

A MODULAR SYSTEM FOR COMPARISON
OF NAVIGATION ALGORITHMS IN
VISUAL DATA EXPLORATION

By

PATRICIA JUSUF

Bachelor of Science

Oklahoma State University

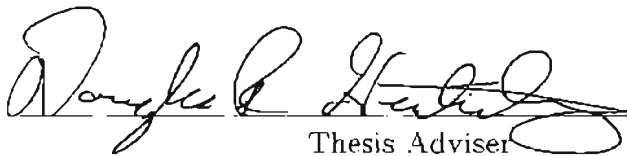
Stillwater, Oklahoma

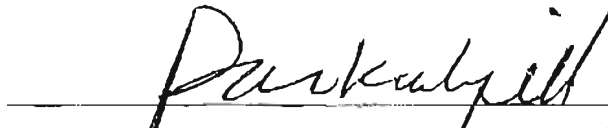
2001

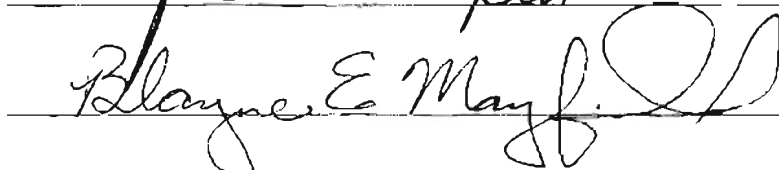
Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
MASTER OF SCIENCE
August 2003

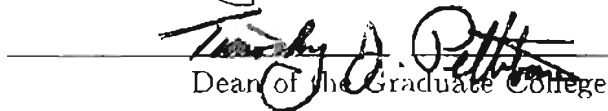
A MODULAR SYSTEM FOR COMPARISON
OF NAVIGATION ALGORITHMS IN
VISUAL DATA EXPLORATION

Thesis Approved:


Thesis Adviser






Dean of the Graduate College

Preface

Navigation of visualization process involves large, complex, unclassified data sets and multidimensional, nonlinear, discontinuous mapping functions. Thus, getting a desirable data from those data sets is usually a painful process. It is then important to know what is the best technique to do the navigation process. Many algorithms have been developed to improve the navigation process. But since each of those algorithms has its own approach and test data sets, a system that can compare the performance of those algorithms is needed.

This thesis is about a modular system that is designed especially for testing and comparing those algorithms with various data sets. The system is divided into six components. Each component can have several different types and can be easily taken off from the system and substituted with other components. The system uses network so that many users can access the system and giving feedback at the same time. This can help speeding up the navigation process. XML template is used to assign values to test data sets instead of having several test data set files. We will compare the system proposed with several test data sets: OpenGL standard objects, real world objects, and scientific data sets.

Acknowledgment

I would like to express my sincere appreciation to Dr. Douglas Heisterkamp, the Chairman of the Advisory Committee, for his assistance, patience, and guidance throughout my study at Oklahoma State University. I would also like to thank my committee members, Dr. Nohpill Park and Dr. Blayne E. Mayfield, for their advice and instructions.

I would like to extend my appreciation and gratitude to my parents and my brothers for their continuous love, support, and encouragement. I am also grateful to my friends and colleagues for their valuable suggestions and support.

Table of Contents

1	INTRODUCTION	1
1.1	Navigation Algorithm Problem	2
1.2	Contribution to the Work	3
2	DEVELOPMENT IN NAVIGATION IN VISUALIZATION	5
2.1	Development in User Interface	5
2.2	Development in Generator	10
3	COMPARING AND TESTING THE NAVIGATION ALGORITHMS IN VISUAL DATA EXPLORATION	20
4	EXPERIMENT	29
4.1	The Architecture of the System	29
4.2	The Result and Discussion of the Experiments	43
4.2.1	User Interaction	44
4.2.2	CPU Time	46

4.2.3	Similarity measure	48
5	SUMMARY	62
6	FUTURE WORKS	65
	APPENDICES	72
A	GLOSSARY	73
B	USER INTERACTION AND CPU TIME TABLES AND FIG- URES	75
C	EUCLIDEAN DISTANCE AND SIMILARITY VALUE TA- BLES AND FIGURES	77
D	EUCLIDEAN DISTANCE AND SIMILARITY VALUE DIS- TRIBUTION TABLES AND FIGURES	107

List of Tables

4.1	Average time needed to find the desired image	45
4.2	Average number of deadends for all data sets tested	45
4.3	CPU time of all data sets for all generators tested	47

List of Figures

2.1	A portion of Image Graph representing the exploration of a foot dataset.	9
2.2	A sequence of spreadsheets displaying the visualization of a foot data set.	18
2.3	A Design Galleries for light selection and placement.	19
4.1	The screenshot of the system	30
4.2	The transition between the displays of images	31
4.3	Diagram of the system	33
4.4	Diagram of the Generator	34
4.5	Diagram of the Renderer	35
4.6	XML template before substitution	36
4.7	XML template after substitution	37
4.8	Diagram of the Systems File Structure	41
4.9	Resource file from client side: client.rc	41
4.10	Resource file from server side: server.rc	42
4.11	Real Object's maximum Euclidean distance value distribution	52

4.12 OpenGL Object's maximum Euclidean distance value distribution . . .	55
4.13 Scientific Data's Euclidean distance and similarity value distributions	59

Chapter 1

INTRODUCTION

Navigation in visualization is a process of exploring complex, large, unclassified-data sets, to get a desirable output image via visualization. In order to get insight from large data sets, two things are needed [12]:

1. Efficient algorithms. Efficient algorithms are designed so that given input parameters, a desirable output image will be generated in a minimum amount of CPU time, user interaction, and feature space.
2. Intuitive user interfaces (UIs). Efficient algorithms will be useless unless there are intuitive user interfaces (UIs) that can help presenting and storing the visualization exploration process.

Many papers and projects have been made in developing efficient algorithms. Those papers and projects try to improve navigation in visualization process by developing algorithms that can yield a desirable output image accurately and economically.

Some user interfaces (UIs) have also been designed to support the algorithms in displaying and storing the navigation process, so that the resulting images throughout the process can be reused and perceived more easily.

User Interfaces (UIs) is also essential in navigation process. Without an intuitive user interface (UI), it will be hard to retrieve the parameters of an image, or to which direction will the exploration process have to be continued. It will also be hard to decide which generator is best for large or small set of data, etc.

Generator, a component where the algorithm is located, is the main part in navigation system, since given a set of random input vector, it is trying to find input parameter vectors which output vectors resulting a dispersed set of images. Generators will then wait for the feedback from the user about the first generated images, and make another set of images based on the feedback, and so on. Therefore, the successful of navigation system is highly depending on the generators (algorithms) and the intuitive user interface to guide the user in perceiving resulting images.

1.1 Navigation Algorithm Problem

Many algorithms and user interfaces (UIs) have been designed to improve the navigation of visualization process. Many generators have been developed; each is developed to make the navigation process more accurate and economical, and some are developed to optimize the previous ones. Some algorithms that are used to do the navigation process are algorithms that originally implemented for content-based image retrieval.

Those types of algorithm are used for classifying images that are in the database. To do navigation process using these types of algorithms, new set of images then has to be computed based on the classification.

With so many algorithms available, it is then hard to decide which algorithms have the overall best performance for which type of datasets tested. Each algorithm is tested with its own test datasets and with its own measurement of performance. Each of those algorithms has its advantages and disadvantages, depends on many factor, such as the type of test dataset used, or the size of the dataset. Thus, to test each dataset efficiently and optimally, it is essential to know which algorithm that should be used.

The problem is, there is no specific system has been especially designed to test and compare the performance of the generators in several measurement aspects. A system that can test and compare the performance of those algorithms is then need to be implemented.

1.2 Contribution to the Work

Since it is essential to know each algorithm's advantages and disadvantages, a modular system that is able to test and compare between the generators is then implemented. Thus, we know what each generator best used for.

This thesis is about a modular system that is especially designed for testing and comparing generators. The interface of the system itself is designed similar to

Design-Galleries [29]. The system is able to test many generators and define each generators advantages and disadvantages. It can measure the performance of each generator in generating input parameter vector; it can measure the time needed to give the user the image that he wants.

The system built is measuring the user interaction (how much time needed to find the desired image and number of deadends), CPU time, and the similarity measures between the current set of images and the desired image. There are four similarity measures used, which are Gabor, Color Histogram, Haralick, and Correlation. And seven types of generator are used for this comparison process, which are Random, Peng [35], PFRL [11, 34], SVM Light [4], SVM-Peng [4, 35], Transductive SVM [21, 31, 43], and BSVM [18].

Chapter 2

DEVELOPMENT IN NAVIGATION IN VISUALIZATION

Navigation of visualization techniques are now developing rapidly. Researchers are intensively developing better and better visualization algorithms and user interfaces. The developments in user interface part are mainly to support the development in algorithms, so that the user can interpret and retrieve the data more easily.

2.1 Development in User Interface

There used to be no specific system was designed to support the navigation process. There was not even any specific algorithm used to select the rendering parameters at that time. All things were done manually. The process of data exploration was more like a process of trial and error (turn-key). The user kept trying various combinations of rendering parameters until he found the output image that he was looking for.

Turn-key method seemed to exhaust the user. Therefore, algorithms started to be used to navigate the selection of input parameters. An actual system with the algorithm in it then started to be designed too to help improving the process of navigation. Data-flow model [10] was widely used for commercial used. This model allows the user to construct directed graphs representing the flow of data through the system. An image graph stores information about data exploration, and is unique because of its intuitive edge representation and dynamic features.

The problem with data-flow model is that there is no way to retrieve the visualization process. The input parameter vectors that generate images between the beginnings until the end of flow nodes are not saved. Therefore, there is no way to retrieve those images back.

As large multidimensional data set is used, navigation of visualization process needs a system that can support visibility so that the whole system can be displayed in one screen, and reusability, which means a user interface that can keep track of the previous images generated (history). Many papers and projects have been done to develop techniques that can solve this visibility and reusability problem.

Some simple techniques used to solve visibility problem are: zoom techniques, graph compression, or focus+context techniques [26], or fisheye lense [10]. Herman et al. [12] has done a survey of visualization and navigation techniques. Keim [23] classified visualization techniques based on the data type to be visualized, the visualization techniques, and the interaction and distortion techniques.

Some other papers developed new techniques, especially visualization techniques where all data can be seen in one screen. Fua *et al.* [8] developed structure-based brushes that allow users to navigate hierarchies of graph by specifying the specific part and the level-of-detail. Keim [22] developed pixel-oriented visualization technique to help exploring and analyzing large amount of multidimensional data. It maps each dimension of multidimensional data to color in a subwindow, and decide the arrangement, shape, and ordering of subwindows. Abello and Korn [1] developed MGVI, a navigation technique for massive multigraphs that combines interactive pixel-oriented 2D and 3D map, statistical displays, color maps, multilinked views, and a zoomable label based interface. Kreuseler and Schumann [25] developed another new visualization technique to gain more insight from the information space, including an intuitive focus+context technique. Some of the techniques will make the graph hard to be visualized. It is hard to find out where we are, and which direction should we search what we want. Each of those techniques will make the resulting images sometimes distorted and hard to be percept and compared.

Parameter-based representation system is then made. This type of representation does not intend to display the whole data in one screen. It displays only a portion of data, and let the user interactively steer the system to display the image that he wants using several techniques, for example: machine learning, artificial intelligence, image graph, or spreadsheet. This way, the data shown on the screen at one time is visible, and so it is easier to be perceived. The systems that fall into this category

are Image Graphs [28], Spreadsheet-like Interface [20], and Design Galleries [29].

Image Graph [28] is a system with a unique nodes-and-edges representation. Each edge connects two different nodes, and represents one of six different rendering parameters: color map, opacity map, rotation, zoom factor, shading, and resampling. It symbolizes the connection between two nodes, noted what parameter changed between the two nodes. Only one parameter can be changed from one node to another. Each node simply represents the image itself, and it also keeps with it the input parameter vector that is used to generate the image.

Figure 2.1 is taken from paper by K. L. Ma [28], shows us a portion of Image Graph representing the exploration of a foot dataset. The numbers added to the graph to show the order of nodes generated. Each edge notates what parameter changes each time. From Node 1, the user changes the color parameter, opacity, and direction of the image to get Node 2 as the resulting image. Node 3 is the result of rotation that is applied to Node 1.

As more images added, Image Graph needs more and more space to display the entire visualization process. Because of the limitation of screen space, and also for visibility aspect, Image Graph is not efficient for large data set with multidimensional rendering parameters. Therefore, when large data set inputs are used, special techniques similar to visualization techniques then have to be applied to maintain the visibility of the system.

Spreadsheet-like system [20] has rows and columns, where each row and column

defines what parameter used and what is the value of it. With this interface, the comparison process can easily be seen, and the history of images can easily be traced back.

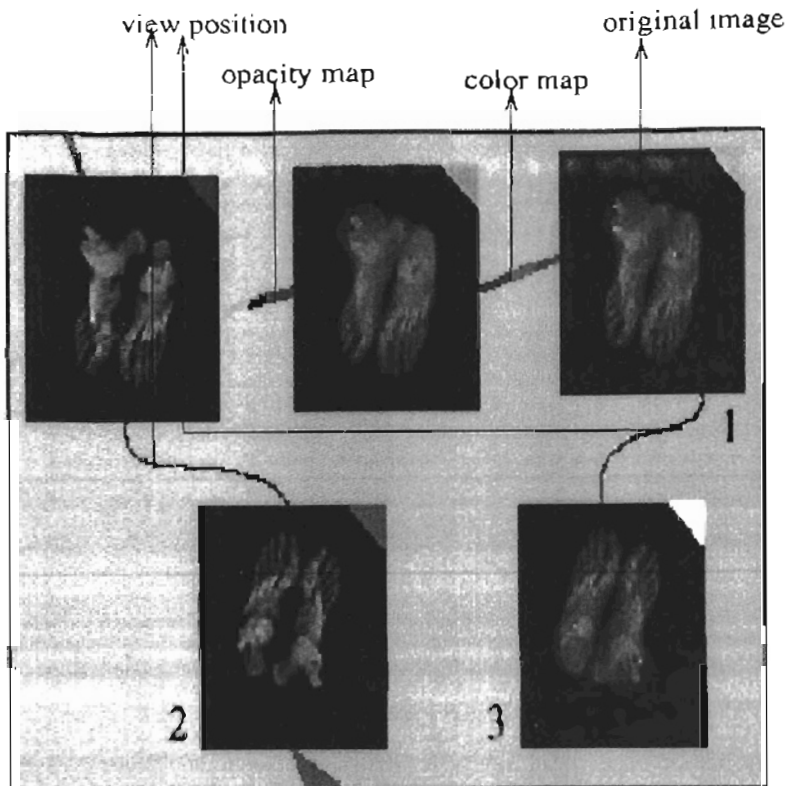


Figure 2.1: A portion of Image Graph representing the exploration of a foot dataset. This figure is taken from paper by K. L. Ma [28] page 83 Figure 3.

Figure 2.2 is taken from paper by K. L. Ma and T. J. Kelly [20], shows the effectiveness of Spreadsheet-like Interface for comparing skin and bone surface. With this interface, the difference between images can be seen more clearly by comparing

between rows and columns. On the first row, the opacity of the foot is determined, then the view position, color, and finally zoom factor.

Sometimes not all kind of data can be explored by using spreadsheet-like interface. Design Galleries [29] uses dispersion algorithm which given a set of light, finding a set of input vector that resulting output vector can optimally yield disperse images. Those images are expected to have the broadest selection of perceptually different graphics that are produced from broadest selection of input-parameter vector. Arrangement technique in Design Galleries will then represent the resulting images in a way so that those results can be percept more easily. The arrangement depends on the w (width) and h (height) value, where w defines the number of images per level, and h defines the number of level.

Figure 2.3 is taken from a paper by Andalman *et al.* [29], shows us the interface of Design Galleries with varying light selection and placement. In this picture, the weight (w) of the interface is 8, and the height (h) of the interface is 3. The user defines these values.

2.2 Development in Generator

Dispersion algorithm is important in finding input parameter vectors that can yield output vectors with disperse resulting images. Nowadays, dispersion algorithm is included in a part of a system called generator (Figure 4.4). In generator, dispersion algorithm based its next sampling on the feedback from the previous sampling process

that inputted to it. It will learn interactively which direction it will sample based on the feedback.

There are many kinds of techniques used to make sampling based on the previous feedback to be effective. Active learning and adaptive resampling are used for this relevance feedback technique. What the advantages and disadvantages of each technique are still questionable. Therefore, a modular system that is able to test and compare the performance of generators needs to be made.

Random Generator is a generator where the dispersion algorithm accepts no feedback from the user. It randomly samples images each time. This generator has random amount of time to find the desired image; the overall performance is predictably not really good.

There are already several projects made to develop more dispersion algorithm that take feedback from the user, and can learn fast from the feedback given. They have to be able to sample images that are closer and closer to the desired image in a smallest amount of time.

One of the generator with relevance feedback technique is Peng Generator [35], which given previous images feedback, makes new samples around the positive samples of the previous images. Given labeled data, it finds the mean value of each feature among the relevant data. It also finds the mean distance from each of the relevant data to the mean data. And from that mean values and mean distance values, new samples are computed by finding data around those mean values, with a

maximum distance of mean distance values from the mean values.

The other technique is based on paper by Peng *et al.* [34] and Heisterkamp *et al.* [11]. Given previous images' feedback, it uses Probabilistic Feature Relevance Learning and its combination with Query Shifting to retrieve similar images. It extracts images features and calculates their distances compare to other images, and return images with minimum distances.

This technique optimizes K-nearest neighbor kind of algorithms. K-nearest neighbor kinds of algorithms use the same weights for measuring each feature importance. Given similarity metric, the weights remain fixed in the computation. PFRL technique optimize this by assigning different weights for different features, depends of their importance in deciding the relevancy of data. This is important, since similarity does not vary with equal strength or in the same proportion in all directions in the feature space emanating from the query image. PFRL uses probabilistic method that enables image retrieval procedures to automatically capture feature relevance based on user's feedback and that is highly adaptive to query location. The weights can be calculated by first estimating the relevancy of each feature. If we have:

$$(x_j, y_j)_1^K$$

with: x_j denotes the feature vector representing j th retrieved image, and y_j represents the label (relevant or irrelevant), then the estimation of relevance, which uses the data from the vicinity of x , at z is:

$$E[y|x_i \dots z] = \frac{\sum_{j=1}^K y_j 1(|x_{j_i} - z| \leq \Omega)}{\sum_{j=1}^K 1(|x_{j_i} - z| < \Omega)}$$

From this estimation, we can define a measure of feature relevance for query z as:

$$r_i = E[f|x_i = z]$$

And the weights is then:

$$w_i(z) = \frac{\exp(T r_i(z))}{\sum_{l=1}^q \exp(T r_l(z))}$$

with T is a parameter that represent the influence of r_i on w_i . If $T = 0$, we have $w_i = 1/q$, which means the weights are considered equal as in conventional K-neighbor algorithm. Thus, the distance between two images is then:

$$D(x, y) = \sqrt{\sum_{i=1}^q w_i(x_i - y_i)^2}$$

I then developed two new techniques that also consider the importance of certain feature in deciding the relevancy of an image. These techniques also consider that one feature of an image may not have the same importance as other features in deciding an image's relevancy.

The first technique (MyGenerator1) finds the feature that has the smallest distance to the mean of relevant samples. The smaller the distance to the mean of relevant sample means the bigger distance to the mean of irrelevant samples. That feature will be the most important feature that decides the relevance of an image.

Consider images A and B (relevant), C and D (irrelevant), with n features each: $A : A_1, A_2, \dots, A_n$, $B : B_1, B_2, \dots, B_n$, $C : C_1, C_2, \dots, C_n$, $D : D_1, D_2, \dots, D_n$. The mean of relevant images is: $AB^+ = \frac{A_1+B_1}{2}, \frac{A_2+B_2}{2}, \dots, \frac{A_n+B_n}{2}$. The mean of irrelevant images is: $CD^- = \frac{C_1+D_1}{2}, \frac{C_2+D_2}{2}, \dots, \frac{C_n+D_n}{2}$. The distance between each of the n

features of relevant samples to mean of relevant images and mean of irrelevant images:

$$\sigma_1^+ = \frac{|A_1 - AB_1| + |B_1 - AB_1|}{n}$$

$$\sigma_1^- = \frac{|A_1 - CD_1| + |B_1 - CD_1|}{n}$$

$$\sigma_2^+ = \frac{|A_2 - AB_2| + |B_2 - AB_2|}{n}$$

$$\sigma_2^- = \frac{|A_2 - CD_2| + |B_2 - CD_2|}{n}$$

.....

$$\sigma_n^+ = \frac{|A_n - AB_n| + |B_n - AB_n|}{n}$$

$$\sigma_n^- = \frac{|A_n - CD_n| + |B_n - CD_n|}{n}$$

From above, the smaller σ_i^+ is, and the larger σ_i^- is, the more relevant a feature is. Thus, to find new samples, the more relevant a feature is, the smaller we alter that feature.

The second technique (MyGenerator2) is also implemented based on the importance of image's features. MyGenerator2 finds the range of values where the features are relevant and irrelevant, and sorts them in ascending order. For example, consider six images A through F, each contains of n features. Images A, B, C, and D are relevant, and image E and F are irrelevant. The k th feature will be: $A_k^+ B_k^+ C_k^+ D_k^+ E_k^- F_k^-$, with $1 \leq k \leq n$. After each feature in the image is sorted, the result of first feature could be: $A_k^+ E_k^- B_k^+ C_k^+ F_k^- D_k^+$, with $1 \leq k \leq n$. Based on these range, the new samples will then be a random number with three ranges of

value. The first range is A_k , the second range is minimum value of B_k and maximum value of C_k , and the third range is D_k .

Other generators use active learning and adaptive resampling [19] in its dispersion algorithm. Active learning is a technique of picking a subset of data, and classifying them by giving them labels of relevance, irrelevance or unknown. Based on this classification, we generate classification model that can label the entire data set. Adaptive resampling is a technique that optimizes the process of classification, so that the classification model is more accurate and precise, and so have a smaller number of possibly misclassify instances.

Support Vector Machine [4] is also one type of powerful generator. It has already been widely used for data classification process, such as speech recognition [32], high-dimensional feature space image classification [5], or text classification [13]. To do the classification, Support Vector Machine first inputs a set of labeled data, and based on those labeled data, it makes a data model. Based on that data model, Support Vector Machine predicts and labels a new set of data [9]. In making a data model, SVM uses hyperplanes to separate the training data, so that each hyperplane marks the limit between classes of data; for binary classification, one side of the hyperplane is of class 1, and the other side of the hyperplane is of class 0. For separable data, Linear Support Vector Machine is used, while for non-separable data, Nonlinear Support Vector Machine is used.

Support Vector Machine maps X dimension original training data into a higher

dimension feature space F via a Mercer kernel operator K that satisfies Mercer's condition:

$$f(x) = \sum_{i=1}^n \alpha_i K(x_i, x) = w \cdot \Phi(x)$$

with:

$$w = \sum_{i=1}^n \alpha_i \Phi(x_i)$$

$f(x)$ then determine the classification process: if $f(x) > 0$ then $x = 1$, otherwise $x = 0$.

The two common kernels used are polynomial kernel and radial basis function kernel. Polynomial kernel, $K(u, v) = (u \cdot v + 1)^p$, induces polynomial boundaries of degree p in the original space X . And radial basis function kernel, $K(u, v) = (e^{-\gamma(u-v) \cdot (u-v)})$, induces boundaries by placing weighted Gaussians upon key training instances.

Bounded-Constraint Support Vector Machine [18] is a type of Support Vector Machine that extends the solution of Support Vector Machine for large classification and regression problems. It consists of two techniques, which are using bounded-constraint formulation for multi-class classification and regression, and also using Crammer and Singer's formulation [6] for multi-class classification.

Support Vector Machine Active Learning [13, 39] is one of the generators using active learning for retrieving images. It combines Support Vector Machines, which already proven to be successful in real-world learning tasks, and active learning. It is

developed as a refinement technique of relevance feedback technique. It grasps users query more quickly by using a usually high-dimensional hyperplanes to differentiate which data are relevant or irrelevant. The active learning part then trains the SVM classifier to classify data from the feedback given to it, and returns the resulting images.

Transductive Support Vector Machine is one of the techniques in optimizing Support Vector Machine technique. This technique [31, 43] is considering unlabeled data in classification process, in addition to relying on labeled training data, to improve the classification accuracy. In Transductive Support Vector Machines, the hyperplane is placed based on both labeled and unlabeled data. Joachims [21] in his paper shows that this can improve the classification process.

Statistical Learning Machine [30, 38] is implemented based on a well-developed statistical decision theory framework. This generator uses learning algorithms that will converge to optimal learning states as the number of learning trials increases. This algorithm will converge faster as the number of trials increases.

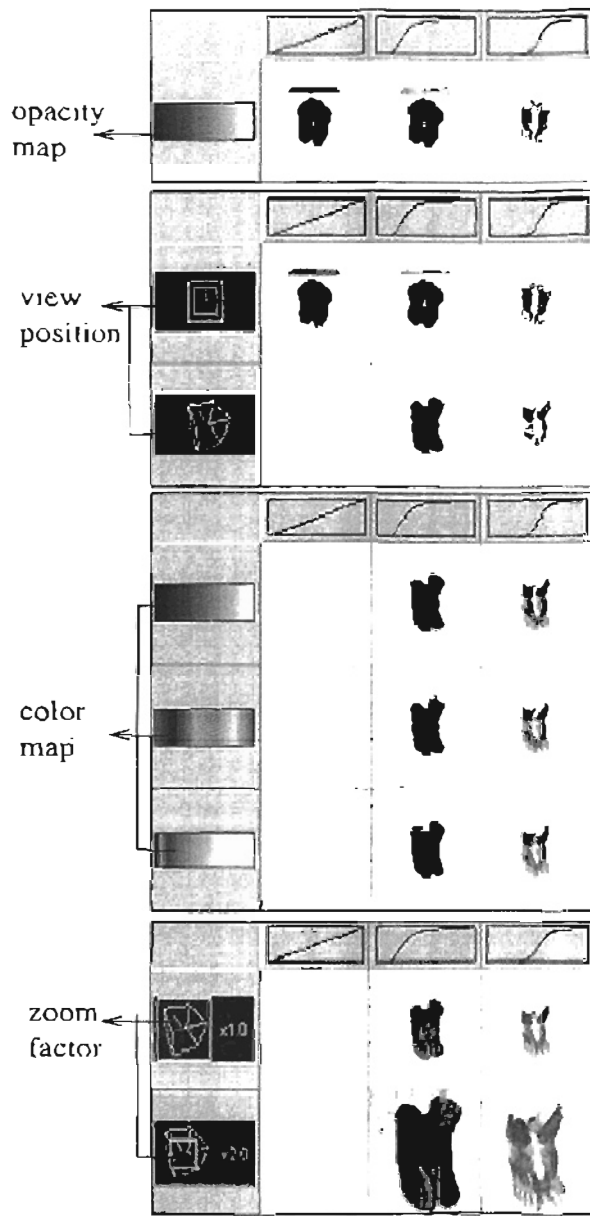


Figure 2.2: A sequence of spreadsheets displaying the visualization of a foot data set. This figure is taken from paper by K. L. Ma and T. J. Kelly [20] page 279 Figure 1.

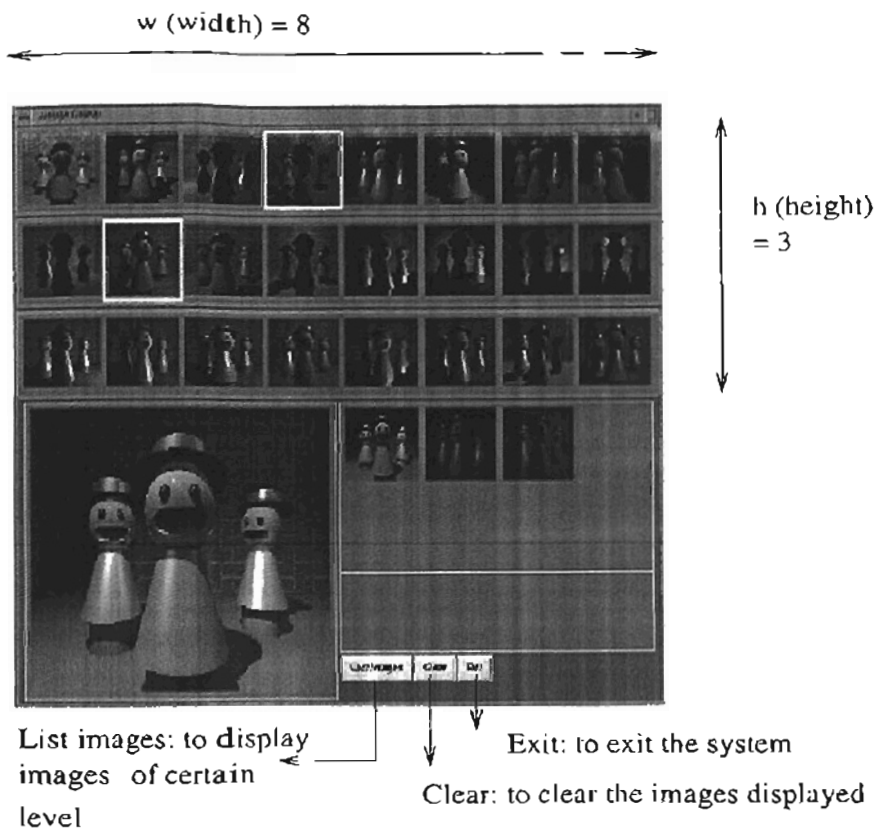


Figure 2.3: A Design Galleries for light selection and placement. This figure is taken from paper by Andalman *et al.* [29] page 397 Figure 9.

Chapter 3

COMPARING AND TESTING THE NAVIGATION ALGORITHMS IN VISUAL DATA EXPLORATION

Many questions arise regarding what are each generators advantages and disadvantage, and in which part are they better or worse than the others. For that, we need a system that can test and compare those generators. It will be difficult for us to test those generators themselves. What we can do is testing and comparing the effects of using those generators in the system, for example: using this particular algorithm in the generator in the system will lower the CPU time of that generator, etc.

When a particular set of data is applied to the system with a particular generator, the Statistic component of the system should record the result of the testing throughout the running of the system, and make a statistic from those results. If we apply that particular set of data to other types of generator, we will have statistic

for each of those generators. We can make a table that compares each generators statistic when that particular set of data is applied. By testing the generators with several sets of data, we will have several tables, and also graph if necessary.

There are two methods that we can use to do the testing to the system. The first method is by having the desired image known before the testing is done. Based on that image, the user then has to label the set of images displayed on the screen as relevant, irrelevant, or unknown, until he finds the desired image. The second method is by letting the user directly labels the images on the screen as relevant, irrelevant, or unknown, without having the desired image known beforehand.

We are focusing on the first method in doing our testing to the system, since by having the desired image to be known, it is easier for the user to do the comparison. The user can directly compare the desired image and images on the screen, without possibly being confused by other factors. If we use the second method, there are more human factors that we have to consider, since there is a bigger chance that the user is not consistent in labeling the images. Being inconsistent in labeling the images will confuse the generator in grasping the users query concept, and thus lower the performance of the generator.

The questions that arise in measuring the performance of the generators are:

-- How much user interaction needed for each generator?

There are two things that can measure user interaction in the exploration process:

1. Number of time the user needs to find the desired image. By counting the number of set of images have to be displayed to find the desired image, we can determine how much user interaction needed to find the desired image. The bigger the number of time means the worse the generator is.
2. Number of deadends that user has to go through during the exploration process. Deadend means the number of times the user feels that the previous set of images is better than the current set of images. The user then has to click the back button to ignore the current set of images, and continue the exploration process from the previous set of images. This means that the bigger the number of deadends is, the more often a user got confused during the exploration process. Thus, the bigger the number of deadends, the worse the generator is.

— How much CPU time needed from the starting of the system until the image desired is found?

There are three CPU times that we can measure:

1. CPU time of the Generator component of the system, which is the CPU time needed for the algorithm in the generator to compute a new set of input vectors, given feedback that it got from the user.
2. CPU time of the Renderer component of the system, which is the CPU time needed for the Renderer to render images, given an input vector parameters.

3. CPU time of the User Interface component of the system, which is the CPU time needed for the user to label and send feedback to the system, given a set of images.

The CPU time of Renderer and User Interface may not vary for all generators tested, but those values will be useful for comparison. By knowing the CPU time of Generator, Renderer, and User Interface for each generator, we can compare which of those component takes most time to finish, and by how much.

- What is the similarity measure between the resulting images so far with the desired image?

The similarity between the images on the screen and the desired image can be measured using several techniques. In this system, four types of feature are used to measure images' similarity, which are Gabor, Color Histogram, Haralick, and Correlation. All of those features try to measure how similar the current images displayed on the screen compare to the desired image, but they use different techniques to do that:

1. Gabor Similarity Measure

This technique is defined in these papers [14, 42]. Gabor is originally implemented as a frequency filter, but then also developed for face and character recognition. Nowadays it is already applied to recognize multivariate laser range

data [36] and it also applies recursively as recursive Gaussian [15]. It measures the similarity of two images by localizing the direction of spatial frequency at certain angle, and outputting maximally at those particular edges with that angle orientation. Thus, we can detect the edges at all orientations of an image.

Gabor filter is used to extract local image features. Consider an input image $I(x, y), (x, y) \in \Omega$, with Ω is the set of image points and 2-D Gabor function $g(x, y), (x, y) \in \Omega$, the Gabor feature image $r(x, y)$ is:

$$r(x, y) = \int \int_{\Omega} I(\zeta, \eta) g(x - \zeta, y - \eta) d\zeta d\eta$$

With Gabor function:

$$g_{\lambda, \theta, \varphi}(x, y) = e^{-((x'^2 + \gamma^2 y'^2)/2\sigma^2)} \cos(2\pi \frac{x'}{\lambda} + \varphi)$$

where $x' = x \cos \theta + y \sin \theta$, $y' = -x \sin \theta + y \cos \theta$, $\sigma = 0.56\lambda$, $\gamma = 0.5$

In this thesis, Gabor technique is used to extract the features of images. The similarity between two images is measured by comparing the dot product and the Euclidean distance of two images.

2. Color Histogram Similarity Measure

This technique is defined in these two papers [16, 37]. It measures the similarity of two images by using color histogram for color image indexing. At a

given color space, each local color range is represented by one histogram bin. Thus, color histogram represents the coarse color distribution in an image. Two colors are considered identical if and only if they are allocated into the same histogram bin. Thus, no matter how similar two colors look like, if they are allocated into different histogram bin, then they are considered totally different.

Histogram Intersection is a technique that can efficiently match model and image histograms. It overcomes some problems that hinder recognition, which are distractions in the background of the object, viewing object from a variety of viewpoints, and occlusion. Histogram Intersection matches the image color histograms of each of the models. The higher the match value the better the fit to the model. With n buckets each, the normalized Histogram Intersection value of two histograms (two images: I as image and M as model), is:

$$H(I, M) = \frac{\sum_{j=1}^n \min(I_j, M_j)}{\sum_{j=1}^n M_j}$$

And the distance metric (a scaled city-block metric) of the Histogram Intersection, which defines by function $1-H$, assuming the histograms are scaled to be the same size, is:

$$1 - H(I, M) = \frac{1}{2T} \sum_{i=1}^n |I_i - M_i|$$

where

$$T = \sum_{i=1}^n M_i = \sum_{i=1}^n I_i$$

Similar to Gabor, Color Histogram is used to extract the features of images. The dot product and Euclidean distance of the images is then compared to measure the similarity.

3. Haralick Similarity Measure

This technique is based on paper by Prof. Robert Haralick [17]. It measures the similarity of two images by using probabilistic measures, which used likelihood that were derived from Bayesian classifier that measures the relevancy of two images. If the likelihoodness between those two images are high, then the two images are similar, and vice versa, if the likelihoodness are low, then the two images are not similar.

