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CERTIFICATE OF APPROVAL

Master's Thesis

This is to certify that the Master's Thesis of

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A ROBUST VISUAL METHOD FOR ASSESSING THE RELATIVE PERFORMANCE OF EDGE DETECTION ALGORITHMS

by

MICHAEL D. HEATH

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Computer Science
Department of Computer Science and Engineering
College of Engineering
University of South Florida

December 1996

Major Professor: Kevin W. Bowyer, Ph.D.

DEDICATION

To my wife, Lynn...

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I wish to express my sincere thanks to my mentor, Dr. Bowyer, for his time, insight and fervor. I also wish to thank Dr. Sarkar and Dr. Sanocki for their guidance throughout this research.

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A ROBUST VISUAL METHOD FOR ASSESSING THE RELATIVE PERFORMANCE OF EDGE DETECTION ALGORITHMS

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An Abstract

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A new method for evaluating the performance of edge detection algorithms is presented. Unlike most of the methods that are currently available for this task, the proposed method tests the performance of algorithms on complex real images and incorporates human subjects into the evaluation process. Edge detectors are evaluated by their ability to produce edges that provide for the quick and accurate recognition as judged by humans of a three dimensional object from a greyscale image of the object in its natural setting. A complete evaluation methodology is presented for determining whether a statistically significant difference exists in the relative performance of edge detection algorithms. This method is applied to measure the relative performance of five modern edge detection algorithms using 28 images. The results indicate that there are statistically significant differences in the performance of these algorithms and that the relative performance depends on the method used for selecting the input parameters. Significantly better performance was attained by the edge detectors when the parameters of each detector were optimized individually for each image than when a single set of parameters is optimized for the entire set of images. The methods used in this evaluation are lengthy and may prohibit the regular application of this method in its complete form. Therfore, a shortened method is presented for evaluating new edge detection algorithms that leverages off of the results presented in this thesis.

Abstract Approved : ______________________________

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Date Approved: ____________________

CHAPTER 1

INTRODUCTION

The boundaries of object surfaces in a scene often lead to oriented, localized changes in intensity in an image, called edges. This observation, combined with a commonly held belief that edge detection is the first step in vision processing, has fueled a long search for a good edge detection algorithm to use in computer vision. This search has constituted a principal area of research in low-level vision and has led to a steady stream of edge detection algorithms published in the computer vision journals over the last 30 years. Even recently, new edge detection algorithms are published each year. Table 1 lists 21 algorithms published in three major journals within the last three years.

Researchers generally agree that substantial improvements have been made in edge detection algorithms since the early days of work in this area by Roberts [30] and Sobel [36], but there is also a belief that edge detection algorithms are reaching an asymptotic level of performance [4]. This conjecture, however, is hard to confirm or disprove since the publications which have presented methods of assessment have not been widely accepted in the edge detection community. This is evident from their limited application in publications.

There is a widely held belief that people can visually evaluate the relative quality of edge maps produced from the same image. The edge maps could be produced from the same algorithm applied with two sets of input parameters or they could be produced by two different algorithms. In the former case, the better edge image would indicate which input parameters to use for the algorithm and in the latter case the better edge image would indicate which algorithm worked better.

This thesis formalizes the idea of using visual comparisons in evaluating edge images and presents a methodology for using visual comparisons to measure the relative performance of edge detection algorithms. The new edge detection assessment method is demonstrated in this thesis by applying it to rank the relative performance of five published edge detection algorithms.

The proposed method for evaluating edge detection algorithms is lengthy in the complete form as described in this thesis because it relies upon human evaluation of a large number of edge images. If the images and results presented in this thesis are used as a basis for evaluations of this type, a shortened methodology can be used to evaluate new edge detectors. The shortened method is presented in the discussion section and the images and data needed to apply it are provided.

This thesis is organized as follows. Chapter 2 provides a brief survey of the published edge detector evaluation methods. Chapter 3 describes the use of visual evaluation in assessing edge detector performance. Chapter 4 describes the edge detectors evaluated in this thesis. Chapter 5 presents a detailed description of the methodology developed and applied in this work. Chapter 6 presents the results of the edge detector comparison. Finally, chapter 7 contains a discussion of the methodology and results.

Source	Nature of the algorithm	Performance presented on	Real image ground truth	Algorithms compared
[17](PAMI, 1995)	Logical/Linear	2 real	0	Canny
[15](PAMI, 1995)	covariance models	3 real	0	none
[29](PAMI, 1994)	expansion matching	1 real	0	Canny
[13](PAMI, 1993)	dispersion of gradient direction	1 real	0	Sobel
[12](PAMI, 1993)	regularization	2 real	0	LoG, Canny
[22](CVGIP, 1994)	voting based	3 real 3 range 2 synth	0	Canny
[43](CVGIP, 1994)	linear filtering	1 real, 1 synth	0	LoG
[33](PR, 1995)	filtering	1 synth, 1 real	0	zero-crossing
[39](PR, 1995)	statistical	1 synth, 3 real	0	Sobel
[40](PR, 1995)	filtering	7 synth, 1 real	0	none
[34](PR, 1995)	filtering	4 real	0	none
[26](PR, 1995)	statistical	4 real	0	Canny, LoG
[10](PR, 1995)	search	1 synth, 3 real	0	Canny, LoG, Ashkar&Modestino
[32](PR, 1995)	filtering	4 real	0	none
[37](PR, 1994)	neural nets	1 synth, 1 real	0	Canny
[3](PR, 1994)	genetic opt.	1 synth, 1 real	0	simulated anneal local search
[25](PR, 1994)	co-occurrence	4 synth, 2 real	0	Canny Jain's stochastic
[16](Pr, 1994)	statistical	1 synth, 1 real	0	Sobel, DoG, Haralick, Anisotropic diffusion
[41](PR, 1993)	local masks	2 synth, 2 real	0	other hierarchical
[45](PR, 1993)	filtering	1 real	0	none
[8](PR, 1993)	statistical	3 real	0	Nalwa, DoG

Table 1. Recently published edge detection algorithms.
Edge detection algorithms in PAMI, CVGIP: Image Understanding (renamed Computer Vision and Image Understanding in January 1995) and PR from 1993 thru 1995. The number of images is counted from the images presented in the paper. Ground truth is counted as objective specification of correct edge pixels. The last column lists the edge algorithms considered in the comparison of algorithms. Note that the Canny edge detector is the one most frequently used for comparison in the papers presenting new algorithms.

CHAPTER 2

BACKGROUND

Evaluation methods for edge detection algorithms can be categorized as shown in Figure 1. At the highest level, evaluation methods can be categorized according to whether they employ a theoretical analysis or an analysis of the edge pixels produced by an algorithm. Edge image analysis methods can be further categorized by whether or not they require “ground truth” locations of the “true” edges in the image.

2.1 Evaluation Methods: Theoretical

The theoretical method for evaluating edge detectors is done by applying a mathematical analysis. In the analysis, the algorithm being assessed is never applied to an image. Instead, the input to the algorithm is mathematically characterized and the performance is determined analytically. The approach is very similar to methods used in the design of edge detection algorithms.

Abdou and Pratt [1] presented a theoretically-based method for comparing the performance of enhancement and thresholding edge detectors. The method relied on measuring two desirable attributes of an edge detector; 1) an invariance in measured edge strength to an edge at different orientations and 2) a response to edges that rapidly diminishes as the detector moves away from an edge. Specific methods for measuring each of these properties were devised using a mathematical model of an ideal step edge. Several edge detectors were then compared using these measures.

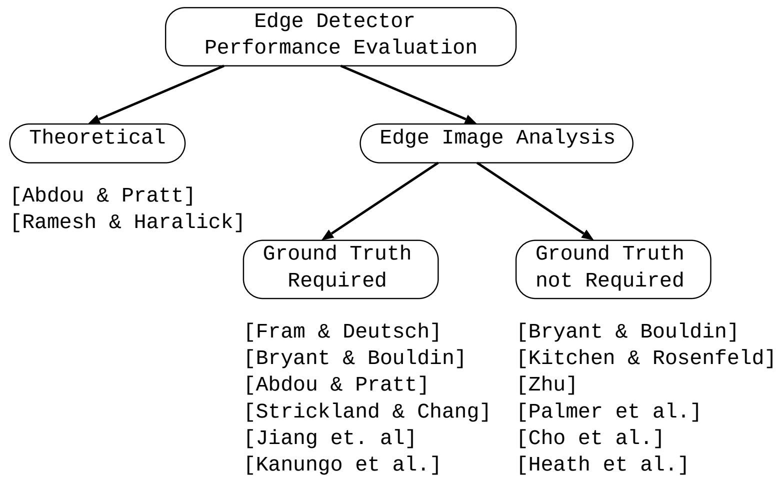


Figure 1. A categorization of methods for edge detector performance evaluation.

Ramesh and Haralick [28] presented a quantitative performance evaluation measure using an edge model of an ideal ramp edge embedded in independent, identically distributed Gaussian noise. Parametric expressions were formulated for the probability of false negatives and false positives as a function of edge strength threshold for (a) an enhancement and thresholding edge detector with hysteresis and (b) a morphological edge detector. These expressions were then evaluated and plotted to form a graph. The relative performance of the algorithms was then determined by examining the area under the curves.

2.2 Evaluation Methods: Edge Image Analysis

The most common method for evaluating the performance of edge detection algorithms is to apply an edge detector to an image and analyze the edges that are found. The techniques that have been developed for evaluating the quality of the edges can be generally categorized by whether or not they rely on ground truth. This is an important distinction, because determining the true edge locations in real images is very difficult. Therefore, the methods that require ground truth usually rely on the use of synthetic images or hand specified ground truth for (simplistic) real images.

2.2.1 Methods that Require Ground Truth

The methods that require ground truth use a variety of approaches to measure the agreement between the detected edges and the ground truth. The most common ways of doing this are to measure the number of false negatives and false positives and the average displacement of the detected edges from their true location.

Fram and Deutsch [11] developed a method for evaluating edge detectors. The method involved measuring the performance of an edge detector on an ideal input image and on a set of degraded edge images using two parameters. These parameters measured the ratio of the number of correctly detected edge pixels to the total number of edge pixels and the fraction of the edge covered by detected edge pixels. The images they used were derived from an idealized vertical edge image of a specified contrast by adding a fixed amount of independent, identically distributed Gaussian noise.

Several edge detectors were compared in their paper. This was done by examining the two parameters and a binary edge detection decision formulated from the two parameters for each image/edge detector combination. Graphs of the results showed that all three parameters generally increased with nominal edge contrast. An attempt was made to confirm the measured performance by applying each detector to a real image and including those images in the paper to allow subjective evaluation by the reader.

