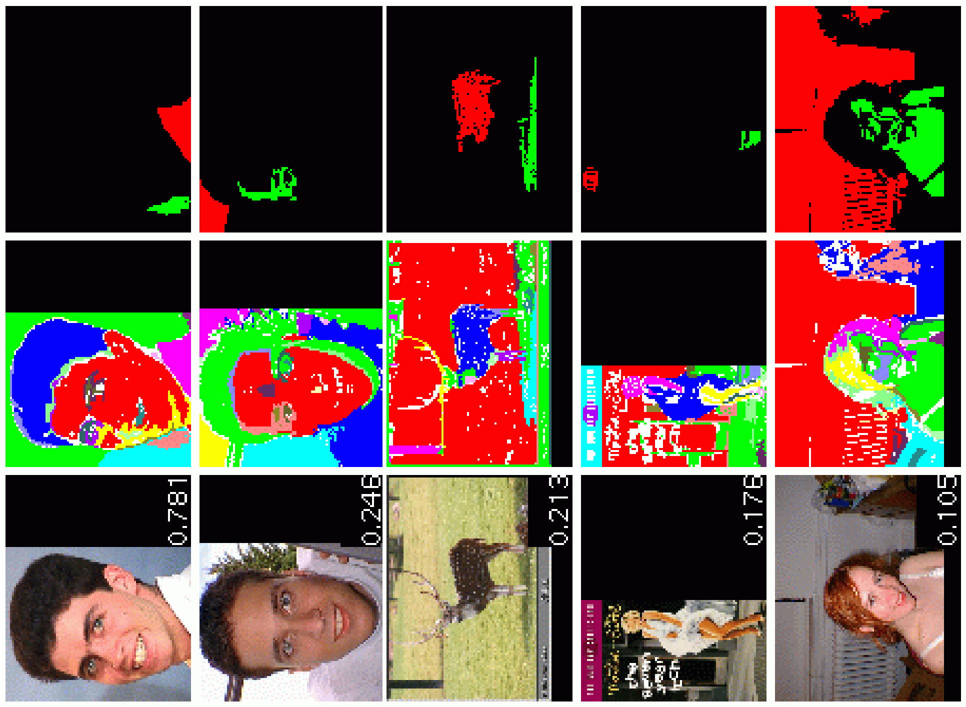

1.092
0.985
0.898
0.161
0.088

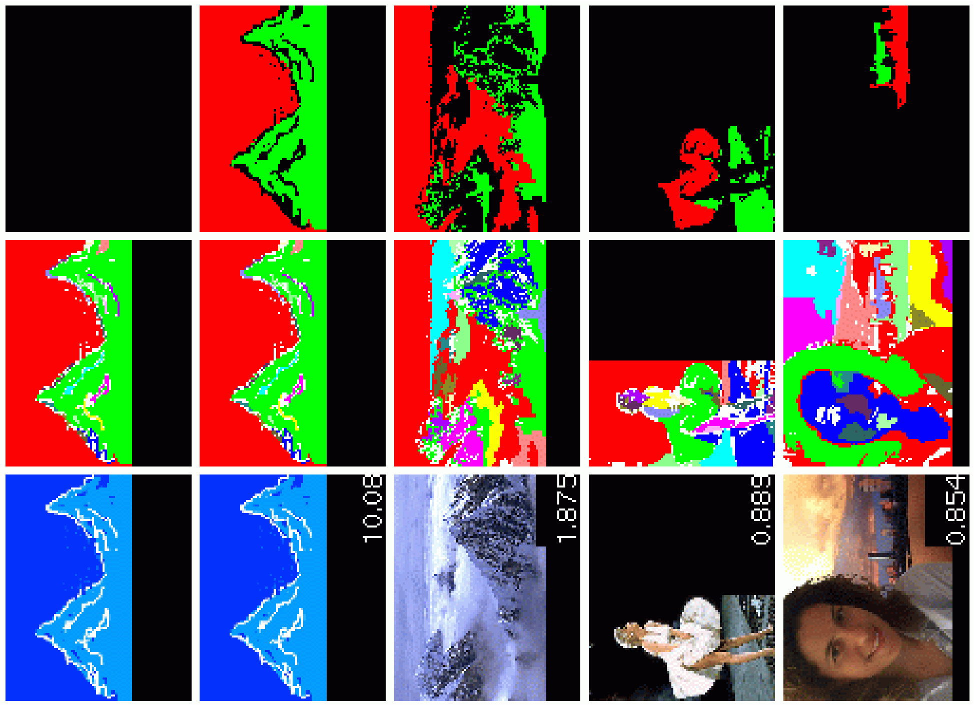

10.78
1.938
1.693
1.594

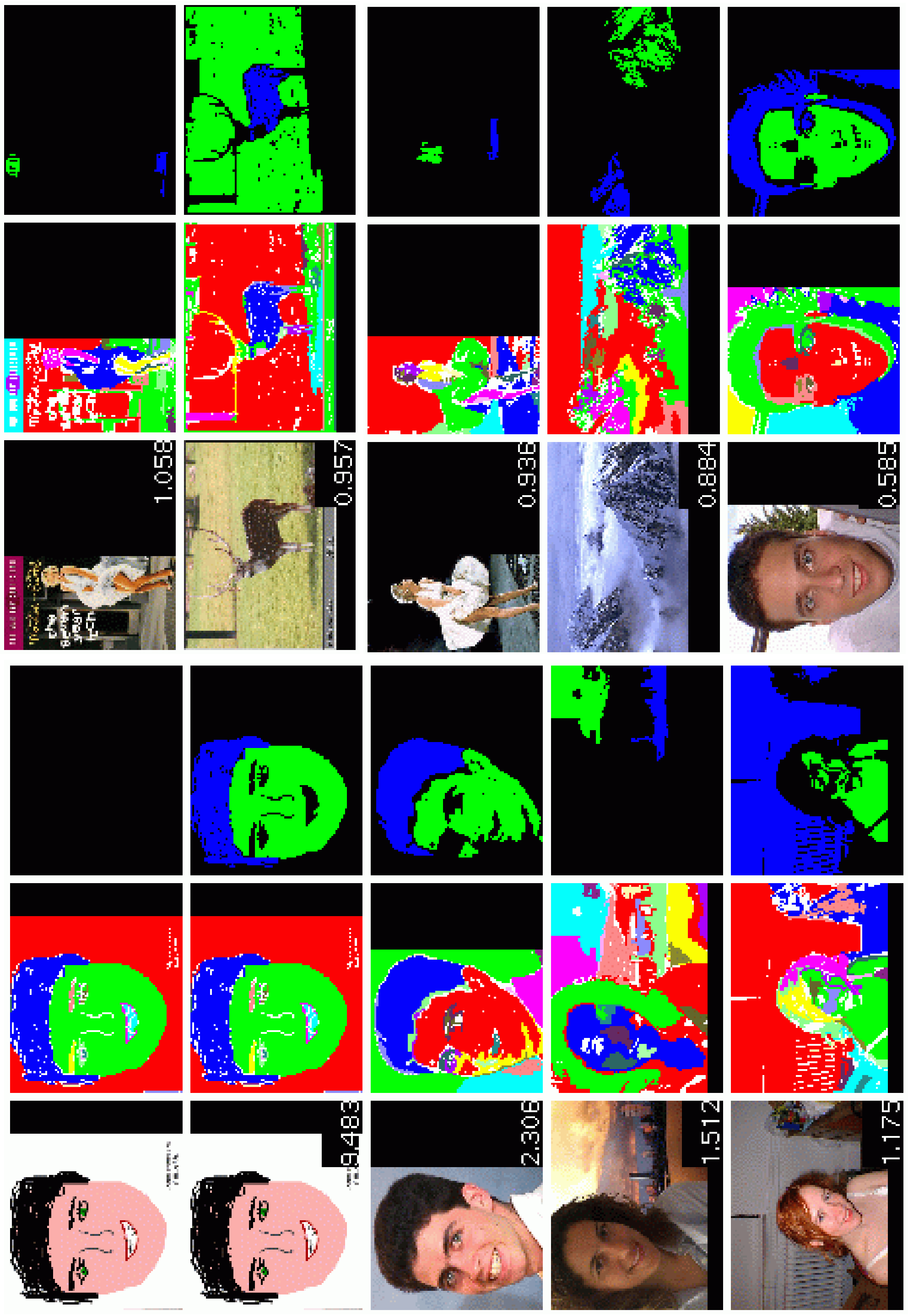