The similarity is not computed in a common way by calculating the distance of feature spaces, instead it is computed using joint posterior probability ratios and then taking their weighted combinations. Haralick Similarity Measure uses Bayesian framework that combine multiple measurements on images. In binary classification, if there are n classifiers with measurement vectors x_1, \dots, x_n , then the equation for Bayesian classifier is:

$$\text{assign}(\zeta_i, \zeta_j) \text{ to } \arg \max_{c \in A, B} \mathcal{P}(c; x_1, \dots, x_n)$$

and assuming equal priors and conditional independence, the Bayesian classifier is:

- Product rule: *assign*(ζ_i, ζ_j) to *arg max* $_{c \in A, B} \prod_{i=1}^n p(c|x_i)$
- Sum rule: *assign*(ζ_i, ζ_j) to *arg max* $_{c \in A, B} \sum_{i=1}^n p(c|x_i)$
- Max rule: *assign*(ζ_i, ζ_j) to *arg max* $_{c \in A, B} \max_{i=1}^n p(c|x_i)$
- Min rule: *assign*(ζ_i, ζ_j) to *arg max* $_{c \in A, B} \min_{i=1}^n p(c|x_i)$
- Median rule: *assign*(ζ_i, ζ_j) to *arg max* $_{c \in A, B} \text{median}_{i=1}^n p(c|x_i)$
- Majority rule: *assign*(ζ_i, ζ_j) to *arg max* $_{c \in A, B} \#\{i|p(c|x_i) > 0.5, i = 1, \dots, n\}$

with $p(c|x_i)$ is the posterior probability given by the classifier i under class c .

In this thesis, Haralick technique is used to extract the features of images. After the features are extracted, the similarity between the two images is calculated by both dot product and Euclidean distance.

4. Correlation Similarity Measure

This technique uses correlation to measure the similarity between two images.

To measure the similarity between image A and B, where both images A and B have r rows and c columns, with pixels of A: $a_{11}, a_{12}, \dots, a_{1c}, \dots, a_{rc}$, and pixels of B: $b_{11}, b_{12}, \dots, b_{1c}, \dots, b_{rc}$, then the Correlation similarity measure will be:

$$A \bullet B =$$

$$a_{11} * b_{11} + a_{12} * b_{12} + \dots + a_{1c} * b_{1c} + \dots + a_{rc} * b_{rc}$$

with $a_{x,y}$ is a normalized pixel

$$a_{x,y} = \frac{\text{the RGB value of pixel } a}{\text{total RGB value}}$$

As the two images compared are getting more similar to each other, the similarity values should be getting bigger.

For each of those measurements of performance, we have a table and a corresponding graph associated to it. The complete table and graph results are attached in the Appendix B, C, and D.

Chapter 4

EXPERIMENT

A modular and reliable system is built to test and compare the generators. The architecture of the system has to be arranged so that the testing procedure can be done as flexible as possible. The system has to be made as independent as possible from any parameter, so that we can compare the results accurately. In this section, we will first describe the architecture of the system and define how we are going to use this system to do the testing and comparison (4.1), and then discuss the experimental results (4.2).

4.1 The Architecture of the System

Figure 4.1 shows us the screenshot of the system. The interface displays twenty images at a time. Those images can be clicked; not clicking the image makes the status of the image unknown (signify by the green border around the image). Right

clicking makes the status of the image relevant (signify by the blue border around the image), and left clicking makes the status of the image irrelevant (signify by the red border around the image).

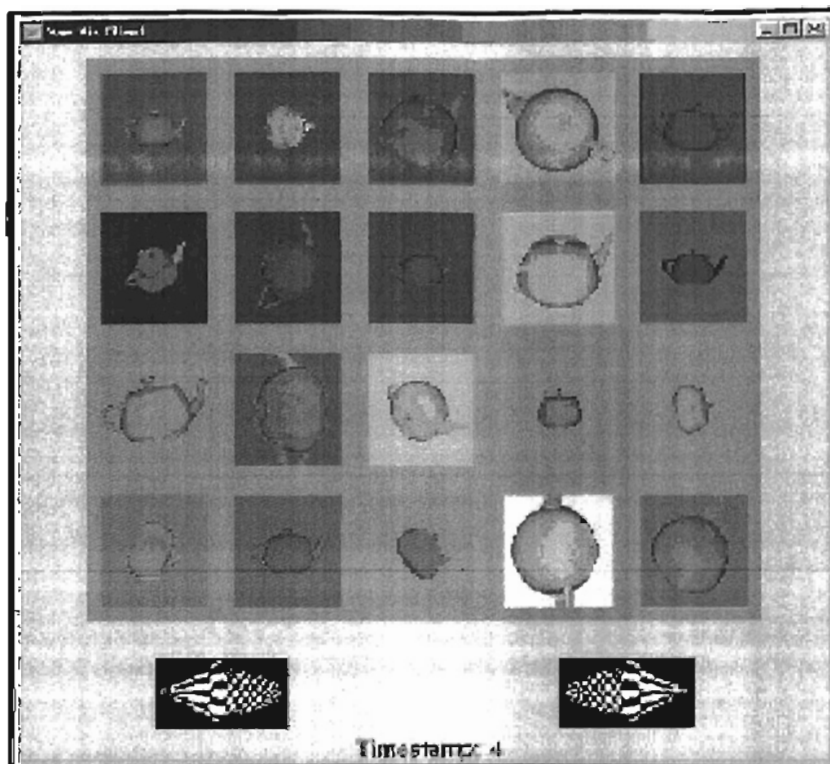


Figure 4.1: The screenshot of the system

The Timestamp on the bottom of the screen shows which set of images set that has been displayed so far; the first set of images is of timestamp 0, the next one is 1, and so on. There are two buttons on the upper side of the Timestamp, which are the Next and Back buttons. When the Next button is clicked, depending on the type of generator used, another set of twenty images is generated. Those images can be clicked again: once, twice, or not clicking at all. The process continues until the

desired image is found, and the user quit the system.

Network is used for this system, so that future experiments on distributed, collaborative visualization is possible. Therefore the interface has to differentiate when the system is in the idle state when it is waiting for a feedback from the current set of images, which is when the Next or Back button is not yet clicked, or when it is at a waiting state, which is when one of the button is already clicked and the system is trying to display a set of images.

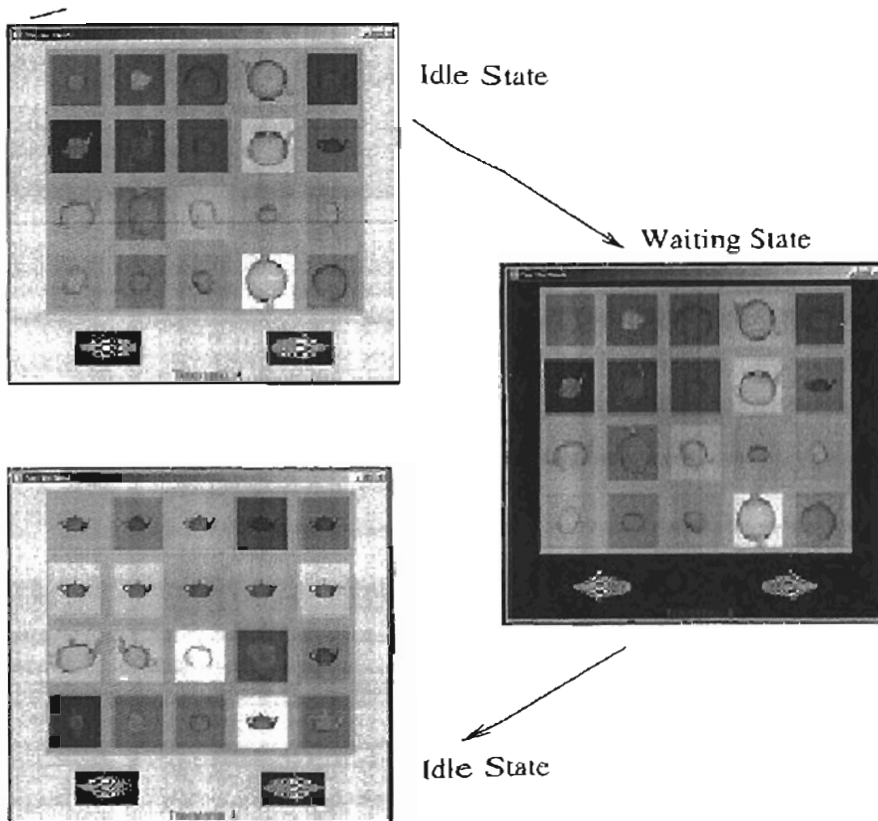


Figure 4.2: The transition between the displays of images

On the idle state, the color of the background of the screen is gray. Otherwise, on the waiting state, the color of the background turns black, and turns back to gray again after the waiting state is finished. On the waiting state, no button should be clicked, since the set of images that will be displayed will be skipped. The next set of images is then calculated based on the skipped set of images instead, and be displayed next. Figure 4.2 shows this state change.

The system consists of six main components, which are Generator, Renderer, Control, History, Statistic, and User Interface. Each of those parts has an independent individual task.

From Figure 4.3, we can see that Control organizes the components of the system. Control connects other parts of the system and controls the run of the system. Control gives input parameters to other parts in the system, and they reports the results back to Control, waiting for Control to pass another input parameters. For example, Control gives Generator (Figure 4.4) a training data, in the form of input parameter vectors, and also previous set of images labels, which is a feedback of the previous set of images from the user. Generator is then outputting a certain number of input parameter vectors based on the two inputs that are given to it. The output of this generator is reported back to Control. The number of training data inputted and outputted depends on the generators setting. Different generators are using different algorithms.

When the system is run for the first time, generator generates a set of random

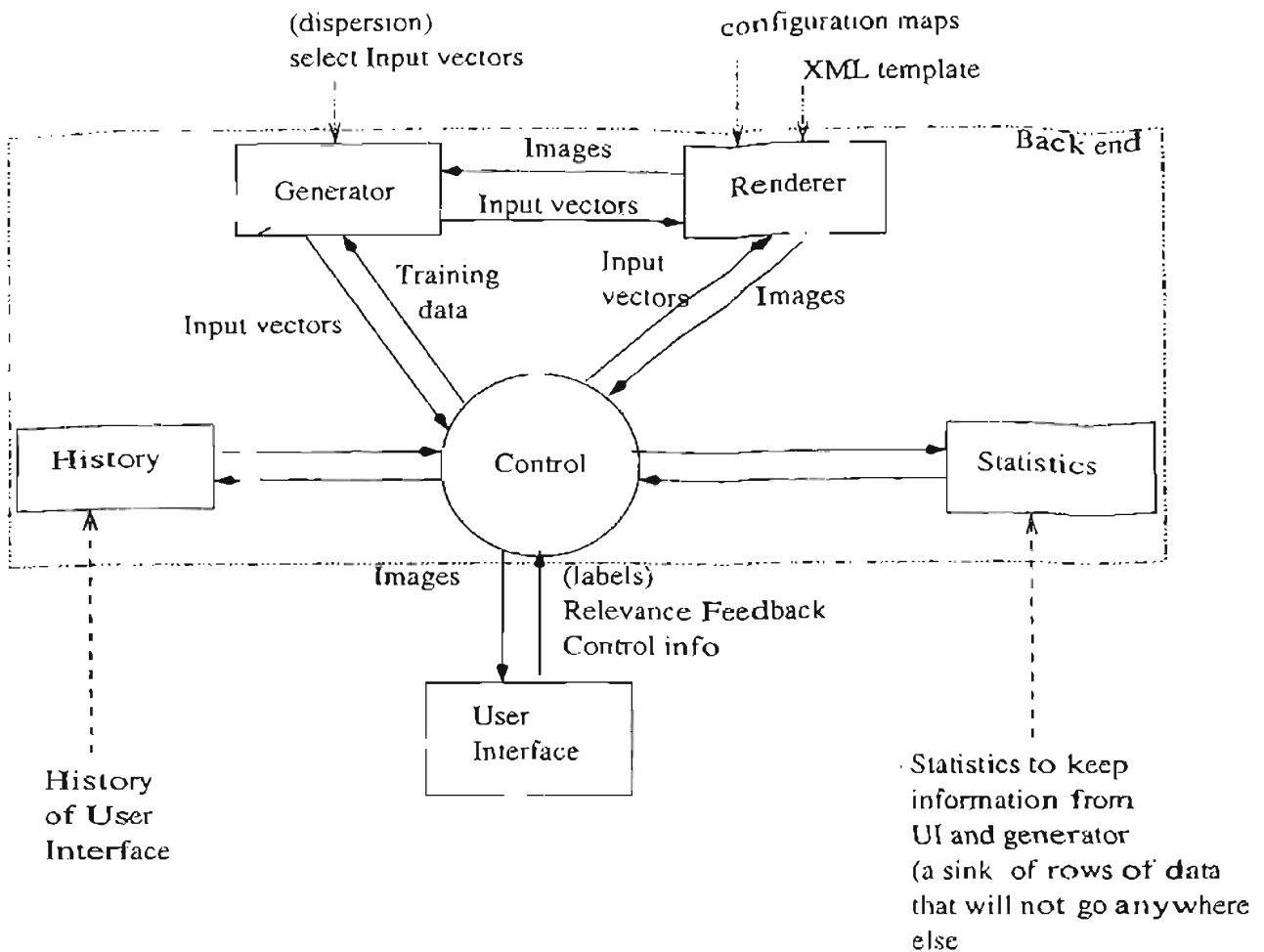


Figure 4.3: Diagram of the system

input parameter vectors. Those first input parameter vectors outputted by the generator are to be generated as dispersed as possible, so that choices of lights are vary. After that, Generator receives input vector from Control, and generate a set a light based on the input vector given.

Control and Generator gives Renderer input vector. Input vector given are of the range 0.0 to 1.0. so that the images compared are not distorted by one of the

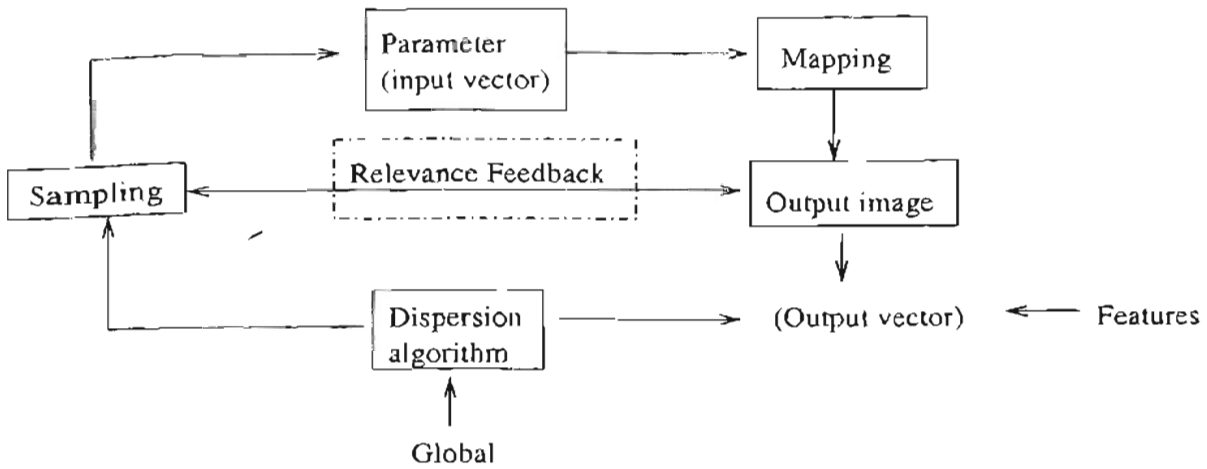


Figure 4.4: Diagram of the Generator

input parameters. Renderer part consists of three other parts, which are Functional Object Mapping, Keyword Substitution, and XML Renderer, as shown in Figure 4.5.

Functional Object Mapping consists of many conversion functions. Functional Object Mapping maps input vector from value range of 0.0 to 1.0 to other value ranges, based on what the conversions are. All of the information of what the input vectors are (object sizes, cameras distance, etc) and what conversions to be used for each of them are kept in server input file, server.rc, under keyword parameter list (Figure 4.5). By reading from the input file, Functional Object Mapping knows what the input vectors are and what conversion to use. After converting the input vector ranges, it passes the result to Keyword Substitution.

Keyword Substitution substitutes the keyword used in XML template with actual values passed by Functional Object Mapping (Figure 4.6 and 4.7). Keyword Substitution knows what the input vectors are from the input file. It then reads from

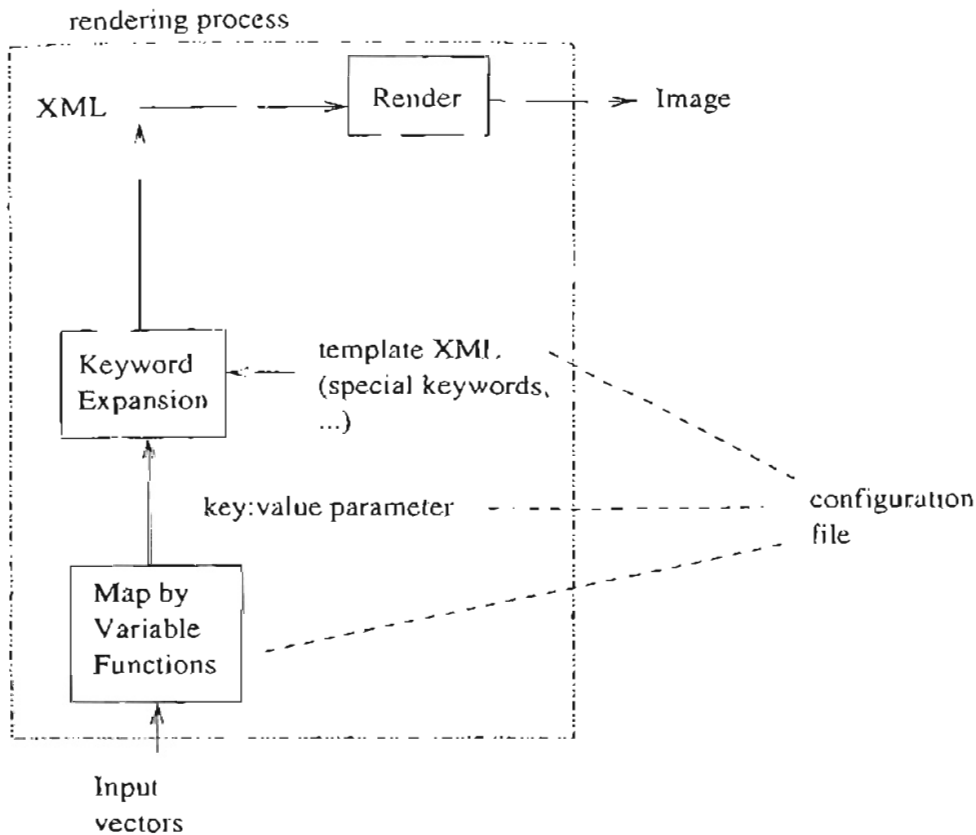


Figure 4.5: Diagram of the Renderer

XML template and match the keyword used for each input parameter, and substitute it with the actual value.

XML Renderer is the last part of Renderer. XML Renderer is the one who actually generates images using XML Parser. XML Parser maps the values in XML template to actual OpenGL codes and creates the image, and pass the image back to Control.

User Interface is connected to Control through network. With this network, many Users can access this system at the same time. A fast machine may render

```

* <Thesis> *
* <View> *
*   <Camera cameraV = "80.0 1 0.2 800.0" > *
*   </Camera> *
* </View> *
* <Scene> *
*   <DesiredImage desiredIm = "desiredIm.ppm" /> *
*   <Material face = "front" type = "diffuse" values = "1 1 1" /> *
*   <FogColor fogColorV = "%(FogColor)s" /> *
*   <Fog fogV = "%(FogInfo)s" /> *
*   <LightSource name = "0" > *
*     <Light pname = "ambient" value = "%(LightAmbiXYZA)s" /> *
*     <Light pname = "diffuse" value = "%(LightDiffXYZA)s" /> *
*     <Light pname = "specular" value = "%(LightSpecXYZA)s" /> *
*     <Light pname = "position" value = "%(LightPosXYZA)s" /> *
*   </LightSource> *
*   <LightModel pname = "modelTwoSide" value = "true" /> *
*   <PlaceObject> *
*     <Translate transV = "0.0 0.0 -350.0" /> *
*     <Rotate rotateV = "%(RotateXYZ1)s" /> *
*     <Translate transV = "-120.0 0.0 30.0" /> *
*     <Color colorV = "%(ColorTeapotRGB)s" /> *
*     <GraphicsObject> *
*       <Teapot size = "150" /> *
*     </GraphicsObject> *
*     <Translate transV = "180.0 0.0 130.0" /> *
*     <Color colorV = "%(ColorCubeRGB)s" /> *
*     <GraphicsObject> *
*       <Cube size = "120" /> *
*     </GraphicsObject> *
*     <Translate transV = "50.0 0.0 -300" /> *
*     <Color colorV = "%(ColorSphereRGB)s" /> *
*     <GraphicsObject> *
*       <Sphere sphereInfo = "120 100 100" /> *
*     </GraphicsObject> *
*   </PlaceObject> *
* </Scene> *
* </Thesis> *

```

Figure 4.6: XML template before substitution

```
*
* <Thesis>
* <View>
*   <Camera cameraV = "80.0 1 0.2 800.0" >
*     </Camera>
* </View>
* <Scene>
*   <DesiredImage desiredIm = "desiredIm.ppm" />
*   <Material face = "front" type = "diffuse" values = "1 1 1" />
*   <FogColor fogColorV = "0.270674 0.560238 1.92013e-308 0" />
*   <Fog fogV = "1.26854 4.54831" />
*   <LightSource name = "0">
*     <Light pname = "ambient" value = "0 0 0" />
*     <Light pname = "diffuse" value = "0 0 0" />
*     <Light pname = "specular" value = "1.92039e-308 0 0" />
*     <Light pname = "position" value = "-100 -100 -100" />
*   </LightSource>
*   <LightModel pname = "modelTwoSide" value = "true" />
*   <PlaceObject>
*     <Translate transV = "0.0 0.0 -350.0" />
*     <Rotate rotateV = "-180 0 0" />
*     <Translate transV = "-120.0 0.0 30.0" />
*     <Color colorV = "0 0 0" />
*     <GraphicsObject>
*       <Teapot size = "150" />
*     </GraphicsObject>
*     <Translate transV = "180.0 0.0 130.0" />
*     <Color colorV = "0 0 0" />
*     <GraphicsObject>
*       <Cube size = "120" />
*     </GraphicsObject>
*     <Translate transV = "50.0 0.0 -300" />
*     <Color colorV = "1 0 0" />
*     <GraphicsObject>
*       <Sphere sphereInfo = "120 100 100" />
*     </GraphicsObject>
*   </PlaceObject>
* </Scene>
* </Thesis>
*
```

Figure 4.7: XML template after substitution

images, for display anywhere. A simple extension would allow multiple machines to be used for rendering. This can make the exploration process much faster, because feedbacks from images arrive more frequently.

Control passes the images that it received from Renderer to User Interface. At the same time, those images parameter are also passed to History. User Interface is then labeling the images to be relevant, irrelevant, and unknown, and then click Next or Back button. When the User clicks Back or Next button, control is given back to Control.

If Next button is clicked, Control passes those images parameter and label to Generator, and passes some data to Statistic. Generator then makes a new set of input parameters based on the input given. These are then be passed to Control and Renderer. New set of images is generated from Renderer to be passed by Control to User Interface. User Interface then repeats the same procedure: marks the images to be relevant, irrelevant, and unknown, and pass it back to Control, etc. If Back button is clicked, Control calls History and tell it to return the input parameters that correspond to a set of images before the current images.

The History component encapsulates a data structure that holds the entire set of images and their associated information. History keeps track of the input parameter used to generate each image. It also keeps track which images are relevant, irrelevant, and unknown. If Next button is clicked, History is adding one more set of input parameters to the list. If Back button is clicked, History moves its current

position one back and return the set of input parameters correspond to the previous set of images.

The Statistic component will store all the testing results that are measured while the system is running. The system will be run several times, each time using a different generator. And in each run, that particular generator will be tested with several different test data sets. Statistic component will record all of those testing results and make a statistic from those results. These statistics will be used for comparing those generators. We will discuss what and how the testing will be done in the next section.

Figure 4.8 shows us the diagram of the system from file structure point of view. As we can see from the diagram, visclient and visserver has their own resource file, which are client.rc (Figure 4.9) and server.rc (Figure 4.10). client.rc defines the servers name and port number, and also the window width and height, while server.rc defines the clients port number, xml template used, parameter list, and mapping functions used for each parameter name.

The words on the bottom right of the boxes are the name of the namespaces under which the files (folders) are belong. visclient and visserver is where the connected ports defined. Then it goes through ServerFacade and ClientFacade, which do not provide the actual services. They are only the interfaces that pass the information to the backend renderer. Net is the actual implementation of the network, while control controls the backend parts and sends back the result through Net, to at the

end displayed through visclient.

Visserver, visclient, history, and control are an independent file, while ServerFacade, Net, KeywordSubstitution, Generator, XMLRenderer, GUIClient, and ImageUtils are folders.

ServerFacade folder contains ServerFacade and ClientFacade files. They are interfaces that pass information to backend renderer. Net contains netclient, netserver, and communicationSpecs files. They are the actual implementation of the network from client to server and vice versa.

KeywordSubstitution contains KeywordExpander file. It changes the keywords used in XML template to the actual values that are generated by the Generator. Generator contains all types of generators that are tested and compared by the system. Each of the generators generates input parameter vectors in its own way.

XMLRenderer contains camera, ElementFunctions, FuncObjMap, VectorToImage, XMLParser, and all other files needed for parsing and generating images. GUIClient contains display, keyboard, mouse, reshape, GUIutil, guiDataStructures, and all other files needed for establishing connection for user interaction with the system. ImageUtils contains simpleppm and imageutils files, which convert images to certain format of file (ppm or something else), and also contains image tools such as resizing and so on.

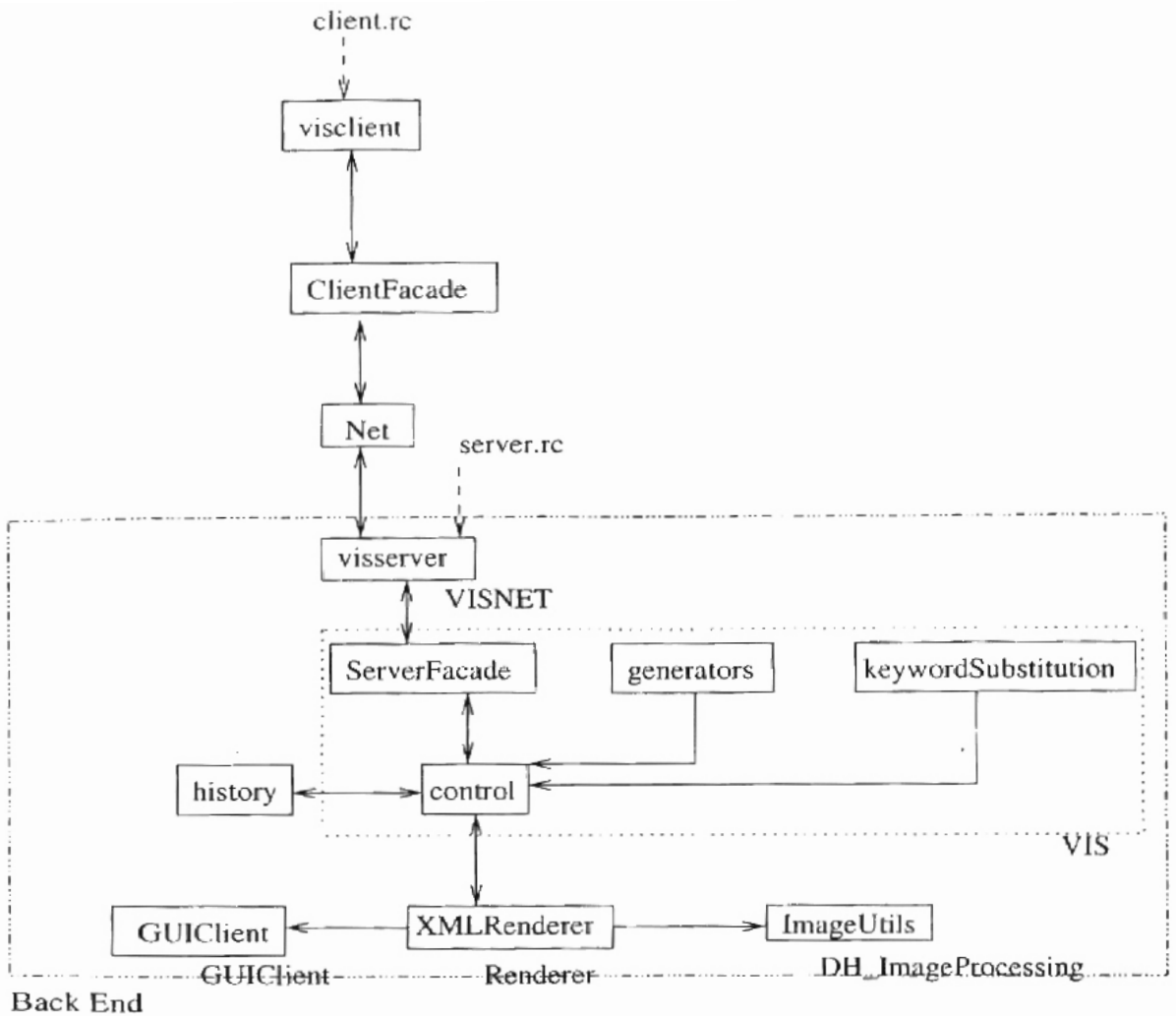


Figure 4.8: Diagram of the Systems File Structure

```

* # configuration file for visualization navigation client,
* # visclient
* server host name = localhost
* server port = 7171
* initial window width = 600
* initial window height = 600
*

```

Figure 4.9: Resource file from client side: client.rc

```

* # configuration file for visualization navigation server,
* # visserver
* server port = 7171
*
* # configuration for XMLRenderer
*
* #configuration file for parameter name list and its associated
* #functional object and input vector indices
* xml template file = template2
* generator = RandomGenerator
* parameter list = dPan dTilt dZoom dMove dMouse CameraOrtho FogInfo FogColor
* MatDiffXYZA LightSrcName LightAmbiXYZA LightDiffXYZA LightSpecXYZA
* LightPosXYZA RotateAXYZ1 ColorTeapotRGB TeapotSize RotateAXYZ2
* ColorCubeRGB CubeSize ColorSphereRGB
* dPan FnObj = DeltaMoveOneOne
* dTilt FnObj = DeltaMoveOneOne
* dZoom FnObj = DeltaMoveOneOne
* dMove FnObj = DeltaMoveOneOne
* dMouse FnObj = IdentityOneOne
* CameraOrtho FnObj = Linear6Param
* FogInfo FnObj = Fog2Param
* FogColor FnObj = Identity4Param
* MatDiffXYZA FnObj = Identity4Param
* LightSrcName FnObj = IdentityOneOne
* LightAmbiXYZA FnObj = Identity4Param
* LightDiffXYZA FnObj = Identity4Param
* LightSpecXYZA FnObj = Identity4Param
* LightPosXYZA FnObj = Linear4Param
* RotateAXYZ1 FnObj = Rotate4Param
* ColorTeapotRGB FnObj = Identity3Param
* TeapotSize FnObj = ObjectSize
* RotateAXYZ2 FnObj = Rotate4Param
* ColorCubeRGB FnObj = Identity3Param
* CubeSize FnObj = ObjectSize
* ColorSphereRGB FnObj = Identity3Param
*

```

Figure 4.10: Resource file from server side: server.rc

4.2 The Result and Discussion of the Experiments

As what we have been discussed in Chapter III, Comparing and Testing Navigation Algorithms in Visual Data Exploration, there are a couple of experiments that we had performed to compare the generators. The system implemented is a modular system that especially designed to do these experiments. In this section, we will discuss how to do those experiments using the system, and then discuss the result of the experiment.

As we have discussed before, there are two methods that we can use to do the measurement. The first one is by knowing the desired image before the system starts. The second one is by trusting the user to guide the system until the desired image is found. In this experiment, we did only the first method for our measurements. It is more trustable, because human factor is not as big as the second method. For future work, the second method can be done too, to see how human factor influence the experimental results.

The experiment is done using seven generators, which are: Random generator, Peng generator, PFRL, SVMlight, SVM-Peng generator, Transductive SVM (TransSVM), and BSVM. In the experiment, Random generator generates new sample set by randomly picking values from range 0.0 to 1.0. Peng generator, based on the user feedback, generates a number of samples around the positive samples. It then picks the most disperse samples among the samples to be the new sample set. PFRL generates a number of input vectors and generates images from those vectors.

It then picks images with closest Gabor distance as the new sample set. SVMLight generates a number of samples by applying MyGenerator1, and generates a new set of images from those samples by using SVM Light. It picks the most disperse samples to get the new sample set. SVM-Peng generator combines Peng generator with BSVM in generating new sample set. TransSVM generates a number of samples by applying MyGenerator1, and generates a new set of images from those samples using Transductive SVM. BSVM generates new sample set by applying MyGenerator2 and BSVM.

Each of those generators is tested with several datasets, which are: OpenGL Object (3 Object: Teapot, Cube, and Sphere), Real Object (AI, Dolphin, F16, Flower, Porsche, Soccer Ball, and Vase), and Scientific Data (electron density of Sodium).

In this section, we will discuss the result of the experiment based on how much user interaction needed, number of deadends, CPU time, and similarity features.

4.2.1 User Interaction

There are two things calculated to measure user interaction needed by each generator, which are the average time needed to find the desired image and the number of deadends.

Data Set	Generator						
	Random	Peng	PFRL	SVMLight	SVM-Peng	TransSVM	BSVM
Real Obj	13	7	4	4	5	4	5
OpenGL Obj	12	5	3	3	6	5	3
Scientific	16	7	4	5	5	4	4

Table 4.1: Average time (number of set of images) needed for Real Object, OpenGL Object, and Scientific data set to find the desired image.

Data Set	Generator						
	Random	Peng	PFRL	SVMLight	SVM-Peng	TransSVM	BSVM
Real Obj	0.09	0.25	0.03	0.02	0.12	0.08	0.12
OpenGL Obj	0.08	0.20	0.00	0.00	0.50	0.20	0.00
Scientific Data	0.06	0.29	0.00	0.00	0.00	0.00	0.00

Table 4.2: Average number of deadends of Real Object, OpenGL Object, and Scientific data set as time increases for all of the generators tested.

Time needed to find desired image

From Table 4.1 we can see that when testing Real object, Random generator needs the most time to find the desired image, while PFRL, SVMLight, and TransSVM needs the least time. When OpenGL Object data set is tested, Random generator needs the most time to find the desired image, while PFRL, SVMLight, and BSVM needs the least time. When Scientific data set is tested, Random generator needs the most time to find the desired image, while PFRL, TransSVM, and BSVM needs the least time. Thus, we can conclude that Random and BSVM generators need the most and least time to find the desired image no matter what the test data set type is.

Deadends

Tables and graphs in Appendix B show the number of deadends of each generator when tested with different test data sets, and in which timestamp it happens. From Table 4.2, the average number of deadends/time between generators can be compared. The bigger the number of deadends/time, the more the user had to back to previous set of images and started over from there. That means the bigger the number of deadends/time, the worse the generator is. Table 4.2 shows that for all Real Object, OpenGL Object, and Scientific data object, Peng has the smallest average number of image clicks/time. For Real Object and Scientific data, Peng has the biggest average number of deadends/time. For OpenGL Object, Peng and TransSVM have the biggest average number of deadends/time.

4.2.2 CPU Time

To measure the CPU time of the Generator, Renderer, and User Interface components, we use the wall system clock to time them. The system clock resides in the Statistic component, where all the measurements and the results also reside. To measure CPU time of a Generator, the clock system records the time when Control passes training data and labels to the Generator. And when the Generator passes back the resulting input parameter vector to Control, the clock system records the time again. The CPU time of the Generator is then the difference between those two times recorded.