Bryant and Bouldin [5] published a method for assessing the performance of an edge detector that uses the edges detected in a real image. This measure, termed absolute grading, expresses the degree of correlation of an edge image with a manually constructed key or target scene. The method was applied to measure the performance of several edge detectors and to measure the benefit of thinning and edge linking in post processing. A real aerial image was used in the edge detector comparison. The ground truth was obtained by drawing an edge by hand on the image. The results showed an improvement made by the post processing.

Abdou and Pratt [1] presented two methods for evaluating enhancement and thresholding edge detectors using synthetic images. The first method involved plotting probability of false positives and false negatives as a function of the set threshold for each edge detector. Visual inspection of these plots indicates the performance of an algorithm by the relative area under the curve.

The second method they described was a extended form of the Pratt figure of merit [27] adapted to include the evaluation of diagonal edges. This figure of merit measures the distance from the detected edge pixels from their true location as specified in the ground truth. This method can be adapted to provide a penalty between smeared and isolated, but offset, edges. A comparison of edge detectors was done using a methodology similar to the one used by Fram and Deutsch. The figure of merit was applied to vertical and diagonal ideal step edges, each degraded to multiple signal to noise ratios by adding independent, identically distributed Gaussian noise. The difference was that the signal to noise was adjusted by adapting the amount of added noise instead of changing the contrast of the edge while holding the noise level constant.

Strickland and Chang [38] described a metric for calculating an edge quality score as linear combination of individual measures of edge continuity, smoothness, thinness, localization, detection and noisiness. The weights are obtained through a training process that requires a user to threshold synthetic edge images. The selection of the weights allows the edge quality score to be adapted to measure the quality of the edges for different users and applications.

Jiang *et al.* [18] presented a method for evaluating edge detectors for range images. The method is distinct from other methods that require ground truth because they used real images and established ground truth using an objective method. The ground truth was obtained by outlining the boundary of each apparent surface patch by hand from range and intensity images of simple, non-textured polyhedral objects. Sixteen performance metrics related to correct edges, spurious edges and missing edges were then calculated for a set of image/ground truth pairs. A statement was then made that some optimality criteria could be defined using the 16 performance measures to do parameter optimization and edge detector comparison, although no particular criteria was defined.

Kanungo *et al.* [19] described a method for characterizing the performance of a system that used edge detection followed by line detection. To do this, they defined a detection problem and measured the system performance for a specified detection threshold. This allowed them to characterize the performance of the system as a function of two variables that characterized the distortion of a vertical edge for a 75% detection rate. These variables were the edge contrast threshold and the angle of a square wave interference pattern. They applied the method to measure the performance of two line detection algorithms that both followed the same edge detection algorithm.

2.2.2 Methods that do not Require Ground Truth

The methods that measure edge detector performance by analyzing the detected edges without using ground truth examine the form of the detected edges or the support for the detected edges measured using a model for the edge. The form of an edge is often characterized by how thin, smooth or continuous it is. Because ground truth is not used, these methods cannot measure the displacement of the detected edges from their true location or whether edge were falsely detected or were missed.

Kitchen and Rosenfeld [21] described a method for evaluating edge detection algorithms using a measure of the coherence of the detected edges. This coherence is defined as a linear combination of individual thinness and the continuation measurements. This method evaluates the form of the edges. However because it can not measure the displacement of the edges from their true locations it does not suitably capture a necessary component of the quality of the edges. For this reason, modern edge detectors that blur the image before detecting the edges can score very highly with this measure by producing very distorted edges with good local form that are not usable for any task.

Bryant and Bouldin [5] presented a method for evaluating the quality of an edge image called relative grading. This method compares an edge image to a consensus decision of the edges detected by a suite of edge detection algorithms. This method is similar to some of the other methods that require ground truth because the edge quality is measured by comparing an edge image to a ground truth scene. The difference is that in relative grading, the ground truth is estimated from the combined output from a set of edge detectors. The problem with this method is that the accuracy of this estimated ground truth may be poor. For example, if actual edges were missed by most of the edge detectors used to make the ground truth, correctly marked edges in the image being evaluated may actually lower evaluated edge quality.

Zhu [44] developed a different way to compute and express the method of local edge coherence developed by Kitchen and Rosenfeld [21]. The new performance measure was applied to both synthetic and real images. The implementation of this new measure is different from the earlier work but its main qualities are the same. Therefore, this implementation has the same limitations of those in the earlier work.

Palmer *et al.* [24] developed a method for evaluating a system for finding lines in images. This system involved edge detection followed by line detection. A measure of edge quality was defined to be a nonlinear combination of individual scores of the support for a line at each edge pixel. These individual measurements are obtained by calculating the ratio of the within class variance to the between class variance of image intensities, where the classes are made up from a sample of pixels on each side of the line. The edge quality obtained from this performance measure tracked with the edge quality obtained from a measure that used ground truth for a synthetic image degraded with noise. Since line detection was used, this measure can not directly be applied to measuring curved edges. However, the authors suggested that a similar quality measure could be constructed for curved edges as well.

Cho *et al.* [7] presented a method for measuring the performance of an edge detector on real images using bootstrapping. The method has three steps. First, the distribution of the edge detectors' responses resulting from perturbations of the input are calculated. Second, these distributions are used to estimate the confidence in the presence of the assumed edge model and the likelihood of an edge being an edge candidate. Finally, the performance measure is calculated as the product of the confidence and likelihood measures. The method was demonstrated for a real image using weighted and unweighted differentiation edge detectors.

Heath *et al.* [14] proposed a method for evaluating edge detection by their performance when applied to real images of complex scenes. The algorithms were evaluated by using human participants to examine the quality of each edge image for the task of recognizing an objects in the image. That work was an initial phase of the work described in this thesis. The evaluation method described in this thesis is an improved form of the method used in the initial work. The evaluation of edge detectors in this thesis also improved on the comparison done in the initial work because 1) a larger sample of images were used, 2) more modern edge detection algorithms were evaluated, and 3) one algorithm was modified to use non-maximal suppression and hysteresis.

Authors	Image Type	Images Used	Requires Ground Truth	Comments
Fram & Deutsch [11] 1975	Synth.	1 Synth. 1 Real	Yes	Vertical step edge image. Real edge images not evaluated.
Bryant & Bouldin [5] 1979	Real	1 Real	Yes and No	Subjective ground truth specified for a single edge by hand.
Abdou & Pratt [1] 1979	Synth.	1 Synth. 3 Real	Yes	Horizontal, vertical and diagonal step edges used.
Kitchen & Rosenfeld [21] 1981	Real	2 Synth.	No	Method demonstrated using only synthetic images.
Ramesh and Haralick [28] 1992	Synth.	1 Synth. 2 Real	Yes	Synthetic images were generated for a ramp edge embedded in noise.
Strickland & Chang [38] 1993	Synth.	1 Synth.	Yes	Adaptable metric that is difficult to use with inclined or curved edges.
Jiang *et al.* [18] 1995	Real	80 Real (Range)	Yes	The use of simple scenes allowed accurate ground truthing by hand.
Kanungo *et al.* [19] 1995	Synth.	1 Synth.	Yes	Vertical edge with added square wave noise. Detection task was used.
Cho *et al.* [7] 1996	Real	1 Real	No	Evaluates edge detectors that rely on the same edge model.
Heath *et al.* [14] 1996	Real	8 Real	No	Performance evaluated using complex scenes and an object recognition task.
Zhu [44] 1996	Real	2 Synth. 2 Real	No	The method is very similar to the one used in [21].
Palmer *et al.* [24] 1996	Real	1 Synth. 5 Real	No	Edge detection is evaluated within a line detection system.

Table 2. Summary of edge detection evaluation methods.

This table lists the papers that have presented methods for doing edge detection evaluation. The image type describes the type of the images used by the evaluation method. The number of images used was measured by counting the number of real images and the number of synthetic images presented in the paper. In the case of synthetic images, the images that were derived by manipulating a synthetic image, were not counted as separate images.

CHAPTER 3

HUMAN VISUAL EVALUATION

If edge detection is the initial step in visual processing, edge detection algorithms should identify edges that contribute to the success of overall vision processing. Therefore, edge detectors should be evaluated in the context of a vison system performing a task.

Edge detection algorithms should be evaluated using real images. Although synthetic images may be useful in preliminary evaluations of the performance of an edge detector during the design phase, they should not be the only ones used in the final evaluation of an algorithm's performance. This is because they do not adequately test the assumptions made during the design of the algorithm. Since edge detectors are developed to find edges in real images (collected by cameras), they should be evaluated with real images.

Using real images to evaluate edge detectors requires that people supply the desired output for an edge detector. The problem with requirement is that specifying the ground truth for real images of complex scenes is very difficult. While it is possible for people to label some of the edges in an image, the difficulty in labeling all of the edges is clear to anyone who has tried to do it. For example, how does one label the edges on a tree or the edges on a desk with wood grain?

Admittedly, there are several several methods for assessing the performance on real images without ground truth [21] [5] [44] [24] [7]. These methods all leave something to be desired. The methods in [21] and [44] do not consider the displacement of detected edges from their true locations. The method in [5] can punish an edge detector for detecting correct edges if they were missed by the majority of the edge detectors used to establish the ground truth. The method in [24] can only be applied to straight line edges. Finally, the measured performance by the method in [7] depends on the choice of the algorithm for establishing the support for perturbing the input.

The only other published edge evaluation method that incorporates the human visual system is one earlier study using the preliminary version of the method used in this work [14]. The method relies on the subjective evaluation of edge images by people. This removes the need for explicitly specifying the ground truth for an image. Edge images are evaluated by a subjective judgment of how useful the detected edges are for recognizing an object in the scene.

There are, of course, issues that must be addressed in order to effectively use the human visual system in evaluating edge detection algorithms. The principal issue is that human evaluations of this type are subjective and inherently noisy. Therefore, a well thought out experimental design must be adopted if human ratings are to be used in assessing the performance of edge detectors. The method is described in detail in chapter 5.

CHAPTER 4

EDGE DETECTORS

We selected five edge detectors to evaluate. Three criteria were used in selecting algorithms to evaluate. These were (1) to include a diverse mix of algorithms including representatives of the state of the art in edge detection, (2) to only evaluate edge detection algorithms that had been presented to the vision community through a refereed publication and (3) to only evaluate algorithms for which code was readily available.

The reasons for including the first two criteria are clear. The third criterion was specified for two reasons. First, the details of an algorithm are often critical to the performance of the method and the precise implementation of a program from a paper is not always possible. Second, the results of a comparison are most useful when researchers can get the programs that were evaluated. Therefore, whenever possible, an implementation of an algorithm was obtained from the authors who developed it.