0.732
0.657
0.577
0.503
0.461

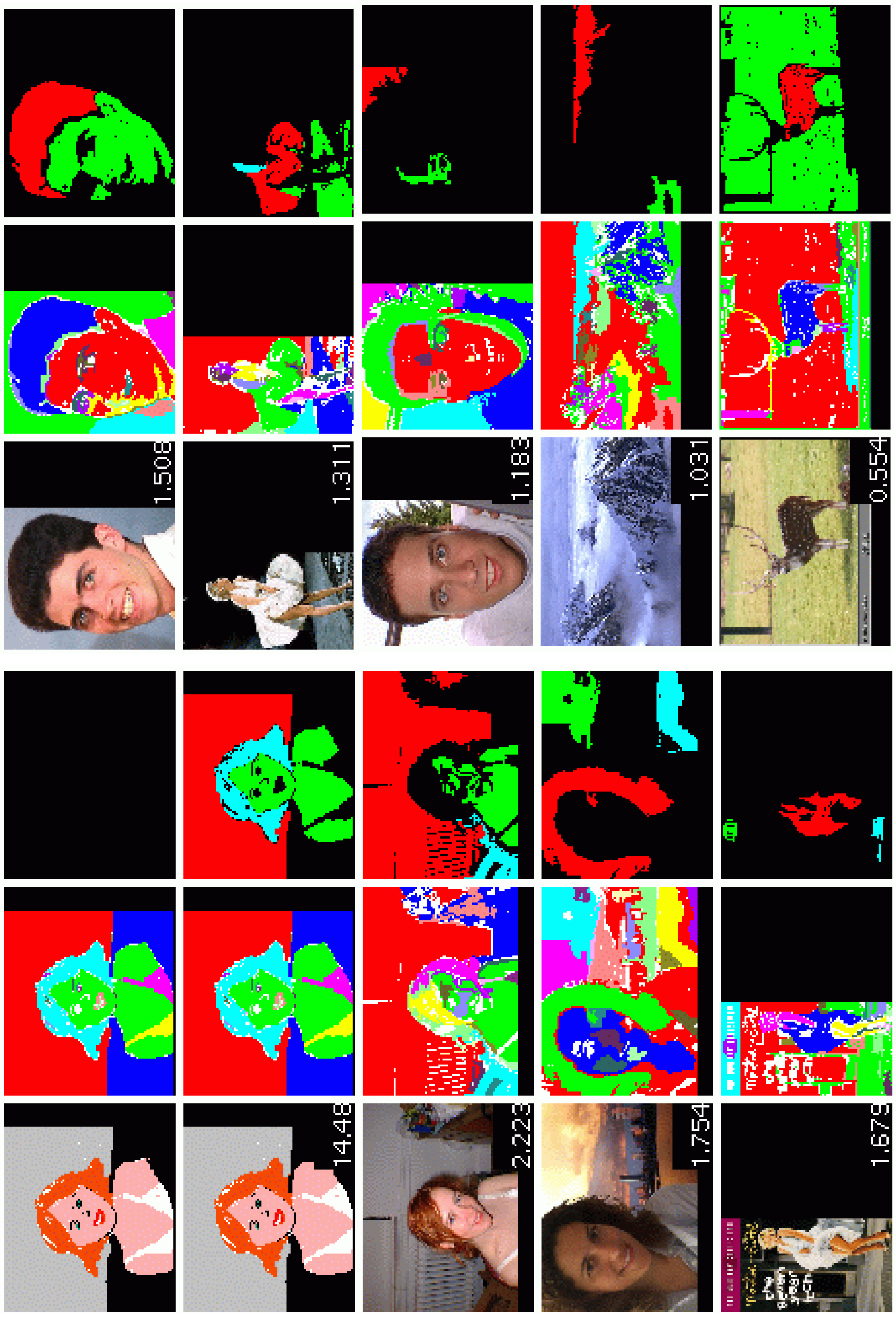

9.300
1.882
0.981
0.823


1.642
1.305
0.743
0.285
0.162
11.97
3.098
2.110
1.958


0.781
0.246
0.213
0.176
0.105