Data Set	Generator (misecond)							
		Random	Peng	PFRL	SVMLight	SVM-Peng	TransSVM	BSVM
Real Obj	Generator	0.0789	1.0073	493.3000	10.6905	11.2441	9.1556	75.9091
	Renderer	145.2071	153.5455	214.2179	214.6727	194.7584	200.3657	175.7211
	UI	0.3953	0.3852	0.4679	0.5476	0.5143	0.4957	0.4544
Open GL Obj	Generator	0.0001	1.4000	491.6670	12.5000	8.2500	11.8000	16.1667
	Renderer	107.6670	114.2000	143.5000	141.8330	94.5000	114.0000	141.6670
	UI	0.4167	0.4000	0.3333	0.5000	0.4167	0.5000	0.5000
Scientific	Generator	0.1250	0.9286	421.8750	11.8000	13.3000	9.6250	16.2500
	Renderer	199.6560	142.7860	203.5000	202.2000	204.5000	204.6250	202.5000
	UI	0.4375	0.5714	0.6250	0.5000	0.4000	0.6250	0.7500

Table 4.3: Generator, Renderer, and UI's CPU time of all Real Object, OpenGL Object, and Scientific Data sets for generators tested

The CPU time of Renderer and User Interface components are measured in the same way.

Table 4.3 shows us the CPU time of all generators when tested with three data set types. When all Real Object, OpenGL Object, and Scientific test data sets are measured, generators with the largest and smallest generator CPU time are PFRL and Random. PFRL has much bigger generator CPU time because each time the generator has to generate a lot of output images, extract the features, and calculate new set of images based on the extracted features. Random basically just randomly generate new input vectors. It does not have to calculate anything else. That is why it takes a very small amount of time to finish.

When Real Object is measured, generators with the largest and smallest renderer CPU time are SVMLight and Random. When OpenGL Object is mea-

sured, they are PFRL and SVM-Peng. When Scientific Data is measured, they are TransSVM and Random.

The bigger the UI CPU time means the more users have to think when labeling the images. This means the generator is not very informative or confusing. When Real Object is measured, generators with the largest and smallest UI CPU time are SVMLight and Peng. When OpenGL Object is measured, they are both TransSVM and BSVM, and PFRL. When Scientific Data is measured, they are BSVM and SVM-Peng.

4.2.3 Similarity measure

Similarity measure is calculated using two methods. The first method is by calculating the Euclidean distance between the two images. The smaller the distance between the two images, the more similar the two images are, and vice versa. Thus, as time increases, the distance of the two images should be getting smaller and smaller. The second method is by calculating the dot product between the two images. This method calculates the similarity value between two images. Thus, the bigger the dot product value between two images, the more similar the two images are.

To define each generator's performance, for each similarity measure technique used, maximum, average, and minimum similarity measure values are calculated. Maximum, average, and minimum similarity measure values are the maximum, average, and minimum similarity values among a set of images compare to the image

that we want to generate.

The discussion of the result will consider two factors. The first one is the performance of each generator as the time increases. This is examined by the tables and graphs on Appendix C. Appendix C has the complete tables and graphs of all maximum, average, and minimum distance and similarity value of all test data sets when measured using all four features as time increases. As the time increases, the set of images generated should have smaller and smaller distance to the desired image.

The second factor is the robustness of the generators, which examined by the tables and graphs on Appendix D. Appendix D has the complete tables and graphs of all maximum, average, and minimum distance and similarity value of all test data sets when measured using all four features. Since it is always possible to construct situations that favor a particular generator over all the others, the issue becomes one of robustness. For each feature of a sample file of a particular data set types, the average of the first three timestamps of maximum, average, and minimum distance tables of each generator are calculated. The distance rate d_m and the distribution (upper and lower quartiles) of each generator's maximum, average, and minimum Euclidean distance can then be calculated from the sample files' maximum, average, and minimum average values calculated above. The similarity rate of each generator is calculated using similar method.

The robustness issue [7, 33] can be captured by computing distance and similarity ratio. The ratio r_m of its distance rate d_m and the smallest distance rate in

a particular example: $r_m = \frac{d_m}{\min_{1 \leq k \leq 7} d_k}$. The ratio r_m of its similarity rate s_m and the biggest similarity rate in a particular example: $r_m = \frac{s_m}{\max_{1 \leq k \leq 7} s_k}$. Thus, the best generator m^* for that example will have $d_m = 1$, and all other generators have larger values $d_m \geq 1_{m \neq m^*}$. Equivalently, it will have $s_m = 1$, and all other generators have smaller values $s_m \leq 1_{m \neq m^*}$. The larger the value of d_m (the smaller s_m) the worse performance of the m th generator is for that example. The distribution of d_m values for each generator over all the problems therefore seems to be a good indicator of robustness. The graphs generated plot a distribution of the distance and similarity rate for each generator. Each has maximum and minimum value, and box that marks the range between upper and lower quartiles, and horizontal line between them that marks the median.

As mentioned above, three test data set types are used in measuring the similarity measure, which are Real Object, OpenGL Object, and Scientific Data. Below we will discuss each of them, with different similarity measure techniques used.

Real Object

Tables and graphs on Appendix C show the generators' performance as the time increases. When all Gabor, Color Histogram, Haralick, and Correlation are used, both PFRL and BSVM are mostly able to generate image with the smaller and smaller minimum distance to the desired image. Only PFRL that is able to generate set of images that have constantly smaller and smaller average and maximum distance

than the previous set of images.

Figure 4.11(a) examines the robustness of the maximum distance distribution of a particular generator over all other generators when all Gabor, Color Histogram, Haralick, and Correlation features are used. Among all generators, TransSVM is the most robust generator. It has the best median performance (1.33), and also the narrowest interquartile range. In half of the problem, its distance rate is no more than 22% than the best case. In 3/4 of the problem it is no more than 33%. And it is 46% in the worst case. PFRL has similar but slightly worse median and interquartile range performance compare to TransSVM. Peng, SVMLight, and TransSVM have average median performance and interquartile range. SVM-Peng has also similar performance to those three generators, but it has the widest interquartile range. Random has the worst distribution, where the corresponding numbers are 1.55, 43%, 50%, and 66%.

From Figure 4.11(b), we can examine how well a particular generator performs on average over all other generators when Gabor, Color Histogram, Haralick, and Correlation features are used. In this particular problem, both TransSVM and PFRL are the most robust generators. TransSVM has among the best interquartile range, but average median performance (1.30). On the other hand, PFRL has the best median performance (1.28), but slightly worse interquartile range compare to TransSVM. In half of the problem, TransSVM has 29% worse distance rate compare to the best case. In 3/4 of the problem and the worst case, they are 51% and 73%. The corresponding numbers for PFRL are 27%, 52%, and 74%. Other generators

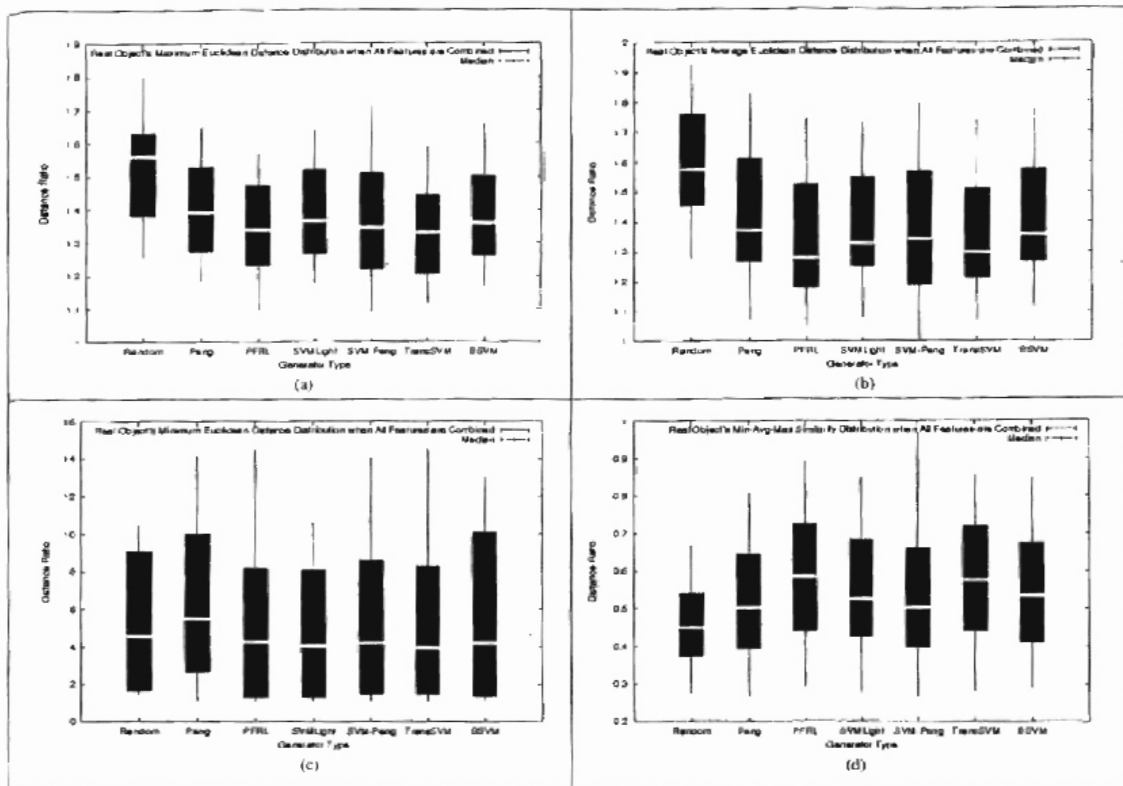


Figure 4.11: (a)-(c) Maximum, average, and minimum Euclidean distance ratio (r_m) distribution for Real Object data set with Gabor, Color Histogram, Haralick, and Correlation features combined. (d) Combination of Maximum, Average, and Minimum similarity value distribution for Real Object data set with Gabor, Color Histogram, Haralick, and Correlation features combined.

have much higher median value and average interquartile ranges. Generator with the widest interquartile range is SVM-Peng. Random is the generator with the worst distribution, where the corresponding numbers are 1.58, 57%, 75%, and 92%.

From Figure 4.11(c), the robustness of the minimum distance distribution of a particular generator over all other generators when all Gabor, Color Histogram, Haralick, and Correlation features can be determined. For this particular problem, both TransSVM and SVMLight are considerably the most robust generators. TransSVM has the best median performance (3.67), and among the best interquartile range. SVMLight has the narrowest interquartile range, but slightly worse median performance (3.84). In half of the problem, TransSVM has 252% higher distance rate than the best case. In 3/4 of the problem and the worst case, they are 694% and 1294%. The corresponding numbers for SVMLight are 268%, 678%, and 922%. BSVM has the widest interquartile range, while Peng has the worst median value. All other generators have average median performance and interquartile range. Among all generators, TransSVM has average interquartile range, the best in median, half, 3/4 of the problem and worst case performance.

Figure 4.11(d) examined the robustness of the similarity distribution of a particular generator over all other generators when all Gabor, Color Histogram, Haralick, and Correlation features are used. In this case, it seems like the generators with best median performance have among the worst interquartile range, and vice versa. PFRL and TransSVM have among the best median performance, but their

interquartile ranges are among the worst. On the other hand, Peng and SVM-Peng have among the worst median performance, but their interquartile ranges are among the best. SVMLight and BSVM have average median performance and interquartile range, while Random has the worst distribution of all, with 0.45 median, 117%, 160%, and 253% higher similarity rate in half, 3/4, and worst case of the problem. If we look at the graph, the interquartile ranges of most generators are almost the same. The difference between the best and the worst interquartile range in this particular problem is not extreme. Thus, if interquartile range performance is ignored, PFRL is the most robust generator, with corresponding numbers 0.58, 69%, 121%, and 231%. If interquartile range performance is essential, then SVMLight is the most robust generator, with corresponding numbers 0.52, 87%, 128%, and 250%. SVMLight is the generator with the most consistent performance, even though its performance is not the best one.

OpenGL Object

Tables and graphs on Appendix C show the generators' performance as the time increases. When all Gabor, Color Histogram, Haralick, and Correlation are used, no generator is able to generate image with the smaller and smaller minimum and average distance to the desired image. Only SVM-Peng that is able to generate set of images that have constantly smaller and smaller maximum distance than the previous set of images.

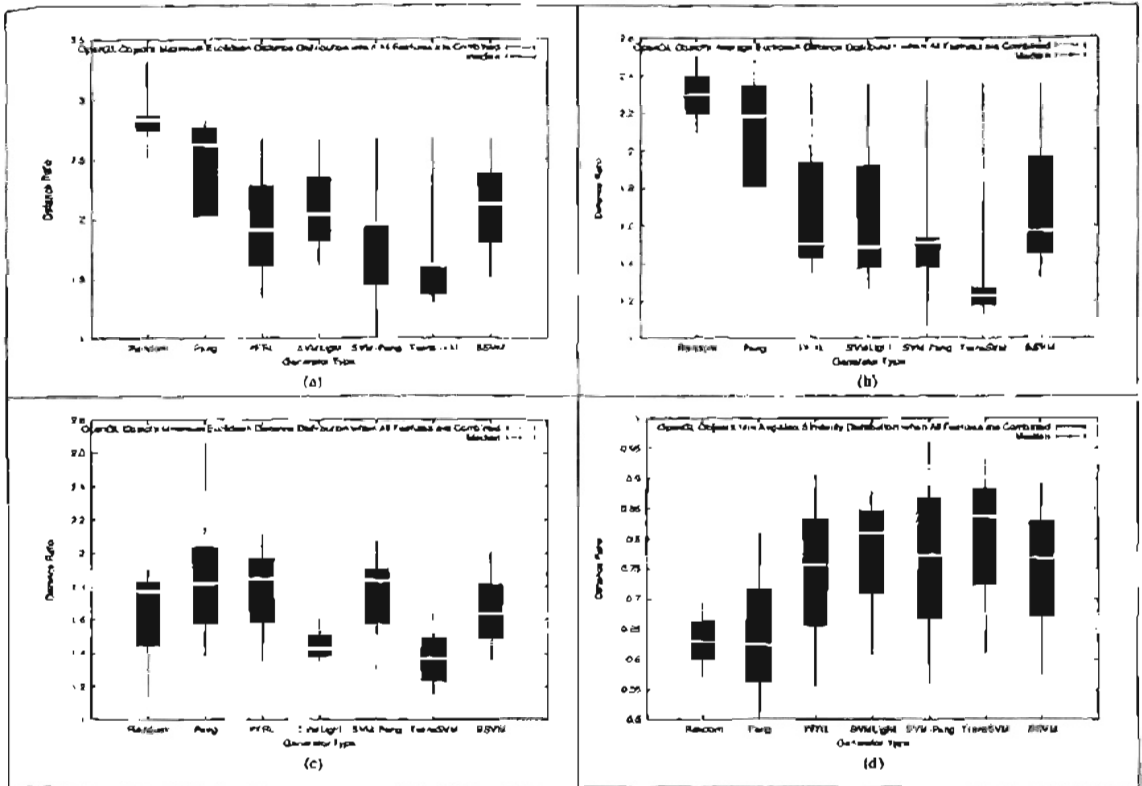


Figure 4.12: (a)-(c) Maximum, average, and minimum Euclidean distance ratio (r_m) distribution for OpenGL Object data set with Gabor, Color Histogram, Haralick, and Correlation features combined. (d) Combination of Maximum, Average, and Minimum similarity value distribution for OpenGL Object data set with Gabor, Color Histogram, Haralick, and Correlation features combined.

From Figure 4.12(a), we can determine the robustness of the maximum distance distribution of a particular generator over all other generators when all Gabor, Color Histogram, Haralick, and Correlation features are used. It is clear from the figure that TransSVM is the most robust generator. It has the best median performance (1.58) and the narrowest interquartile range. In half of the problem, it has 58% higher distance rate compare to the best case. In 3/4 of the problem and the worst case, they are 59% and 166%. Peng has the widest interquartile range, while Random has the worst median performance. Other generators have average interquartile range and median performance. Random has the worst distribution, with corresponding numbers 2.81, 180%, 185%, and 230%. Its distance rates are high in all cases, which means it is at all time performs badly.

Figure 4.12(b) shows us that TransSVM is clearly the most robust generator on average over all other generators when Gabor, Color Histogram, Haralick, and Correlation features are used. It has the best median performance (1.23) and the narrowest interquartile range. In half of the problem, it has only 15% higher distance rate than the best case. In 3/4 of the problem and the best case, they are 19% and 121%. SVM-Peng is the most robust generator after TransSVM. PFRL, SVMLight, and BSVM have similar performance, with average median performance and interquartile range. Random and Peng's distance rates are far above other generators. This means that both Random and Peng performs worst compare to other generators most of the time. Random has the worst distribution with corresponding

numbers 2.29, 115%, 125%, and 135%.

From Figure 4.12(c), we can determine the robustness of the minimum distance distribution of a particular generator over all other generators when all Gabor, Color Histogram, Haralick, and Correlation features are used. For this particular case, TransSVM has considerably consistent performance. It has best median performance (1.34) and among the narrowest interquartile range. It has 19% higher distance rate in half of the problem, and 31% and 45% in 3/4 of the problem and the worst case. SVMLight has narrower interquartile range compare to TransSVM, but TransSVM's range has better performance with lower distance rate. SVMLight interquartile range is 1.38-1.51, while TransSVM's is 1.23-1.49. Peng has the widest interquartile range, while PFRL has the worst median performance. Other generators have average median performance and interquartile range.

Figure 4.12(d) examined the robustness of the similarity distribution of a particular generator over all other generators when all Gabor, Color Histogram, Haralick, and Correlation features are used. As we can see from the Figure, the interquartile ranges of most generators tested are almost the same. Among all generators, TransSVM has considerably consistent performance. It has the best median performance (0.84) and average interquartile performance. It has 15%, 33%, and 57% higher similarity rate in half, 3/4, and worst case of the problem. SVMLight has narrower performance compare to TransSVM, but its median performance is worse. SVM-Peng has the widest interquartile range, while Peng has the worst median performance. All

other generators have average median and interquartile range. Random has the worst distribution with similarity distances far below other generators, which means most of the time it performs worse than other generators. Its corresponding numbers are 0.63, 52%, 60%, 68%.

Scientific Data

Tables and graphs on Appendix C show the generators' performance as the time increases. When all Gabor, Color Histogram, Haralick, and Correlation are used, no generator is able to generate image with the smaller and smaller minimum, average, and maximum distance to the desired image.

Figure 4.13(a) examines the robustness of the maximum distance distribution of a particular generator over all other generators when all Gabor, Color Histogram, Haralick, and Correlation features are used. In this case, TransSVM, the generator with best median performance (1.98), seems to have the widest interquartile range. It has 98%, 107%, and 117% higher distance rate compare to the best case in half, 3/4, and worst case of the problem. SVM-Peng has the second best median performance after TransSVM (2.03), and it has considerably narrow interquartile range. Its corresponding numbers are 103%, 110%, 117%. As we can see from the figure, the interquartile range difference is not much. But, if interquartile range is essential, we can say that SVM-Peng has among the best median performance, and considerably consistent performance in general. If interquartile range is ignored, then TransSVM is

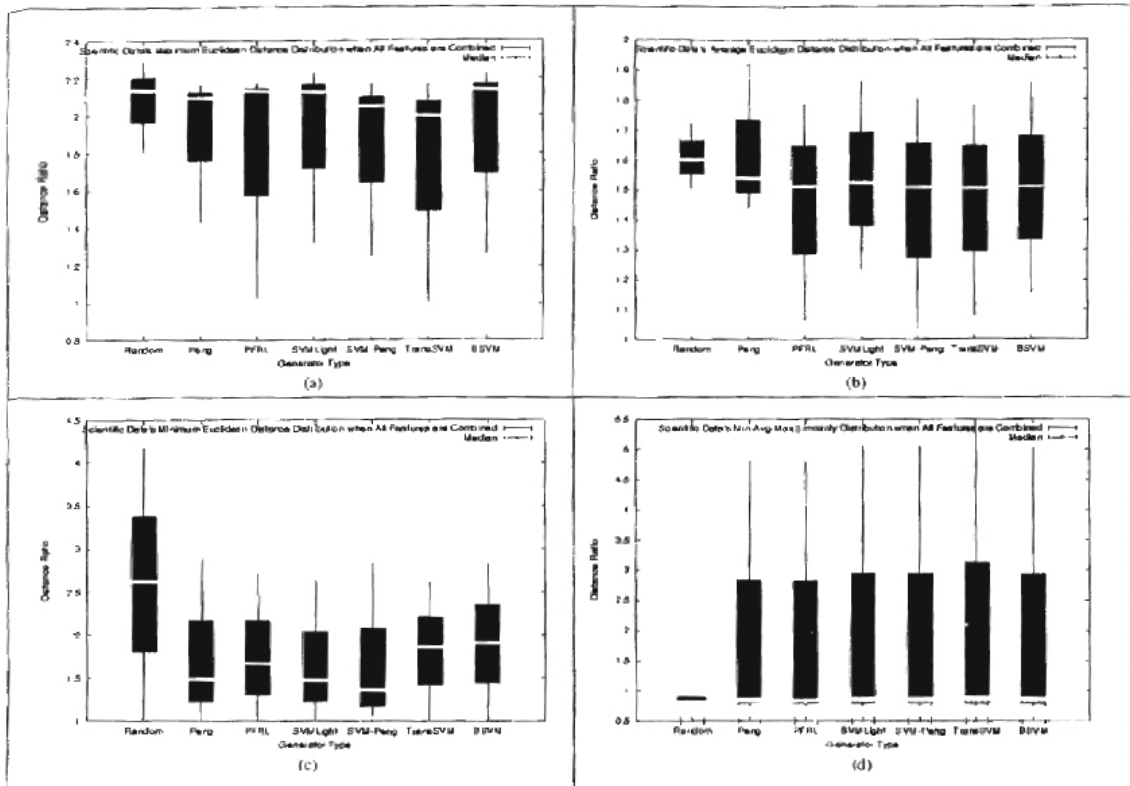


Figure 4.13: (a)-(c) Maximum, average, and minimum Euclidean distance ratio (r_m) distribution for Scientific data set with Gabor, Color Histogram, Haralick, and Correlation features combined. (d) Combination of Maximum, Average, and Minimum similarity value distribution for Scientific data set with Gabor, Color Histogram, Haralick, and Correlation features combined.

the most robust generator. PFRL and Random have the worst median performance. All other generators have average median performance and interquartile range. Random has the worst distribution with corresponding numbers 2.12, 112%, 120%, 129%.

From Figure 4.13(b), we can determine how well a particular generator performs on average over all other generators when Gabor, Color Histogram, Haralick, and Correlation features are used. As we can see clearly from the Figure, all PFRL, SVM-Peng, TransSVM, and BSVM have the same (lowest) median value (1.51). Among those four generators, BSVM has the narrowest interquartile range, but its distance rate distribution is worse than TransSVM. Even though TransSVM has wider interquartile range, it has better performance. Thus, we can conclude that TransSVM is the most robust generator in this case. In half of the problem, it has 46% higher distance rate compare to the best case. In 3/4 of the problem and the worst case, they are 59% and 73%. SVM-Peng has the widest interquartile range, while Random has the worst median performance. All other generators have average median performance and interquartile range. Random is the generator with the worst distribution, with corresponding numbers 1.60, 55%, 61%, 67%. Even though Random has the narrowest interquartile range, but its distance rate is far above other generators, which means it performs badly most of the time.

From Figure 4.13(c), the robustness of the minimum distance distribution of a particular generator over all other generators when all Gabor, Color Histogram, Haralick, and Correlation features are used can be determined. SVM-Peng has the

best median performance (1.33), but among the widest interquartile range. SVMLight has slightly worse median performance (1.44) but among the lowest interquartile range. Thus, we can say that SVMLight has among the best median performance, and considerably consistent performance in general. In half of the problem, it has 44% higher distance rate compare to the best case. In 3/4 of the problem and worst case, they are 104% and 165%. Random has the worst median performance and the widest interquartile range. Its distance rates are far above other generators. It also has the worst distribution, with corresponding numbers 2.59, 159%, 239%, and 317%.

Figure 4.13(d) examined the robustness of the similarity distribution of a particular generator over all other generators when all Gabor, Color Histogram, Haralick, and Correlation features are used. In this case, Peng is the most robust generator. It has the best median performance (0.84) and narrowest interquartile range among all generators but Random. In half of the problem, it has 542% higher similarity rate compare to the best case. In 3/4 of the problem and worst case, they are 578% and 618%. Random has the narrowest interquartile range, but among the worst median performance. In general, it performs worse than other generators most of the time. Its corresponding distribution numbers are 0.83, 554%, 579%, and 606%.

Chapter 5

SUMMARY

Data recognition and classification process is one of the most difficult parts in computer graphics. Many papers and projects have been done to improve the navigation of visualizations process. Many algorithms and intuitive user interfaces have been designed, but no specific system has been developed to test and compare them. The system is a modular system that tests and compares the effects of using each of the generators. Using the system that we developed, we are able to define the advantages and disadvantages of each generator compare to others. The system is built especially to compare all the existing generators in a couple of important aspects. The system is made to be as compatible as possible to do the comparison and testing. All input parameters are inputted from a file (input vector file and XML template file), so that they can be changed easily without changing the system. The system also allows many users to access the system at the same time, to speed up the exploration process.

The system has been used to compare the performance of seven generators, which are Random generator, Peng generator, PFRL, SVMLight, SVM-Peng, TransSVM, and BSVM. Three types of data set are used to test each of these generators, which are Real object, OpenGL object, and Scientific data set.

Two measurements are calculated to measure how much user interactions are needed during the navigation process. They are the time needed to find the desired image and the number of deadends. The experimental result shows that no matter what the data type tested, Random needs the most time to find the desired image, while PFRL needs the least time. The result also shows that generators that contain Peng algorithm in them have the largest number of deadends, while SVMLight has the smallest number. When CPU time is measured, for all data types, PFRL have the largest Generator CPU time, while Random generator has the least.

This thesis discusses in detail the experimental results when all Gabor, Color Histogram, Haralick, and Correlation features are combined. When all features are combined, for Real Object data set, the most robust generators for maximum, average, and minimum Euclidean distance distributions are TransSVM, both TransSVM and PFRL, and both TransSVM and SVMLight. For OpenGL Object data set, the most robust generator for maximum, average, and minimum Euclidean distance distributions is TransSVM. For Scientific data set, the most robust generator for maximum and average Euclidean distance distributions is TransSVM. The most robust generator for minimum Euclidean distance distribution is SVMLight.

For Real Object data set, the most robust generators for maximum, average, and minimum similarity distributions are both TransSVM and PFRL. For OpenGL Object data set, it is TransSVM. For Scientific data set, it is Peng.

The complete experimental results are attached on Appendix B, C, and D. Appendix B contains the tables and figures of user interaction (time needed to find desired image and number of deadends) and CPU time of all generators. Appendix C contains the tables and figures of Euclidean distance and similarity value of all generators as time increases. Appendix D contains the tables and figures of Euclidean distance and similarity value distributions of all generators tested.

Chapter 6

FUTURE WORKS

As we can see from above, the performance of each generator is greatly influenced by the type of data set tested and which similarity measure used. Besides data set type and similarity measure used, there are several factors that can influence the performance of each generator. The system that is built for this thesis has several areas that can be improved in the future.

PFRL has the worst generator and renderer CPU time. This is because PFRL generates a new set of images based on the output features of images. Thus, each time PFRL has to generate a new set of images, it has to generate a number of input vectors, and generate images from those input vectors. Finally it has to extract each image's features, and pick a new set of images based on those features. Instead of generating full size images, thumbnail of images can be generated in the future to reduce the generator CPU time of PFRL.

In BSVM, MyGenerator2 is used to generate new samples that BSVM used

to generate a new set of images. In MyGenerator2, for each feature of an image, there are several ranges of value that are used to generate new samples. For example, if there are n features in an image, then feature 1 has k_1 ranges of value, feature 2 has k_2 ranges of value, feature n has k_n ranges of value. Thus, to generate a dispersed new samples, each feature's range of value has to be the combination of all other features' range of values, with possible number of new samples generated: $k_1 * k_2 * \dots * k_n$. MyGenerator2 does not apply this. Thus, new samples generated by MyGenerator2 may not give the samples that user wanted. This can significantly influenced the performance of the generator tested, which is BSVM. In the future, in order to get a dispersed sample, new samples have to be generated by considering all possible features' ranges as described above.

The system built already calculated the number of mouse clicks/timestamp and image clicks/timestamp of the exploration process. These numbers can also be used to measure generators' performance in the future. For example to examine whether as time increases the user clicks more relevant or irrelevant images. Also whether the user often clicking and unclicking images, which can measure whether the user is often confused by the generator.

There also exist several directions for future research in expanding this comparison system. The system can be designed and put in the web, so that exploration process can take place instant places at the same time. Bender et al. [3] gives us a good reference of the framework of web-based visualization system. The intermediate

testing and comparison of dispersion algorithms can also be done in the future, so that we will not only have the final result of the algorithms, but also the resulting images in-between the starting point and the ending point of the algorithms. Kim et al. [24] gives us good reference for this. We can also try to reduce the preprocessing time of the system in displaying images on the screen. Lum et al. [27] do research that can be continued in the future.

References

- [1] J. Abello and J. Korn. MGVis: A System for Visualizing Massive Multigraphs. *In IEEE Transactions on Visualization and Computer Graphics*, Vol. 8, No. 1, January-March 2002.
- [2] E. Angel. *Interactive Computer Graphics: A Top-Down Approach with OpenGL*, Second Edition, Addison Wesley, 2000.
- [3] M. Bender, R. Klein, A. Disch, and A. Ebert. A Functional Framework for Web-Based Information Visualization Systems. *In IEEE Transactions on Visualization and Computer Graphics*, Vol. 6, No. 1, January-March 2000.
- [4] C. J. C. Burges. A Tutorial on Support Vector Machines for Pattern Recognition. *In Data Mining and Knowledge Discovery*, Vol. 2, No. 2, pages 121-167, 1998.
- [5] O. Chapelle, P. Haffner, and V. N. Vapnik. Support Vector Machines for Histogram-Based Image Classification. *In IEEE Transactions on Neural Networks*, Vol. 10, No. 5, September 1999.
- [6] K. Crammer and Y. Singer. *Algorithmic Implementation of Multiclass Kernel-Based Support Vector Machines*, Technical Report, School of Computer Science and Engineering, Hebrew University, 2001.
- [7] J. H. Friedman. *Flexible Metric Nearest Neighbor Classification*, Technical Report, Department of Statistics, Stanford University, 1994.
- [8] Y. H. Fua, M. O. Ward, and E. A. Rundensteiner. Structure-Based Brushes: A Mechanism for Navigating Hierarchically Organized Data and Information Spaces. *In IEEE Transactions on Visualization and Computer Graphics*, Vol. 6, No. 2, April-June 2000.
- [9] G. Fung and O. L. Mangasarian. Data Selection for Support Vector Machine Classifiers. *In Proceeding of Third International Workshop on Web Information and Data Management*, pages 1-8, November 2001.
- [10] G. W. Furnas. Generalized Fisheye Views. *In Proceeding of CHI Human Factors in Computing Systems*, pages 16-23, April 1986.
- [11] D. R. Heisterkamp, J. Peng, and H. K. Dai. Feature Relevance Learning with Query Shifting for Content-Based Image. *In Proceeding International Conference on Pattern Recognition*, Barcelona, Spain, pages 250-253, September 3-7, 2000.

- [12] I. Herman, G. Melancon, and M. S. Marshall. Graph Visualization and Navigation in Information Visualization: A Survey. In *IEEE Transactions on Visualization and Computer Graphics*, Vol. 6, No. 1, January-March 2000.
- [13] K. S. Goh, E. Chang, and K. T. Cheng. Classification: SVM Binary Classifier Ensembles for Image Classification. In *Proceeding of the Tenth International Conference on Information and Knowledge Management*, pages 395-402, October 2001.
- [14] S. E. Grigorescu, N. Petkov, and P. Kruizinga. Comparison of Texture Features Based on Gabor Filters. In *IEEE Transactions on Image Processing*, Volume 11, Number 10, pages 1160-1167, October 2002.
- [15] M. H. Gross and R. Koch. Visualization of Multidimensional Shape and Texture Features in Laser Range Data Using Complex-Valued Gabor Wavelets. In *IEEE Transactions on Visualization and Computer Graphics*, Volume 1, Number 1, pages 44-59, March 1995.
- [16] J. Han and K. K. Ma. Fuzzy Color Histogram and Its Use in Color Image Retrieval. In *IEEE Transactions on Image Processing*, Volume 11, Number 8, pages 944-952, August 2002.
- [17] S. Aksoy and R. M. Haralick. A Classification Framework for Content-Based Image Retrieval. In *Proceeding of 16th International Conference on Pattern Recognition*, Vol. 2, No. 3, 2002.
- [18] C. W. Hsu and C. J. Lin. A Comparison of Methods for Multi-Class Support Vector Machines. In *IEEE Transactions on Neural Networks*, pages 415-425, 2002.
- [19] V. S. Iyengar, C. Apte, and T. Zhang. Active Learning using Adaptive Resampling. In *Proceedings of the Sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 91-98, August 2000.
- [20] T.J. Jankun-Kelly and K.L. Ma. Visualization Exploration and Encapsulation via a Spreadsheet-Like Interface. In *IEEE Transactions on Visualization and Computer Graphics*, Vol. 7, No. 3, July-September 2001.
- [21] T. Joachims. Transductive Inference for Text Classification Using Support Vector Machines. In *International Conference on Machine Learning, 1999*.
- [22] D. A. Keim. Designing Pixel-Oriented Visualization Techniques: Theory and Applications. In *IEEE Transactions on Visualization and Computer Graphics*, Vol. 6, No. 1, January-March 2002.
- [23] D. A. Keim. Information Visualization and Visual Data Mining. In *IEEE Transactions on Visualization and Computer Graphics*, Vol. 8, No. 1, January-March 2002.

- [24] K. Kim, M. Wittenbrink, and A. Pang. Extended Specifications and Test Data Sets for Data Level Comparisons of Direct Volume Rendering Algorithms. *In IEEE Transactions on Visualization and Computer Graphics*, Vol. 7, No. 4, October-December 2001.
- [25] M. Kreuzeler and H. Schumann. A Flexible Approach for Visual Data Mining. *In IEEE Transactions on Visualization and Computer Graphics*, Vol. 8, No. 1, January-March 2002.
- [26] J. Lamping, R. Rao, and P. Pirolli. A Focus+Context Technique Based On Hyperbolic Geometry for Visualizing Large Hierarchies. *In Conference Proceeding on Human Factors in Computing Systems*, pages 401-408, May 1995.
- [27] E. B. Lum, K. L. Ma, and J. Clyne. A Hardware-Assisted Scalable Solution for Interactive Volume Rendering of Time-Varying Data. *In IEEE Transactions on Visualization and Computer Graphics*, Vol. 8, No. 3, July-September 2002.
- [28] K.L. Ma. Image-Graphs A Novel Approach to Visual Data Exploration. *In Proceeding IEEE Visualization 1999*, pages 81-88, October 1999.
- [29] J. Marks, B. Ardalman, P.A. Beardsley, W. Freeman, S. Gibson, J. Hodgins, T. Kang, B. Mirtich, H. Pfister, W. Ruml, K. Ryall, J. Seims, and S. Shieber. Design Galleries: A General Approach to Setting Parameters for Computer Graphics and Animation. *In Proceedings of SIGGRAPH 97*, Los Angeles, pages 389-400, August 1997.
- [30] Z. Nie, S. Kambhampati, U. Nambiar, and S. Vaddi. Mining Source Coverage Statistics for Data Integration. *In Proceeding of the Third International Workshop on Web Information and Data Management*, pages 1-8, 2001.
- [31] K. Nigam and R. Ghani. Analyzing the Effectiveness and Applicability of Co-training. *In Proceeding of the Ninth International Conference on Information and Knowledge Management*, pages 86-93, November 2000.
- [32] P. Niyogi, C. Burges, and P. Ramesh. Distinctive Feature Detection Using Support Vector Machines. *In Proceedings of the International Conference on Acoustics, Speech, and Signal Processing*, Phoenix, Arizona, pages 425-428, 1999.
- [33] J. Peng, D. R. Hoisterkamp, and H. K. Dai. LDA/SVM Driven Nearest Neighbor Classification. *In Proceeding of IEEE Conference on Computer Vision and Pattern Recognition*, Kauai, Hawaii, Vol. 1, pages 58-63, December 9-14, 2001.
- [34] J. Peng, B. Bhanu, and S. Qing. Probabilistic Feature Relevance Learning for Content-Based Image Retrieval. *In Computer Vision and Image Understanding, Special Issue on Content-Based Access of Image and Video Libraries*, pages 150-164, July-August 1999.
- [35] X. Peng. *Local Feature Relevance for Efficient Navigation and Visualization of Large Data Sets*, Computer Science Thesis, 2002.