Ideally, our objective was to not modify the the code we received. Unfortunately, this was necessary in several cases. Some reasons for doing this were that the evaluation methodology required the detected edges to be represented as edge images in a common format, or that we decided to add non-maximal suppression or hysteresis thresholding.

Based on these criteria, algorithms by Canny [6], Nalwa [23], Iverson [17], Bergholm [2] and Rothwell [31] were selected. The choice to include only five algorithms was made to keep the experimental comparisons at a reasonable size.

Because every program, except the Bergholm edge focusing program, was modified to some degree, it is important that the results of the performance evaluation be attributed to the implementation of the algorithm that was used. I take full responsibility for all of the changes we made to the algorithms.

Information is given in a separate subsection for each of the five algorithms included in the evaluation. The information in each section includes the reason for selecting the algorithm, the source of the implementation, the parameters the algorithm requires and all of the modifications made to the code.

4.1 Canny Algorithm

The Canny edge detection algorithm is a considered a "standard method" and it is used by many researchers. Including it in the comparison was very useful because the result of the performance evaluation is a relative rating of the performance of the edge detection algorithms.

Canny edge detection uses linear filtering with a Gaussian kernel to smooth noise and then computes the edge strength and direction for each pixel in the smoothed image. This is done by differentiating the image in two orthogonal directions and computing the gradient magnitude as the root sum of squares of the derivatives. The gradient direction is computed using the arctangent of the ratio of the derivatives. Candidate edge pixels are identified as the pixels that survive a thinning process called non-maximal suppression. In this process, the edge strength of each candidate edge pixel is set to zero if its edge strength is not larger than the the edge strength of the two adjacent pixels in the gradient direction. Thresholding is then done on the thinned edge magnitude image using hysteresis. In hysteresis, two edge strength thresholds are used. All candidate edge pixels below the lower threshold are labeled as non-edges and all pixels above the low threshold that can be connected to any pixel above the high threshold through a chain of edge pixels are labeled as edge pixels.

The Canny edge detector requires the user to input three parameters. The first is *sigma*, the standard deviation of the Gaussian filter specified in pixels. The second parameter, *low*, is the low threshold which is specified as a fraction of a computed high threshold. The third parameter *high*, is the high threshold to use in the hysteresis and is specified as a percentage point in the distribution of gradient magnitude values for the candidate edge pixels.

The implementation of the Canny edge detector used was originally written at the University of Michigan. Parts of the code were rewritten to have better structure and to allow the processing of non-square images.

4.2 Nalwa Algorithm

The Nalwa edge detection algorithm was selected because it represented the method of edge detection by surface fitting. It differs from the linear filtering approach used in the Canny edge detector because the derivative of the image is not computed. Instead, tanh and quadratic functions are fit to the image intensities in a 5x5 pixel window that is scanned across the image. If the tanh fit has a lower error than the quadratic fit, then a candidate edge is marked, otherwise an edge was not found. The contrast of the candidate edge pixels is then thresholded to reduce the number of spurious edges.

The implementation of the algorithm was obtained from the Vic Nalwa. The output format was originally a text file that indicated the sub-pixel location of each edgel as well as the edge contrast and orientation. To use our evaluation methodology, it was necessary to modify the algorithm to produce an edge image by plotting the edge points on a grid with the dimensions of the image. The edge images produced by the modified algorithm were in some cases more than one pixel thick. To take care of this, the non-maximal suppression algorithm from the Canny edge detector was added to thin the edges. Twice the edge contrast was used in place of the gradient magnitude in this process. Hysteresis was added, at the suggestion of Vic Nalwa, in a personal communication. Without adding hysteresis, the Nalwa algorithm could not be tuned to each image as specifically as the Canny algorithm could.

The Nalwa edge detector initially required the user to specify one parameter, but the modified program required the user to specify three parameters. The range used for the *blur* parameter was 0.6 to 1.5. It was determined from a recommendation from Vic Nalwa to use values in this range. The values of the hysteresis thresholds, *low* and *high*, were obtained through experimentation.

4.3 Iverson Algorithm

The Iverson logical/linear edge detector was included in the evaluation because it presented a method to improve the performance of a linear edge detection algorithm by modifying it to include logical checks for the existence of an edge. The motivation for doing this was to reduce the number of false positive edges detected with linear edge detectors without losing sensitivity to detecting true edges.

The edge detector implementation (version 1.0.3) was down loaded from an FTP site (ftp://ftp.cim.mcgill.ca/pub/people/leei/loglin.tar.gz). The program itself was not modified at all, but post processing was applied to the output. This was done because the algorithm output a postscript file of edge segments plotted on a grid with a higher resolution than the original image. Since we required all of the algorithms to represent the edges in a binary image with the dimensions of the original image, each edgel was plotted as a pixel in this image. Since the algorithm initially allowed for detecting multiple edgels at the same position with different orientations, the edge direction was taken to be the direction with the largest associated edge strength. Non-maximal suppression was added to assure that thin edges were produced and hysteresis was added to allow greater flexibility for tuning the algorithm to each image.

The algorithm initially did not require the user to specify any parameters, however, the modified version allowed the user to specify three parameters. Default values were specified for the degree and the threshold. The *direction* parameter controls the number of directions the algorithm looks in to find edges. This parameter was set at four values between four and ten. The values to use for the hysteresis, *low* and *high*, were obtained through experimentation. Both thresholds were set to zero to effectively remove the hysteresis thresholding process for some of the parameter combinations specified for the algorithm. This edge detector is capable of separately detecting step edges and both positive and negative contrast lines. Only step edges were searched for in this evaluation.

4.4 Bergholm Algorithm

The Bergholm edge focusing algorithm was selected because it represented an approach that used a scale space representation to try to find edges that are “significant”.

Edges are first detected in at a course resolution. This is done by blurring the image with a Gaussian filter, and finding the the pixels that have gradient that is both a local maximum and that is is greater than a threshold value. The algorithm then “focuses” these edges by tracking them back through scale space to finer resolutions (images that were smoothed less with Gaussian filters). At successively finer scales, edges are only searched for near image positions where edges were found at the next coarser scale.

The implementation of the Bergholm detector was obtained as part of the Candela image processing package obtained by anonymous FTP (from ftp.bion.kth.se/cvap/2.1). The program was not changed at all. The edge images were re-mapped to display the edges in black on a white background.

The algorithm required three parameters to be set; the *starting sigma*, the *ending sigma* and an edge *threshold.* The range of values for the *starting sigma* and the *ending sigma* were 5 to 0.5. This is consistent with the parameter values in the journal paper that presented the algorithm [2]. The range of values for the *threshold* was 5 to 20 and was determined through experimentation.

4.5 Rothwell Algorithm

The last algorithm included in the experiment was unique in that it employed dynamic thresholding that varied the edge strength threshold across the image. Overall, the algorithm was very similar to the Canny algorithm because Gaussian smoothing was followed by differentiation. The difference between the two algorithms was that the Rothwell algorithm does edge thinning as a post edge detection process and that dynamic thresholding is used instead of hysteresis. The reason for not using non-maximal suppression to do the thinning was a claim that it fails at the junctions in images because of the smoothing process. The reason for not using hysteresis was a belief that the strength of an edge has no particular relevance to its value for higher level vision processing (such as object recognition). Instead of the hysteresis, a single threshold is used.

The implementation of this algorithm was constructed from combining pieces of the Canny edge detector code and pieces of C++ code obtained from the authors of the paper [31].

This algorithm required that the user input three parameters. These are the smoothing amount *sigma*, the edge *threshold* and a parameter *alpha* that adapts the edge threshold to increase the detection of pixels that are near other edges. The range of values for *sigma* was 0.5 to 2.0 pixels. The value of *alpha* was set between 0.8 and 0.95, to include the value of 0.9 used in the journal paper where this algorithm was presented.

CHAPTER 5

PERFORMANCE EVALUATION METHODOLOGY

Evaluating the performance of edge detection algorithms involves more than simply evaluating the edges produced by an algorithm. It also involves selecting images over which to assess the performance and determining the parameters to use for the algorithms in an unbiased manor.

Several criteria were adapted to shape the methodology presented in this thesis. These general criteria should probably be incorporated into any edge detection performance method. The criteria are:

1) Edge detector performance evaluation should be done in the context of a vision task. Although one could conceivably measure the "quality" of edges outside the context of a vision task, the results that are obtained would be difficult to interpret in terms of vision processing.

2) The domain of images that will be processed by a system executing a certain task must be defined. The performance of the vision system should then be evaluated by processing real images that are representative of that domain.

3) An unbiased method of determining the input parameters must be used. The choice of parameters can have a substantial effect on the results, so parameters must be set in a fair way that does not bias any algorithm.

4) The evaluation of edge detectors must be done in a blind fashion. During the evaluation of an algorithm, the identity of each algorithm should not be known. This is good scientific practice to avoid biasing the results.

The proposed edge detector evaluation methodology relies on the human vision system and a statistical analysis for assessing edge detector performance. Selecting the human vision system to do this task assumes that researchers accept using human evaluation of edge images. While this may be controversial, it can be argued that this is, and has been, the standard that edge detection researchers have used. The human vision system was selected because, at the present time, it is the only way to incorporate high level visual processing into the evaluation process.

The evaluation methodology relies on estimating the ability of the human vision system to perform three dimensional object recognition using the edges produced from a grey scale image by an edge detection algorithm. To do this, images were collected and were processed by algorithms using input parameters that were optimized to the images. The resulting edge images were evaluated by a number of subjects in a controlled experiment. The subjective ratings that were obtained in the experiment were then evaluated to determine the statistically significant differences in edge detector performance.

The methodology in this research was developed and applied to investigate the reliability of human evaluations of edge images for the purpose of edge detector evaluation, to measure the magnitude of the effect of adapting the input parameters for edge detectors to a set of images vs. to individual images, and to evaluate the relative performance of edge detection algorithms.