10.08
1.875
0.889
0.854


1.058
0.957
0.936
0.884
0.585
9.483
2.306
1.512
1.175


1.508
1.311
1.183
1.031
0.554
14.48
2.223
1.754
1.679

Appendix E

Image User Queries and Matches

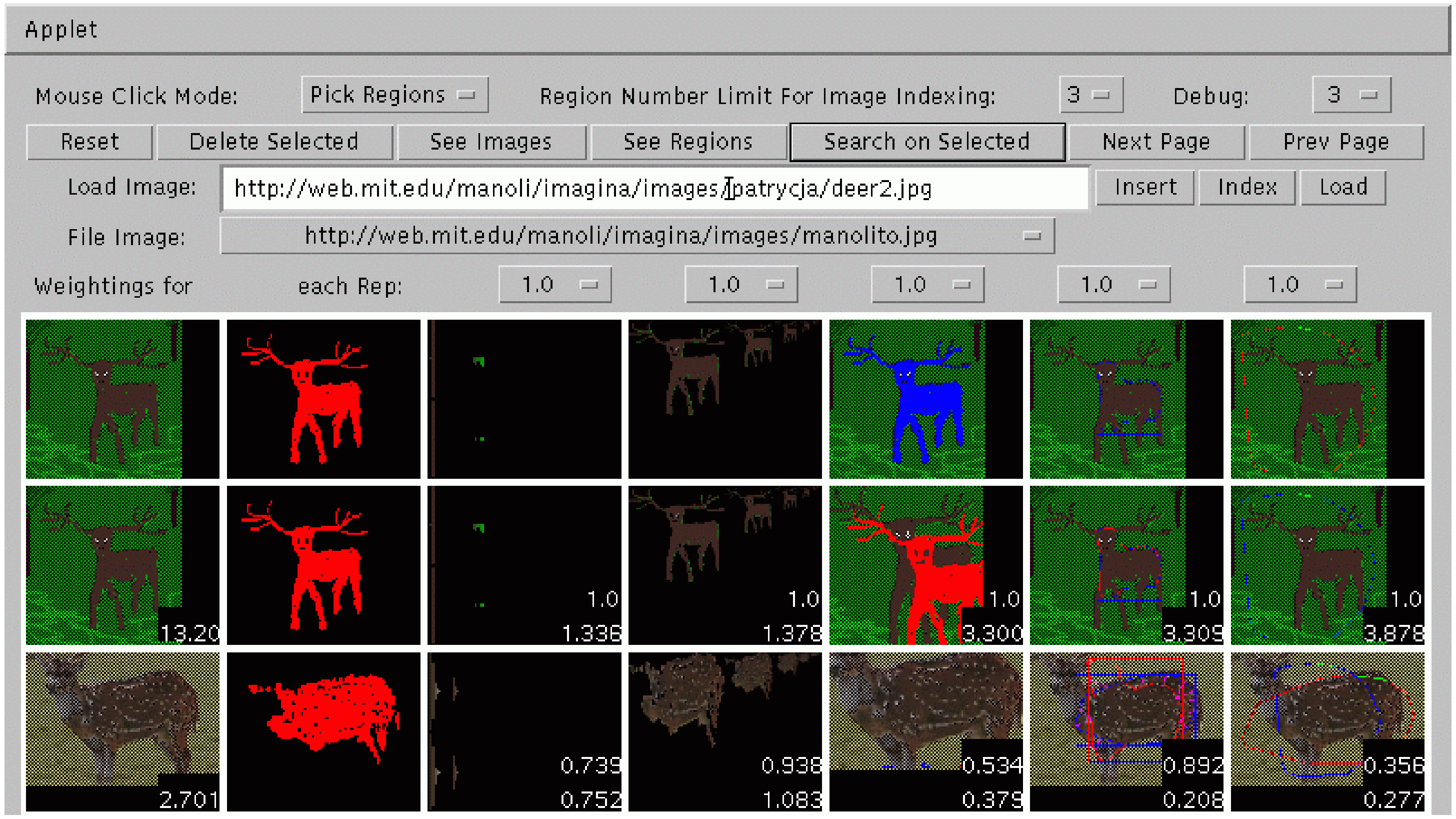
The queries listed here are based on the same query set as the queries in appendix D. These queries highlight the methodology of region matching.