- [36] M. Porat and Y. Y. Zeevi. Pattern Analysis and Texture Discrimination in the Gabor Space. *In Proceedings of International Conference on Pattern Recognition*, Vol. 88, pages 700-702, 1998.
- [37] M. J. Swain and D. H. Ballard. Indexing via Color Histogram. *In Proceedings of the Third International Conference on Computer Vision*, pages 390-393, 1990.
- [38] Y. Takefuji, R. Jannarone, Y. B. Cho, and T. Chen. Multinomial Conjointoid Statistical Learning Machines. *In Proceedings of the Fifteenth IEEE International Symposium on Computer Architecture*, pages 12-17, 1998.
- [39] S. Tong and E. Chang. Support Vector Machine Active Learning for Image Retrieval. *In Proceedings of the Ninth ACM International Conference on Multimedia*, pages 102-118, October 2001.
- [40] OpenGL Architecture Review Board, M. Woo, J. Neider, and T. Davis. *OpenGL Programming Guide: The Official Guide to Learning OpenGL*, Version 1.2, 1999.
- [41] R. S. Wright, Jr and M. Sweet. *OpenGL Superbible*, Second Edition, Corte Madera, CA: Waite Group Press, 2000.
- [42] I. T. Young, L. J. van Vliet, and M. van Ginkel. Recursive Gabor Filtering. *In IEEE Transactions on Signal Processing*, Volume 50, Number 11, pages 2798-2805, November 2002.
- [43] S. Zelikovitz and H. Hirsh. Text Extraction and Summarization: Using LSI for text Classification in the Presence of Background text. *In Proceeding of the Tenth International Conference on Information and Knowledge Management*, pages 113-118, November 2001.

APPENDICES

Appendix A

GLOSSARY

Graphical User Interface	A computer program designed to allow a computer user to interact easily with the computer typically by using a mouse to make choices from menus or groups of icons.
Multidimensional Data	Data that relates to or has more than three dimensions, or data that has several different aims, qualities, or aspects.
Scientific Visualization	A visualization that concerns with exploring data and information in such a way as to gain understanding and insight into the data. The goal is to promote a deeper level of understanding of the data under investigation and to foster new insight into the underlying process, relying on the humans' powerful ability to visualize.

Timestamp

A device for recording the set of images' numbers that sent out by the navigation algorithm throughout the exploration process.

OpenGL Library

A trademark of Silicon Graphics Inc and is a cross-platform standard for 3D rendering and 3D hardware acceleration first developed in 1992. It is required in some computer games.

Appendix B

USER INTERACTION AND CPU TIME

TABLES AND FIGURES

OSM OBJECT
TIMESTAMP

Time	Random	Pengs	PFR	SVMLight	SVM-Pengs	TransActive	BSVM
0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1
2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	3
4	4	4	4	4	4	4	4
5	5	5	5	5	5	5	5
6	6	6	6	6	6	6	6
7	7	7	7	7	7	7	7
8	8	8	8	8	8	8	8
9	9	9	9	9	9	9	9
10	10	10	10	10	10	10	10
11	11	11	11	11	11	11	11
12	12	12	12	12	12	12	12
13	13	13	13	13	13	13	13

USIA INTERACTION

Random	Pengs	PFR	SVMLight	SVM-Pengs	TransActive	BSVM
12.8521	7.2757	2.4286	7.6005	5.8090	4.2877	5.4785
0.0868	0.2454	0.0286	0.0230	0.1147	0.0717	0.1238

CPU TIME

Random	Pengs	PFR	SVMLight	SVM-Pengs	TransActive	BSVM
0.0789	1.0573	430.3070	10.8803	11.2441	9.1611	73.9081
145.2671	153.5433	214.7479	214.6782	164.7567	200.3057	175.7311
0.2653	0.3852	0.4679	0.5478	0.5143	0.4892	0.7361

OPENING OBJECT
TIMESTAMP

Time	Random	Pengs	PFR	SVMLight	SVM-Pengs	TransActive	BSVM
0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1
2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	3
4	4	4	4	4	4	4	4
5	5	5	5	5	5	5	5
6	6	6	6	6	6	6	6
7	7	7	7	7	7	7	7
8	8	8	8	8	8	8	8
9	9	9	9	9	9	9	9
10	10	10	10	10	10	10	10
11	11	11	11	11	11	11	11

USIA INTERACTION

Random	Pengs	PFR	SVMLight	SVM-Pengs	TransActive	BSVM
13.0000	5.1000	3.0000	3.0000	1.0000	5.0000	3.0000
0.0855	0.2000	0.0700	0.3000	0.0500	0.2000	0.3000

CPU TIME

Random	Pengs	PFR	SVMLight	SVM-Pengs	TransActive	BSVM
0.0000	1.4000	491.6878	12.3000	0.2000	11.0000	16.1667
137.9678	114.2998	143.5200	141.5330	94.6000	114.0000	141.0070
0.4167	0.4000	0.3333	0.6000	0.1667	0.3000	0.5000

SCIENTIFIC DATA
TIMESTAMP

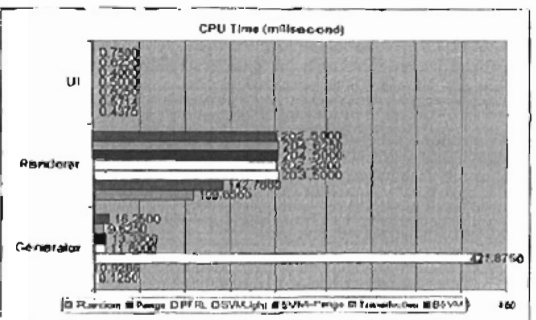
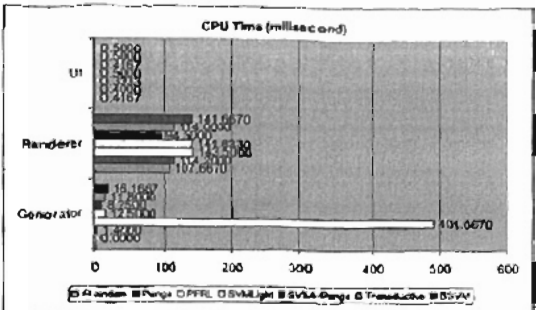
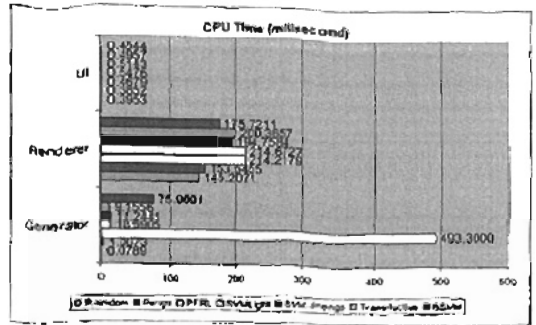
Time	Random	Pengs	PFR	SVMLight	SVM-Pengs	TransActive	BSVM
0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1
2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	3
4	4	4	4	4	4	4	4
5	5	5	5	5	5	5	5
6	6	6	6	6	6	6	6
7	7	7	7	7	7	7	7
8	8	8	8	8	8	8	8
9	9	9	9	9	9	9	9
10	10	10	10	10	10	10	10
11	11	11	11	11	11	11	11
12	12	12	12	12	12	12	12
13	13	13	13	13	13	13	13
14	14	14	14	14	14	14	14
15	15	15	15	15	15	15	15

USIA INTERACTION

Random	Pengs	PFR	SVMLight	SVM-Pengs	TransActive	BSVM
18.0000	7.0000	4.0000	5.0000	0.0000	4.0000	4.0000
8.9678	0.2657	0.0900	0.0000	0.0000	0.0000	0.0000

CPU TIME

Random	Pengs	PFR	SVMLight	SVM-Pengs	TransActive	BSVM
0.1150	0.3000	421.8781	11.0000	13.3000	9.0750	18.2660
149.8500	143.7878	203.6000	202.2000	204.5000	204.5000	202.0000
3.4375	0.8144	0.4050	0.5000	3.4000	0.0000	0.7860

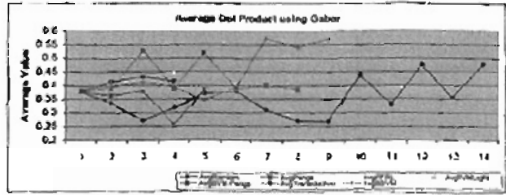


Appendix C

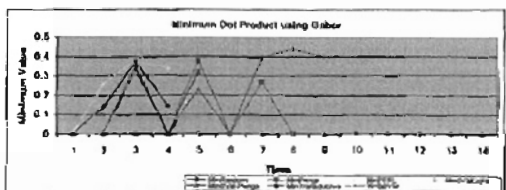
EUCLIDEAN DISTANCE AND SIMILARITY

VALUE TABLES AND FIGURES

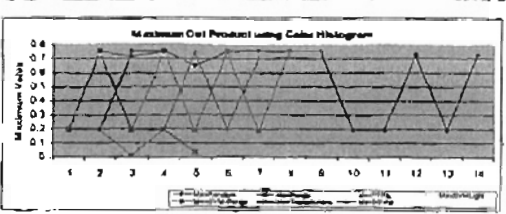
AVERAGE VALUE						
Time	Amplitude	Average	Min/Max	Min/Max	Min/Max	Min/Max
0	0.1111	0.3777	0.2111	0.5111	0.3777	0.5111
1	0.1111	0.3888	0.4177	0.5000	0.4927	0.4137
2	0.1111	0.2735	0.432	0.5788	0.3777	0.4137
3	0.1111	0.3888	0.467	0.5000	0.4927	0.4137
4	0.1111	0.3888	0.467	0.5000	0.4927	0.4137
5	0.1111	0.3888	0.467	0.5000	0.4927	0.4137
6	0.1111	0.3888	0.467	0.5000	0.4927	0.4137
7	0.1111	0.3888	0.467	0.5000	0.4927	0.4137
8	0.1111	0.3888	0.467	0.5000	0.4927	0.4137
9	0.1111	0.3888	0.467	0.5000	0.4927	0.4137
10	0.1111	0.3888	0.467	0.5000	0.4927	0.4137
11	0.1111	0.3888	0.467	0.5000	0.4927	0.4137
12	0.1111	0.3888	0.467	0.5000	0.4927	0.4137
13	0.1111	0.3888	0.467	0.5000	0.4927	0.4137



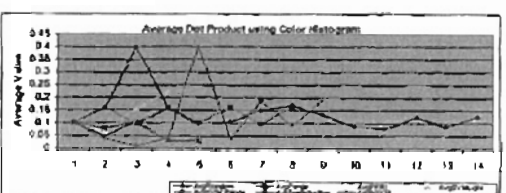
MINIMUM VALUE						
Time	Amplitude	Min/Max	Min/Max	Min/Max	Min/Max	Min/Max
0	0	0	0	0	0	0
1	0	0.2074	0.2146	0	0.2146	0.2074
2	0	0.2074	0.2146	0	0.2146	0.2074
3	0	0.3374	0	0.3174	0	0.2264
4	0	0.3374	0	0.3174	0	0.2264
5	0	0.3374	0	0.3174	0	0.2264
6	0	0.3374	0	0.3174	0	0.2264
7	0	0.3374	0	0.3174	0	0.2264
8	0	0.3374	0	0.3174	0	0.2264
9	0	0.3374	0	0.3174	0	0.2264
10	0	0.3374	0	0.3174	0	0.2264
11	0	0.3374	0	0.3174	0	0.2264
12	0	0.3374	0	0.3174	0	0.2264
13	0	0.3374	0	0.3174	0	0.2264



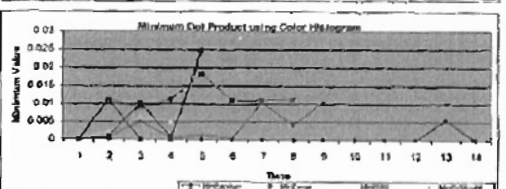
COLOR HISTOGRAM						
Time	Amplitude	Average	Min/Max	Min/Max	Min/Max	Min/Max
0	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
1	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
2	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
3	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
4	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
5	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
6	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
7	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
8	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
9	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
10	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
11	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
12	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
13	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586



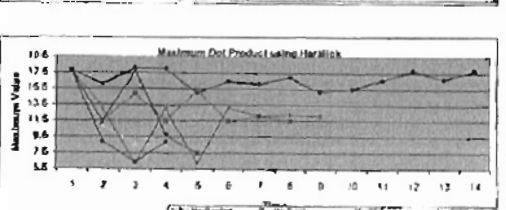
AVERAGE VALUE						
Time	Amplitude	Average	Min/Max	Min/Max	Min/Max	Min/Max
0	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
1	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
2	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
3	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
4	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
5	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
6	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
7	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
8	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
9	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
10	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
11	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
12	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086
13	0.0914	0.6086	0.5074	0.6086	0.6086	0.6086



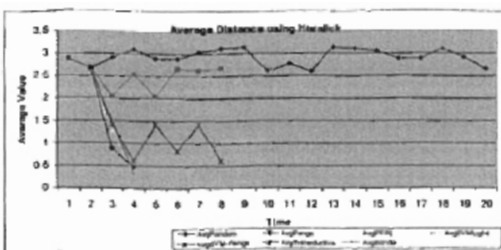
MINIMUM VALUE						
Time	Amplitude	Min/Max	Min/Max	Min/Max	Min/Max	Min/Max
0	0	0	0	0	0	0
1	0	0.0814	0.0914	0	0.0914	0.0814
2	0	0.0814	0.0914	0	0.0914	0.0814
3	0	0.0814	0.0914	0	0.0914	0.0814
4	0	0.0814	0.0914	0	0.0914	0.0814
5	0	0.0814	0.0914	0	0.0914	0.0814
6	0	0.0814	0.0914	0	0.0914	0.0814
7	0	0.0814	0.0914	0	0.0914	0.0814
8	0	0.0814	0.0914	0	0.0914	0.0814
9	0	0.0814	0.0914	0	0.0914	0.0814
10	0	0.0814	0.0914	0	0.0914	0.0814
11	0	0.0814	0.0914	0	0.0914	0.0814
12	0	0.0814	0.0914	0	0.0914	0.0814
13	0	0.0814	0.0914	0	0.0914	0.0814



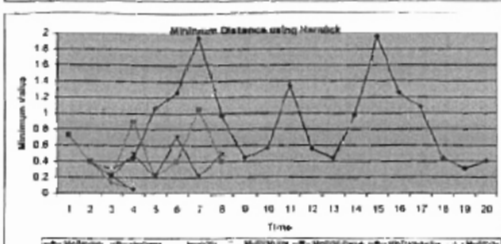
MAXIMUM VALUE						
Time	Amplitude	Average	Min/Max	Min/Max	Min/Max	Min/Max
0	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
1	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
2	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
3	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
4	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
5	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
6	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
7	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
8	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
9	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
10	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
11	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
12	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586
13	0.1314	0.7586	0.7074	0.7586	0.7586	0.7586



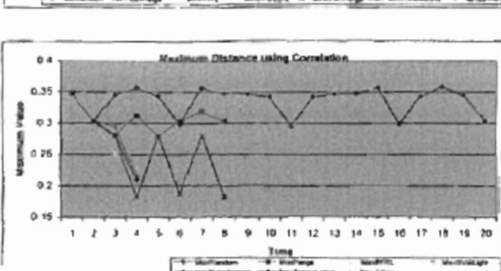
AVERAGE VALUE						
Time	AugFunction	AugPrime	AugPI32	Aug/2/Algo	Aug/2/Prime	Aug/2/Algo
0	2.2748	2.8742	2.8746	2.8748	2.8748	2.8748
1	2.8652	2.6649	2.6649	2.6650	2.6650	2.6650
2	2.9421	2.6452	1.8634	1.6839	1.6173	0.85318
3	2.8069	2.8064	0.53545	0.4942	0.50255	1.49954
4	2.84162	2.6452			1.41573	0.31124
5	2.81178	2.6663			0.6276	
6	2.80262	2.8212			1.41573	
7	2.80565	2.6899			0.50255	
8	2.80271					
9	2.77722					
10	2.80791					
11	2.8228					
12	2.82991					
13	2.82232					
14	2.80178					
15	2.80781					
16	2.80565					
17	2.81724					
18	2.80688					



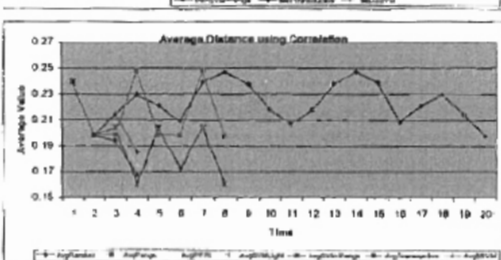
MINIMUM VALUE						
Time	AugFunction	AugPrime	AugPI32	Aug/2/Algo	Aug/2/Prime	Aug/2/Algo
0	0.72021	0.72021	0.72021	0.72021	0.72021	0.72021
1	0.5831	0.9031	0.5831	0.5831	0.5831	0.5831
2	0.34012	0.71449	0.72739	0.55649	0.21448	0.13031
3	0.43429	0.4081	0.56873	0.13683	0.48901	0.04558
4	1.00054	0.21448			0.21448	
5	1.79473	0.31521			0.72000	
6	1.80128	1.50164			0.71666	
7	0.97231	0.1932			0.66044	
8	0.42007					
9	0.96017					
10	1.56101					
11	0.95637					
12	0.41627					
13	0.87291					
14	1.84828					
15	1.75623					
16	1.00054					
17	0.42825					
18	0.34012					
19	0.5333					



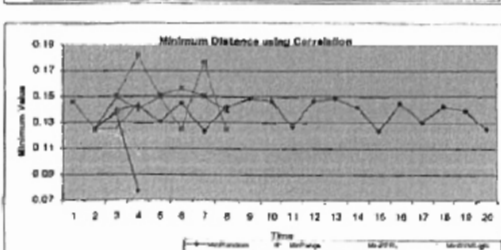
CORRELATION						
MAXIMUM VALUE						
Time	AugFunction	AugPrime	AugPI32	Aug/2/Algo	Aug/2/Prime	Aug/2/Algo
0	0.30221	0.30221	0.30221	0.30221	0.30221	0.30221
1	0.40288	0.30258	0.30288	0.30288	0.30288	1.30288
2	0.46442	0.17608	0.16128	0.29662	0.27660	0.28076
3	0.43557	0.12234	0.23868	0.20341	0.18210	0.21902
4	0.34245	0.27900			0.27900	
5	0.29801	0.20268			0.18782	
6	0.11507	0.21782			0.27809	
7	0.34860	0.30288			0.18210	
8	0.34868					
9	0.34066					
10	0.75965					
11	0.34066					
12	0.34008					
13	0.34858					
14	0.36874					
15	0.36861					
16	0.34243					
17	0.36867					
18	0.14142					
19	0.35218					



AVERAGE VALUE						
Time	AugFunction	AugPrime	AugPI32	Aug/2/Algo	Aug/2/Prime	Aug/2/Algo
0	0.22961	0.22961	0.22961	0.22961	0.22961	0.22961
1	0.18760	0.18768	0.18768	0.18762	0.18766	0.18768
2	0.21409	0.10818	0.20221	0.20236	0.20435	0.18402
3	0.22074	0.24824	0.17891	0.17753	0.18015	0.187
4	0.22285	0.10818			0.20435	
5	0.20855	0.10788			0.17536	
6	0.22036	2.1817			0.20425	
7	0.20666	0.18768			0.18015	
8	0.22768					
9	0.20477					
10	0.21209					
11	0.22706					
12	0.20684					
13	0.23018					
14	0.26020					
15	0.22853					
16	0.22674					
17	0.21650					
18	0.18766					



MINIMUM VALUE						
Time	AugFunction	AugPrime	AugPI32	Aug/2/Algo	Aug/2/Prime	Aug/2/Algo
0	0.14978	0.14978	0.14978	0.14978	0.14978	0.14978
1	0.12482	0.12482	0.12482	0.12482	0.12482	0.12482
2	0.12912	0.12608	0.12680	0.12658	0.12609	0.12744
3	0.14202	0.18190	0.19921	0.19797	0.19635	0.19721
4	0.13041	0.15009			0.15009	
5	0.13504	0.12942			0.13601	
6	0.12924	0.11014			0.12606	
7	0.18192	0.12642			0.13601	
8	0.14887					
9	0.12711					
10	0.14887					
11	0.14887					
12	0.14887					
13	0.14192					
14	0.12324					
15	0.14887					
16	0.13041					
17	0.14282					
18	0.13912					
19	0.12482					

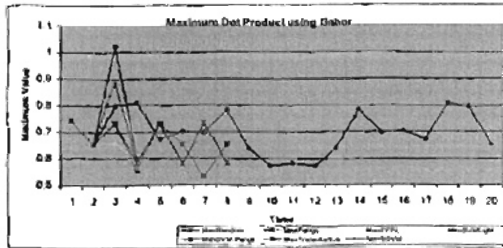


2. GUY PRODUCT

BAHAR

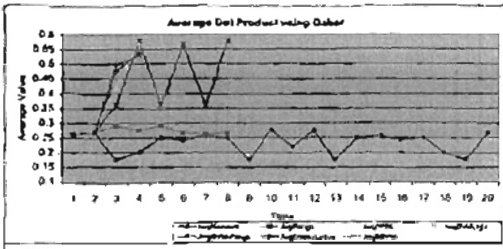
MAXIMUM VALUE

Time	Maximum	Maximum	Maximum	Maximum	Maximum	Maximum	Maximum
1	0.94223	0.74221	0.74222	0.74222	0.74222	0.74222	0.74222
2	0.65229	0.65229	0.65229	0.65229	0.65229	0.65229	0.65229
3	0.76751	0.76751	0.66281	0.66281	0.66281	0.66281	0.66281
4	0.67181	0.73076	0.56113	0.62772	0.73076	0.56113	0.57841
5	0.70206	0.62222			0.70206		
6	0.69504	0.51127			0.58008		
7	0.76183	0.65229			0.56184		
8	0.63825						
9	0.71238						
10	0.67805						
11	0.67238						
12	0.63825						
13	0.76183						
14	0.69504						
15	0.70707						
16	0.67181						
17	0.60789						
18	0.70751						
19	0.65227						



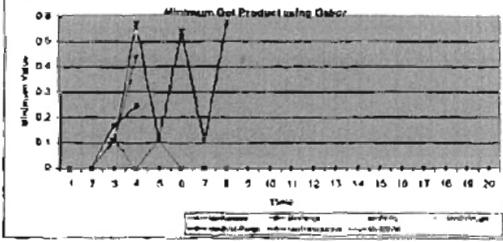
AVERAGE VALUE

Time	Average	Average	Average	Average	Average	Average	Average
0	0.29915	0.29915	0.29915	0.29915	0.29915	0.29915	0.29915
1	0.65025	0.26895	0.26895	0.26895	0.26895	0.26895	0.26895
2	0.73588	0.26134	0.42002	0.44132	0.20137	0.47073	0.40136
3	0.18028	0.27488	0.81182	0.64002	0.57087	0.53315	0.52188
4	0.3498				0.56132		
5	0.21134	0.26002			0.6628		
6	0.27274	0.26008			0.56132		
7	0.21864	0.26005			0.67081		
8	0.77447						
9	0.32811						
10	0.29461						
11	0.17444						
12	0.24466						
13	0.25756						
14	0.24116						
15	0.24988						
16	0.18888						
17	0.17588						
18	0.26009						
19	0.26009						



MINIMUM VALUE

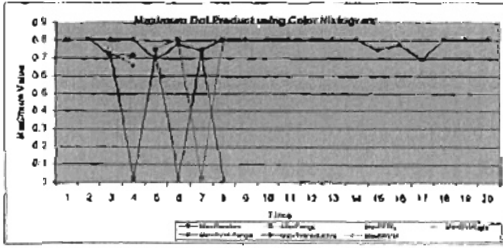
Time	Minimum	Minimum	Minimum	Minimum	Minimum	Minimum	Minimum
1	0	0	0	0	0	0	0
2	0	0.10821	0.14820	0.10821	0.10821	0.10821	0.10821
3	0	0	0.54337	0.24038	0.11718	0.24283	0.10821
4	0	0	0	0	0.14511	0	0
5	0	0	0	0	0.14511	0	0
6	0	0	0	0	0.14511	0	0
7	0	0	0	0	0.14511	0	0
8	0	0	0	0	0.14511	0	0
9	0	0	0	0	0.14511	0	0
10	0	0	0	0	0.14511	0	0
11	0	0	0	0	0.14511	0	0
12	0	0	0	0	0.14511	0	0
13	0	0	0	0	0.14511	0	0
14	0	0	0	0	0.14511	0	0
15	0	0	0	0	0.14511	0	0
16	0	0	0	0	0.14511	0	0
17	0	0	0	0	0.14511	0	0
18	0	0	0	0	0.14511	0	0
19	0	0	0	0	0.14511	0	0
20	0	0	0	0	0.14511	0	0



3. COLOR HISTOGRAM

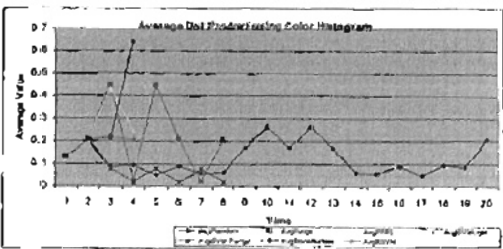
MAXIMUM VALUE

Time	Maximum	Maximum	Maximum	Maximum	Maximum	Maximum	Maximum
0	0.29915	0.29915	0.29915	0.29915	0.29915	0.29915	0.29915
1	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884
2	0.80884	0.74028	0.74028	0.74028	0.74028	0.74028	0.74028
3	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884
4	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884
5	0.77485	0.80884			0.77485		
6	0.74718	0.80884			0.74718		
7	0.80884	0.80884			0.80884		
8	0.80884						
9	0.80884						
10	0.80884						
11	0.80884						
12	0.80884						
13	0.80884						
14	0.80884						
15	0.80884						
16	0.80884						
17	0.80884						
18	0.80884						
19	0.80884						
20	0.80884						



AVERAGE VALUE

Time	Average	Average	Average	Average	Average	Average	Average
0	0.29915	0.29915	0.29915	0.29915	0.29915	0.29915	0.29915
1	0.40185	0.26718	0.26718	0.26718	0.26718	0.26718	0.26718
2	0.74028	0.64736	0.64736	0.64736	0.64736	0.64736	0.64736
3	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884
4	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884
5	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884
6	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884
7	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884	0.80884
8	0.80884						
9	0.80884						
10	0.80884						
11	0.80884						
12	0.80884						
13	0.80884						
14	0.80884						
15	0.80884						
16	0.80884						
17	0.80884						
18	0.80884						
19	0.80884						
20	0.80884						



DATA SET: TEMPLATEDALORFLOW

1. EUCLIDEAN DISTANCE

GABOR

MAXIMUM VALUE							
Time	MaxRandom	MaxPanga	MaxPFR	MaxVM-light	MaxVM-Panga	MaxTransductive	MaxSVM
0	0.59998	0.58598	0.58598	0.58598	0.58598	0.58598	0.58598
1	0.58598	0.58598	0.58598	0.58598	0.58598	0.58598	0.58598
2	0.58598	0.58598	0.53472	0.48096	0.58598	0.44231	0.58598
3	0.83248	0.58598	0.21404	0.21407	0.20908		0.21998
4	0.77261	0.58598					0.2917
5	0.58598	0.58598					0.58598
6	0.77261	0.58598					0.58598
7	0.83248	0.58598					
8	0.58598	0.58598					
9	0.58598						

AVERAGE VALUE							
Time	AvgRandom	AvgPanga	AvgPFR	AvgVM-light	AvgVM-Panga	AvgTransductive	AvgSVM
0	0.48547	0.48547	0.48547	0.48547	0.48547	0.48547	0.48547
1	0.39117	0.39117	0.39117	0.39117	0.39117	0.39117	0.39117
2	0.52111	0.38288	0.27698	0.34894	0.3732	0.28124	
3	0.4742	0.24910	0.1701	0.26455	0.24910		0.17483
4	0.4174	0.38601					0.26839
5	0.47815	0.26815					0.2917
6	0.4174	0.39117					
7	0.4742						
8	0.52111						
9	0.39117						

MINIMUM VALUE							
Time	MinRandom	MinPanga	MinPFR	MinVM-light	MinVM-Panga	MinTransductive	MinSVM
0	0.20688	0.20688	0.20688	0.20688	0.20688	0.20688	0.20688
1	0.13427	0.13427	0.13427	0.13427	0.13427	0.13427	0.13427
2	0.18368	0.15852	0.08293	0.20011	0.17861	0.08334	
3	0.19559	0.13331	0.13359	0.12836	0.22031		0.11674
4	0.16915	0.16982					0.16988
5	0.2476	0.13331					0.13427
6	0.14916	0.15852					
7	0.18368	0.13427					
8	0.18368						
9	0.13427						

COLOR HISTOGRAM

MAXIMUM VALUE							
Time	MaxRandom	MaxPanga	MaxPFR	MaxVM-light	MaxVM-Panga	MaxTransductive	MaxSVM
0	1.3409	1.3409	1.3409	1.3409	1.3409	1.3409	1.3409
1	1.3409	1.3409	1.3409	1.3409	1.3409	1.3409	1.3409
2	1.3409	1.3409	1.33609	1.3409	1.3409	1.32852	
3	1.3409	1.3409	1.26741	1.2693	1.26349		1.2647
4	1.3409	1.34031					1.2858
5	1.3409	1.3409					1.3409
6	1.3409	1.3409					
7	1.3409	1.3409					
8	1.3409						
9	1.3409						

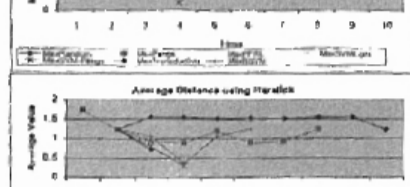
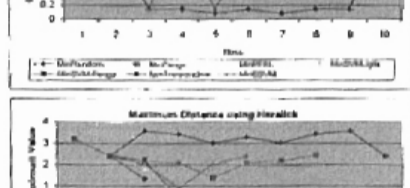
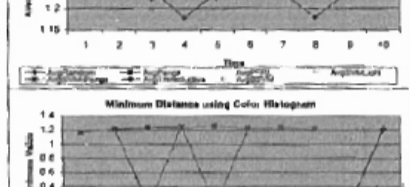
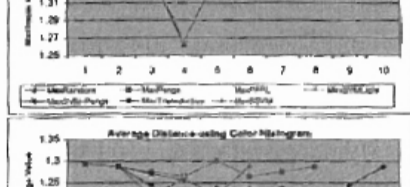
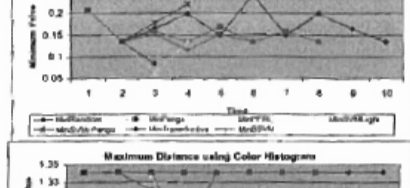
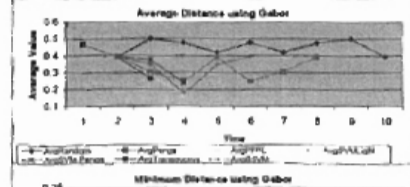
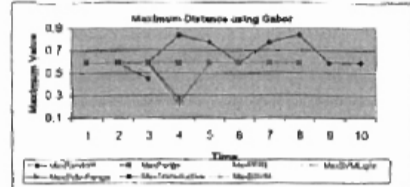
AVERAGE VALUE							
Time	AvgRandom	AvgPanga	AvgPFR	AvgVM-light	AvgVM-Panga	AvgTransductive	AvgSVM
0	1.28251	1.28251	1.28251	1.28251	1.28251	1.28251	1.28251
1	1.2858	1.2858	1.2858	1.2858	1.2858	1.2858	1.2858
2	1.24177	1.2421	1.20386	1.27420	1.28868	1.27064	
3	1.17826	1.26034	1.26034	1.26048	1.25475		1.25842
4	1.2202	1.28858					1.21914
5	1.23332	1.26354					1.2858
6	1.2382	1.27421					
7	1.18328	1.2858					
8	1.24177						
9	1.2858						

MINIMUM VALUE							
Time	MinRandom	MinPanga	MinPFR	MinVM-light	MinVM-Panga	MinTransductive	MinSVM
0	1.18618	1.18618	1.18618	1.18618	1.18618	1.18618	1.18618
1	1.21171	1.21171	1.21171	1.21171	1.21171	1.21171	1.21171
2	0.14087	1.23386	1.22865	1.18286	1.23015	1.2276	0.12583
3	0.08083	1.2286	1.26843	1.23888	1.24818		1.25485
4	0.08083	1.28979					0.12303
5	0.14087	1.2228					1.21171
6	0.08083	1.23386					
7	0.14087	1.21171					
8	0.14087						
9	1.21171						

HARALICK

MAXIMUM VALUE							
Time	MaxRandom	MaxPanga	MaxPFR	MaxVM-light	MaxVM-Panga	MaxTransductive	MaxSVM
0	3.19485	3.19485	3.19485	3.19485	3.19485	3.19485	3.19485
1	2.39442	2.39442	2.39442	2.39442	2.39442	2.39442	2.39442
2	3.56786	2.15577	1.62886	2.18577	3.18577	1.32166	0.13195
3	3.41365	2.56577	0.41783	1.83627	0.37388		0.89238
4	3.18881	3.37926					2.01389
5	3.29481	2.05077					2.39442
6	3.01691	2.18577					
7	3.41365	3.39442					
8	3.56786						
9	2.39442						

AVERAGE VALUE							
Time	AvgRandom	AvgPanga	AvgPFR	AvgVM-light	AvgVM-Panga	AvgTransductive	AvgSVM
0	1.72082	1.72082	1.72082	1.72082	1.72082	1.72082	1.72082
1	1.22881	1.22881	1.22881	1.22881	1.22881	1.22881	1.22881
2	1.95245	0.91838	0.83838	1.05017	0.78339	0.71039	1.05298
3	1.83888	0.85884	0.31171	0.52452	0.38888		0.85314
4	1.90255	1.18724					1.05298
5	1.53017	0.88944					
6	1.50235	0.91838					
7	1.93888	1.22881					
8	1.95245						
9	1.22881						



MINIMUM VALUE

Time	MinRandom	MinPenge	MinPFR	MinSVM_Light	MinSVM_Penge	MinTransductive	MinSVM
0	0.59245	0.59245	0.59245	0.59245	0.59245	0.59245	0.59245
1	0.19088	0.19088	0.19088	0.19088	0.19088	0.19088	0.19088
2	0.58182	0.54278	0.46233	0.15271	0.42074	0.30817	0.34250
3	0.45316	0.15585	0.19858	0.15785	0.23245		0.24154
4	0.33107	0.41031					0.34228
5	0.35478	0.19545					0.19658
6	0.33107	0.44278					
7	0.48316	0.19052					
8	0.34152						
9	0.19088						

CORRELATION

Time	MaxRandom	MaxPenge	MaxPFR	MaxSVM_Light	MaxSVM_Penge	MaxTransductive	MaxSVM
0	0.25245	0.25245	0.25245	0.25245	0.25245	0.25245	0.25245
1	0.22634	0.22634	0.22634	0.22634	0.22634	0.22634	0.22634
2	0.27898	0.19585	0.26253	0.16583	0.48643	0.47729	0.19043
3	0.32183	0.19559	0.09643	0.1639	0.11431		0.11473
4	0.2098	0.16586					0.19643
5	0.32682	0.19559					0.20374
6	0.2965	0.19583					
7	0.32183	0.22634					
8	0.27588						
9	0.22634						

AVERAGE VALUE

Time	AvgRandom	AvgPenge	AvgPFR	AvgSVM_Light	AvgSVM_Penge	AvgTransductive	AvgSVM
0	0.19324	0.19324	0.19324	0.19324	0.19324	0.19324	0.19324
1	0.15138	0.15138	0.15138	0.15138	0.15138	0.15138	0.15138
2	0.17912	0.15723	0.14567	0.1525	0.1431	0.13295	0.15184
3	0.1821	0.16548	0.07648	0.1462	0.10356		0.08686
4	0.19271	0.1380					0.15164
5	0.17572	0.15068					0.15139
6	0.18731	0.15723					
7	0.1831	0.15138					
8	0.17912						
9	0.15138						