5.1 Task Specification

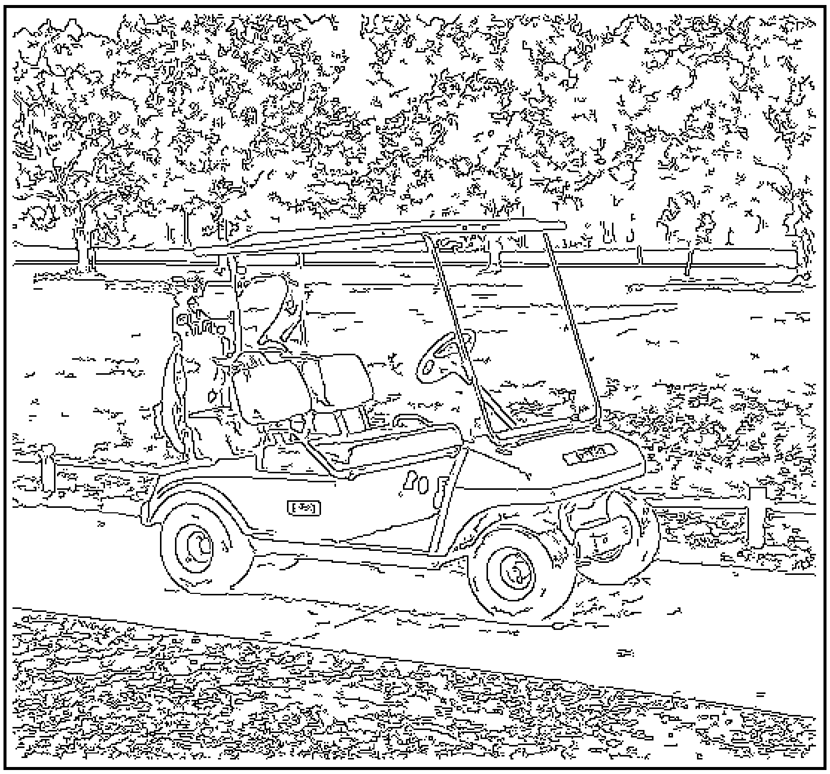
The vision task used in this evaluation was to rate how well the detected edges in an image support object recognition. It is important to note that the accuracy of recognizing objects was not directly measured in this work. Instead, a subjective measure of the perceived ease of recognizing an object from an edge image was used because it allowed the participants in the experiments to evaluate the output from several algorithms produced from the same grey scale image. If the accuracy of recognizing objects had been used, each participant could only have evaluated a single edge image produced from each grey scale image because the participant would have learned the identity of the object during the experiment.

In the experiments, participants were shown a grey scale image accompanied by the edge images produced from a set of edge detection algorithms and were instructed to rate each edge image. The purpose of including the grey scale image was to assure that all participants knew the true identity of the central object. The rating indicated how well the participant judged that the edges in the image supported the accurate recognition of the central object.

A rating scale with a range of one to seven was provided. The scale was defined for a 7 to indicate that the “Information allows for easy, quick and accurate recognition of the object”. A 1 indicated that there was “No coherent information from which to recognize the object”. Intermediate numbers indicated intermediate ratings. An example edge image with the rating scale can be seen in Figure 2.

5.2 Image Selection and Categorization

Since object recognition was the vision task, a set of images was collected that contained objects that people could readily recognize. A wide variety of objects was desired, and so objects were categorized as man-made or natural and as textured or exp2_d_2.0_1.0_15.0



Information allows for easy, quick and accurate recognition of the object.	7	6	5	4	3	2	1	**No coherent information from which to recognize the object.**

Figure 2. An example evaluation sheet.

The label in the upper left corner is a coded identifier for this image. The edges appear in black on a white background. The rating scale appeared on each evaluation sheet.

non-textured and images of each type of object were collected. Images were collected by photographing common objects in their natural settings. The photographs were taken so that the objects were centered in the image, occupied a large portion of the scene and appeared in an intuitively typical orientation.

All photographs were taken with a 35mm camera on color negative film using a 50mm lens. The images were then scanned onto PhotoCD by a commercial lab. The images were then extracted from the CD in the 768x512, 24bit/pixel format. They were then converted to grey scale by combining the color planes in a ratio of 0.299 RED + 0.587 GREEN + 0.114 BLUE. The grey scale images were then cropped to obtain images nearly 512x512 in size, in which the object of interest was clearly in the center of the image. Finally, the images were scaled to adjust the brightness and contrast to look good on a computer monitor.

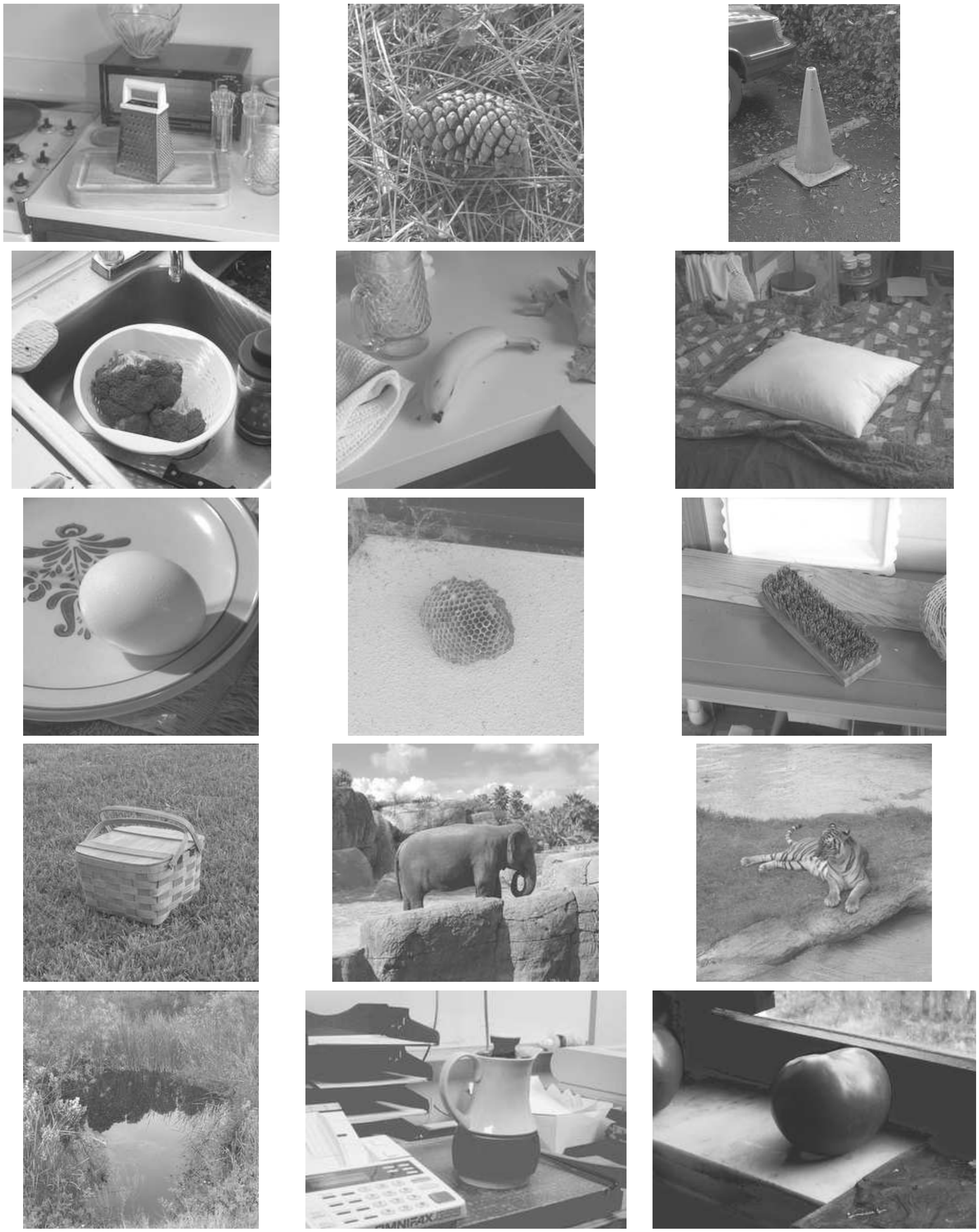
5.2.1 Object Naming Consistency

The ability of participants to recognize the central object in the images was experimentally verified by measuring the consistency of the labels that humans spontaneously provide for the object in each image. In this experiment, 36 participants viewed each image and wrote down the name of the central object. The images were displayed using a slide projector with a timer to project the images for everyone to see at one time. The slide of each object was obtained by writing the color image to 35mm color slide film with a Polaroid film writer.

Each slide was projected on a screen for a one second duration. After viewing each image, the participants were instructed to write down the name of the object they saw in the middle of the image. Later, the names were compared to a key and were graded as correct or incorrect. Synonyms of the correct names were scored as correct. After the grading, the percentage of times each object was correctly identified

Figure 3. Photographs that were collected for the experiments.
(Continued on next page)

Figure 3. (Continued)



was calculated as the number of times the object was correctly named divided by the number of times correct and incorrect names were given. If participants named an object in the scene other than the central object, their result was not counted in the calculation. (It turned out that this happened very infrequently.)

The results from this experiment served as a filter to remove any images containing objects that could not be recognized and named consistently. The results of the naming experiment are provided in section 6.1.

5.2.2 Image Categorization

Images were categorized as man-made or natural and as textured or non-textured, according to the properties of the object in the center of the image. This categorization is best viewed as a partitioning of the images rather than a construction of representative image types. No claim is made that the images in each category are representative of the corresponding class of images. This step was not necessary for assessing the overall edge detector performance, however, it allowed for a check on the consistency of the results across meaningful subsets of the images.

A working definition of a textured object was adopted to label the images as textured or non-textured. According to this definition, a textured object is one whose image contains some repetitive visual pattern that is judged to be necessary for recognizing the object.

The textured/non-textured image classifications were experimentally verified. In the experiment, 6 participants viewed prints of the images and answered three questions for each image. These were (1) How prominent is visual texture on the central object?, (2) How prominent is visual texture in the background? and (3) How important is visual texture in recognizing the central object? The answers were given on a scale from 1 to 5. The results are given in section 6.2.