Two search screens are shown at nearly full size, and a third is shown shrunken. Each of these displays a single query result. Although the query results are multiple pages long, only the top matches are displayed in this appendix.

In the search screen, the query region is shown in the first row of the display. The regions which match the best are listed in sequential order, from best to worst, below this. Because the image which contains the query region was inserted into the database before searching in both cases, the query region also shows up as its own best match. This is a good sanity check of the functionality of the comparison mechanisms employed.

Two color and three shape matching metrics are used for region comparison. These are, in order from left to right: color histograms, color mappings, volume-based representation, segment-based representation, and angle-based representation.

The top value displayed in each screen field is the computed match of that region with the query region based on the given representation. The second value is the normalized value for the given representation space. The goodness value of each region is the weighted sum of these values. For the queries shown, the default weights of 1 for every representation space were used.



Applet

Mouse Click Mode: Pick Regions

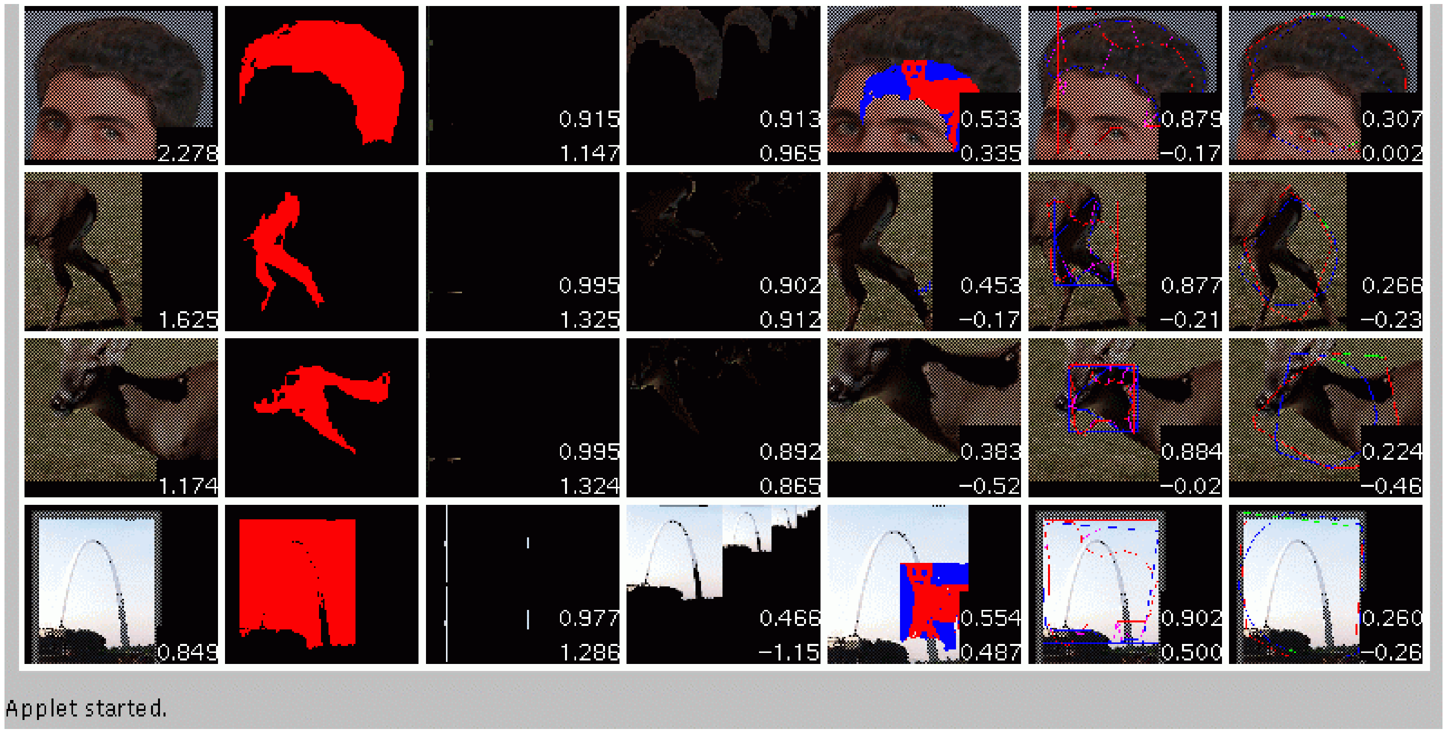
Region Number Limit For Image Indexing: 3