MINIMUM VALUE

Time	MinRandom	MinPenge	MinPFR	MinSVM_Light	MinSVM_Penge	MinTransductive	MinSVM
0	0.15705	0.15705	0.15705	0.15705	0.15705	0.15705	0.15705
1	0.05451	0.08451	0.05451	0.08451	0.08451	0.08451	0.08451
2	0.11818	0.14985	0.08396	0.06036	0.18856	0.08349	0.10796
3	0.11128	0.09789	0.06590	0.06005	0.02002		0.07723
4	0.11441	0.13277					0.1086
5	0.10481	0.09736					0.08451
6	0.11441	0.14683					
7	0.11128	0.08451					
8	0.10191						
9	0.08451						

2. DOT PRODUCT

LABOR

MAXIMUM VALUE

Time	MaxRandom	MaxPenge	MaxPFR	MaxSVM_Light	MaxSVM_Penge	MaxTransductive	MaxSVM
0	0.54188	0.54188	0.54188	0.54188	0.54188	0.54188	0.54188
1	0.4458	0.4458	0.4458	0.4458	0.4458	0.4458	0.4458
2	0.64514	0.48508	0.47631	0.40386	0.40386	0.48247	0.50173
3	0.76212	0.41177	0.34714	0.44812	0.42038		0.39782
4	0.75896	0.3857					0.5077
5	0.57245	0.41777					0.4658
6	0.76289	0.40386					
7	0.78112	0.4056					
8	0.64514						
9	0.4458						

AVERAGE VALUE

Time	AvgRandom	AvgPenge	AvgPFR	AvgSVM_Light	AvgSVM_Penge	AvgTransductive	AvgSVM
0	0.19213	0.19213	0.19213	0.19213	0.19213	0.19213	0.19213
1	0.2059	0.2059	0.2059	0.2059	0.2059	0.2059	0.2059
2	0.14086	0.29105	0.33321	0.24247	0.3138	0.3066	0.29907
3	0.18258	0.33346	0.38112	0.3881	0.41976		0.39971
4	0.34543	0.18818					0.28677
5	0.17318	0.37114					0.2858
6	0.24543	0.39105					
7	0.18288	0.3059					
8	0.14086						
9	0.2059						

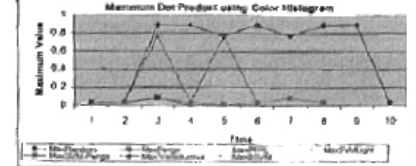
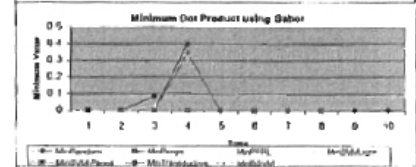
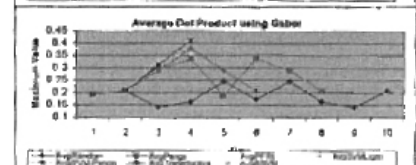
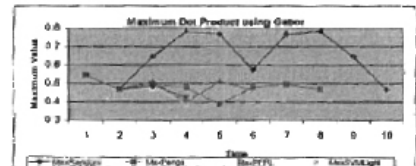
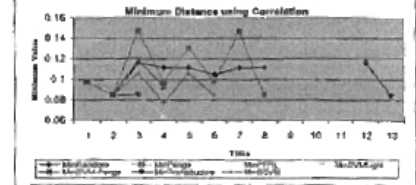
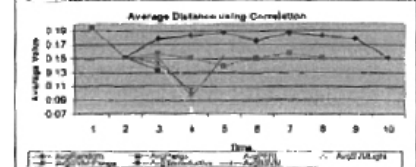
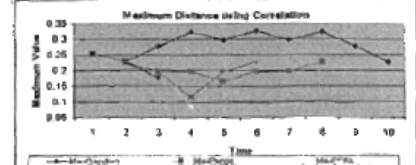
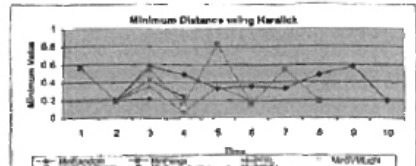
MINIMUM VALUE

Time	MinRandom	MinPenge	MinPFR	MinSVM_Light	MinSVM_Penge	MinTransductive	MinSVM
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	0.03083	0	0	0.0957	0
3	0	0	0.34083	0.30248	0.3096		0.34320
4	0	0					0
5	0	0					0
6	0	0					0
7	0	0					0
8	0	0					0
9	0	0					0

COLOR HISTOGRAM

MINIMUM VALUE

Time	MinRandom	MinPenge	MinPFR	MinSVM_Light	MinSVM_Penge	MinTransductive	MinSVM
0	0.03074	0.03074	0.03074	0.03074	0.03074	0.03074	0.03074
1	0.02922	0.02922	0.03122	0.03122	0.03122	0.03122	0.03122
2	0.08809	0.08809	0.08128	0.08128	0.08278	0.08972	0.08996
3	0.08809	0.03074	0.06022	0.0999	0.0071		0.08918
4	0.08739	0.06752					0.08918
5	0.08809	0.03074					0.08918
6	0.08809	0.08278					0.08996
7	0.08809	0.03122					0.08996
8	0.08809						0.08918
9	0.03122						0.03122



AVERAGE VALUE

Time	AvgRandom	AvgPanga	AvgPFRL	AvgSVMLight	AvgSVM-Panga	AvgTransductive	AvgBSVM
0	0.01361	0.01381	0.01381	0.01381	0.01381	0.01381	0.01381
1	0.00709	0.00709	0.00709	0.00709	0.00709	0.00709	0.00709
2	0.05582	0.0145	0.01316	0.01201	0.012	0.014	0.0456
3	0.10103	0.09883	0.00774	0.00822	0.00187		0.0434
4	0.0474	0.00413					0.0456
5	0.05532	0.00683					0.00709
6	0.0474	0.0146					
7	0.10103	0.00709					
8	0.05582						
9	0.00709						

MINIMUM VALUE

Time	MinRandom	MinPanga	MinPFRL	MinSVMLight	MinSVM-Panga	MinTransductive	MinBSVM
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	0.00113	0	0	0.00141	0
3	0	0	0.0073	0.00099	0.00194		0.00273
4	0	0.00079					0
5	0	0					0
6	0	0					0
7	0	0					0
8	0	0					0
9	0	0					0

NADALICK

MAXIMUM VALUE

Time	MaxRandom	MaxPanga	MaxPFRL	MaxSVMLight	MaxSVM-Panga	MaxTransductive	MaxBSVM
0	0.20392	0.20392	0.20392	0.20392	0.20392	0.20392	0.20392
1	0.83746	0.83746	0.83746	0.83746	0.83746	0.83746	0.83746
2	1.54427	4.87628	5.89143	5.94773	4.87628	5.26394	5.94687
3	8.88039	8.00746	4.50716	5.76631	4.18199		4.91892
4	0.00709	0.19544					5.84667
5	4.05677	4.88746					8.83746
6	6.67608	4.87628					
7	8.88039	9.92746					
8	1.54427						
9	6.83746						

AVERAGE VALUE

Time	AvgRandom	AvgPanga	AvgPFRL	AvgSVMLight	AvgSVM-Panga	AvgTransductive	AvgBSVM
0	4.06179	4.06179	4.06179	4.06179	4.06179	4.06179	4.06179
1	4.27866	4.27866	4.27866	4.27866	4.27866	4.27866	4.27866
2	4.02516	4.30026	4.54346	4.27866	4.02235	3.8924	4.40714
3	3.83532	4.68787	4.27472	4.49366	4.05607		4.28677
4	4.25506	3.02379					4.40714
5	4.1877	4.68787					4.27866
6	4.25506	4.38028					
7	3.93547	4.27866					
8	4.02516						
9	4.27866						

MINIMUM VALUE

Time	MinRandom	MinPanga	MinPFRL	MinSVMLight	MinSVM-Panga	MinTransductive	MinBSVM
0	4.06179	4.06179	4.06179	4.06179	4.06179	4.06179	4.06179
1	4.27866	4.27866	4.27866	4.27866	4.27866	4.27866	4.27866
2	4.02516	4.30026	4.54346	4.27866	4.02235	3.8924	4.40714
3	3.83532	4.68787	4.27472	4.49366	4.05607		4.28677
4	4.25506	3.02379					4.40714
5	4.1877	4.68787					4.27866
6	4.25506	4.38028					
7	3.93547	4.27866					
8	4.02516						
9	4.27866						

CORRELATION

MAXIMUM VALUE

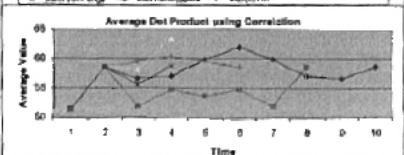
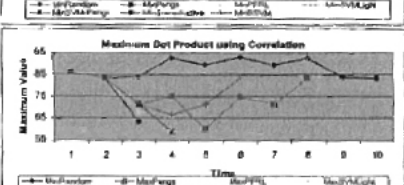
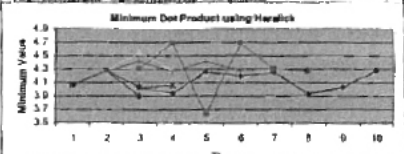
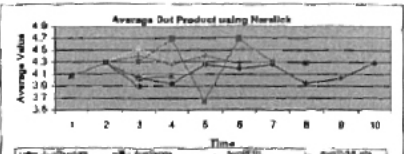
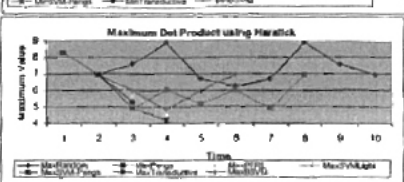
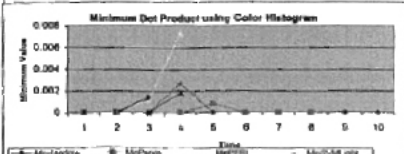
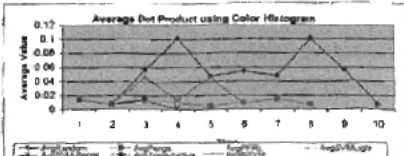
Time	MaxRandom	MaxPanga	MaxPFRL	MaxSVMLight	MaxSVM-Panga	MaxTransductive	MaxBSVM
0	86.0072	86.0072	86.0072	86.0072	86.0072	86.0072	86.0072
1	83.2299	83.2299	83.2299	83.2299	83.2299	83.2299	83.2299
2	83.8730	71.227	67.6935	71.227	71.227	83.1232	71.227
3	92.4057	74.583	68.9607	83.4504	80.9190		66.3687
4	80.2426	59.8449					71.227
5	82.5819	74.583					83.2299
6	80.2426	71.227					
7	92.4082	83.2299					
8	83.8730						
9	83.2299						

AVERAGE VALUE

Time	AvgRandom	AvgPanga	AvgPFRL	AvgSVMLight	AvgSVM-Panga	AvgTransductive	AvgBSVM
0	51.4192	51.4192	51.4192	51.4192	51.4192	51.4192	51.4192
1	58.5782	58.5782	58.5782	58.5782	58.5782	58.5782	58.5782
2	56.8408	51.8847	58.154	56.987	58.6105	56.858	58.0507
3	57.0273	54.7017	63.4579	60.2682	58.7306		60.5666
4	59.8408	53.8779					60.5687
5	61.9814	54.7017					58.5782
6	59.8408	51.2647					
7	57.0273	58.5782					
8	56.8408						
9	58.5782						

MINIMUM VALUE

Time	MinRandom	MinPanga	MinPFRL	MinSVMLight	MinSVM-Panga	MinTransductive	MinBSVM
0	9.73722	9.73722	9.73722	9.73722	9.73722	9.73722	9.73722
1	33.6012	33.6012	33.6012	33.6012	33.6012	33.6012	33.6012
2	15.8384	41.2739	48.2689	41.2739	41.2739	49.9255	48.0278
3	5.08633	48.1852	60.5873	57.1699	58.4794		50.5118
4	30.4183	47.7777					46.0278
5	34.9	48.1852					33.6012
6	30.4183	41.2739					
7	5.08633	33.6012					
8	15.8384						
9	33.6012						



AVERAGE VALUE							
Time	AvgRandom	AvgPenge	AvgPFR	AvgSVMLight	AvgSVMPenge	AvgTransduktive	AvgSSVM
0	0	0	0	0	0	0	0
1	0,22756	0,22755	0,22755	0,22756	0,22755	0,22755	0,22755
2	0,11302	0,15141	0,34304	0,29989	0,15375	0,2141	0,32748
3	0,1395	0,03966	0,13558	0,22699	0,01753	0,07785	0,22765
4	0,091	0,15111			0,15375		0,22744
5	0,37762	0,89577					
6	0,10548						
7	0,12752						
8	0,091						
9	0,1395						
10	0,11302						

MINIMUM VALUE							
Time	MinRandom	MinPenge	MinPFR	MinSVMLight	MinSVMPenge	MinTransduktive	MinSSVM
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0,01726	0,01738	0,00996	0,01726	0,01436	0
4	0	0	0	0	0	0	0
5	0	0,01712					
6	0						
7	0						
8	0						
9	0						
10	0						

HARALICK

MAXIMUM VALUE							
Time	MaxRandom	MaxPenge	MaxPFR	MaxSVMLight	MaxSVMPenge	MaxTransduktive	MaxSSVM
0	14,4304	14,4304	14,4304	14,4304	14,4304	14,4304	14,4304
1	12,7254	12,7254	12,7254	12,7254	12,7254	12,7254	12,7254
2	15,7361	14,6989	16,3365	15,2904	14,6988	16,0124	17,5453
3	10,9216	14,0274	16,8642	14,5845	14,0274	15,8895	12,7254
4	12,9923	14,6989			14,6989		12,6149
5	14,2729	14,8401					
6	12,7807						
7	14,2729						
8	12,9923						
9	10,9216						
10	15,7361						

AVERAGE VALUE							
Time	AvgRandom	AvgPenge	AvgPFR	AvgSVMLight	AvgSVMPenge	AvgTransduktive	AvgSSVM
0	6,13205	6,13205	6,13205	6,13205	6,13205	6,13205	6,13205
1	8,11829	8,11829	8,11829	8,11829	8,11829	8,11829	8,11829
2	5,7521	8,83238	12,5309	9,75716	8,35383	11,6888	10,1995
3	4,31596	6,22386	14,542	12,3217	13,8443	13,7877	6,18829
4	0	6,83238			6,83238		5,47213
5	6,0863	6,02703					
6	4,28453						
7	6,0863						
8	0						
9	4,31596						
10	5,7521						

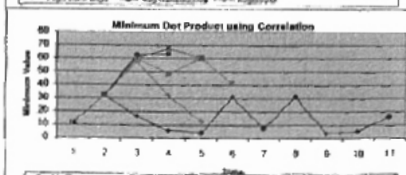
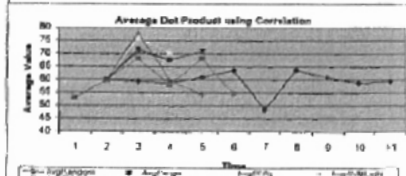
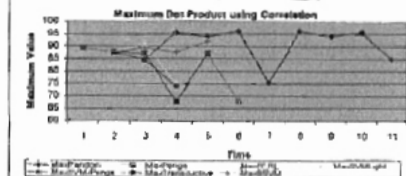
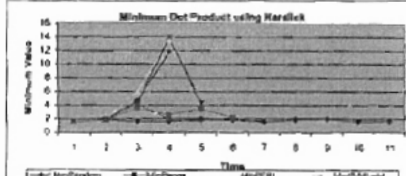
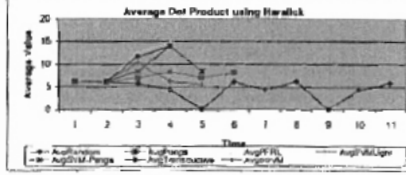
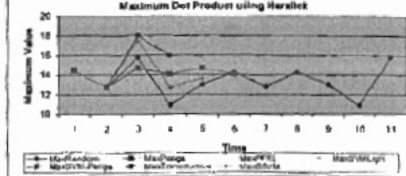
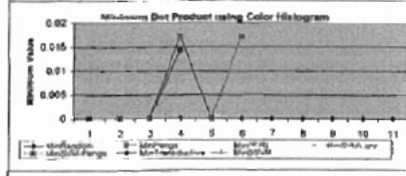
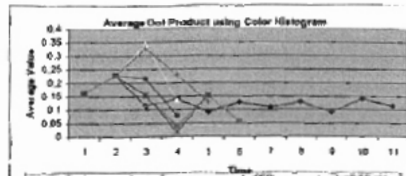
MINIMUM VALUE							
Time	MinRandom	MinPenge	MinPFR	MinSVMLight	MinSVMPenge	MinTransduktive	MinSSVM
0	1,61837	1,61837	1,61837	1,61837	1,61837	1,61837	1,61837
1	1,81904	1,81904	1,81904	1,81904	1,81904	1,81904	1,81904
2	1,63985	3,49486	9,97622	4,21332	4,21332	4,57994	4,21332
3	1,58317	2,47227	13,4932	9,40583	13,894	11,1288	1,81904
4	1,9069	3,49486			4,21332		1,63985
5	1,5871	2,10513					
6	1,58317						
7	1,60711						
8	1,9069						
9	1,58317						
10	1,63985						

CORRELATION

MAXIMUM VALUE							
Time	MaxRandom	MaxPenge	MaxPFR	MaxSVMLight	MaxSVMPenge	MaxTransduktive	MaxSSVM
0	89,1515	89,1515	89,1515	89,1515	89,1515	89,1515	89,1515
1	97,583	97,583	97,583	97,583	97,583	97,583	97,583
2	84,8533	87,2455	80,8781	85,6252	87,2455	84,4213	89,2175
3	85,4825	87,6187	75,2208	70,1211	87,6187	74,0585	87,583
4	93,9614	87,2455			87,2495		91,5377
5	98,9801	87,8407					
6	78,2721						
7	98,9801						
8	93,9614						
9	98,4855						
10	84,8533						

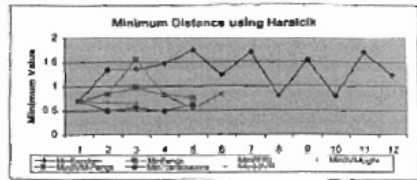
AVERAGE VALUE							
Time	AvgRandom	AvgPenge	AvgPFR	AvgSVMLight	AvgSVMPenge	AvgTransduktive	AvgSSVM
0	52,7692	52,7692	52,7692	52,7692	52,7692	52,7692	52,7692
1	59,7918	59,7918	59,7918	59,7918	59,7918	59,7918	59,7918
2	59,2368	68,3772	75,9231	73,6922	76,1966	71,7821	77,0098
3	58,6202	57,853	70,4048	67,5418	67,5875	61,3069	59,7918
4	60,8544	68,3772			70,7666		54,1548
5	63,8303	54,5842					
6	48,4981						
7	63,8303						
8	60,8544						
9	58,6202						
10	59,2368						

MINIMUM VALUE							
Time	MinRandom	MinPenge	MinPFR	MinSVMLight	MinSVMPenge	MinTransduktive	MinSSVM
0	10,7189	10,7189	10,7189	10,7189	10,7189	10,7189	10,7189
1	31,7011	31,7011	31,7011	31,7011	31,7011	31,7011	31,7011
2	16,2455	60,1325	60,0049	60,1325	60,1325	62,5856	57,6372
3	5,37432	48,1567	69,2459	63,1125	87,4147	93,3053	31,7011
4	3,84062	60,1325			60,1325		12,3032
5	31,1129	41,1459					
6	7,7664						
7	31,1129						
8	3,84062						
9	5,37432						
10	16,2455						



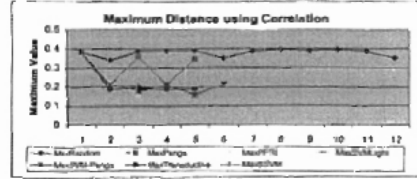
MINIMUM VALUE

Time	MinRandom	MinPerge	MinPPRL	MinVMLight	MinVM-Perge	MinTransductive	MinSVM
0	0.69235	0.69235	0.69235	0.69235	0.69235	0.69235	0.69235
1	1.33204	0.82713	0.59053	0.85581	0.82713	0.49607	0.99199
2	1.35025	1.59819	0.67793	0.67088	0.97122	0.59581	0.69303
3	1.49501	0.82713			0.82713	0.49607	
4	1.74647	0.74288			0.54136	0.8192	
5	1.23166						
6	1.59496						
7	0.75693						
8	1.52922						
9	0.79893						
10	1.89496						
11	1.27166						



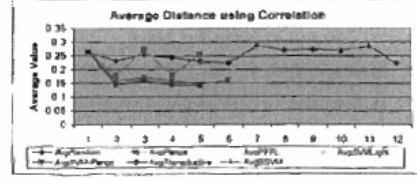
CORRELATION

Time	MaxRandom	MaxPerge	MaxPPRL	MaxVMLight	MaxVM-Perge	MaxTransductive	MaxSVM
0	0.3842	0.3842	0.3842	0.3842	0.3842	0.3842	0.3842
1	0.33863	0.20975	0.22116	0.25975	0.20975	0.16992	0.2003
2	0.38707	0.35795	0.16396	0.18196	0.17965	0.16049	0.20715
3	0.38788	0.28975			0.20695	0.16992	
4	0.38959	0.38427			0.15675	0.18573	
5	0.3501				0.20975		
6	0.38997						
7	0.38544						
8	0.38772						
9	0.38544						
10	0.38997						
11	0.3501						



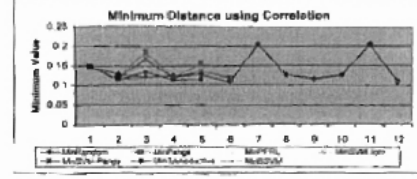
AVERAGE VALUE

Time	AvgRandom	AvgPerge	AvgPPRL	AvgVMLight	AvgVM-Perge	AvgTransductive	AvgSVM
0	0.26273	0.26273	0.26273	0.26273	0.26273	0.26273	0.26273
1	0.23	0.17819	0.14994	0.15311	0.15929	0.14287	0.14668
2	0.25215	0.27061	0.15242	0.14403	0.17039	0.15729	0.16616
3	0.24199	0.17819			0.15929	0.14287	
4	0.22742	0.25197			0.14301	0.13883	
5	0.22201				0.15929		
6	0.28578						
7	0.26699						
8	0.27544						
9	0.26699						
10	0.28578						
11	0.22201						



MINIMUM VALUE

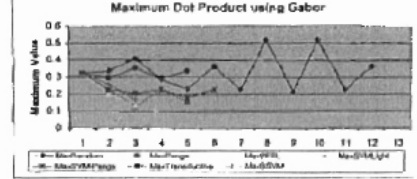
Time	MinRandom	MinPerge	MinPPRL	MinVMLight	MinVM-Perge	MinTransductive	MinSVM
0	0.14727	0.14727	0.14727	0.14727	0.14727	0.14727	0.14727
1	0.12866	0.11845	0.114	0.11845	0.11845	0.11466	0.11942
2	0.12115	0.15369	0.14444	0.11392	0.30671	0.19654	0.11946
3	0.12508	0.11845			0.11845	0.11466	
4	0.125	0.1543			0.1348	0.11466	
5	0.16673				0.11845		
6	0.28444						
7	0.126						
8	0.11805						
9	0.126						
10	0.20444						
11	0.10873						



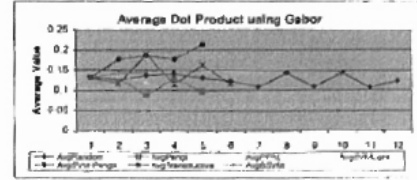
2 DOT PRODUCT

GABOR

Time	MaxRandom	MaxPerge	MaxPPRL	MaxVMLight	MaxVM-Perge	MaxTransductive	MaxSVM
0	0.32412	0.32412	0.32412	0.32412	0.32412	0.32412	0.32412
1	0.33531	0.22911	0.19687	0.30671	0.22411	0.29331	0.29692
2	0.40879	0.11732	0.13613	0.302	0.29272	0.38244	0.19714
3	0.28482	0.22411			0.22411	0.29331	
4	0.22929	0.19522			0.17778	0.32412	
5	0.3266				0.22411		
6	0.22403						
7	0.51921						
8	0.21330						
9	0.51921						
10	0.22403						
11	0.3608						

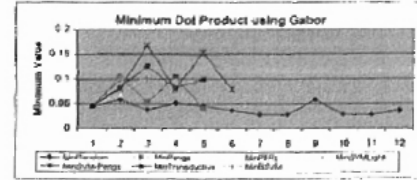


Time	AvgRandom	AvgPerge	AvgPPRL	AvgVMLight	AvgVM-Perge	AvgTransductive	AvgSVM
0	0.13199	0.13195	0.13195	0.13195	0.13195	0.13195	0.13195
1	0.12662	0.12629	0.13725	0.12231	0.11432	0.17696	0.14176
2	0.1369	0.09756	0.11908	0.17061	0.18948	0.18564	0.14451
3	0.14025	0.12629			0.11432	0.17696	
4	0.13129	0.0972			0.16308	0.21222	
5	0.12332				0.11432		
6	0.10772						
7	0.14259						
8	0.10356						
9	0.14259						
10	0.10772						
11	0.12332						



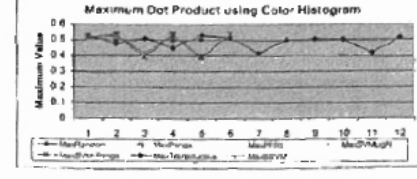
MINIMUM VALUE

Time	MinRandom	MinPerge	MinPPRL	MinVMLight	MinVM-Perge	MinTransductive	MinSVM
0	0.04499	0.04499	0.04499	0.04499	0.04499	0.04499	0.04499
1	0.05752	0.10374	0.0965	0.10257	0.07867	0.08142	0.09679
2	0.04373	0.05306	0.107	0.10913	0.16608	0.12404	0.1
3	0.04127	0.10374			0.07867	0.08142	
4	0.04566	0.04058			0.15271	0.08255	
5	0.03628				0.17897		
6	0.02813						
7	0.02782						
8	0.05125						
9	0.02782						
10	0.02813						
11	0.03628						



COLOR HISTOGRAM

Time	MaxRandom	MaxPerge	MaxPPRL	MaxVMLight	MaxVM-Perge	MaxTransductive	MaxSVM
0	0.52291	0.52291	0.52291	0.52291	0.52291	0.52291	0.52291
1	0.47328	0.53111	0.52948	0.53111	0.53111	0.49477	0.52532
2	0.50804	0.41481	0.41515	0.43579	0.46608	0.46608	0.48821
3	0.44882	0.53111			0.53111	0.49477	
4	0.53009	0.38743			0.3917	0.50918	
5	0.51138				0.53111		
6	0.41724						
7	0.58052						
8	0.50384						
9	0.58052						
10	0.41724						
11	0.51138						

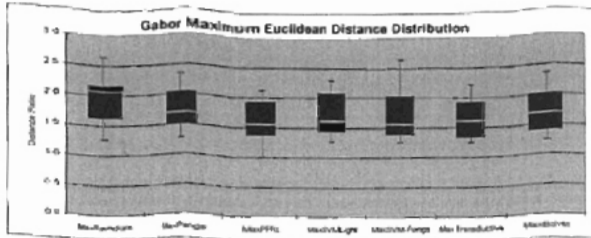


Appendix D

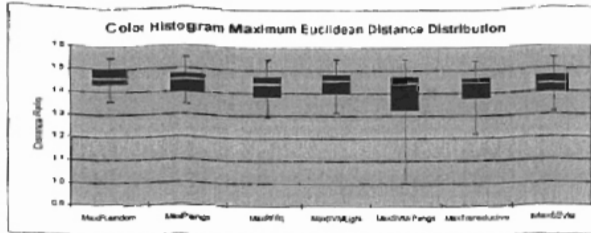
EUCLIDEAN DISTANCE AND SIMILARITY VALUE DISTRIBUTION TABLES AND FIGURES

REAL OBJECT
EUCLIDEAN DISTANCE

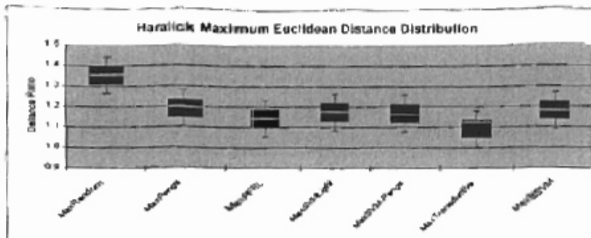
	High	Max	Min	Low	Med	Q1Pct	Q3Pct	WorstCase
MaxRandom	2.1500	2.0300	1.2718	1.4830	2.0740	1.07450	1.75821	2.01511
MaxPango	2.0254	2.3638	1.2114	1.4902	1.9102	0.91917	1.63429	1.94502
MaxPFR	1.9307	2.0257	1.0000	1.3746	1.5213	0.91293	1.63207	1.92724
MaxPRLite	2.0015	2.2500	1.2714	1.4431	1.6079	0.91681	1.66107	1.98823
MaxPRLitePango	2.0254	2.6930	1.2141	1.5041	1.9210	0.91029	1.63428	1.94511
MaxTransActive	1.9191	2.2110	1.0473	1.3240	1.6278	0.91001	1.61407	1.91400
MaxDiff	2.0120	2.3020	1.2019	1.3952	1.6234	0.91400	1.61216	1.96230



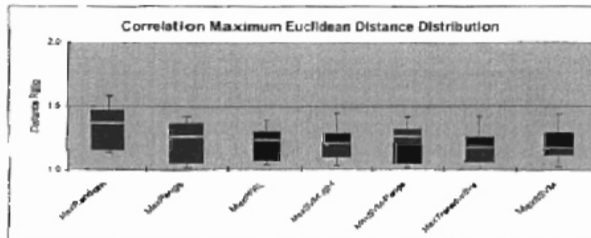
	High	Max	Min	Low	Med	Q1Pct	Q3Pct	WorstCase
MaxRandom	1.8954	1.5431	1.3300	1.4333	1.6027	0.88953	1.49240	1.81177
MaxPango	1.7149	1.5613	1.3600	1.3902	1.6007	0.88953	1.49199	1.81177
MaxPFR	1.8721	1.5416	1.2000	1.3020	1.4940	0.88953	1.49199	1.81177
MaxPRLite	1.8621	1.5651	1.3132	1.3590	1.4607	0.88953	1.49240	1.81177
MaxPRLitePango	1.8224	1.5691	1.0000	1.3070	1.4454	0.88953	1.49240	1.81177
MaxTransActive	1.6650	1.5413	1.2110	1.3104	1.4930	0.88953	1.49199	1.81177
MaxDiff	1.8724	1.5491	1.3100	1.3650	1.4930	0.88953	1.49240	1.81177



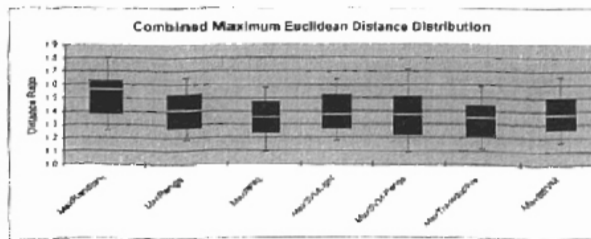
	High	Max	Min	Low	Med	Q1Pct	Q3Pct	WorstCase
MaxRandom	1.2503	1.4430	1.2541	1.3200	1.3940	1.13500	1.38800	1.41320
MaxPango	1.2201	1.2500	1.0000	1.1400	1.1800	1.01110	1.21110	1.26000
MaxPFR	1.1801	1.2217	1.0510	1.0900	1.1410	1.01110	1.16110	1.21000
MaxPRLite	1.2100	1.2617	1.0800	1.1200	1.1730	1.13810	1.18551	1.23000
MaxPRLitePango	1.2121	1.2617	1.0711	1.1211	1.1670	1.01110	1.16000	1.21000
MaxTransActive	1.1343	1.1917	1.0000	1.0440	1.0600	1.01110	1.06000	1.11000
MaxDiff	1.2221	1.2617	1.0810	1.1210	1.1711	1.13210	1.18210	1.23000



	High	Max	Min	Low	Med	Q1Pct	Q3Pct	WorstCase
MaxRandom	1.4671	1.5010	1.1302	1.1510	1.2000	1.04310	1.17710	1.21700
MaxPango	1.3652	1.4000	1.0100	1.0472	1.1221	1.01000	1.01000	1.11000
MaxPFR	1.2901	1.3000	1.0100	1.0600	1.1220	1.01000	1.01000	1.11000
MaxPRLite	1.3500	1.4410	1.0200	1.0440	1.1020	1.01000	1.01000	1.11000
MaxPRLitePango	1.3121	1.3710	1.0111	1.0211	1.0700	1.01000	1.01000	1.11000
MaxTransActive	1.2600	1.4100	1.0000	1.0500	1.1000	1.01000	1.01000	1.11000
MaxDiff	1.3221	1.4300	1.0200	1.1000	1.1400	1.01000	1.01000	1.11000



	High	Max	Min	Low	Med	Q1Pct	Q3Pct	WorstCase
MaxRandom	1.4300	1.6000	1.2000	1.2300	1.3510	0.91000	1.35100	1.43000
MaxPango	1.5271	1.6470	1.1810	1.2100	1.3250	0.88000	1.31200	1.41000
MaxPFR	1.4720	1.5720	1.0600	1.2000	1.3220	0.88000	1.31000	1.40000
MaxPRLite	1.5201	1.6370	1.1400	1.2000	1.3000	0.88000	1.31000	1.40000
MaxPRLitePango	1.4100	1.5147	1.0900	1.2100	1.3400	0.88000	1.31000	1.40000
MaxTransActive	1.4000	1.5070	1.1000	1.2000	1.3110	0.88000	1.31000	1.40000
MaxDiff	1.5010	1.6000	1.1000	1.2000	1.3010	0.88000	1.31000	1.40000



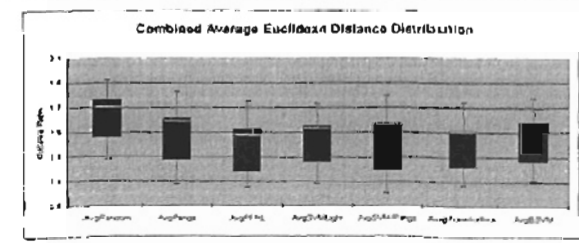
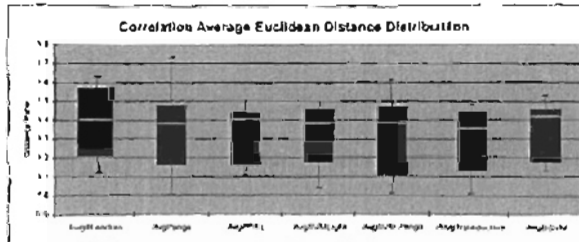
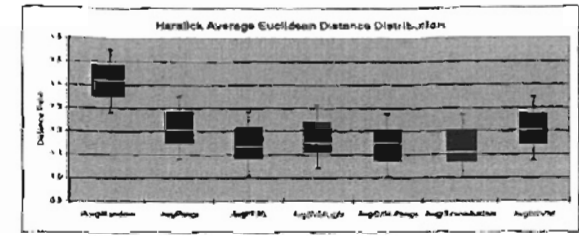
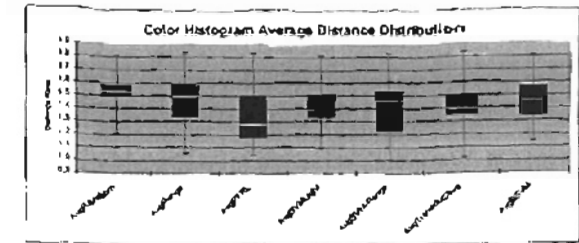
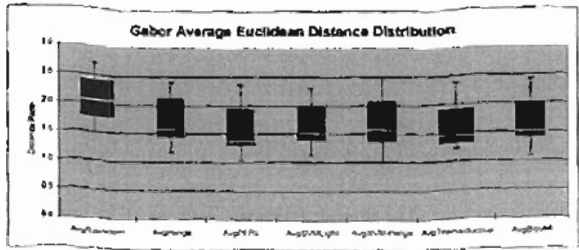
AVERAGE VALUE CLASSIFICATION									
	High	Low	Min	Max	Mean	1-SD	2-SD	3-SD	Warning
Aug10:emotion	2.4161	2.719	1.4998	1.7880	2.0711	1.0710	1.4142	1.8579	769.7730
Aug10:color	7.1300	7.4919	4.1323	4.4281	5.1340	3.1531	3.7130	4.6230	142.1000
Aug10:fil	1.8024	2.0714	1.0243	1.2031	1.4254	0.8009	0.9866	1.1613	136.7013
Aug10:light	1.8024	2.0714	1.0243	1.2031	1.4254	0.8009	0.9866	1.1613	136.7013
Aug10:emotion	2.0708	2.1971	1.0203	1.3051	1.5178	0.7829	1.0270	1.2741	127.4713
Aug10:emotion	1.7148	2.2736	1.2853	1.9383	1.6560	0.8027	1.0324	1.3140	131.8013
Aug10:color	2.1190	2.3323	1.0449	1.5277	1.8304	0.9043	1.2063	1.5230	142.8304