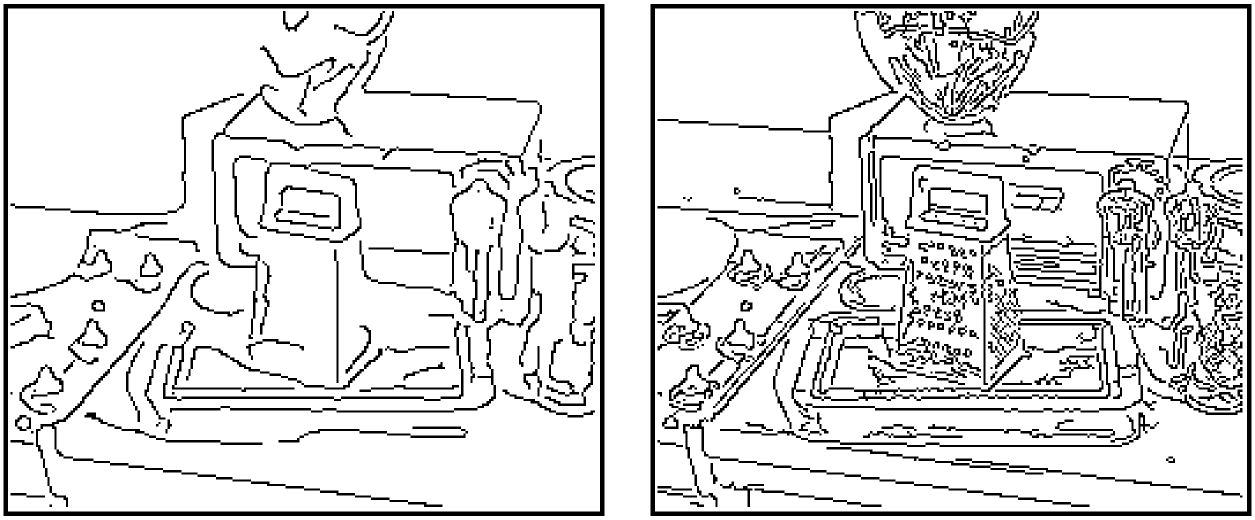


Figure 4. An example of the effect of the choice of input parameters. Both images were produced by the Canny edge detector. The image on the left was created with input parameters *sigma*=1.80, *low*=0.20 and *high*=0.60 while the image on the right was created with input parameters *sigma*=0.60, *low*=0.20 and *high*=0.60.

Twenty-eight images were selected for use in the evaluation of the edge detectors. Twenty of these images were categorized as man-made/natural and as textured/non-textured with 5 images in each category. Eight of the 28 images that were selected were used in [14] and were carried forward to these experiments. All the decisions regarding parameter selection and the statistical tests used data from the twenty images unless otherwise stated. This was done because the additional eight images did not fit equally into the four image categories. If we had used them in making decisions, it could have biased the later analyses involving the image types.

5.3 Parameter Selection

Each edge detection method required input parameters to be set. The values of these parameters can substantially change the edges that are detected. Figure 4 shows an example of two edge images produced from the same image by the same algorithm using two different sets of input parameters. For this reason, parameters had to be selected for each algorithm before the algorithms could be compared.

Determining the parameters to use for each edge detection algorithm for each image is not easy. This is because some criteria must be defined for evaluating the quality of the edges for different parameter settings. Establishing the criteria is the main difficulty in both this task and in edge detector evaluation.

Each of the edge detectors the were included in our study required three input parameters. Originally each algorithm required 2-3 parameters but all of the programs were modified to allow a user to set three parameters. See chapter 4 for the details of how this was done for each edge detector.

5.3.1 Overview of the Process

The method of parameter selection started with a large sampling of the input parameter space for each algorithm. The goal was to sample a broad enough region of each parameter space without sampling it too coarsely. The number of parameter selections that were made was limited by the practical constraints of computing and evaluating the edge images produced by each parameter combination.

To maximize the parameter combinations considered, the selection process was initiated with a lot of parameters combinations and one person, the parameter screener, was used to select the best few edge images for each input image. The results of this initial screening were then used to select a subset of the initial parameters that did well on the entire set of input images, but more specifically, included at least one of the best results for each input image as determined by the parameter screener. This reduced set of parameter combinations was then used to generate edge images for a large group of participants to evaluate.

The screening process just described could allow the parameter screener to remove good edge images from later evaluation by the set of participants. To evaluate the effect of this, the score that the participants gave for the images selected by the parameter screener relative to the other edge images the participants evaluated was calculated. Since the parameters screener judged his selections to be better than all of the other parameter combinations, high scores on these images relative to the others rated by the participants would indicate an agreement in the evaluation done by the screener and the participants.

The ratings for each parameter combination for each image were then added together for all of the participants. The parameters combinations that produced the edge images with the highest scores were then identified and selected for the edge detector evaluation experiment.

5.3.2 The Details of the Process

The range of input values for each parameter was determined from suggestions made by the authors and by experimentation. Samples from this range were made for each parameter, and these were combined to produce an initial set of 64 samples from each parameter space. Edge images were then generated for all 28 grey scale images using the 64 parameter combinations. The 64 parameter combinations that were selected for each algorithm are listed in APPENDIX 2.

The five best edge images for each grey scale image were then identified by a parameter screener. These were selected using a software tool that displayed two edge images side by side; each overlayed in red on the grey scale image. The tool did a partial bubble sort using the results of comparisons made by the user. In each comparison, the screener selected the edge image that contained the most important edges and the least distracting edges. An example display from this tool is shown in Figure 5. The reason for selecting five images without ranking them was to find the domain in the parameter space that worked well for each image. Often times several parameter combinations resulted in edge images whose relative quality was

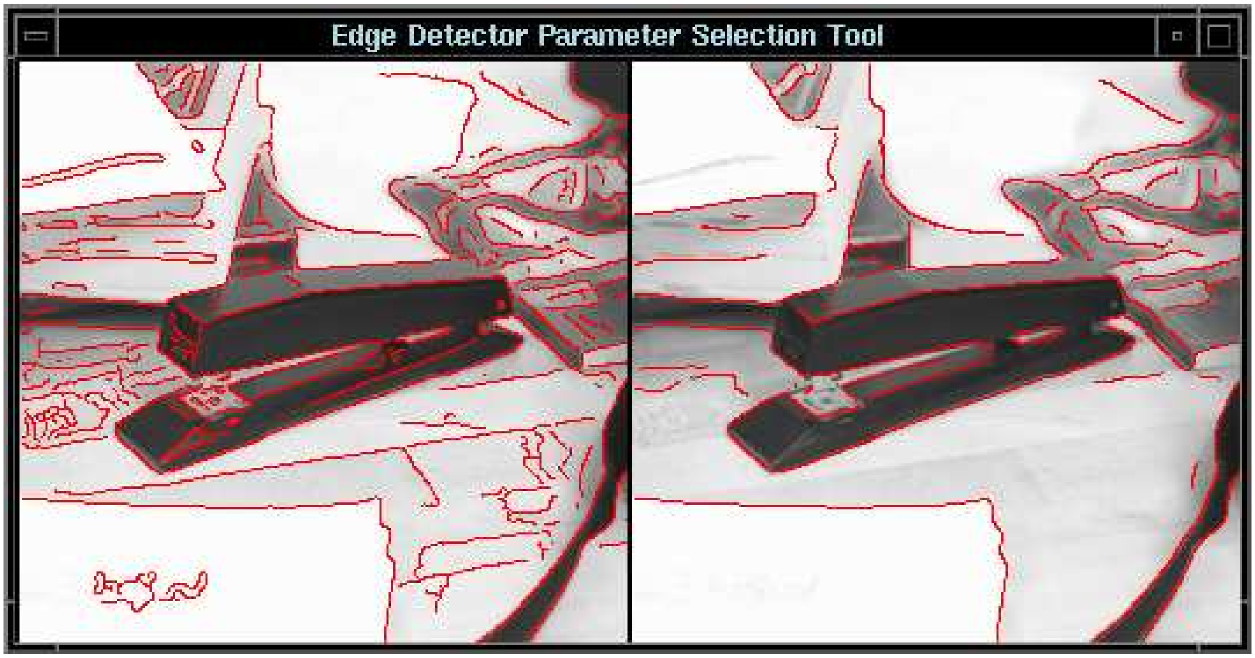


Figure 5. A sample of the display from the edge detector parameter selection tool. Both images were produced by the Canny edge detector. The image on the left was created with input parameters *sigma*=1.20, *low*=0.20 and *high*=0.60 while the image on the right was created with input parameters *sigma*=2.40, *low*=0.30 and *high*=0.60.

hard to distinguish. Therefore by selecting several parameter combinations for each image, the images voted for particular parameter combinations. Each image placed five votes.

The best five parameter combinations for each image were then input to a greedy search algorithm that determined the best subset of 12 (of the initial 64) parameter combinations to use. The search initially selected the parameter combination that included the largest number of preferred edge images (previously selected in the top 5 of 64). It then determined which images were included the least number of times and searched for a new parameter set that reduced this number the most. This process was repeated until 12 parameter sets were selected. The decision to find exactly 12 parameter sets was somewhat arbitrary. The objective was to find a "small" number of parameters sets for each algorithm to use in a visual evaluation experiment. Another goal was to ensure that at least one edge image rated in the top

5 of 64 parameter sets for each image by the parameter screener, was included in the parameter selection experiment. The results of the initial parameter selection are in subsection 6.3.1 on page 39.

An experiment was then done in which participants were asked to evaluate edge images produced with the 12 input parameter combinations. Evaluation sets were created ((1 grey scale image + 12 edge images) x 28 images). Each evaluation sheet in the set had an edge image and a rating scale on it. The edge evaluation sets were photocopied to produce a separate copy for each participant.

Nine students from a graduate computer vision class participated in the experiments. They each received one evaluation set and were verbally instructed to rate each edge image according to how well it facilitated the recognition of the central object. Additionally, written instructions were also given to each participant with the images. These stated the following:

> "We want you to rate each edge image. There are 28 sets of images in your stack. Each set contains one grey scale image and 12 edge images that were derived from the grey scale image. Please go through the 28 sets of images in the order they appear in your stack. You are encouraged to spread out the edge images in each set out on the table before you assign any ratings. Use numbers between 7 and 1 to indicate your rating. A 7 means that the 'Information allows for easy, quick and accurate recognition of the object.' A 1 means 'No coherent information from which to recognize the object.' Use intermediate numbers for intermediate ratings. (i.e. circle a single number on each and every image) Use each number as often as you feel it is warranted."

There was no time limit imposed on the participants. Individual times varied between one and two hours. The experiment was done for each of the edge detectors by the same nine students. The five experiments were staggered throughout the semester.

The results from each experiment were then analyzed to determine if the ratings of the judges were consistent. Without consistent results, analysis of the data is problematic. The method used for determining the consistency between the participants was the interclass correlation coefficient. The method used was the "ICC(3,k)" correlation measure from [35]. The results are given in section 6.3.2 in chapter 6.

A check was then done to determine how highly the participants rated the images that were selected by the parameter screener. This check was done to determine how well the parameter screener's preferences for edges agreed with the preferences of the participants in the experiment.

The ratings of the edge images were then used to determine the best fixed parameter set to use for each algorithm. Parameter sets were selected that had the highest rating averaged across images and participants while also yielding the best edge image for the largest number of pictures. Only the twenty images categorized by image type were used to determine the best parameter set. This method determined the best fixed parameter setting.