Debug: 3

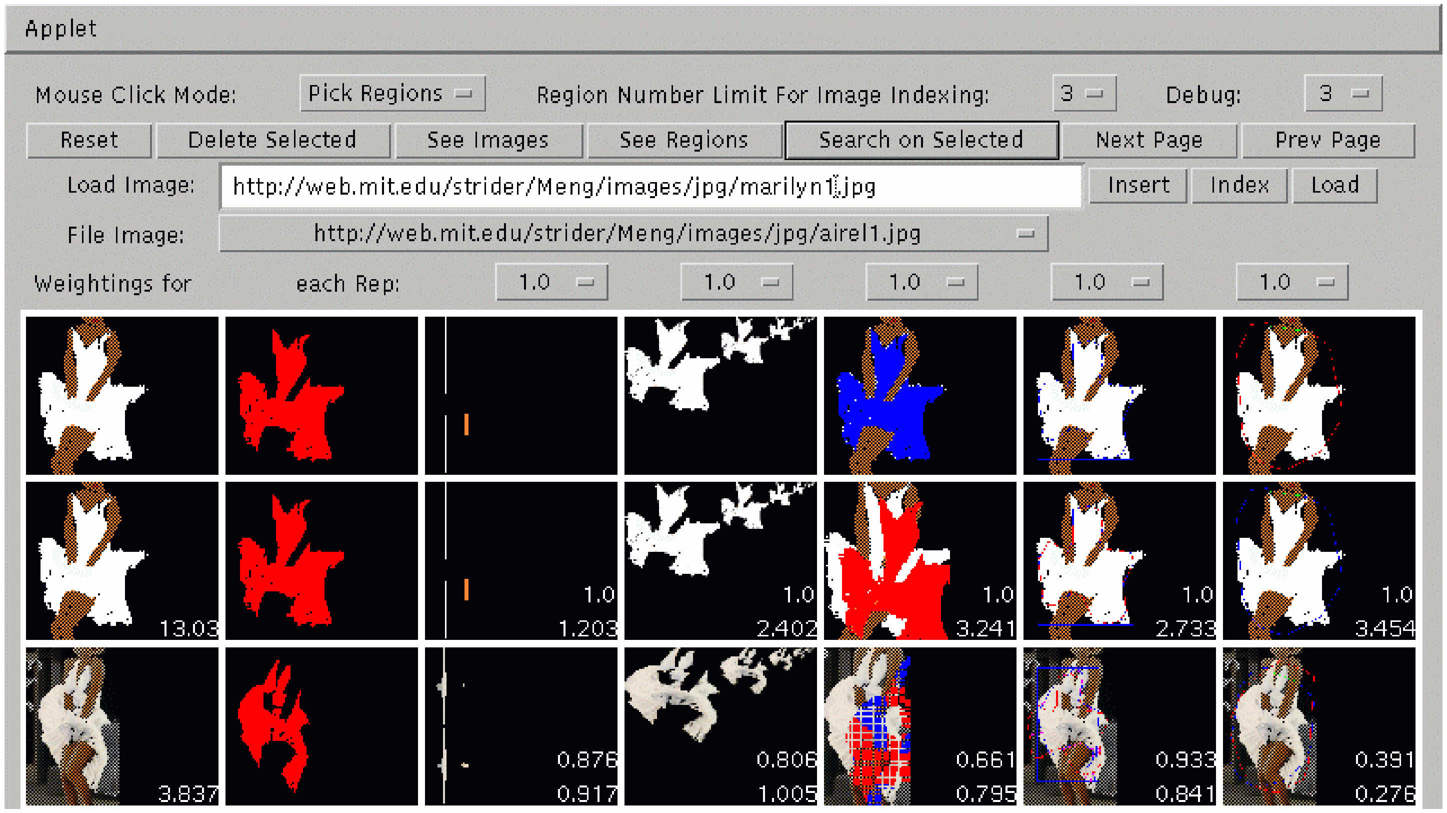
Load Image: http://web.mit.edu/manoli/imagina/images/patrycja/deer2.jpg

File Image: http://web.mit.edu/manoli/imagina/images/manolito.jpg

Weightings for each Rep: 1.0 1.0 1.0 1.0 1.0



Applet started.