COLOR HISTOGRAM									
	High	Min	Max	Mean	1-SD	2-SD	3-SD	Warning	
Aug10:emotion	1.1776	1.6241	1.2084	1.4684	1.5732	1.1328	1.7935	2.1930	
Aug10:color	1.2413	1.2248	1.2627	1.2043	1.4084	1.0448	1.1938	1.4493	
Aug10:fil	1.3462	1.5246	1.0407	1.1757	1.2909	1.0339	1.0369	1.1392	
Aug10:light	1.5114	1.8116	1.0411	1.0544	1.0725	1.0725	1.0725	1.0725	
Aug10:emotion	1.5114	1.8116	1.0411	1.0544	1.0725	1.0725	1.0725	1.0725	
Aug10:emotion	1.5114	1.8116	1.0411	1.0544	1.0725	1.0725	1.0725	1.0725	
Aug10:emotion	1.5114	1.8116	1.0411	1.0544	1.0725	1.0725	1.0725	1.0725	
Aug10:color	1.5114	1.8116	1.0411	1.0544	1.0725	1.0725	1.0725	1.0725	

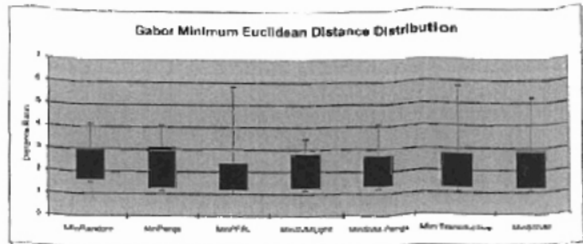
HALLUCINATION									
	High	Low	Min	Max	Mean	1-SD	2-SD	3-SD	Warning
Aug10:emotion	1.4524	1.8315	1.0004	1.3483	1.4460	1.1157	1.2188	1.3122	
Aug10:color	1.3524	1.3522	1.0784	1.1173	1.1417	1.0820	1.1420	1.1919	
Aug10:fil	1.2139	1.3634	1.0134	1.0742	1.1438	1.0489	1.1089	1.1689	
Aug10:light	1.3628	1.4128	1.0463	1.1071	1.1767	1.0818	1.1418	1.2018	
Aug10:emotion	1.2083	1.3578	1.0028	1.0711	1.1406	1.0457	1.1057	1.1657	
Aug10:emotion	1.3073	1.3573	1.0317	1.0925	1.1621	1.0672	1.1272	1.1872	
Aug10:emotion	1.3073	1.3573	1.0317	1.0925	1.1621	1.0672	1.1272	1.1872	

CORRELATION									
	High	Low	Min	Max	Mean	1-SD	2-SD	3-SD	Warning
Aug10:emotion	1.1708	1.2207	1.0709	1.2247	1.2010	1.0700	1.1444	1.2189	
Aug10:color	1.1708	1.2207	1.0709	1.2247	1.2010	1.0700	1.1444	1.2189	
Aug10:fil	1.1708	1.2207	1.0709	1.2247	1.2010	1.0700	1.1444	1.2189	
Aug10:light	1.1708	1.2207	1.0709	1.2247	1.2010	1.0700	1.1444	1.2189	
Aug10:emotion	1.1708	1.2207	1.0709	1.2247	1.2010	1.0700	1.1444	1.2189	
Aug10:emotion	1.1708	1.2207	1.0709	1.2247	1.2010	1.0700	1.1444	1.2189	
Aug10:emotion	1.1708	1.2207	1.0709	1.2247	1.2010	1.0700	1.1444	1.2189	
Aug10:emotion	1.1708	1.2207	1.0709	1.2247	1.2010	1.0700	1.1444	1.2189	

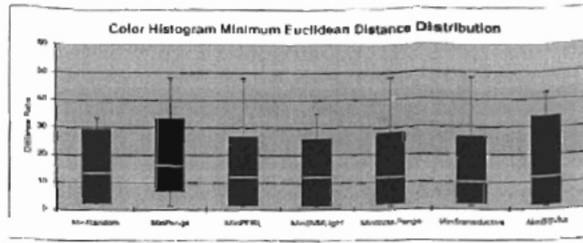
ALL DIMENSION COLOR-HISTOGRAM-HALLUCINATION-CORRELATION COMBINED									
	High	Low	Min	Max	Mean	1-SD	2-SD	3-SD	Warning
Aug10:emotion	1.7817	1.8316	1.0705	1.4035	1.5713	1.0710	1.4142	1.8579	
Aug10:color	1.4127	1.4297	1.0784	1.1173	1.1417	1.0820	1.1420	1.1919	
Aug10:fil	1.4213	1.4483	1.0411	1.1071	1.1767	1.0818	1.1418	1.2018	
Aug10:light	1.5064	1.5564	1.0463	1.1071	1.1767	1.0818	1.1418	1.2018	
Aug10:emotion	1.5064	1.5564	1.0463	1.1071	1.1767	1.0818	1.1418	1.2018	
Aug10:emotion	1.5064	1.5564	1.0463	1.1071	1.1767	1.0818	1.1418	1.2018	
Aug10:emotion	1.5064	1.5564	1.0463	1.1071	1.1767	1.0818	1.1418	1.2018	
Aug10:emotion	1.5064	1.5564	1.0463	1.1071	1.1767	1.0818	1.1418	1.2018	



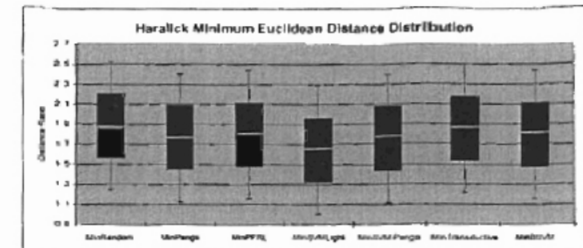
Histogram Statistics									
	High	Max	Min	Low	Med	1.75th	3.75th	WorstCase	
MinPRange	2 1224	4 1320	1 1912	1 8857	2 1021	142 1748	282 2370	426 2020	4 2 2020
MinPRange	3 0800	4 0601	1 1043	1 2844	1 6037	14 3792	304 3978	3028 3010	4 2 2020
MinPRange	3 2656	5 5185	1 0000	1 1778	1 8130	61 7008	136 4841	48 1 6000	4 2 2020
MinPRange	2 7812	3 4695	1 1603	1 2488	1 4373	45 7807	178 4855	2165 564 1	4 2 2020
MinPRange	2 6792	4 0611	1 1874	1 3384	1 5837	58 2732	101 2239	8098 3102	4 2 2020
MinPRange	2 7266	5 7583	1 0316	1 2333	1 4028	46 1288	117 1263	1 17 10278	4 2 2020
MinPRange	2 8861	2 2188	1 1872	1 1972	1 4714	47 1365	181 1655	4 2 2020	4 2 2020



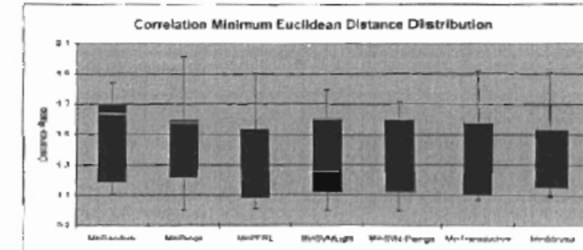
Color Histogram Statistics									
	High	Max	Min	Low	Med	1.75th	3.75th	WorstCase	
MinPRange	26 4300	33 4769	1 1972	3 3284	12 2207	122 4747	2543 5524	3247 6475	4 2 2020
MinPRange	35 3676	45 0044	1 2047	3 7684	9 7684	18 2253	122 4278	3288 5614	4 2 2020
MinPRange	38 8380	41 9084	1 0000	1 6961	15 1761	57 7376	2542 4230	4800 4368	4 2 2020
MinPRange	38 1061	35 8738	1 2057	4 6015	10 8794	892 3742	2510 4007	24007 3631	4 2 2020
MinPRange	32 1138	45 0044	1 0000	4 8821	10 8794	892 3742	2510 4007	4800 4368	4 2 2020
MinPRange	38 8158	42 6200	1 1778	3 0018	10 2338	903 4995	254 1 1044	4800 4368	4 2 2020
MinPRange	34 3317	43 7728	1 2021	1 6378	10 8794	903 4995	3303 4555	4 17 2020	4 2 2020



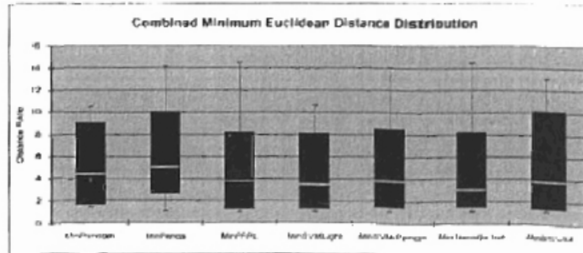
Histogram Statistics									
	High	Max	Min	Low	Med	1.75th	3.75th	WorstCase	
MinPRange	7 8822	2 1076	1 1451	3 995	1 6955	85 1548	128 5173	192 6108	4 2 2020
MinPRange	2 0854	2 4054	1 054	1 4433	1 7584	15 5374	128 5173	192 6108	4 2 2020
MinPRange	2 1881	3 8261	1 1882	1 5862	1 7565	70 2048	111 5072	143 5088	4 2 2020
MinPRange	1 9681	2 2801	1 1000	1 3330	1 5401	64 2050	86 2078	128 5173	4 2 2020
MinPRange	2 6792	2 3656	1 1452	1 6349	1 7565	70 2048	111 5072	143 5088	4 2 2020
MinPRange	2 1794	2 4944	1 1482	1 5383	1 6984	83 5294	117 5382	148 5408	4 2 2020
MinPRange	2 1177	2 4217	1 1078	1 4778	1 7073	70 2048	111 5072	143 5088	4 2 2020



Correlation Statistics									
	High	Max	Min	Low	Med	1.75th	3.75th	WorstCase	
MinPRange	1 9682	1 5814	1 1915	1 1817	1 5055	67 2422	67 2238	84 1431	4 2 2020
MinPRange	1 9688	2 1736	1 0000	1 2173	1 4388	48 4978	50 3895	501 2647	4 2 2020
MinPRange	1 5328	1 8810	1 0721	1 0827	1 4978	65 1807	50 3895	80 1 1000	4 2 2020
MinPRange	1 5083	1 7950	1 0000	1 1327	1 4681	48 4978	48 4978	70 1 1000	4 2 2020
MinPRange	1 5043	1 1180	1 0000	1 1048	1 4588	49 4978	49 4978	74 1 1000	4 2 2020
MinPRange	1 9681	1 6145	1 0668	1 1062	1 3128	31 2572	38 2801	91 4472	4 2 2020
MinPRange	1 3788	1 6024	1 0000	1 1 184	1 4103	41 0205	52 1 1000	92 1 1000	4 2 2020



All Color, Color Histogram, Haralick, Correlation Combined Statistics									
	High	Max	Min	Low	Med	1.75th	3.75th	WorstCase	
MinPRange	9 0771	10 4844	1 4471	1 6748	4 4289	32 1222	10 8384	806 8975	4 2 2020
MinPRange	18 0718	14 1381	1 1106	2 6182	5 2022	424 1818	952 481 1	1 2101 5000	4 2 2020
MinPRange	8 2378	16 5308	1 0423	1 7961	4 0134	181 0888	488 4326	3201 1 770	4 2 2020
MinPRange	8 1131	10 8130	1 0881	1 8330	3 6390	210 3252	676 3895	1072 1 111	4 2 2020
MinPRange	8 8135	14 5251	1 0553	1 6015	3 9184	170 1461	726 4146	1 268 3000	4 2 2020
MinPRange	8 2743	14 5250	1 1271	1 4892	3 0953	181 9544	693 5436	1260 5478	4 2 2020
MinPRange	10 1381	13 0831	1 1 955	1 3605	2 6184	172 1 178	872 3214	1 105 4800	4 2 2020



COI PRODUCT MAXIMUM VALUE CHANGES

	High	Mid	Low	Mid	High	Low	Mid	High
Max/Min	0.7540	0.6619	0.2893	0.3001	0.8888	0.9202	0.8773	0.7110
Max/Min	0.6044	0.5712	0.2857	0.4826	0.5029	0.7206	0.7291	0.5504
Max/Min	0.4373	0.7619	0.2565	0.4043	0.5033	0.9246	0.9246	0.134
Max/Min	0.7300	0.7612	0.2405	0.4653	0.5081	0.7165	0.8463	0.5709
Max/Min	0.7020	0.8778	0.2312	0.4826	0.5330	0.7265	0.7265	0.667
Max/Min	0.6483	0.7616	0.2676	0.4826	0.5027	0.7085	0.7480	0.706
Max/Min	0.6977	0.7616	0.2676	0.4826	0.5027	0.7085	0.7480	0.706

COI HISTOGRAM

	High	Mid	Low	Mid	High	Low	Mid	High
Max/Min	0.6670	0.6501	0.2491	0.4257	0.6204	0.7207	0.8189	0.8189
Max/Min	0.6141	0.6140	0.0980	0.7003	0.5065	0.6744	0.6130	0.6131
Max/Min	0.6413	0.6715	0.0968	0.3191	0.6623	0.7729	0.8196	0.8196
Max/Min	0.6996	0.7076	0.1030	0.4714	0.6666	0.6666	0.6666	0.6666
Max/Min	0.6411	0.6512	0.1068	0.2624	0.6665	0.6774	0.6410	0.6411
Max/Min	0.6612	0.6612	0.0978	0.3489	0.6718	0.6718	0.6718	0.6718
Max/Min	0.6414	0.6414	0.1291	0.2485	0.6666	0.6774	0.6410	0.6411

COI CORRELATION

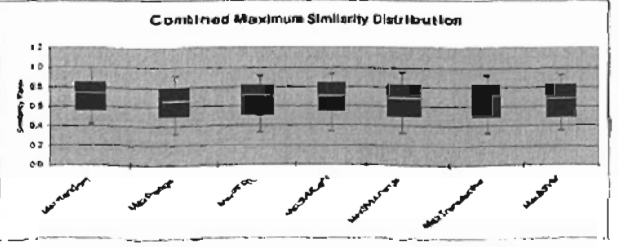
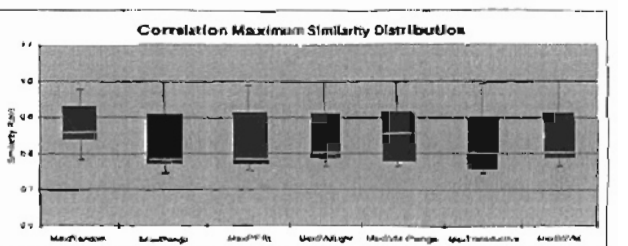
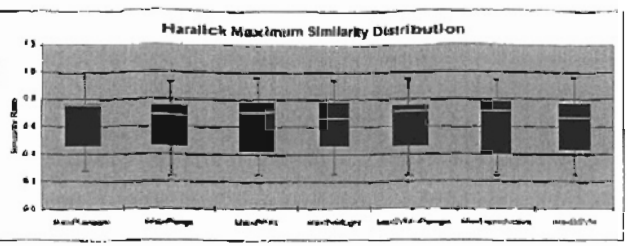
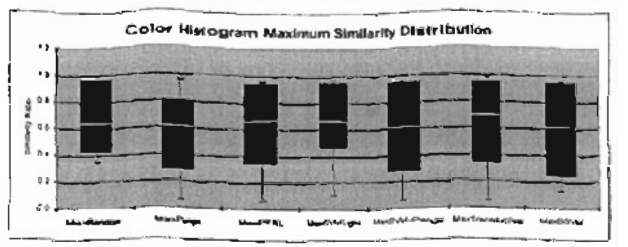
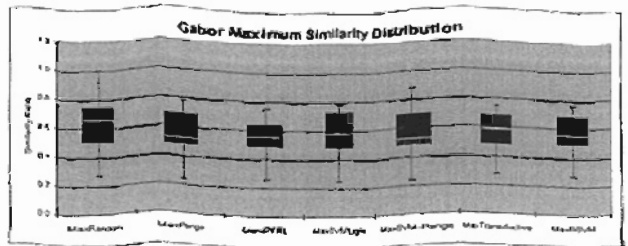
	High	Mid	Low	Mid	High	Low	Mid	High
Max/Min	0.7411	0.6266	0.2771	0.4811	0.6211	0.6666	0.7276	0.7411
Max/Min	0.6113	0.6266	0.2400	0.4021	0.5368	0.6003	0.6442	0.6706
Max/Min	0.7781	0.6233	0.2620	0.4266	0.5638	0.6192	0.6473	0.6266
Max/Min	0.7022	0.6464	0.2531	0.4114	0.5070	0.5568	0.6063	0.6164
Max/Min	0.6555	0.6479	0.2613	0.4371	0.5590	0.6008	0.6166	0.6166
Max/Min	0.7183	0.6444	0.2638	0.4820	0.5446	0.5981	0.6166	0.6166
Max/Min	0.7061	0.6416	0.2530	0.4336	0.5336	0.5718	0.6166	0.6166

COI CORRELATION

	High	Mid	Low	Mid	High	Low	Mid	High
Max/Min	0.7014	0.6766	0.2753	0.4368	0.6751	0.7113	0.7271	0.7113
Max/Min	0.6051	0.6077	0.2481	0.3742	0.7153	0.7173	0.7187	0.6827
Max/Min	0.6111	0.6071	0.2644	0.3727	0.7260	0.7173	0.7113	0.6827
Max/Min	0.6182	0.6203	0.2613	0.3754	0.7067	0.6989	0.7060	0.6827
Max/Min	0.6180	0.6177	0.2613	0.3785	0.6825	0.6825	0.6825	0.6827
Max/Min	0.6203	0.6203	0.2645	0.3786	0.6825	0.6825	0.6825	0.6827
Max/Min	0.6181	0.6203	0.2613	0.3784	0.6825	0.6825	0.6825	0.6827

ALL CHANGES COI HISTOGRAM HARALICK & CORRELATION COMBINED

	High	Mid	Low	Mid	High	Low	Mid	High
Max/Min	0.6136	0.6759	0.2188	0.3175	0.6902	0.7138	0.7209	0.7138
Max/Min	0.7019	0.6198	0.2381	0.3807	0.6101	0.6101	0.6101	0.6101
Max/Min	0.6171	0.6164	0.2399	0.3807	0.6165	0.6165	0.6165	0.6165
Max/Min	0.6166	0.6166	0.2430	0.3807	0.6166	0.6166	0.6166	0.6166
Max/Min	0.6234	0.6166	0.2350	0.3808	0.6166	0.6166	0.6166	0.6166
Max/Min	0.6206	0.6166	0.2429	0.3808	0.6166	0.6166	0.6166	0.6166
Max/Min	0.6217	0.6166	0.2429	0.3808	0.6166	0.6166	0.6166	0.6166



AVERAGE VALUE TABLE

	Height	Width	Area	Perim	Volume	Surface Area	Weight
AugSimSim	0.9080	0.7153	0.6523	0.7120	0.3991	153.7529	229.9299
AugSimSim	0.7840	0.5844	0.4573	0.4722	0.2041	81.3790	111.7913
AugSimSim	0.7994	0.5824	0.4639	0.4810	0.2101	81.3051	111.7254
AugSimSim	0.8445	0.6648	0.5609	0.6091	0.3130	113.0920	162.8961
AugSimSim	0.7333	0.5001	0.3669	0.3805	0.1705	67.4207	91.4191
AugSimSim	0.8122	0.6040	0.4923	0.5201	0.2404	94.7291	130.0113
AugSimSim	0.8071	0.5974	0.4873	0.5105	0.2305	91.3907	127.3663

EDGE HISTOGRAM

	Height	Width	Area	Perim	Volume	Surface Area	Weight
AugSimSim	0.8047	0.6329	0.5093	0.5289	0.2657	105.8761	147.7061
AugSimSim	0.6595	0.4724	0.3104	0.3292	0.1641	64.4246	87.9454
AugSimSim	0.7047	0.5008	0.3530	0.3644	0.1875	70.4677	95.5115
AugSimSim	0.8285	0.7189	0.5957	0.6219	0.3190	124.8007	169.1801
AugSimSim	0.7420	0.5620	0.4169	0.4286	0.2075	81.3035	110.7099
AugSimSim	0.8004	0.7168	0.5749	0.6013	0.3113	121.844	164.4752
AugSimSim	0.8011	0.6024	0.4824	0.5017	0.2400	94.2184	127.3663

HAAR WAVE

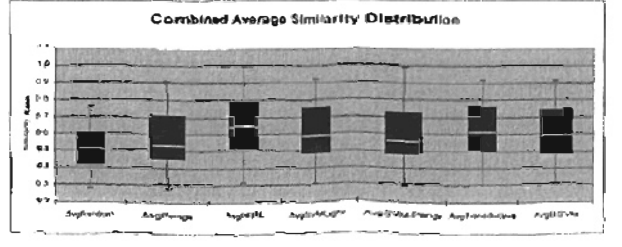
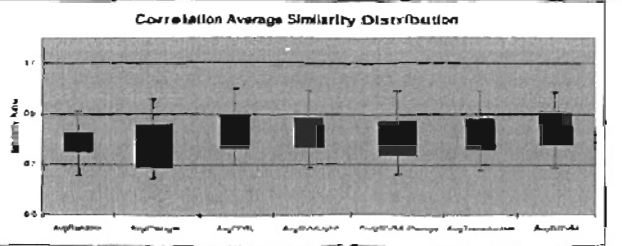
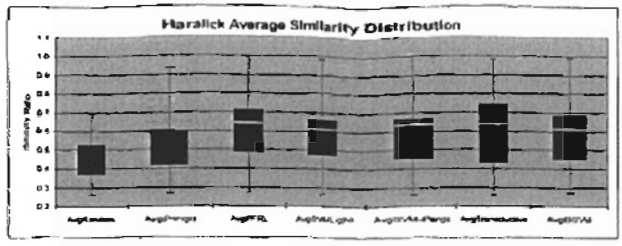
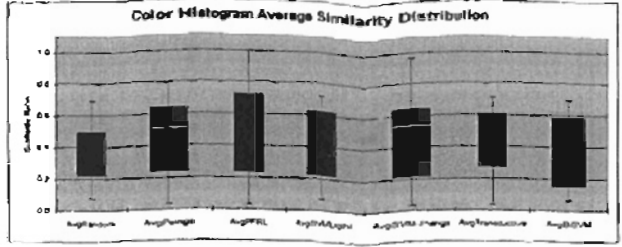
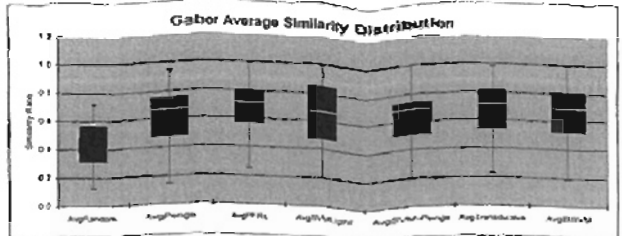
	Height	Width	Area	Perim	Volume	Surface Area	Weight
AugSimSim	0.7329	0.5524	0.4053	0.4244	0.2044	79.0036	107.2809
AugSimSim	0.6590	0.4748	0.3112	0.3297	0.1641	64.4246	87.9454
AugSimSim	0.7144	0.5466	0.3907	0.4091	0.2041	79.0036	107.2809
AugSimSim	0.6620	0.4823	0.3165	0.3350	0.1641	64.4246	87.9454
AugSimSim	0.8014	0.6000	0.4809	0.5000	0.2400	94.2184	127.3663
AugSimSim	0.7454	0.5624	0.4189	0.4374	0.2189	84.4677	113.0920
AugSimSim	0.8013	0.5954	0.4804	0.5000	0.2400	94.2184	127.3663

1.1.1.1.1.1.1

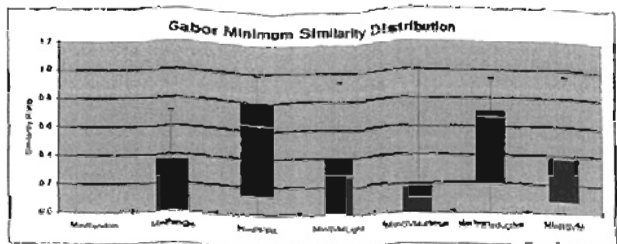
	Height	Width	Area	Perim	Volume	Surface Area	Weight
AugSimSim	0.6942	0.5134	0.3560	0.3750	0.1875	70.4677	95.5115
AugSimSim	0.6590	0.4748	0.3112	0.3297	0.1641	64.4246	87.9454
AugSimSim	0.6620	0.4823	0.3165	0.3350	0.1641	64.4246	87.9454
AugSimSim	0.8014	0.6000	0.4809	0.5000	0.2400	94.2184	127.3663
AugSimSim	0.7454	0.5624	0.4189	0.4374	0.2189	84.4677	113.0920
AugSimSim	0.8013	0.5954	0.4804	0.5000	0.2400	94.2184	127.3663

1.1.1.1.1.1.1

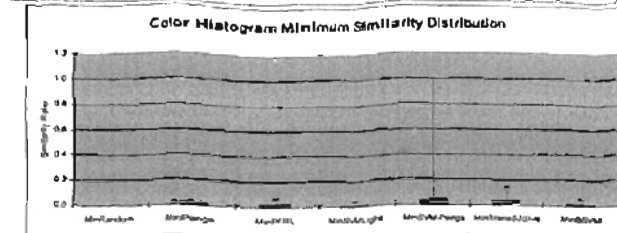
	Height	Width	Area	Perim	Volume	Surface Area	Weight
AugSimSim	0.6942	0.5134	0.3560	0.3750	0.1875	70.4677	95.5115
AugSimSim	0.6590	0.4748	0.3112	0.3297	0.1641	64.4246	87.9454
AugSimSim	0.6620	0.4823	0.3165	0.3350	0.1641	64.4246	87.9454
AugSimSim	0.8014	0.6000	0.4809	0.5000	0.2400	94.2184	127.3663
AugSimSim	0.7454	0.5624	0.4189	0.4374	0.2189	84.4677	113.0920
AugSimSim	0.8013	0.5954	0.4804	0.5000	0.2400	94.2184	127.3663



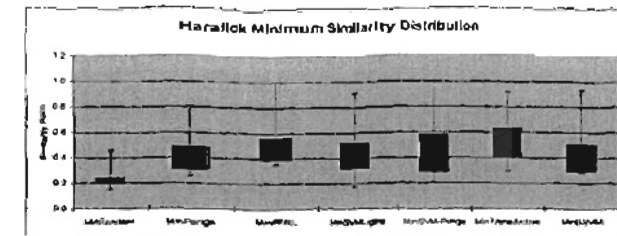
	WAVELENGTH VALUE							
	Min	Max	Min	Max	1.25th	3.75th	Worst Case	
MinRandom	0.17743	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinPange	0.23823	0.7000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinPRL	0.23823	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Light	0.38779	0.8000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Pange	0.18108	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Random	0.17743	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4PRL	0.23823	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000



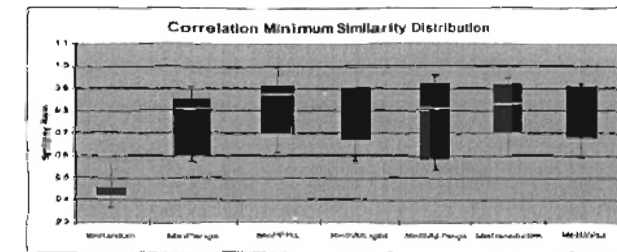
	COLOR HISTOGRAM							
	Min	Max	Min	Max	1.25th	3.75th	Worst Case	
MinRandom	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinPange	0.7000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinPRL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Light	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Pange	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Random	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4PRL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000



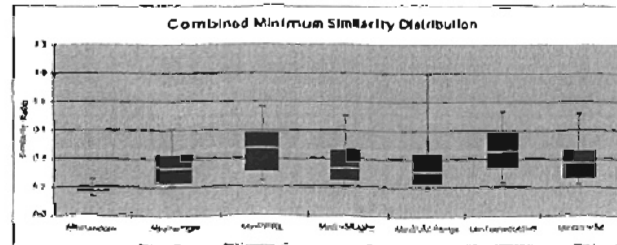
	HARRIS CORNER							
	Min	Max	Min	Max	1.25th	3.75th	Worst Case	
MinRandom	0.2394	0.0000	0.1113	0.1827	0.0000	0.0000	0.0000	0.0000
MinPange	0.4035	0.1000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinPRL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Light	0.5221	0.1113	0.1782	0.2387	0.0000	0.0000	0.0000	0.0000
MinM4Pange	0.5813	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Random	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4PRL	0.5073	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000



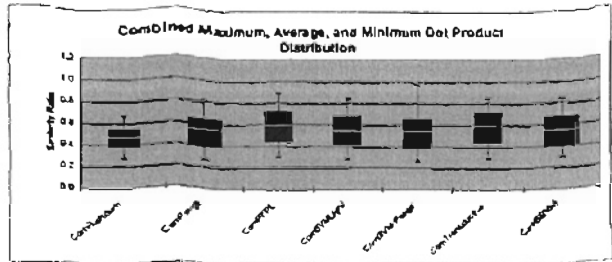
	CORRELATION							
	Min	Max	Min	Max	1.25th	3.75th	Worst Case	
MinRandom	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinPange	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinPRL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Light	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Pange	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Random	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4PRL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000



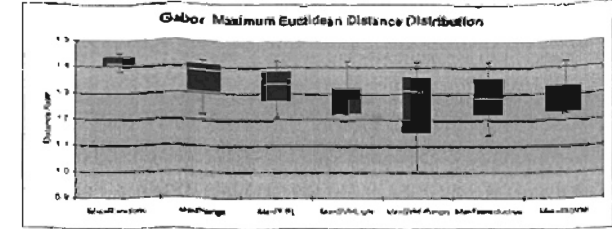
	ALL METHODS, COLOR HISTOGRAM, HARRIS CORNER, & CORRELATION COMBINED							
	Min	Max	Min	Max	1.25th	3.75th	Worst Case	
MinRandom	0.17743	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinPange	0.4035	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinPRL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Light	0.18108	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Pange	0.4035	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4Random	0.17743	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MinM4PRL	0.23823	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000



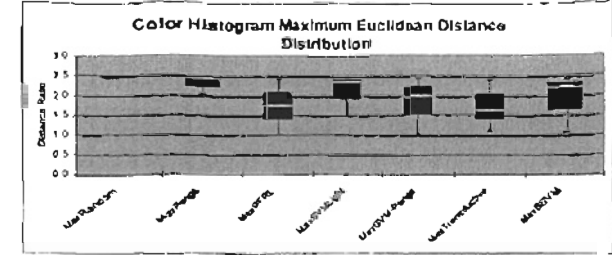
	High	Min	Max	Mean	StdDev	Skewness	Kurtosis	Normal Q-Q
Constrained	0.5833	0.4668	0.7190	0.5747	0.1490	1.173767	1.603753	252.8588
Constrained	0.8448	0.8127	0.8962	0.8351	0.0379	1.915978	1.464579	265.8888
Constrained	0.7264	0.6935	0.7595	0.7192	0.0309	1.907891	1.293716	239.8144
Constrained	0.6851	0.6484	0.7270	0.6972	0.0395	1.710566	1.273091	290.3834
Constrained	0.4838	0.4738	0.4938	0.4868	0.0088	3.943075	1.441817	287.4881
Constrained	0.7921	0.7823	0.8023	0.7923	0.0097	2.100807	1.293029	241.7588
Constrained	0.8737	0.8641	0.8938	0.8800	0.0149	1.916197	1.171398	233.8241



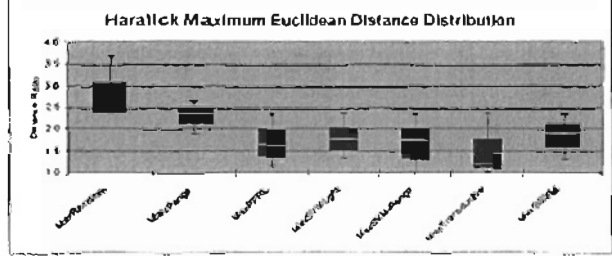
	High	Min	Max	Mean	StdDev	Skewness	Kurtosis	Normal Q-Q
Constrained	1.4294	1.4089	1.5174	1.4281	0.0478	1.179864	1.453421	44.9421
Constrained	1.4970	1.4708	1.5208	1.4858	0.0252	1.31314	1.414278	42.0794
Constrained	1.3636	1.3298	1.3788	1.3569	0.0238	2.418332	1.61388	49.0794
Constrained	1.3023	1.2788	1.3169	1.2956	0.0198	2.218388	1.623336	42.0794
Constrained	1.3251	1.3008	1.3505	1.3187	0.0258	2.048388	1.613111	42.0794
Constrained	1.3251	1.3058	1.3428	1.3214	0.0174	2.017378	1.613029	42.0794
Constrained	1.3238	1.3078	1.3388	1.3257	0.0154	1.918388	1.613029	42.0794



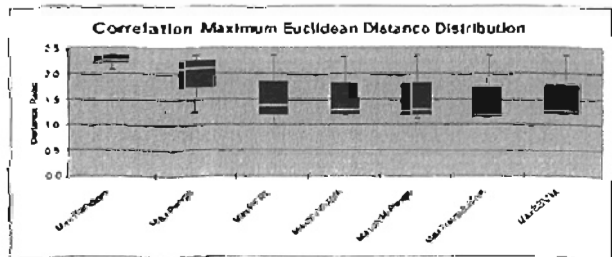
	High	Min	Max	Mean	StdDev	Skewness	Kurtosis	Normal Q-Q
Constrained	2.2481	2.2357	2.2587	2.2467	0.0097	1.114111	1.634168	162.4270
Constrained	1.4312	1.4167	1.4668	1.4340	0.0238	1.127774	1.481429	148.4892
Constrained	1.4009	1.3851	1.4200	1.3948	0.0172	1.101141	1.100916	148.4892
Constrained	2.8175	2.8167	2.8165	2.8165	0.0000	1.100000	1.417383	148.4892
Constrained	2.2814	2.2827	2.2818	2.2814	0.0007	1.041195	1.241198	148.4892
Constrained	1.1682	1.1687	1.1684	1.1685	0.0000	1.000000	1.001198	148.4892
Constrained	2.2007	2.2017	2.2015	2.2016	0.0000	1.001198	1.181000	148.4892



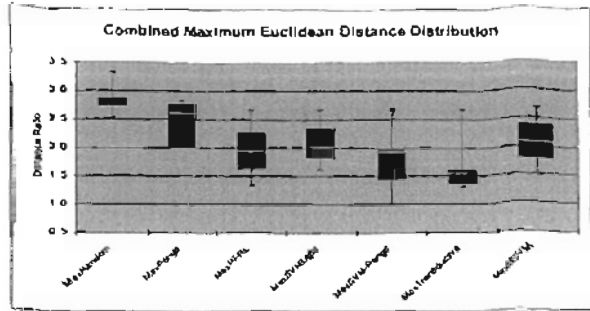
	High	Min	Max	Mean	StdDev	Skewness	Kurtosis	Normal Q-Q
Constrained	3.1800	3.1007	3.1800	3.1415	0.0493	1.150371	1.150371	270.3476
Constrained	3.1270	3.0678	3.1800	3.1242	0.0375	1.367188	1.517025	168.7581
Constrained	2.9910	2.9879	2.9971	2.9925	0.0024	1.034078	1.034078	130.7988
Constrained	3.0823	3.0836	3.0811	3.0823	0.0000	1.034078	1.034078	130.7988
Constrained	3.0222	3.0279	3.0200	3.0243	0.0024	1.034078	1.034078	130.7988
Constrained	1.7467	1.7473	1.7467	1.7467	0.0000	1.183333	1.183333	130.7988
Constrained	3.1320	3.1370	3.1300	3.1361	0.0030	1.183333	1.183333	130.7988