Another set of parameters were found for each algorithm. These were the best parameters as determined separately for each image. The reasons for setting the parameters in both ways were 1) to evaluate the importance of adjusting the parameters to each image and 2) to evaluate the potential improvement that might be made in edge detection if one could find a good automated method for adaptively setting the parameters on an image by image basis. Both sets of parameters were used in the next experiment.

5.4 Comparison of Edge Detection Algorithms

The final step in evaluating edge detectors was to perform an experiment where participants evaluated the edges images produced by all detectors at one time. The parameter combinations identified by the parameter setting experiment were used. To remove any biases participants may have for a particular algorithm, the names of the algorithms were not associated with the edge images. To remove any other potential sources of bias for any algorithm, the order of the edge images was randomized separately for each subject.

After the ratings were collected, the correlation between the participants was calculated using the "ICC(3,k)" statistic from [35]. This was done to determine the consistency of the ratings. This was important because it estimates the reliability of these ratings for edge detection evaluation. The results are given in Chapter 6.

An analysis was done on the ratings. The analysis was guided to answer three questions. These are: (1) Does the performance of the algorithms change substantially when the parameters are fixed for each edge detector vs. when they are adapted to each image?, (2) What is the relative performance of the edge detection algorithms?, and (3) How does the measure of the relative performance of the edge detectors depend on the selection of images used in the evaluation.

The main tool used in the analysis of the data was analysis of variance (ANOVA). A brief description of analysis of variance is given in APPENDIX 6. and an introduction to the subject can be found in [42].

CHAPTER 6

RESULTS

Summaries of the results obtained from each experiment conducted throughout the methodology are presented in this chapter. Raw scores from the experiments can be found in the Appendices.

6.1 Object Naming Consistency

A naming consistency experiment was done on a set of thirty photographs that were collected for this experiment. The percentages of participants agreeing on the designated concept for the images in Figure 3 are in the first 30 rows of the Table 3. The data in the last eight rows of the table was collected in a separate, similar, naming experiment conducted for a previous study.

The first column in the table contains number that identifies each image, the second column lists the most common name given by the participants for the central object in each image and the third column indicates the percentage of times the object was named correctly. The fourth and fifth columns indicate the initial classifications of image type for a subset of twenty images.

The results of the naming consistency experiment indicate that the images caused the participants to access a mental label or concept, and that the concept was consistent across participants. The only exception was the image of the tree stump. The most common name given for this object was wood, but it or a synonym were given only 40.6% of the time. This implies that participants did not access the same mental label for the object. Therefore it was removed from the set of images that could be used in the experiments.

6.2 Image Categorization

An image classification experiment was conducted to validate the initial categorization of textured or non-textured assigned to twenty of the images. Figure 6 shows the mean ratings from 6 participants to two questions: 1) "How important is visual texture in recognizing the central object?" and 2) "How prominent is the visual texture on the central object?". The images that were initially classified as textured are plotted with an x, and the images that were initially classified as non-textured are plotted with an o. Each plotted point is labeled with a number that corresponds to the name of the object in Table 3 on page 38.

The figure illustrates that although neither question perfectly separates the images of textured and non-textured objects, together the two questions yield a linear separation. The points near the line indicate the images that are most difficult to classify. These are the shopping cart, feather, mailbox and pond images. The images that are easiest to classify as textured or non-textured objects were the tire and pine cone, and stapler and banana images, respectively.

6.3 Parameter Selection

Parameter selection for the algorithms involved a multi-step process. The results obtained from each step are presented in this section.

Number	Image Name	Naming Consistency	Man-made or Natural	Textured or Non-textured
1	golf cart	100.0%	man-made	non-textured
2	pitcher	91.7%	man-made	non-textured
3	stapler	100.0%	man-made	non-textured
4	mailbox	100.0%	man-made	non-textured
5	pillow	97.2%	man-made	non-textured
6	brush	97.2%	man-made	textured
7	shopping cart	100.0%	man-made	textured
8	tire	100.0%	man-made	textured
9	grater	88.6%	man-made	textured
10	picnic basket	100.0%	man-made	textured
11	orange	94.4%	natural	non-textured
12	banana	100.0%	natural	non-textured
13	egg	100.0%	natural	non-textured
14	elephant	100.0%	natural	non-textured
15	pond	100.0%	natural	non-textured
16	pine cone	88.9%	natural	textured
17	feather	100.0%	natural	textured
18	beehive	80.6%	natural	textured
19	turtle	91.7%	natural	textured
20	tiger	97.2%	natural	textured
A	brick	100.0%	not applicable	not applicable
B	fan	100.0%	not applicable	not applicable
C	alligator	100.0%	not applicable	not applicable
D	bucket	100.0%	not applicable	not applicable
E	wood	40.6%	not applicable	not applicable
F	grate	100.0%	not applicable	not applicable
G	newspaper	93.3%	not applicable	not applicable
H	broccoli	83.3%	not applicable	not applicable
I	tomato	94.4%	not applicable	not applicable
J	cone	97.2%	not applicable	not applicable
21	briefcase	100.0%	not applicable	not applicable
22	trash can	100.0%	not applicable	not applicable
23	video camera	96.9%	not applicable	not applicable
24	coffee maker	100.0%	not applicable	not applicable
25	flower	93.8%	not applicable	not applicable
26	airplane	100.0%	not applicable	not applicable
27	traffic cone	96.9%	not applicable	not applicable
28	stairs	100.0%	not applicable	not applicable

Table 3. Results from the object naming consistency experiment.
The most common name that the participants provided for the central object in each image is listed in the second column in the table. For each image, the percentage of the subjects that provided the correct name, or a synonym, are given in the third column. A subset of twenty of the images were labeled using two properties of the central object in the image. The results are listed in the last two columns of the table.

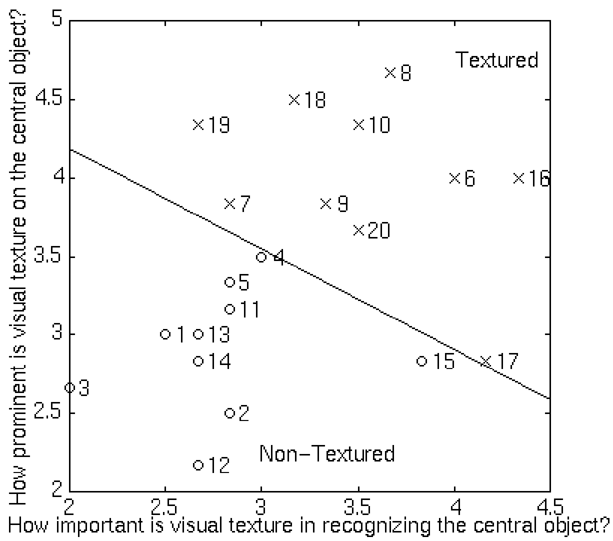


Figure 6. Selected results from the texture classification experiment.
The figure illustrates the mean ratings obtained from two of the questions that were asked in the texture classification experiment. Each point in the plot represents an image. The numbers correspond to the name of the images. The x's are textured images and the o's are non-textured images. A linear separation of the image types is obtainable from the responses to the two questions.

6.3.1 Initial Parameter Selection

The initial 64 parameter combinations used for each edge detection algorithm are listed in APPENDIX 2. The parameters are listed in tables broken down by edge detector. In the top table, the initial 64 parameter combinations that were specified for each image are listed. In the bottom table, the subset of 5 parameter combinations that were selected using the parameter selection tool are listed. Combination number 1 was the set of parameters that produced the best edge image and combination number five produced the fifth best edge image.

The five best parameter combinations were then input to a greedy search algorithm that found a subset of 12 of the 64 parameter combinations that produced at least one good edge image for each of the grey scale images. The details of this algorithm are given in the methodology section. The 12 parameter combinations that were selected for each algorithm are listed in Table 4.

6.3.2 Parameter Selection Experiment

In the parameter selection experiments, nine participants, rated 336 edge images in each of 5 separate experiments; one for each algorithm. It is important to note that the participants were volunteers that gave informed consent. They also received monetary compensation for their participation. The edge images were generated by applying an algorithm to each of the 28 images with the 12 parameter combinations given in table 4. All together, 15,120 individual ratings were collected. The raw scores are provided in APPENDIX 3. Figure 7 illustrates the range in ratings collected in the experiment. The 12 images in the figure were generated by the Canny algorithm from the tire image using the parameters in table 4. For display, the images were arranged by increasing average rating. It is easy to see the that the ratings track with the quality of the edge images.

6.3.2.1 Correlation Between Participant Responses

The intraclass correlation coefficient between the ratings given by each participant are given in Table 5. The correlation is given for each of the edge detection algorithms for the subset of 20 categorized images and for the set of all 28 images. As the table shows, the correlation in participant responses did not change much when the additional eight images were included.

As the table shows, the correlations were very high; the minimum correlation between participants was 0.8933. This means that the participants rated the edge images in a similar fashion and indicates that there is a concept of “edge goodness” that the subjects share. This was an important result because it validated the the ability of human subjects to evaluate edge images. If the participants’ responses were

Canny Edge Detector												
	Combination Number											
Parameter	1	2	3	4	5	6	7	8	9	10	11	12
sigma	1.2	1.8	0.6	1.2	0.6	1.2	1.2	1.2	2.4	0.6	1.2	1.8
low	0.4	0.2	0.3	0.2	0.5	0.3	0.4	0.2	0.2	0.3	0.4	0.3
high	0.8	0.7	0.9	0.6	0.9	0.8	0.6	0.8	0.6	0.8	0.9	0.9

Nalwa Edge Detector												
	Combination Number											
Parameter	1	2	3	4	5	6	7	8	9	10	11	12
blur	1.50	1.50	0.60	1.20	1.50	0.60	1.50	1.20	1.20	1.50	0.60	1.50
low	0.10	0.20	0.15	0.10	0.15	0.10	0.15	0.05	0.05	0.05	0.05	0.05
high	0.60	0.60	0.60	0.60	0.15	0.60	0.45	0.15	0.30	0.45	0.30	0.15

Iverson Edge Detector												
	Combination Number											
Parameter	1	2	3	4	5	6	7	8	9	10	11	12
directions	8	8	8	4	8	8	4	6	8	8	6	10
low	0.00	0.20	0.00	0.20	0.00	0.20	0.00	0.00	0.00	0.20	0.00	0.00
high	0.55	0.05	0.00	0.55	0.05	0.30	0.05	0.00	0.30	0.55	0.30	0.05

Bergholm Edge Detector												
	Combination Number											
Parameter	1	2	3	4	5	6	7	8	9	10	11	12
start sigma	2.0	2.0	3.0	3.0	2.0	2.0	3.0	4.0	4.0	3.0	4.0	5.0
end sigma	2.0	1.5	1.5	2.0	1.0	2.0	2.0	1.5	2.0	2.0	1.5	1.5
threshold	20	15	10	20	15	15	5	20	10	15	5	10

Rothwell Edge Detector												
	Combination Number											
Parameter	1	2	3	4	5	6	7	8	9	10	11	12
sigma	1.0	1.0	1.0	1.5	1.0	1.5	1.5	2.0	0.5	1.0	1.0	1.5
threshold	8	8	13	8	13	3	3	3	18	18	18	13
alpha	0.90	0.95	0.85	0.85	0.80	0.90	0.80	0.95	0.80	0.80	0.85	0.80

Table 4. The parameters that were used in the parameter selection experiment. These tables list 12 parameter combinations that were chosen for each edge detector to use in the parameter selection experiment. These parameters were obtained by evaluating 64 parameters combinations for each picture and then selecting a subset of 12 parameter combinations that provided at least one good edge image for each picture.