Applet

Mouse Click Mode: Pick Regions

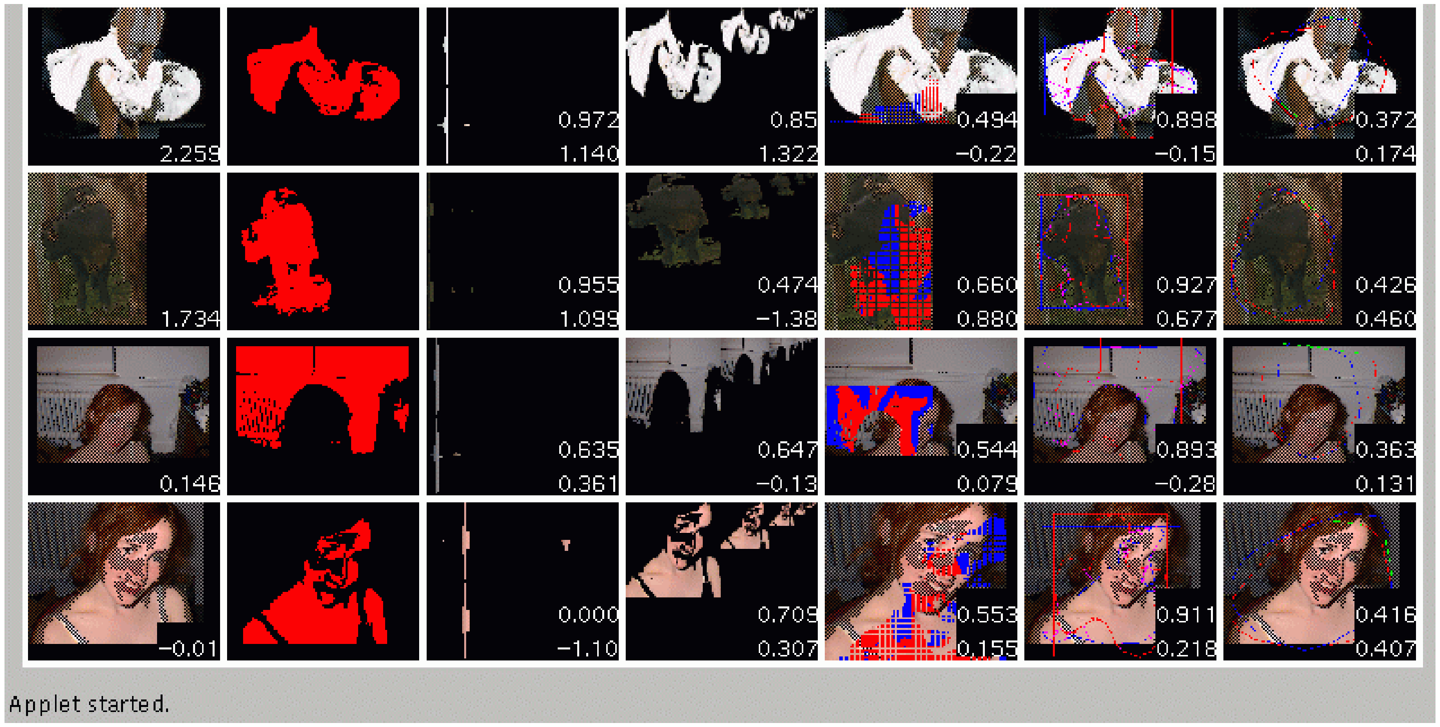
Region Number Limit For Image Indexing: 3