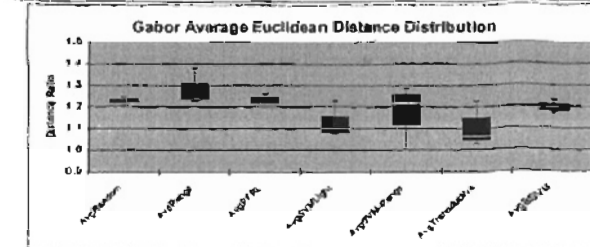
	High	Min	Max	Mean	StdDev	Skewness	Kurtosis	Normal Q-Q
Constrained	2.2320	2.2079	2.2581	2.2340	0.0243	1.348354	1.691007	154.0148
Constrained	2.2320	2.2402	2.2294	2.2312	0.0038	1.168158	1.061374	154.0148
Constrained	1.8988	1.8133	1.9036	1.8744	0.0469	1.168158	1.168158	154.0148
Constrained	1.8970	1.8433	1.9088	1.8829	0.0279	1.168158	1.168158	154.0148
Constrained	1.8172	1.8033	1.8298	1.8141	0.0132	1.168158	1.168158	154.0148
Constrained	1.7969	1.7433	1.8200	1.7868	0.0348	1.168158	1.168158	154.0148
Constrained	1.8253	1.8433	1.8218	1.8301	0.0098	1.168158	1.168158	154.0148



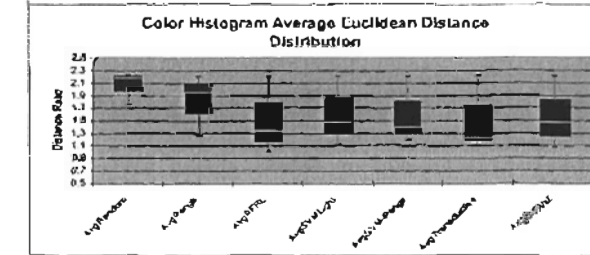
MAX SAGEIN - Gabor Filter Features - HARRIS & CORRELATION COMBING									
	Mean	Max	Min	Low	High	Low	High	3. Min	3. Max
AugAvgFeature	2.9779	3.8884	2.9197	2.1498	2.9784	190.4167	750.4208	200.4884	
AugAvgRange	2.1111	3.8319	2.0205	2.0205	2.9784	194.6214	775.3230	180.6679	
AugAvgAll	2.9284	3.7114	1.9284	1.9195	2.9782	187.4623	726.7627	146.4222	
AugAvgAllRange	2.9424	3.7114	1.9595	1.9195	2.9782	192.0428	731.1631	149.6222	
AugAvgAllHigh	1.9475	2.1111	1.0247	1.0247	1.6475	80.4407	303.6497	146.6222	
AugAvgAllLow	1.9823	2.1111	1.9584	1.9883	1.9823	97.8430	58.9490	146.6222	
AugAvgAllLow	2.2710	3.8790	1.9890	2.7947	2.0890	107.5010	136.8012	145.6222	



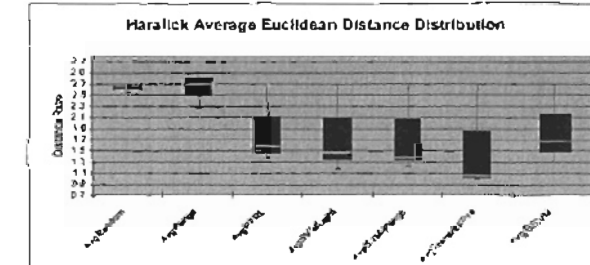
AVE PASC VALUE									
	High	Max	Min	Low	High	Low	High	3. Min	3. Max
AugAvgFeature	1.2264	1.2603	1.2000	1.1175	1.2260	72.0000	72.0000	72.0000	74.0000
AugAvgRange	1.2603	1.2673	1.2000	1.2000	1.2603	83.0000	83.0000	83.0000	87.0000
AugAvgAll	1.2442	1.2565	1.1875	1.1199	1.2442	82.0000	82.0000	76.0000	79.0000
AugAvgAllRange	1.2365	1.2388	1.0774	1.0600	1.2365	83.0000	83.0000	83.0000	83.0000
AugAvgAllHigh	1.2398	1.2390	1.0000	1.1199	1.2398	82.0000	79.0000	79.0000	79.0000
AugAvgAllLow	1.1111	1.2029	1.0276	1.0000	1.1111	83.0000	83.0000	83.0000	83.0000
AugAvgAllLow	1.2420	1.2466	1.2000	1.1792	1.2420	80.0000	80.0000	71.0000	71.0000



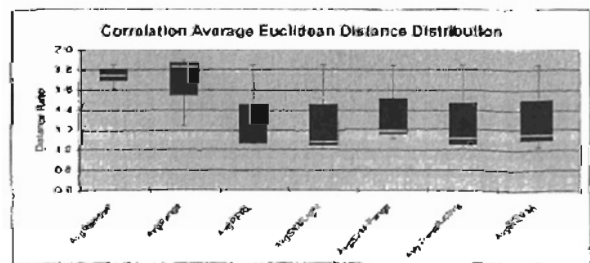
AVE Gabor Filter Features									
	High	Max	Min	Low	High	Low	High	3. Min	3. Max
AugAvgFeature	1.2264	1.2567	1.1994	1.0792	1.2111	111.0000	122.4700	122.4700	123.0000
AugAvgRange	1.2444	1.2477	1.2000	1.0771	1.2444	85.0000	100.0000	100.0000	101.0000
AugAvgAll	1.2162	1.2191	1.0000	1.0161	1.2162	111.0000	111.0000	111.0000	111.0000
AugAvgAllRange	1.2161	1.2197	1.1000	1.0000	1.2161	111.0000	111.0000	111.0000	111.0000
AugAvgAllHigh	1.1900	1.2127	1.0000	1.0000	1.1900	111.0000	111.0000	111.0000	111.0000
AugAvgAllLow	1.1700	1.2127	1.0000	1.0000	1.1700	111.0000	111.0000	111.0000	111.0000
AugAvgAllLow	1.2114	1.2197	1.0000	1.1171	1.2114	111.0000	111.0000	111.0000	111.0000



AVE Harris									
	High	Max	Min	Low	High	Low	High	3. Min	3. Max
AugAvgFeature	2.2624	2.2668	2.2414	2.2400	2.2620	100.0000	100.0000	100.0000	100.0000
AugAvgRange	2.2624	2.2671	2.2400	2.2400	2.2624	100.0000	100.0000	100.0000	100.0000
AugAvgAll	2.2170	2.2170	2.2071	2.2000	2.2170	100.0000	100.0000	100.0000	100.0000
AugAvgAllRange	2.2170	2.2170	2.2071	2.2000	2.2170	100.0000	100.0000	100.0000	100.0000
AugAvgAllHigh	2.2170	2.2170	2.2071	2.2000	2.2170	100.0000	100.0000	100.0000	100.0000
AugAvgAllLow	2.2170	2.2170	2.2071	2.2000	2.2170	100.0000	100.0000	100.0000	100.0000
AugAvgAllLow	2.2170	2.2170	2.2071	2.2000	2.2170	100.0000	100.0000	100.0000	100.0000

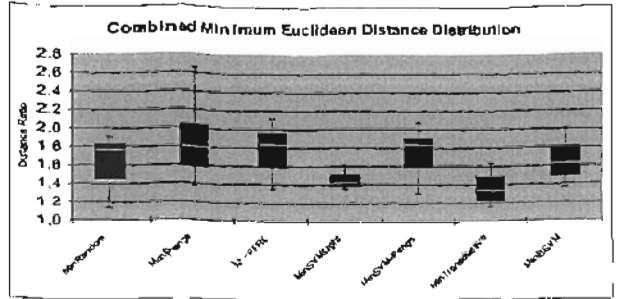


AVE Correlation									
	High	Max	Min	Low	High	Low	High	3. Min	3. Max
AugAvgFeature	1.0000	1.0015	1.0000	1.0000	1.0000	10.0000	10.0000	10.0000	10.0000
AugAvgRange	1.0000	1.0000	1.0000	1.0000	1.0000	10.0000	10.0000	10.0000	10.0000
AugAvgAll	1.0000	1.0015	1.0000	1.0000	1.0000	10.0000	10.0000	10.0000	10.0000
AugAvgAllRange	1.0000	1.0015	1.0000	1.0000	1.0000	10.0000	10.0000	10.0000	10.0000
AugAvgAllHigh	1.0000	1.0015	1.0000	1.0000	1.0000	10.0000	10.0000	10.0000	10.0000
AugAvgAllLow	1.0000	1.0015	1.0000	1.0000	1.0000	10.0000	10.0000	10.0000	10.0000
AugAvgAllLow	1.0000	1.0015	1.0000	1.0000	1.0000	10.0000	10.0000	10.0000	10.0000



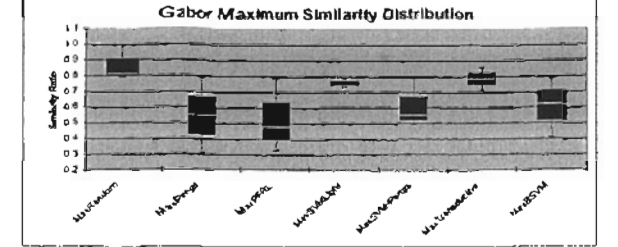
ALL GABOR COEFFICIENTS AND CORRELATION COEFFICIENTS

Filter	Mag	Max	Min	Low	High	1-Phase	3-Phase	Wavelet
Max-Entropy	1.8259	1.8058	1.1504	1.6424	1.7420	84.4620	81.0256	81.6277
Max-Phase	1.9406	1.6667	1.1776	1.6701	1.7879	80.5626	79.9712	74.4211
Max-RL	1.9454	2.1111	1.1813	1.5864	1.8200	80.5360	77.3440	68.1547
Max-RL-Phase	1.5295	1.6117	1.1246	1.5423	1.6708	76.3867	33.1664	47.8204
Max-RL-Entropy	1.8070	2.0704	1.1000	1.5866	1.8183	69.3761	80.2000	82.1120
Max-Entropy-Phase	1.8053	1.0251	1.1535	1.5232	1.6648	10.0064	51.3412	44.5106
Max-RL-RL	1.6114	2.0064	1.1378	1.4478	1.8181	42.0328	80.7662	78.4675



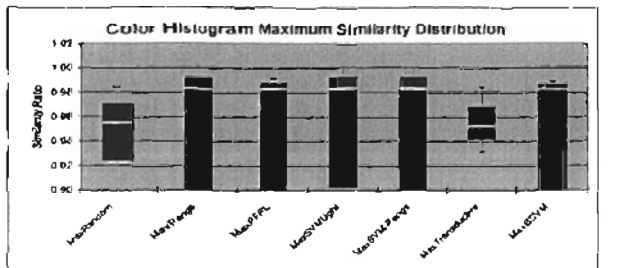
DOT PRODUCT MAXIMUM SIMILARITY DISTRIBUTION

Filter	Mag	Max	Min	Low	High	1-Phase	3-Phase	Wavelet
Max-Entropy	0.9091	1.0000	0.7540	0.8048	0.8100	27.2960	34.2544	26.4245
Max-Phase	0.9520	0.7910	0.8107	0.8268	0.8460	43.8477	132.3072	224.8511
Max-RL	0.9331	0.7810	0.7470	0.8004	0.8488	108.1413	147.8219	205.5056
Max-RL-Phase	0.9720	0.7310	0.7870	0.7464	0.7938	38.3020	33.8765	35.0843
Max-RL-Entropy	0.9265	0.7310	0.6547	0.8268	0.8460	63.8477	82.0410	109.1406
Max-Entropy-Phase	0.8204	0.8601	0.7135	0.7362	0.7611	20.1865	38.7548	29.7825
Max-RL-RL	0.9229	0.7310	0.6018	0.8174	0.8460	71.4660	83.2920	145.1911



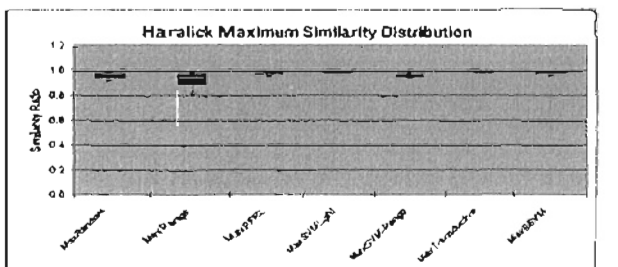
COLOR HISTOGRAM

Filter	Mag	Max	Min	Low	High	1-Phase	3-Phase	Wavelet
Max-Entropy	0.9727	0.8848	0.8510	0.8240	0.8968	4.4806	4.3504	13.2783
Max-Phase	0.9425	1.0000	0.7310	0.8523	0.8648	1.3601	13.2776	26.0099
Max-RL	0.9878	0.9912	0.7817	0.8814	0.9048	1.5651	14.2316	25.9281
Max-RL-Phase	0.9023	1.0000	0.8308	0.9028	0.9048	1.5641	16.7080	31.6730
Max-RL-Entropy	0.9023	1.0000	0.7500	0.8114	0.8648	1.3681	14.0200	35.2836
Max-Entropy-Phase	0.8684	0.9047	0.8015	0.8478	0.8923	1.0123	0.8572	7.3888
Max-RL-RL	0.9484	0.9881	0.7817	0.8480	0.8968	1.5627	12.6810	18.9763



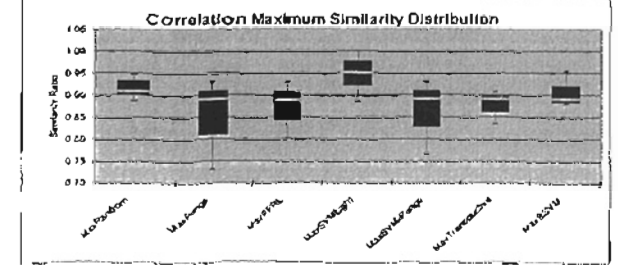
HARALICK

Filter	Mag	Max	Min	Low	High	1-Phase	3-Phase	Wavelet
Max-Entropy	0.8811	0.9918	0.9227	0.8885	0.9700	1.0716	8.8518	8.4743
Max-Phase	0.9762	0.9918	0.8137	0.8870	0.9048	4.0742	12.7212	22.7076
Max-RL	0.9503	0.9918	0.9610	0.9744	0.9871	4.3346	2.7860	2.6664
Max-RL-Phase	0.9051	0.9047	0.8681	0.9044	0.9048	0.8665	1.0007	1.2067
Max-RL-Entropy	0.9742	0.9918	0.8883	0.9537	0.9660	4.1767	4.8860	8.0327
Max-Entropy-Phase	0.8677	0.9900	0.9545	0.9634	0.9913	0.8415	0.6610	1.4183
Max-RL-RL	0.8818	0.9818	0.9059	0.8530	0.9313	0.8363	2.0420	3.2945

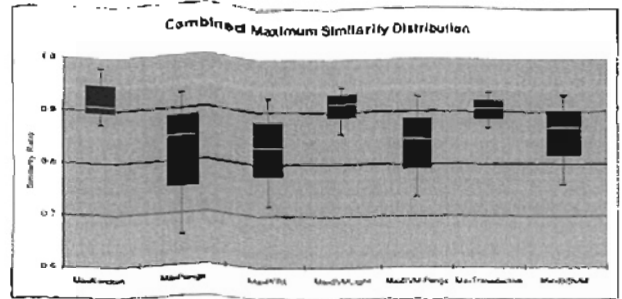


CORRELATION

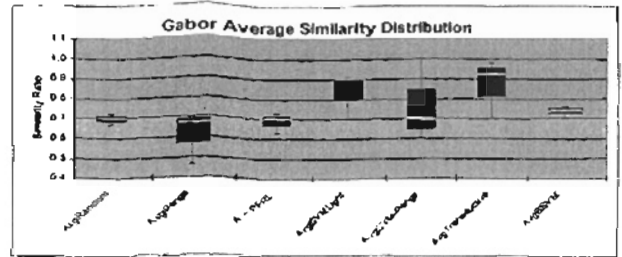
Filter	Mag	Max	Min	Low	High	1-Phase	3-Phase	Wavelet
Max-Entropy	0.9127	0.9680	0.8902	0.9025	0.9188	0.8380	10.8036	12.4197
Max-Phase	0.9082	0.9725	0.7308	0.8051	0.8807	12.6827	20.8417	36.4309
Max-RL	0.9088	0.9816	0.8808	0.8833	0.8883	12.6727	16.1711	24.6193
Max-RL-Phase	0.9171	1.0000	0.8862	0.9053	0.9543	4.7674	6.1654	11.8077
Max-RL-Entropy	0.9082	0.9025	0.7655	0.8204	0.8813	12.6827	11.0127	32.4365
Max-Entropy-Phase	0.8068	0.8915	0.8206	0.8568	0.8817	12.0477	15.2601	18.8136
Max-RL-RL	0.9082	0.9816	0.8750	0.8826	0.8997	12.8127	13.2881	18.7161



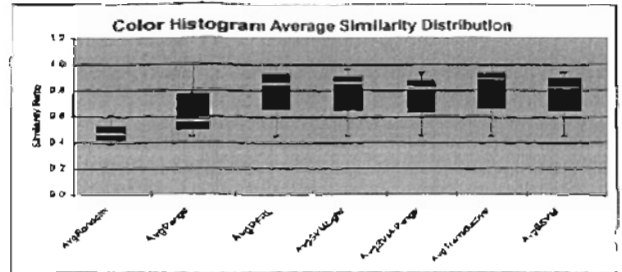
ALL GABOR COLOR HISTOGRAM HARALICK & CORRELATION COMBINED							
	High	Med	Low	Low	High	Low	High
High/Random	0.8466	0.8001	0.8221	0.8944	0.8162	70677	91483
High/Range	0.8067	0.6221	0.4585	0.7548	0.8466	161080	304474
High/PTNL	0.5828	0.9203	0.7176	0.7182	0.8346	173058	258413
High/RandomLight	0.8243	0.8476	0.8286	0.8695	0.8476	84109	102168
High/RandomRange	0.8441	0.8281	0.7801	0.7807	0.8446	461000	243200
High/RandomLow	0.8211	0.8260	0.8680	0.8811	0.8502	0.2192	103400
High/PTNL	0.8010	0.8318	0.7861	0.8102	0.8223	124718	201920



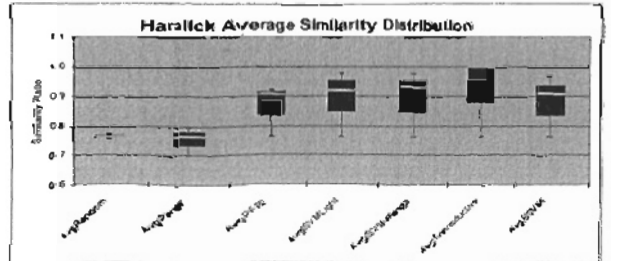
AVERAGE VALUES							
	High	Med	Low	Low	High	Low	High
High/Random	0.7704	0.7325	0.7092	0.6973	0.6964	433696	144889
High/Range	0.6467	0.4086	0.4429	0.5008	0.6711	174640	181900
High/PTNL	0.7106	0.7246	0.7025	0.6929	0.6904	433696	144889
High/RandomLight	0.6969	0.6806	0.6709	0.7064	0.6876	110829	251291
High/RandomRange	0.6462	0.6000	0.6028	0.5490	0.6064	433696	144889
High/RandomLow	0.6476	0.6504	0.6384	0.6141	0.6149	71176	112306
High/PTNL	0.7059	0.7217	0.7069	0.7253	0.7151	424824	144889



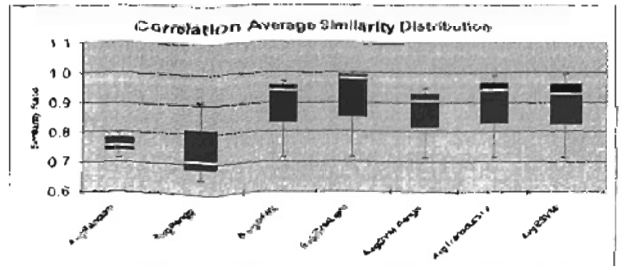
COLOR HISTOGRAM							
	High	Med	Low	Low	High	Low	High
High/Random	0.5341	0.4099	0.3822	0.4143	0.4449	123080	161801
High/Range	0.7790	0.4888	0.4464	0.4974	0.5475	320458	1004751
High/PTNL	0.5432	0.6648	0.4664	0.5079	0.5674	481764	514802
High/RandomLight	0.4114	0.6043	0.4644	0.4628	0.5772	760951	851190
High/RandomRange	0.4119	0.6288	0.4174	0.4242	0.4193	323641	676312
High/RandomLow	0.4650	0.6000	0.4154	0.4683	0.4687	134476	504912
High/PTNL	0.5761	0.6466	0.4664	0.4600	0.5417	481764	514802



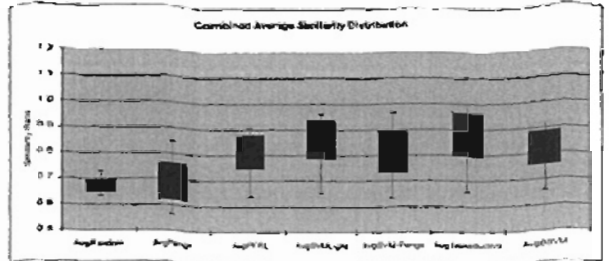
HARALICK							
	High	Med	Low	Low	High	Low	High
High/Random	0.7656	0.7342	0.7443	0.7626	0.7692	2014076	3112168
High/Range	0.7818	0.7390	0.6370	0.6711	0.7002	4034178	901107
High/PTNL	0.5143	0.6918	0.7042	0.6905	0.6889	4818481	1014790
High/RandomLight	0.6430	0.6716	0.7249	0.6478	0.6886	176676	181900
High/RandomRange	0.6964	0.6762	0.7042	0.6644	0.6825	177719	1218666
High/RandomLow	0.6466	0.6900	0.7042	0.6746	0.6907	424802	414816
High/PTNL	0.7048	0.6403	0.7042	0.6367	0.6877	1019928	1018717



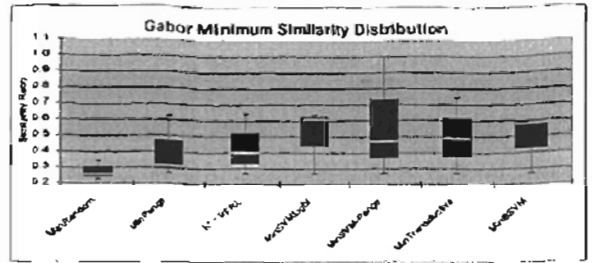
CORRELATION							
	High	Med	Low	Low	High	Low	High
High/Random	0.7834	0.7979	0.7180	0.7284	0.7288	3019089	3012472
High/Range	0.8140	0.6060	0.5428	0.6019	0.7149	4012023	451480
High/PTNL	0.6540	0.6900	0.7180	0.7089	0.7008	516654	201481
High/RandomLight	0.6629	0.6900	0.7180	0.6940	0.6964	41664	471380
High/RandomRange	0.6041	0.6400	0.7180	0.6111	0.6108	211466	4012472
High/RandomLow	0.6447	0.6800	0.7180	0.6772	0.6807	0.2279	1019928
High/PTNL	0.6876	0.6974	0.7180	0.6773	0.6786	71666	811814



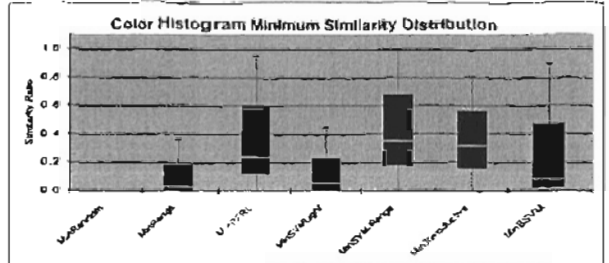
ALL CATEGORIES COMBINED								
	High	Min	Max	Low	Mean	Q1 (25%)	Q3 (75%)	Median
Augmented	0.921	0.726	0.931	0.846	0.866	0.800	0.900	0.850
AugImage	0.782	0.659	0.944	0.823	0.821	0.752	0.898	0.825
AugIRL	0.858	0.707	0.936	0.784	0.851	0.788	0.917	0.852
AugIRL+Aug	0.903	0.763	0.936	0.789	0.818	0.754	0.889	0.821
AugIRL+Image	0.921	0.805	0.935	0.799	0.829	0.764	0.903	0.825
AugIRL+Color	0.884	0.694	0.936	0.789	0.800	0.751	0.850	0.800
AugIRL+L	0.884	0.810	0.936	0.782	0.855	0.800	0.900	0.850



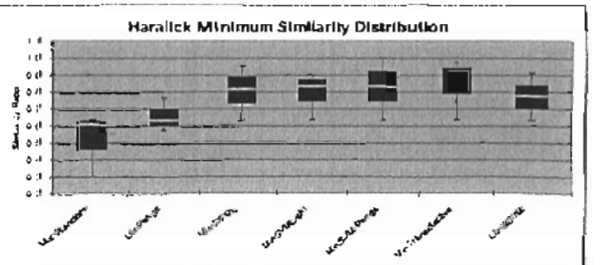
MINIMUM VALUES								
	High	Min	Max	Low	Mean	Q1 (25%)	Q3 (75%)	Median
MinIRL	0.904	0.744	0.928	0.789	0.789	0.729	0.849	0.825
MinImage	0.865	0.676	0.928	0.789	0.782	0.718	0.846	0.799
MinIRL+L	0.921	0.815	0.936	0.783	0.887	0.827	0.920	0.899
MinIRL+Aug	0.914	0.839	0.936	0.844	0.849	0.800	0.891	0.855
MinIRL+Image	0.920	0.800	0.936	0.800	0.810	0.729	0.900	0.825
MinIRL+Color	0.884	0.743	0.936	0.782	0.801	0.751	0.850	0.800
MinIRL+L	0.884	0.805	0.936	0.782	0.853	0.800	0.900	0.850



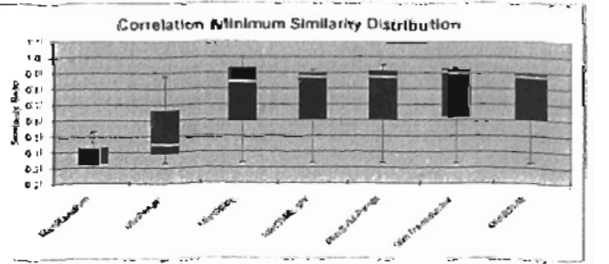
COLOR HISTOGRAM								
	High	Min	Max	Low	Mean	Q1 (25%)	Q3 (75%)	Median
MinIRL	0.904	0.744	0.928	0.789	0.789	0.729	0.849	0.825
MinImage	0.865	0.676	0.928	0.789	0.782	0.718	0.846	0.799
MinIRL+L	0.921	0.815	0.936	0.783	0.887	0.827	0.920	0.899
MinIRL+Aug	0.914	0.839	0.936	0.844	0.849	0.800	0.891	0.855
MinIRL+Image	0.920	0.800	0.936	0.800	0.810	0.729	0.900	0.825
MinIRL+Color	0.884	0.743	0.936	0.782	0.801	0.751	0.850	0.800
MinIRL+L	0.884	0.805	0.936	0.782	0.853	0.800	0.900	0.850



HARRIS CORNER								
	High	Min	Max	Low	Mean	Q1 (25%)	Q3 (75%)	Median
MinIRL	0.934	0.832	0.936	0.846	0.887	0.800	0.900	0.850
MinImage	0.865	0.749	0.936	0.800	0.829	0.718	0.891	0.825
MinIRL+L	0.921	0.807	0.936	0.783	0.887	0.827	0.920	0.899
MinIRL+Aug	0.914	0.839	0.936	0.844	0.849	0.800	0.891	0.855
MinIRL+Image	0.920	0.800	0.936	0.800	0.810	0.729	0.900	0.825
MinIRL+Color	0.884	0.743	0.936	0.782	0.801	0.751	0.850	0.800
MinIRL+L	0.884	0.805	0.936	0.782	0.853	0.800	0.900	0.850

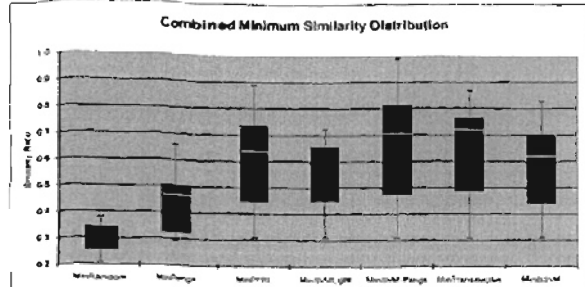


CORRELATION								
	High	Min	Max	Low	Mean	Q1 (25%)	Q3 (75%)	Median
MinIRL	0.916	0.825	0.936	0.811	0.820	0.752	0.887	0.825
MinImage	0.867	0.774	0.936	0.800	0.807	0.718	0.891	0.825
MinIRL+L	0.916	0.825	0.936	0.811	0.820	0.752	0.887	0.825
MinIRL+Aug	0.916	0.825	0.936	0.811	0.820	0.752	0.887	0.825
MinIRL+Image	0.916	0.825	0.936	0.811	0.820	0.752	0.887	0.825
MinIRL+Color	0.916	0.825	0.936	0.811	0.820	0.752	0.887	0.825
MinIRL+L	0.916	0.825	0.936	0.811	0.820	0.752	0.887	0.825



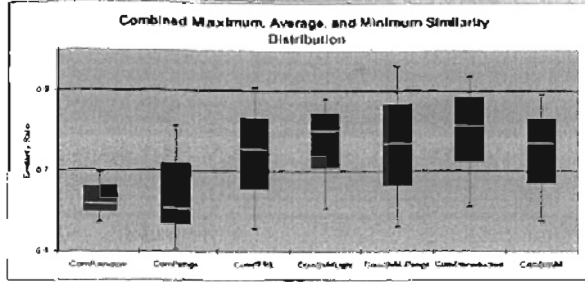
ALL GABOR COLOR HISTOGRAMS, HARRIS CORNERS, & CORRELATION COEFFICIENTS

	High	Mid	Low	Mean	1-StdDev	3-StdDev	W/CorrCoeff
MapHistogram	0.0414	0.0781	0.2000	0.2965	0.3004	225.8994	204.3026
MapRange	0.3662	0.6864	0.7524	0.5074	0.3621	478.4407	205.8764
MapHarris	0.7367	0.8673	0.3085	0.4633	0.5621	69.3600	421.8774
MapHarrisRange	0.0010	0.2148	0.2085	0.4493	0.3054	67.1189	418.3299
MapHarrisMid	0.6120	0.8967	0.3085	0.4727	0.6380	84.4308	108.2924
MapHarrisLow	0.1680	0.3676	0.5085	0.4884	0.6845	48.5372	190.8908
MapHarrisMean	0.0462	0.4863	0.3089	0.4352	0.8701	71.0281	126.4170



ALL GREEN DOT PROFILES, L MAPS, AND CORRELATION COEFFICIENTS

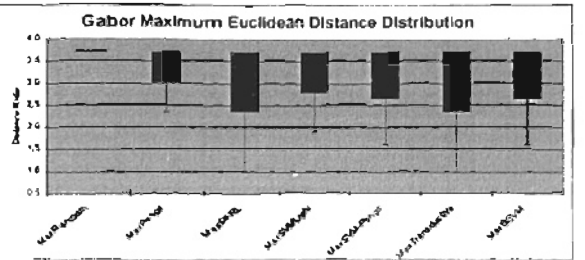
	High	Mid	Low	Mean	1-StdDev	3-StdDev	W/CorrCoeff
Combined	0.0422	0.4890	0.1709	0.3033	0.5283	53.1866	1.115
CombinedRange	0.7187	0.9114	0.3655	0.5481	0.5244	64.7406	1.0495
CombinedHarris	0.8314	0.8988	0.3365	0.5003	0.7489	38.3076	48.3872
CombinedHarrisRange	0.0462	0.4834	0.1674	0.3187	0.5100	18.5334	36.4806
CombinedHarrisMid	0.6573	0.8923	0.1692	0.4664	0.7743	34.6870	46.0245
CombinedHarrisLow	0.0544	0.3327	0.1918	0.3735	0.6362	14.6581	34.7534
CombinedHarrisMean	0.0380	0.3218	0.1780	0.3087	0.7803	28.3088	43.4484



SCALAR DATA
EUCLIDEAN DISTANCE

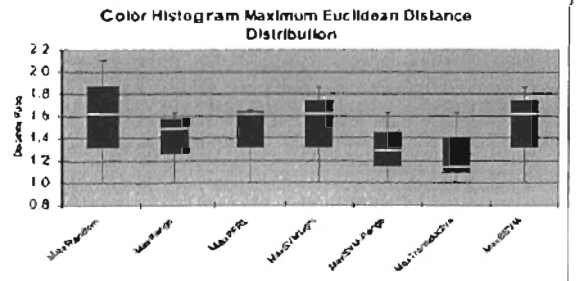
SCALAR DATA
EUCLIDEAN DISTANCE

	High	Mid	Low	Mean	1-StdDev	3-StdDev	W/CorrCoeff
MapHistogram	2.7018	3.7018	1.7018	3.7018	0.7000	270.1813	270.1813
MapRange	2.7018	3.7018	1.7018	3.7018	0.7000	270.1813	270.1813
MapHarris	3.7014	3.7010	1.6993	3.7010	0.7000	270.1813	270.1813
MapHarrisRange	1.7014	3.7015	1.6988	3.7000	0.7000	270.1813	270.1813
MapHarrisMid	1.7016	3.7015	1.6104	3.6997	0.7000	270.1813	270.1813
MapHarrisLow	3.7016	3.7016	1.6997	3.7000	0.7000	270.1813	270.1813
MapHarrisMean	1.7016	3.7016	1.6993	3.7016	0.7000	270.1813	270.1813



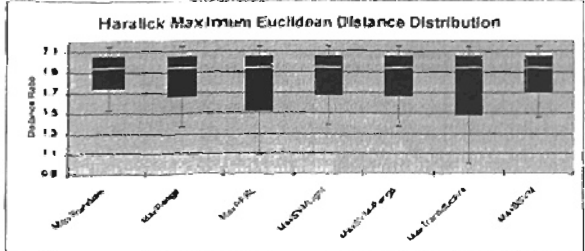
COLOR HISTOGRAMS

	High	Mid	Low	Mean	1-StdDev	3-StdDev	W/CorrCoeff
MapHistogram	1.8620	1.0000	1.0000	1.0000	0.8174	83.8668	109.8545
MapRange	1.8716	1.0000	1.0000	1.2629	0.8178	82.1363	57.1165
MapHarris	1.8623	1.0010	1.0000	1.3188	0.8299	92.9734	56.7847
MapHarrisRange	1.7414	1.8581	1.0000	1.3189	0.8297	82.9736	56.7845
MapHarrisMid	1.7417	1.8581	1.0000	1.3188	0.8297	82.9736	56.7845
MapHarrisLow	1.7415	1.8581	1.0000	1.3188	0.8297	82.9736	56.7845
MapHarrisMean	1.7414	1.8581	1.0000	1.3189	0.8297	82.9734	56.7845