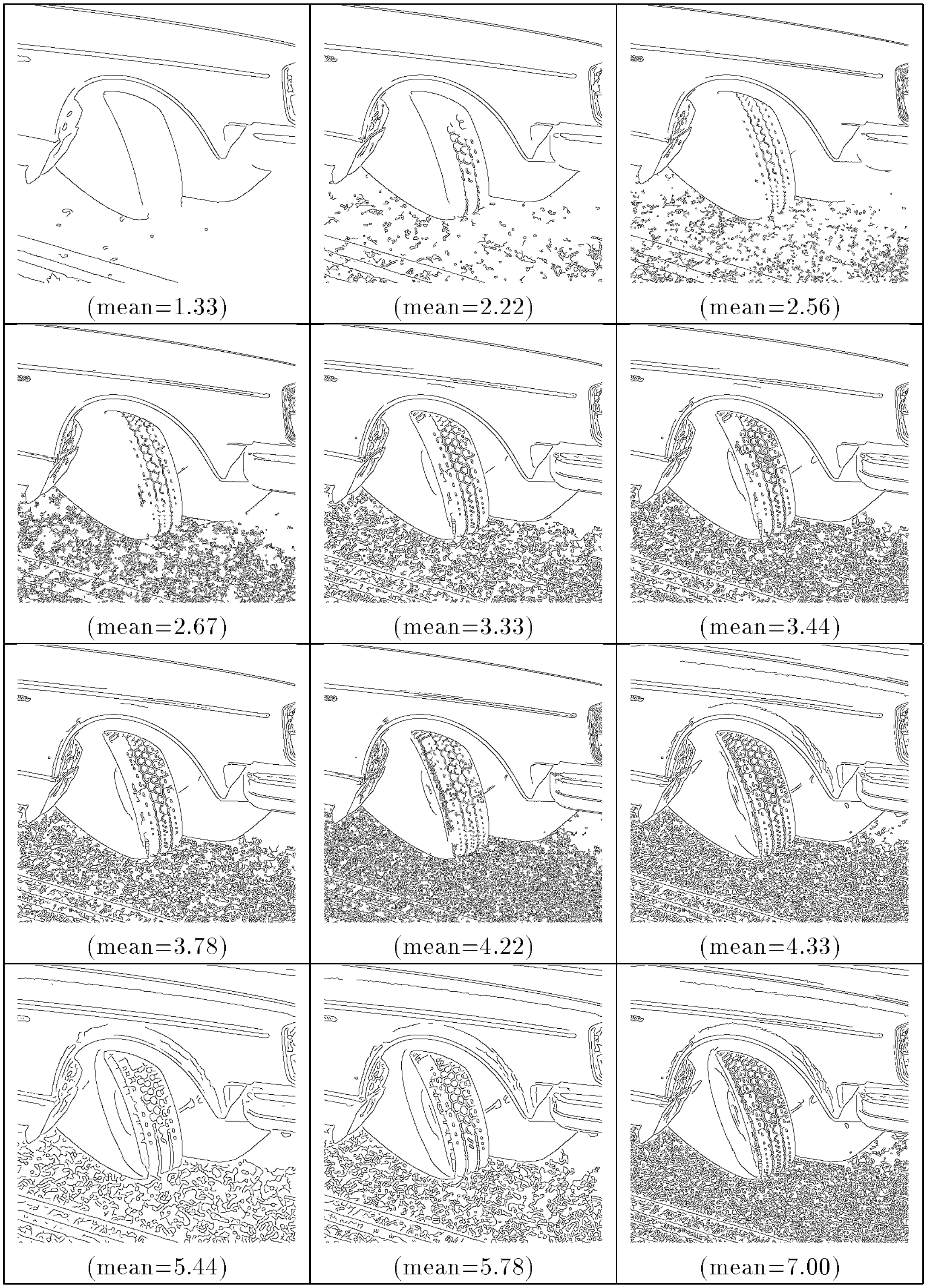


Figure 7. A sample of the rating collected in the parameter selection experiment. These are the 12 edge images generated from the tire image by the Canny edge detector. The mean below each image is the average of the ratings from the 9 participants. The images were arranged in the figure according to increasing average ratings. The sequence of images illustrates that the mean ratings track closely with the edge quality.

Detector	20 Image ICC(3,4)	28 Image ICC(3,4)
Canny	0.913	0.917
Nalwa	0.923	0.921
Iverson	0.893	0.895
Bergholm	0.908	0.897
Rothwell	0.926	0.925

Table 5. The correlation in the subject ratings that were collected in each of the parameter selection experiments.

not correlated, it would indicate a large amount of noise in the ratings. Further processing of the data would have then been problematic.

6.3.2.2 Confirmation of the Initial Parameter Selection

The multi-step process used to find parameter combinations for each algorithm raises the question of the consistency between the preference of the parameter screener and the preferences of the participants in the parameter selection experiment. The parameter filtering process reduced the number of parameter combinations from 64 to 12 to reduce the size of the parameter setting experiment. If all 64 parameter combinations were used in the parameter setting experiment then 80,640 ratings would have been collected instead of the 15,120 that were collected using 12 parameter combinations.

The consistency in the preferences can be estimated by calculating the relative score of the edge images produced from the parameter combinations selected by the parameter screener. This was done for each image and then the results were averaged across the 28 images.

For each picture, the maximum and minimum average ratings, MAX and MIN respectively, were determined, as was the the maximum average rating, P, of the images selected by the parameter screener. A relative rating of each edge image selected by the parameter screener was then computed as $\frac{P-MIN}{MAX-MIN}$. The relative ratings were then averaged across the 28 images and are listed for each edge detector in Table 6.

Detector	Relative Rating
Canny	92.0%
Nalwa	84.2%
Iverson	88.4%
Bergholm	91.9%
Rothwell	91.2%

Table 6. Subjects ratings of initially selected parameters by detector.

These results show that the edge images that were selected by the parameter screener were rated highly by the participants in the parameter selection experiments. Given the noise in participant ratings as expressed by the participant rating correlations in Table 5, the relative ratings of 84.2% to 92.0% for these images are good.

6.3.2.3 Resulting Parameter Selections

The raw scores collected in the parameter selection experiment were used to determine the best parameters for each algorithm in two ways. First, the parameter combinations were found that produce the best edge image for each individual image. These are called the adaptive parameters. Second, the best single parameter set to use across all 20 images was found. This parameter combination is defined as the fixed parameters for each algorithm. The purpose of having two parameter sets was to measure the benefit of doing adaptive parameter specification and to determine the best algorithm to use depending on whether the parameters are to be set adaptively or in a fixed manner in an application.

The best adaptive parameters were determined by summing the participants' responses for each parameter combination for each image and then finding the parameter combination that has the maximum sum for each image.

The best fixed parameters were determined by summing the ratings across participants and then summing across images for each parameter combination. The maximum of the resulting sums identified the best fixed parameter combination. If several sums were close to the maximum, then the best overall parameter combination was determined by the number of images that had a maximum score with that parameter combination.

The results are listed in tables in APPENDIX 4. There is one table for each edge detection algorithm. In each table, the image is listed in each column and the twelve parameter combinations are listed in the row headings. All of the other entries in the table are the summed ratings for each parameter combination for each image. The best parameter combination across all images (fixed parameter) is displayed in italics in the first row of the table. In each subsequent row, the best adapted parameter combination for each image is displayed in italics. The underlined entries indicate the parameter combinations that were selected by the parameter screener that were included in the parameter setting experiment.

6.4 Comparison of Edge Detection Algorithms

After determining the parameters to use for each algorithm for each image, and across all images, another rating experiment was done to measure the performance of the edge detection algorithms. The edge images from all five algorithms were evaluated this experiment. To avoid the potential for biasing the results in favor of any algorithm, the evaluation sheets did not identify the algorithms, and the order of the presentation of the edge images was randomized individually for each of the 28 images for each participant.

The edge image ratings were analyzed to answer three questions. These are: (1) Does the performance of the algorithms improve substantially when the parameters are adapted for each image rather than adapted to a set of images and held fixed for all of the images?, (2) What is the relative performance of the edge detection algorithms?, and (3) Does the measure of the relative performance of the edge detectors depend on the selection of images used in the evaluation?

The scope of this experiment was a little smaller than that in the parameter setting experiments because only 10 edge images were produced for each image instead of the 12 edge images rated in the previous experiments. Ten images were generated for each image because there were five edge detection algorithms, each run with two parameter combinations.

There were sixteen participants in the experiment. Each participant volunteered and gave informed consent. Six of them had participated in the parameter setting experiments. The reason that three of the nine participants from the parameter setting experiments did not participating in this experiment was they they were not available because they graduated or left for summer jobs. Each of the sixteen participants received instructions that were similar to those used in the parameter selection experiment. The only difference in the instructions was that the number of images to evaluate was 280 instead of 336. All of the participants had studied computer vision. The participants all participated in the experiment on the same day.

The results of the statistical analysis used to examine the performance of each algorithm are given in this subsection. A discussion of those results was reserved for the next chapter.

6.4.1 Correlation Between Participant Responses

The same interclass correlation measure that was applied to the parameter setting data was applied to the data collected in this experiment. Again, it is important

Detectors	20 Image ICC(3,4)	28 Image ICC(3,4)
All	0.939	0.928

Table 7. The interclass correlation coefficient for the edge detector comparison experiment.