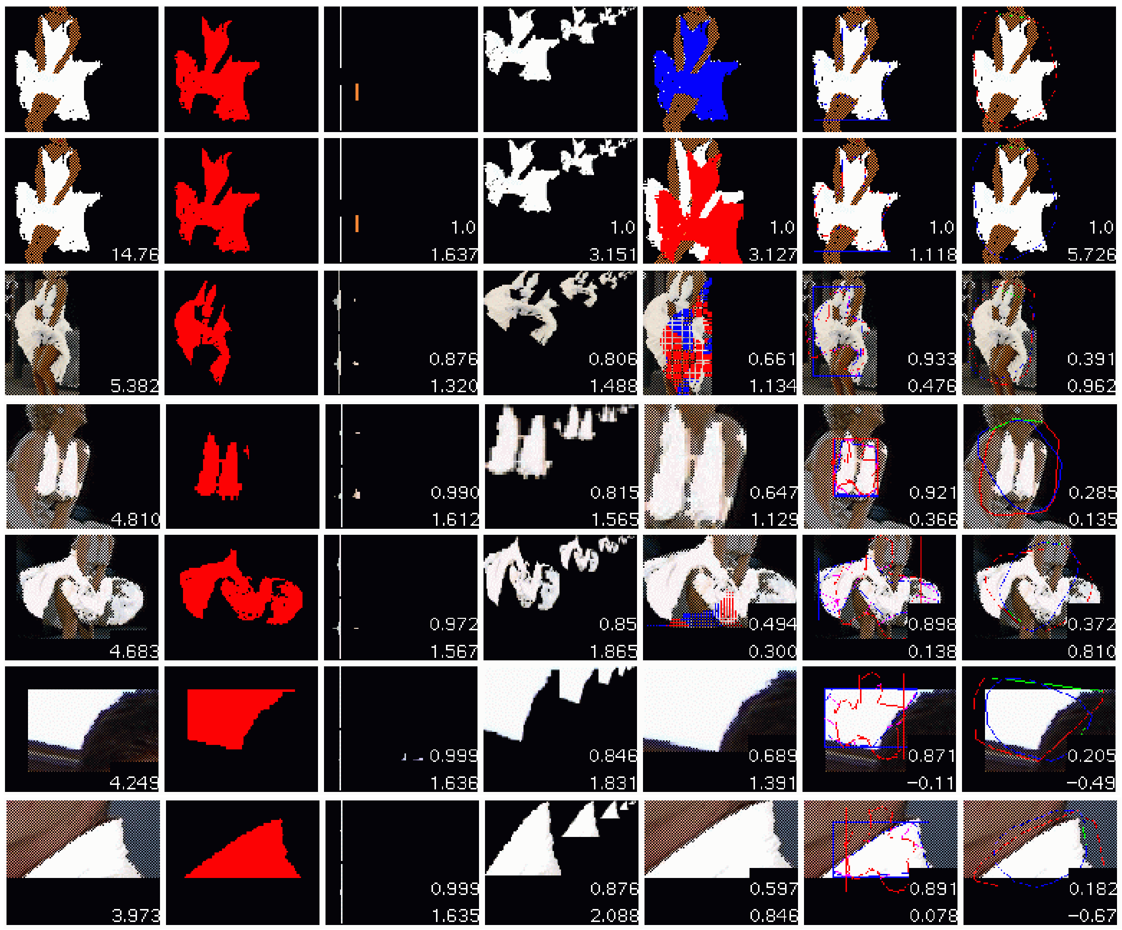
Debug: 3

Load Image: http://web.mit.edu/strider/Meng/images/jpg/marilyn1.jpg

File Image: http://web.mit.edu/strider/Meng/images/jpg/airel1.jpg

Weightings for each Rep: 1.0 1.0 1.0 1.0 1.0


2.259
0.972
1.140
0.85
1.322
0.494
−0.22
0.898
−0.15
0.372
0.174
1.734
0.955
1.099
0.474
−1.38
0.660
0.880
0.927
0.677
0.426
0.460
0.146
0.635
0.361
0.647
−0.13
0.544
0.079
0.893
−0.28
0.363
0.131
−0.01
0.000
−1.10
0.709
0.307
0.553
0.155
0.911
0.218
0.416
0.407
Applet started.



14.76
1.0
1.637
1.0
3.151
1.0
3.127
1.0
1.118
1.0
5.726
5.382
0.878
1.320
0.806
1.488
0.661
1.134
0.933
0.476
0.391
0.962
4.810
0.990
1.612
0.815
1.565
0.647
1.129
0.921
0.366
0.285
0.135
4.683
0.972
1.567
0.85
1.865
0.494
0.300
0.898
0.138
0.372
0.810
4.249
0.999
1.636
0.846
1.831
0.689
1.391
0.871
−0.11
0.205
−0.49
3.973
0.999
1.635
0.876
2.088
0.597
0.846
0.891
0.078
0.182
−0.67

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