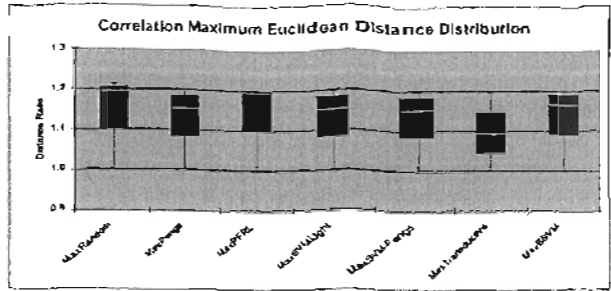


HARRIS CORNERS

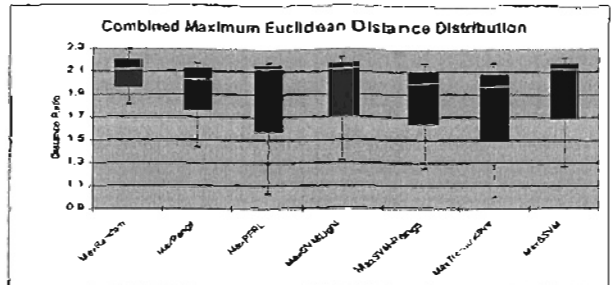
	High	Mid	Low	Mean	1-StdDev	3-StdDev	W/CorrCoeff
MapHistogram	2.0674	2.1421	1.2695	1.8688	1.4607	85.1879	104.7400
MapRange	2.0674	2.1421	1.2695	1.8688	1.4607	85.1879	104.7400
MapHarris	2.0674	2.1421	1.2695	1.8688	1.4607	85.1879	104.7400
MapHarrisRange	2.0674	2.1421	1.2695	1.8688	1.4607	85.1879	104.7400
MapHarrisMid	2.0674	2.1421	1.2695	1.8688	1.4607	85.1879	104.7400
MapHarrisLow	2.0674	2.1421	1.2695	1.8688	1.4607	85.1879	104.7400
MapHarrisMean	2.0674	2.1421	1.2695	1.8688	1.4607	85.1879	104.7400



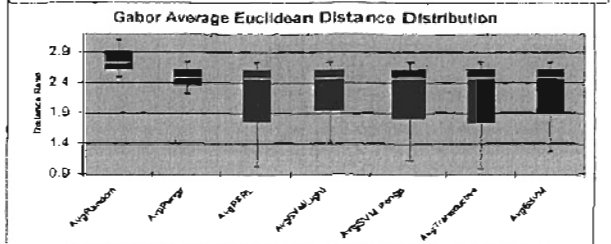
CORRELATION									
	High	Med	Min	Low	Med	1-20%	3-40%	More than 40%	
Avg Random	1.2063	1.2156	1.0000	1.0992	1.1667	16.3676	20.0297	21.2170	
Avg Range	1.1215	1.1510	1.0000	1.0943	1.1654	18.3618	18.1426	19.5624	
Avg RL	1.1076	1.2000	1.0000	1.0927	1.1654	18.8424	18.8660	20.0295	
Avg RL+Light	1.1335	1.1834	1.0000	1.0943	1.1646	18.0516	17.1371	18.8424	
Avg RL+Range	1.1335	1.1954	1.0000	1.0943	1.1646	18.0516	17.1371	18.8424	
Avg RL+Color	1.1660	1.1964	1.0000	1.0926	1.1623	8.1706	14.4645	19.8624	
Avg RL+Har	1.1661	1.1964	1.0000	1.0926	1.1617	14.1721	14.0213	19.8624	



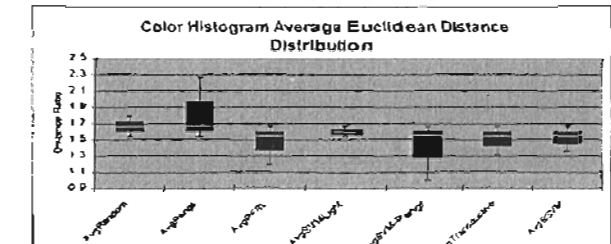
ALL GABOR COLOR HISTOGRAM HARALICK CORRELATION COMBINED									
	High	Med	Min	Low	Med	1-20%	3-40%	More than 40%	
Avg Random	2.3048	2.2891	1.8670	1.8670	2.1304	112.0410	120.4776	126.8144	
Avg Range	2.2711	2.1983	1.4340	1.7954	2.0465	102.3609	117.7121	118.2191	
Avg RL	2.1484	2.1750	1.0247	1.5714	2.1764	114.0410	114.8050	117.5019	
Avg RL+Light	2.1505	2.2241	1.1144	1.5146	2.1424	114.2050	118.8545	122.4114	
Avg RL+Range	2.0917	2.1402	1.2477	1.8560	2.0317	108.1105	116.0726	118.4277	
Avg RL+Color	2.0728	2.1023	1.0000	1.4848	1.9774	87.7374	105.2025	118.8177	
Avg RL+Har	2.1702	2.2314	1.1649	1.8524	2.1147	111.6335	117.0153	122.4114	



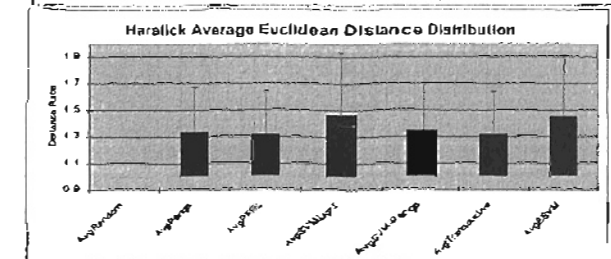
AVERAGE VALUE									
	High	Med	Min	Low	Med	1-20%	3-40%	More than 40%	
Avg Random	2.9180	3.1014	2.1790	2.8140	2.7348	173.4746	141.7826	210.1122	
Avg Range	2.9116	2.7340	2.1777	2.3988	2.6490	146.8000	161.4887	173.4736	
Avg RL	2.6148	2.7348	1.4246	1.9023	2.4902	148.7000	161.4887	173.4736	
Avg RL+Light	2.6148	2.7348	1.4246	1.9023	2.4902	148.7000	161.4887	173.4736	
Avg RL+Range	2.6148	2.7348	1.4246	1.9023	2.4902	148.7000	161.4887	173.4736	
Avg RL+Color	2.6148	2.7348	1.4246	1.9023	2.4902	148.7000	161.4887	173.4736	
Avg RL+Har	2.9148	2.7348	1.4246	1.9023	2.4902	148.7000	161.4887	173.4736	



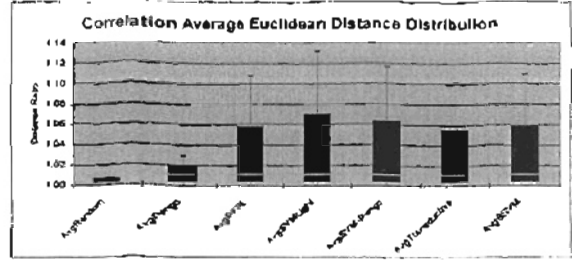
COLOR HISTOGRAM									
	High	Med	Min	Low	Med	1-20%	3-40%	More than 40%	
Avg Random	1.7217	1.7228	1.5311	1.5648	1.6415	86.4534	12.8816	70.2834	
Avg Range	1.6560	2.2870	1.2231	1.9848	1.6741	84.4324	61.8940	108.7107	
Avg RL	1.5084	1.6615	1.0000	1.5614	1.5334	33.3081	52.8622	62.1421	
Avg RL+Light	1.6735	1.6974	1.5111	1.5714	1.5810	58.2041	67.3263	76.1424	
Avg RL+Range	1.6268	1.6544	1.0000	1.4741	1.5317	77.3061	76.8402	82.4124	
Avg RL+Color	1.6268	1.6544	1.0000	1.4741	1.5317	77.3061	76.8402	82.4124	
Avg RL+Har	1.6268	1.6544	1.0000	1.4741	1.5317	77.3061	76.8402	82.4124	



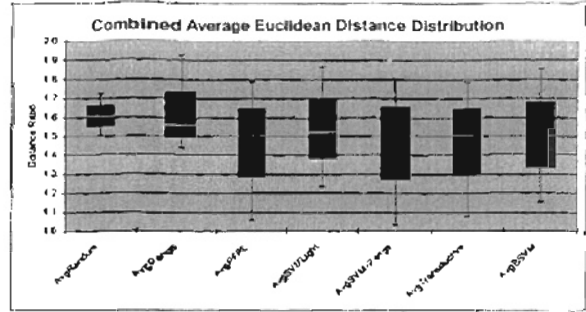
HARALICK									
	High	Med	Min	Low	Med	1-20%	3-40%	More than 40%	
Avg Random	1.0797	1.6610	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
Avg Range	1.3363	1.4129	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
Avg RL	1.3111	1.4943	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
Avg RL+Light	1.4081	1.6132	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
Avg RL+Range	1.3111	1.4943	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
Avg RL+Color	1.3111	1.4943	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
Avg RL+Har	1.3111	1.4943	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	



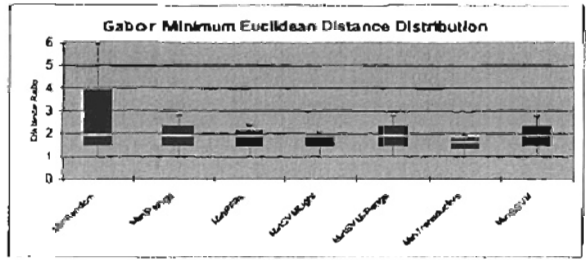
	CORRELATION							
	High	Med	Low	Min	Max	1-200ms	2-400ms	400ms-600ms
High/median	1.0000	0.9998	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
High/low	0.9999	1.0000	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
High/Min	0.9999	0.9999	0.9999	1.0000	0.9999	0.9999	0.9999	0.9999
High/Max	0.9999	0.9999	0.9999	0.9999	1.0000	0.9999	0.9999	0.9999
High/1-200ms	0.9999	0.9999	0.9999	0.9999	0.9999	1.0000	0.9999	0.9999
High/2-400ms	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	1.0000	0.9999
High/400ms-600ms	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	1.0000



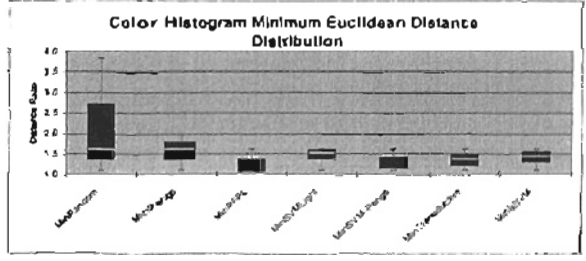
	ALL (GABOR, COLOR HISTOGRAM, HARRIS ET AL., & HAZALTEK) COMBINED							
	High	Med	Low	Min	Max	1-200ms	2-400ms	400ms-600ms
High/median	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
High/low	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
High/Min	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
High/Max	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
High/1-200ms	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
High/2-400ms	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
High/400ms-600ms	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000



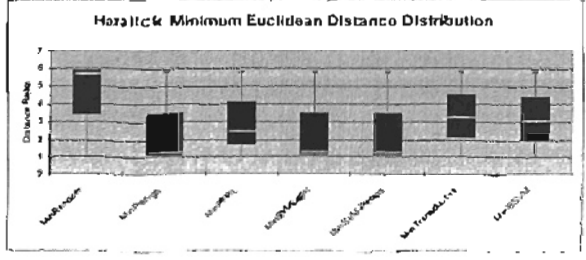
	MINIMUM VALUE							
	High	Med	Low	Min	Max	1-200ms	2-400ms	400ms-600ms
High/median	3.5011	4.6816	1.8001	1.4271	8.8113	91.4262	780.1033	446.7807
High/low	1.9421	1.7256	1.3070	0.9482	1.6044	54.2095	48.9045	491.9124
High/Min	1.7560	1.3050	1.4317	1.4091	1.5670	49.1837	47.7948	491.2001
High/Max	1.6181	1.7862	1.2925	1.2843	1.5052	49.0743	48.3796	73.7000
High/1-200ms	1.6981	1.8000	1.2547	1.2780	1.3314	27.1163	48.8227	491.4875
High/2-400ms	1.5955	1.3033	1.4334	1.3915	1.4058	45.8743	48.8009	74.1037
High/400ms-600ms	1.6473	1.7862	1.0742	1.1117	1.3022	45.8748	48.3223	73.4003
High/All	1.6119	1.6814	1.1145	1.2411	1.3052	45.9742	48.3798	73.3879



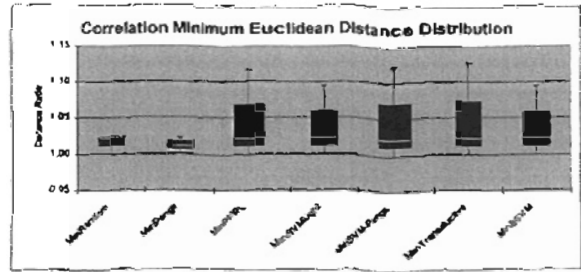
	EUCLIDEAN DISTANCE							
	High	Med	Low	Min	Max	1-200ms	2-400ms	400ms-600ms
High/median	3.7868	3.8154	1.0992	0.9395	1.0250	64.2076	412.8232	287.4439
High/low	1.8131	1.7602	1.2042	0.9395	1.0420	44.3022	41.7420	481.2201
High/Min	1.3706	1.5497	0.9007	0.9046	0.9922	33.8161	41.0803	481.2001
High/Max	1.4337	1.5420	0.9007	1.0001	1.0214	42.1390	41.1705	481.2001
High/1-200ms	1.4128	1.6430	0.9007	0.9114	1.0205	18.2034	40.3941	481.2001
High/2-400ms	1.4128	1.6430	0.9007	0.9114	1.0205	30.3043	41.0445	481.2001
High/400ms-600ms	1.5614	1.6420	0.9007	1.0000	1.0500	44.0821	41.1044	481.2001



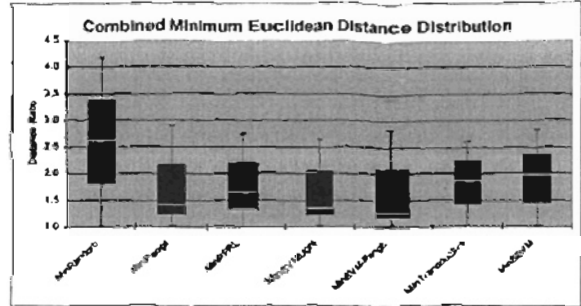
	HARRIS ET AL.							
	High	Med	Low	Min	Max	1-200ms	2-400ms	400ms-600ms
High/median	5.4767	5.8422	0.9865	0.9827	5.7469	478.5529	487.4807	473.7007
High/low	1.4053	1.7884	1.0000	1.0000	1.1111	27.1163	290.1044	478.5529
High/Min	1.4304	1.7884	1.0000	1.0000	1.1111	444.8500	342.0417	478.5529
High/Max	3.0083	1.7884	1.0000	1.0000	1.2514	70.1183	290.1044	478.5529
High/1-200ms	3.0083	1.7884	1.0000	1.0000	1.1111	20.3203	290.1044	478.5529
High/2-400ms	4.0441	1.7884	1.0000	1.0000	1.1111	120.3407	340.4790	478.5529
High/400ms-600ms	4.1216	1.7884	1.0000	1.0000	1.0574	69.3409	340.4790	478.5529



	CORRELATION							
	High	Mid	Mid	Low	Mid	Low	Mid	
MinEuclidean	1.0273	1.0294	1.0003	1.0118	1.0279	1.0264	1.0265	1.0274
MinPerp	1.0181	1.0229	1.0003	1.0286	1.0133	1.0243	1.0099	1.0264
MinPFL	1.0095	1.1112	1.0003	1.1115	1.0279	1.2044	1.0089	1.1233
MinPFL_1gh	1.0443	1.0647	1.0003	1.0418	1.0279	1.0294	1.0099	1.0443
MinPFL_Perp	1.0789	1.0777	1.0003	1.0745	1.0279	1.0264	1.0099	1.0774
MinPFL_MinEuclidean	1.0743	1.115	1.0003	1.0740	1.0279	1.0264	1.0099	1.0743
MinPFL_MinPerp	1.0577	1.1047	1.0003	1.0573	1.0279	1.0264	1.0099	1.0577

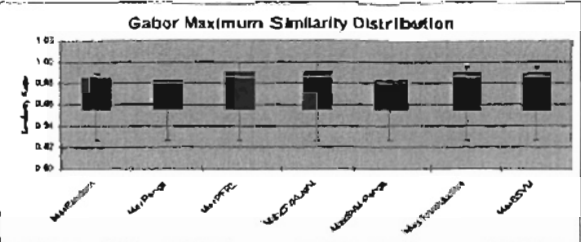


	ALL ON-BOX COLOR HISTOGRAM MAXIMUM SIMILARITY CORRELATION COMBINED							
	High	Mid	Mid	Low	Mid	Low	Mid	
MinEuclidean	1.0000	1.1124	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPerp	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPFL	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPFL_1gh	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPFL_Perp	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPFL_MinEuclidean	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPFL_MinPerp	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

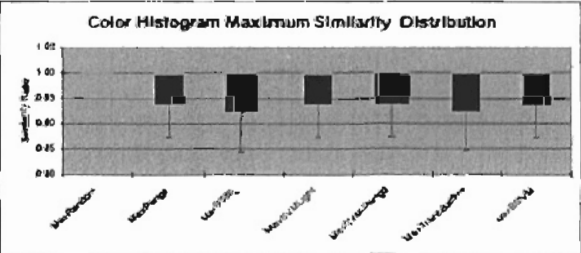


BOX PLOT OF ALL ON-BOX COLOR HISTOGRAM MAXIMUM SIMILARITY CORRELATION COMBINED

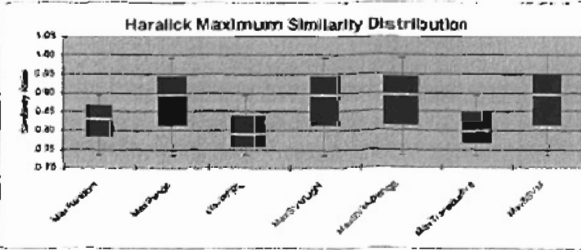
	GABOR							
	High	Mid	Mid	Low	Mid	Low	Mid	
MinEuclidean	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPerp	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPFL	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPFL_1gh	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPFL_Perp	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPFL_MinEuclidean	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPFL_MinPerp	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000



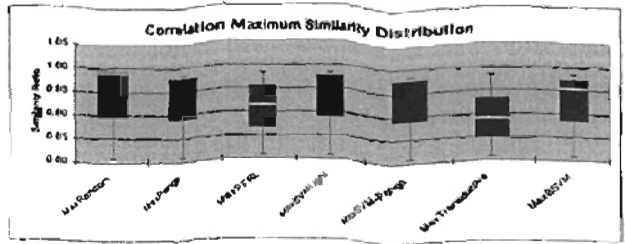
	COLOR HISTOGRAM							
	High	Mid	Mid	Low	Mid	Low	Mid	
MinEuclidean	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPerp	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPFL	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPFL_1gh	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPFL_Perp	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPFL_MinEuclidean	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MinPFL_MinPerp	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000



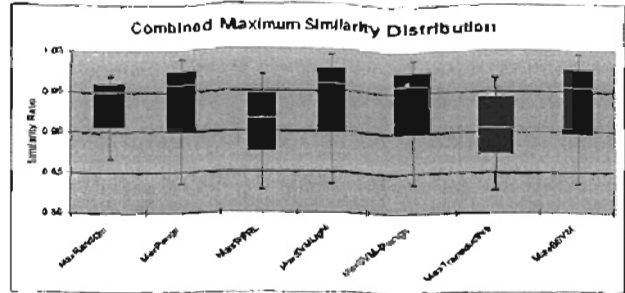
	HARRIS							
	High	Mid	Mid	Low	Mid	Low	Mid	
MinEuclidean	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPerp	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPFL	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPFL_1gh	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPFL_Perp	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPFL_MinEuclidean	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000
MinPFL_MinPerp	0.8830	0.8837	0.8830	0.8830	0.8830	1.0000	1.0000	1.0000



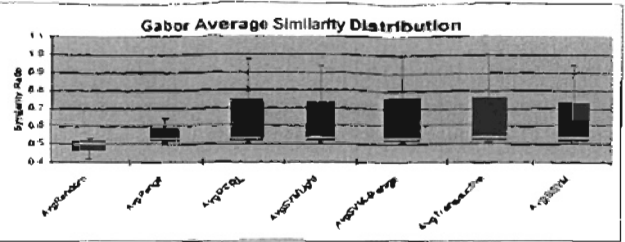
CORRELATION										
	High	Mid	Low	Mid	High	High	High	High	High	
Aug15-2008	0.9218	1.0000	0.8263	0.5957	0.9632	1.7079	11.6294	25.1204		
Aug16-2008	0.9737	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		
Aug17-2008	0.9547	0.9632	0.8081	0.5972	0.9691	1.6906	13.3489	23.7204		
Aug18-2008	0.8262	0.8412	0.6081	0.4822	0.9392	1.6689	12.4594	23.7204		
Aug19-2008	0.9767	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		
Aug20-2008	0.9547	0.9632	0.8081	0.5972	0.9691	1.6906	13.3489	23.7204		
Aug21-2008	0.9737	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		



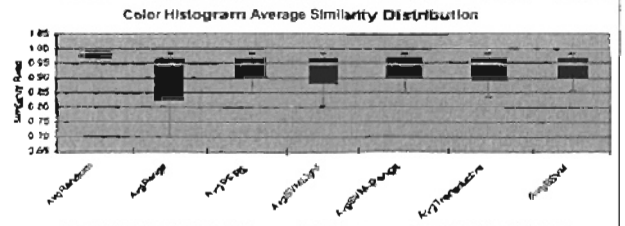
AVERAGE VALUE										
	High	Mid	Low	Mid	High	High	High	High	High	
Aug15-2008	0.9218	1.0000	0.8263	0.5957	0.9632	1.7079	11.6294	25.1204		
Aug16-2008	0.9737	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		
Aug17-2008	0.9547	0.9632	0.8081	0.5972	0.9691	1.6906	13.3489	23.7204		
Aug18-2008	0.8262	0.8412	0.6081	0.4822	0.9392	1.6689	12.4594	23.7204		
Aug19-2008	0.9767	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		
Aug20-2008	0.9547	0.9632	0.8081	0.5972	0.9691	1.6906	13.3489	23.7204		
Aug21-2008	0.9737	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		



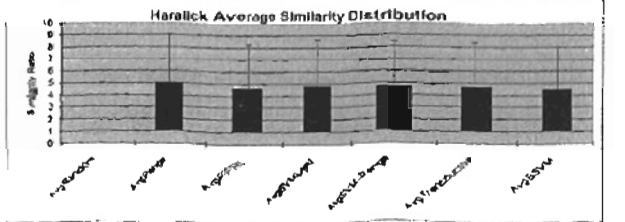
AVERAGE VALUE										
	High	Mid	Low	Mid	High	High	High	High	High	
Aug15-2008	0.9218	1.0000	0.8263	0.5957	0.9632	1.7079	11.6294	25.1204		
Aug16-2008	0.9737	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		
Aug17-2008	0.9547	0.9632	0.8081	0.5972	0.9691	1.6906	13.3489	23.7204		
Aug18-2008	0.8262	0.8412	0.6081	0.4822	0.9392	1.6689	12.4594	23.7204		
Aug19-2008	0.9767	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		
Aug20-2008	0.9547	0.9632	0.8081	0.5972	0.9691	1.6906	13.3489	23.7204		
Aug21-2008	0.9737	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		



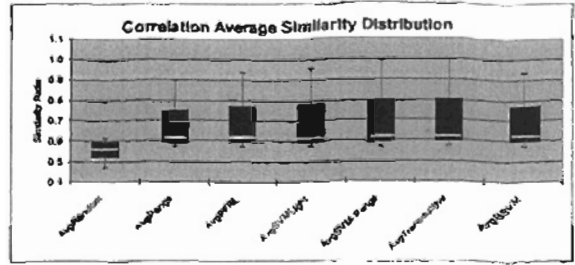
AVERAGE VALUE										
	High	Mid	Low	Mid	High	High	High	High	High	
Aug15-2008	0.9218	1.0000	0.8263	0.5957	0.9632	1.7079	11.6294	25.1204		
Aug16-2008	0.9737	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		
Aug17-2008	0.9547	0.9632	0.8081	0.5972	0.9691	1.6906	13.3489	23.7204		
Aug18-2008	0.8262	0.8412	0.6081	0.4822	0.9392	1.6689	12.4594	23.7204		
Aug19-2008	0.9767	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		
Aug20-2008	0.9547	0.9632	0.8081	0.5972	0.9691	1.6906	13.3489	23.7204		
Aug21-2008	0.9737	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		



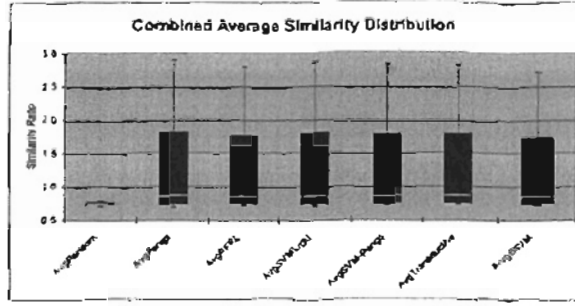
AVERAGE VALUE										
	High	Mid	Low	Mid	High	High	High	High	High	
Aug15-2008	0.9218	1.0000	0.8263	0.5957	0.9632	1.7079	11.6294	25.1204		
Aug16-2008	0.9737	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		
Aug17-2008	0.9547	0.9632	0.8081	0.5972	0.9691	1.6906	13.3489	23.7204		
Aug18-2008	0.8262	0.8412	0.6081	0.4822	0.9392	1.6689	12.4594	23.7204		
Aug19-2008	0.9767	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		
Aug20-2008	0.9547	0.9632	0.8081	0.5972	0.9691	1.6906	13.3489	23.7204		
Aug21-2008	0.9737	0.9833	0.8081	0.5952	0.9702	1.6689	12.4594	23.7204		



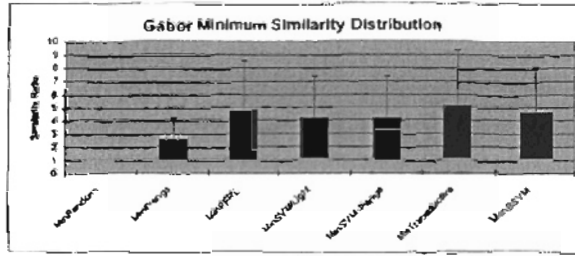
CORRELATION									
	High	Mid	Low	Min	Max	1-2Pval	3-4Pval	5-6Pval	Mean/Std
logPsimon	0.2824	0.6115	0.4447	0.5202	0.6720	74.5209	82.0000	113.5000	
logPsimon	0.7524	0.8021	0.5771	0.5926	0.8144	63.4070	63.5113	74.5209	
logPsimon	0.7524	0.8337	0.5320	0.5926	0.8144	63.4070	67.1143	74.5209	
logPsimon	0.7545	0.8571	0.5320	0.5926	0.8144	63.4070	67.1143	74.5209	
logPsimon	0.8030	0.7863	0.7720	0.5926	0.8144	63.4070	67.1143	74.5209	
logPsimon	0.8030	1.0000	0.5720	0.5926	0.8144	63.4070	67.1143	74.5209	
logPsimon	0.7720	0.8320	0.5720	0.5926	0.8144	63.4070	67.1143	74.5209	



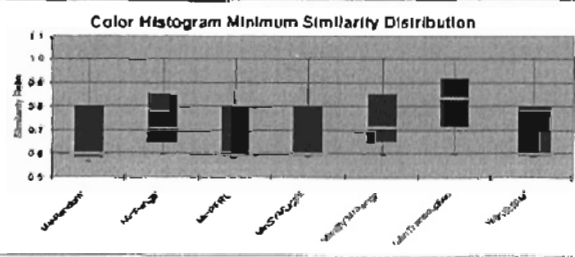
ALL DANCE, COLOR HISTOGRAM, HARALICK, & CORRELATION COMBINE									
	High	Mid	Low	Min	Max	1-2Pval	3-4Pval	5-6Pval	Mean/Std
logPsimon	0.7761	0.7647	0.7060	0.7176	0.7650	77.2303	291.8000	327.1144	
logPsimon	1.8363	2.0600	0.8614	0.7324	1.7714	274.4357	206.2000	246.1276	
logPsimon	1.8781	3.7066	0.7524	0.7324	0.7113	274.4357	206.2000	246.1276	
logPsimon	1.8780	2.7062	0.7715	0.7444	0.7113	274.4357	206.2000	246.1276	
logPsimon	1.8865	2.6472	0.7320	0.7518	0.7113	274.4357	206.2000	246.1276	
logPsimon	1.8410	2.4211	0.7314	0.7087	0.7113	274.4357	206.2000	246.1276	
logPsimon	1.5444	1.7761	0.7262	0.7520	0.7113	274.4357	206.2000	246.1276	



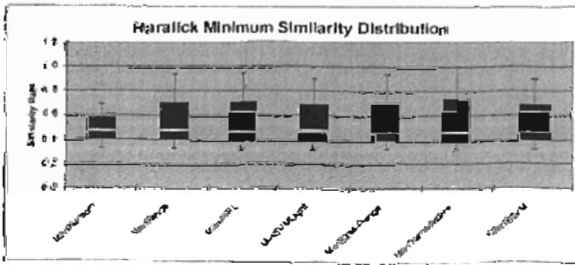
MINIMUM SIMILARITY (GABOR)									
	High	Mid	Low	Min	Max	1-2Pval	3-4Pval	5-6Pval	Mean/Std
logPsimon	1.0000	1.0000	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
logPsimon	2.0297	4.2149	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
logPsimon	1.7021	4.5644	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
logPsimon	1.1469	7.3266	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
logPsimon	4.1949	7.3266	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
logPsimon	1.1426	8.2917	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	
logPsimon	0.1664	5.1264	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000	



COLOR HISTOGRAM									
	High	Mid	Low	Min	Max	1-2Pval	3-4Pval	5-6Pval	Mean/Std
logPsimon	1.1174	1.0770	0.9454	0.9291	0.9464	88.1004	77.2000	84.7400	
logPsimon	1.1174	1.0770	0.9454	0.9291	0.9464	88.1004	77.2000	84.7400	
logPsimon	1.1174	1.0770	0.9454	0.9291	0.9464	88.1004	77.2000	84.7400	
logPsimon	1.1174	1.0770	0.9454	0.9291	0.9464	88.1004	77.2000	84.7400	
logPsimon	1.1174	1.0770	0.9454	0.9291	0.9464	88.1004	77.2000	84.7400	
logPsimon	1.1174	1.0770	0.9454	0.9291	0.9464	88.1004	77.2000	84.7400	
logPsimon	1.1174	1.0770	0.9454	0.9291	0.9464	88.1004	77.2000	84.7400	



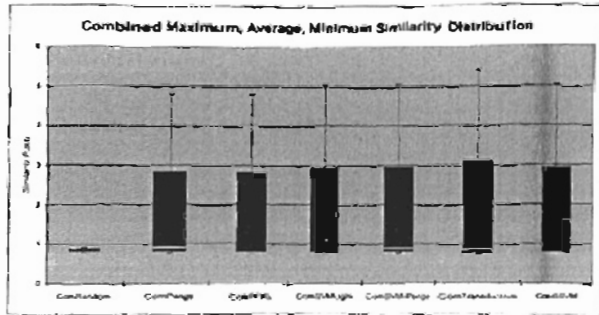
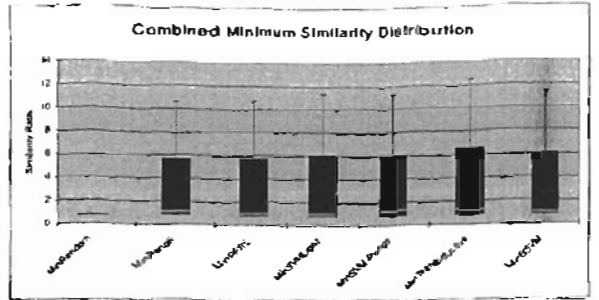
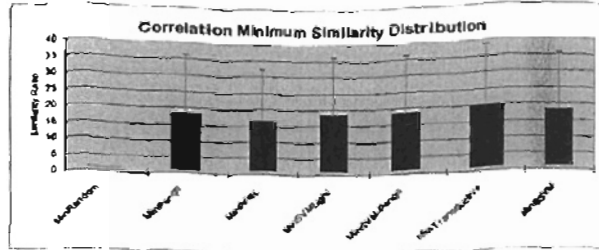
HARALICK									
	High	Mid	Low	Min	Max	1-2Pval	3-4Pval	5-6Pval	Mean/Std
logPsimon	0.5420	0.5466	0.5414	0.4870	0.4738	1.412024	1.421211	209.1300	
logPsimon	0.7064	0.5005	0.5414	0.4870	0.4738	1.412024	1.421211	209.1300	
logPsimon	0.7812	0.5005	0.5414	0.4870	0.4738	1.412024	1.421211	209.1300	
logPsimon	0.6408	0.5771	0.5414	0.4870	0.4738	1.412024	1.421211	209.1300	
logPsimon	0.7812	0.5771	0.5414	0.4870	0.4738	1.412024	1.421211	209.1300	
logPsimon	0.7812	1.0000	0.5414	0.4870	0.4738	1.412024	1.421211	209.1300	
logPsimon	0.5420	0.5771	0.5414	0.4870	0.4738	1.412024	1.421211	209.1300	



CORRELATION								
	High	Max	Min	Low	Mid	1-20%	3-20%	WorstCase
Combinator	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
ComPurge	0.3295	0.3660	0.0000	1.0000	1.0000	0.0000	0.0000	0.0000
ComPRL	0.2270	0.3455	0.0000	1.0000	1.0000	0.0000	0.0000	0.0000
ComSARigh	0.3295	0.3660	0.0000	1.0000	1.0000	0.0000	0.0000	0.0000
ComSARLeft	0.3295	0.3660	0.0000	1.0000	1.0000	0.0000	0.0000	0.0000
ComSARMid	0.3295	0.3660	0.0000	1.0000	1.0000	0.0000	0.0000	0.0000

ALL DATA COLOR HISTOGRAM RESULTS & CORRELATION COMBINED								
	High	Max	Min	Low	Mid	1-20%	3-20%	WorstCase
Combinator	0.0000	0.0000	0.7926	0.7926	0.7926	1.205581	1.602149	16.314324
ComPurge	0.3295	0.3660	0.7926	0.7926	0.7926	1.402149	1.702149	16.314324
ComPRL	0.2270	0.3455	0.7926	0.7926	0.7926	1.205581	1.602149	16.314324
ComSARigh	0.3295	0.3660	0.7926	0.7926	0.7926	1.402149	1.702149	16.314324
ComSARLeft	0.3295	0.3660	0.7926	0.7926	0.7926	1.402149	1.702149	16.314324
ComSARMid	0.3295	0.3660	0.7926	0.7926	0.7926	1.402149	1.702149	16.314324

ALL DATA COLOR HISTOGRAM RESULTS & CORRELATION COMBINED								
	High	Max	Min	Low	Mid	1-20%	3-20%	WorstCase
Combinator	0.0000	0.0000	0.7926	0.7926	0.7926	1.205581	1.602149	16.314324
ComPurge	0.3295	0.3660	0.7926	0.7926	0.7926	1.402149	1.702149	16.314324
ComPRL	0.2270	0.3455	0.7926	0.7926	0.7926	1.205581	1.602149	16.314324
ComSARigh	0.3295	0.3660	0.7926	0.7926	0.7926	1.402149	1.702149	16.314324
ComSARLeft	0.3295	0.3660	0.7926	0.7926	0.7926	1.402149	1.702149	16.314324
ComSARMid	0.3295	0.3660	0.7926	0.7926	0.7926	1.402149	1.702149	16.314324



2

VTPA

Patricia Jusuf

Candidate for the Degree of
Master of Science

Thesis: A MODULAR SYSTEM FOR COMPARISON OF NAVIGATION ALGORITHMS IN VISUAL DATA EXPLORATION

Major Field: Computer Science

Biographical:

Personal Data: Born in Bandung, Indonesia. On March 18, 1978, daughter of Jusuf Sutrisno and Emmi Lombri.

Education: Graduated from Saint Aloysius High School, Bandung, Indonesia in August 1996; received Bachelor of Science degree in Computer Science from Oklahoma State University, Oklahoma, USA in August 2001. Completed the requirements for the Master of Science degree at the Computer Science Department at Oklahoma State University in May 2003.

Experience: Employed as a graduate teaching assistant at Computer Science Department, Oklahoma State University in 2001.