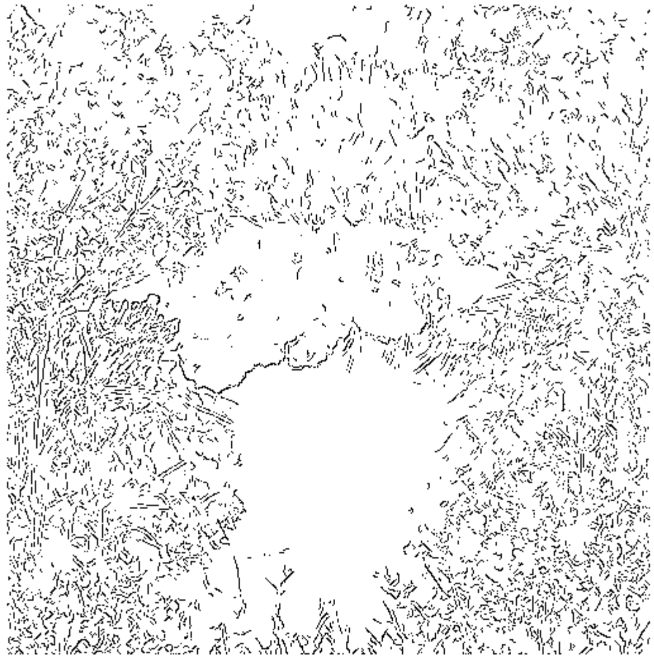
to have a high correlation between participants because the ratings from different participants will are used as multiple observations in the calculations the data analysis. Table 7 lists the interclass correlations for the 20 and 28 image results. The correlation is strong, indicating a good agreement between the participants' ratings.

6.4.2 Analysis of the Edge Detector Ratings

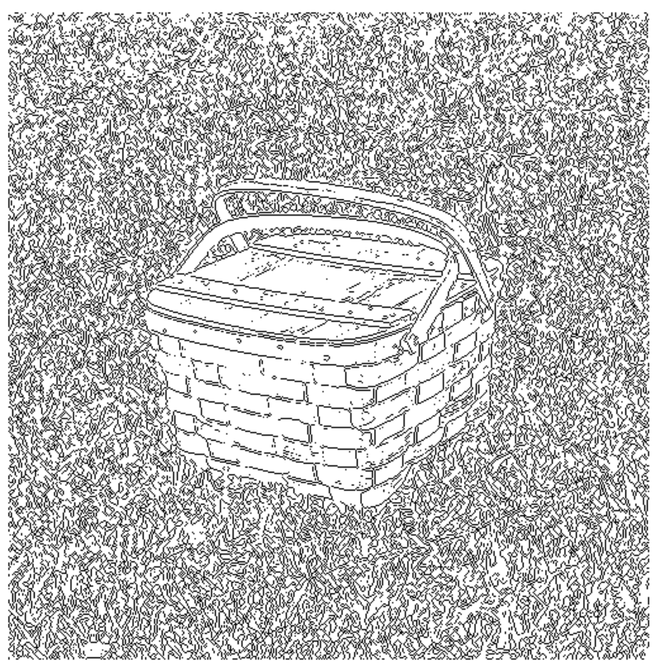
The results in this section answer three questions. These are: (1) Does the performance of the algorithms improve substantially when the parameters are adapted for each image rather than adapted to a set of images and then held fixed for all of the images?, (2) What is the relative performance of the edge detection algorithms?, and (3) How does the measure of the relative performance of the edge detectors depend on the selection of images used in the evaluation?

Before presenting the numerical results for the evaluation, selected results are presented to visually calibrate the reader to the scale numerical scale of edge ratings. The lowest and the highest ratings (averaged across participants) for any single image in the evaluation are displayed in Figure 8.

The correlation between the participant responses reported in section 6.4.1 showed a strong agreement between the relative ratings of participants. It also showed that there was not a perfect agreement in the relative ratings. Figure 9 shows the two edge images that had the lowest, and the highest, variance of the sixteen participant ratings.

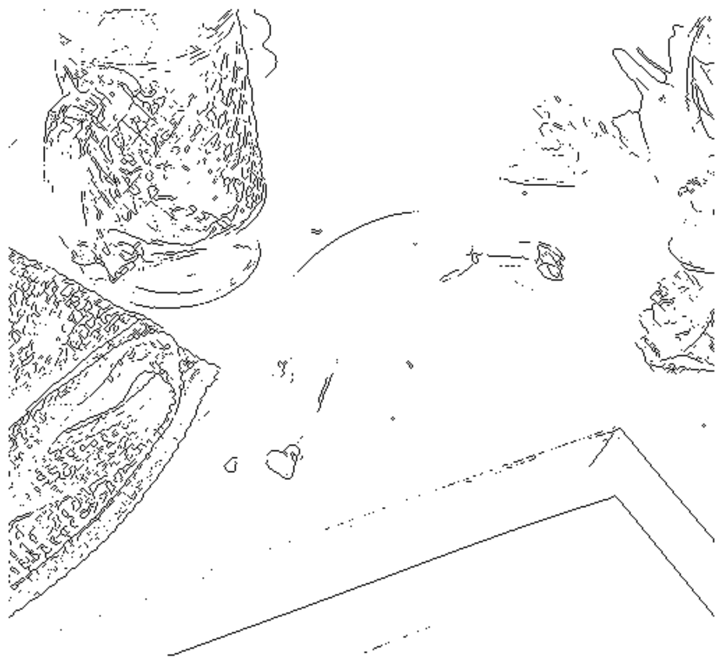


(a) Edges detected by the Nalwa algorithm in the pond image. (mean rating = 1.44)

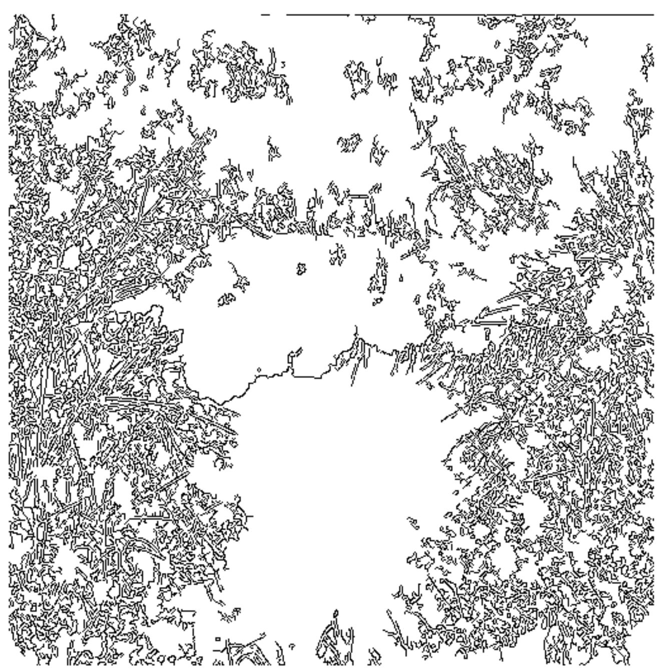


(b) Edges detected by the Rothwell algorithm in the basket image. (mean rating = 6.31)

Figure 8. Example of the lowest and highest rated edge images.
Image (a) was produced by the Nalwa edge detector with input parameters *blur*=1.50, *low*=0.20 and *high*=0.60. Image (b) was produced by the Rothwell edge detector with input parameters *sigma*=0.50, *low*=18.0 and *alpha*=0.80.



(a) Image with the lowest variance in ratings (mean=1.56,std=0.75)



(b) Image with the highest variance in ratings (mean=2.63,std=2.00)

Figure 9. Edge images that had the lowest and highest variance in the ratings. Image (a) was produced by the Rothwell edge detector with input parameters *sigma*=0.50, *low*=18.0 and *alpha*=0.80. Image (b) was produced by the Canny edge detector with input parameters *sigma*=0.60, *low*=0.30 and *high*=0.90.

To help further understand the range of the scale, the five edge images that had the smallest range of average ratings are displayed in Figures 10 and the five edge images that had the largest range of average ratings are displayed in Figure 11.

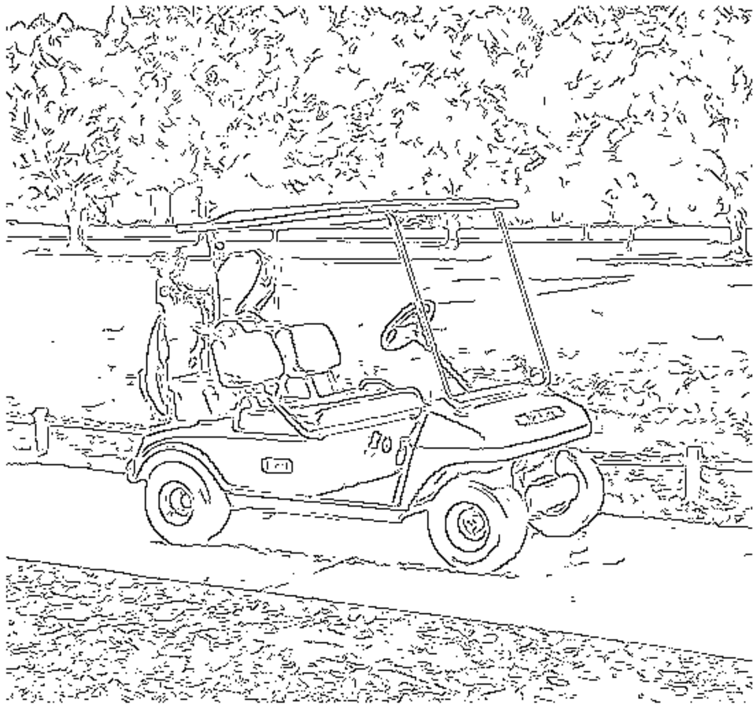
Does the performance of the edge detectors depend on whether the parameters are held constant for all of the images or are adapted to each image?

Table 8 shows results from an analysis of variance computed using a model that contains the parameter combination term in each source of variation measured. The table indicates that there is a significant difference (Pr>F=0.0001) in the ratings of the edge images that were generated with fixed and adapted parameters. The edge images produced with the adapted parameters were rated 4.60 on average and the edge images produced with the fixed parameters were rated 4.15 on average. Thus, the edge detectors performed significantly better with adapted, rather than, fixed parameters.

The table also indicates that all of the interactions between the factors are significant. This implies that the size of the difference in the ratings obtained with the fixed and adapted parameters varies with the other factors.

What is the relative performance of the five edge detection algorithms?

The data collected in this experiment was split into two pieces to answer this question. One subset contained the data for the adapted parameters and the other contained the data for the fixed parameters. A separate analysis was done on each of these data sets because the performance of an edge detector should be evaluated using either adaptive or fixed parameters, but not both.

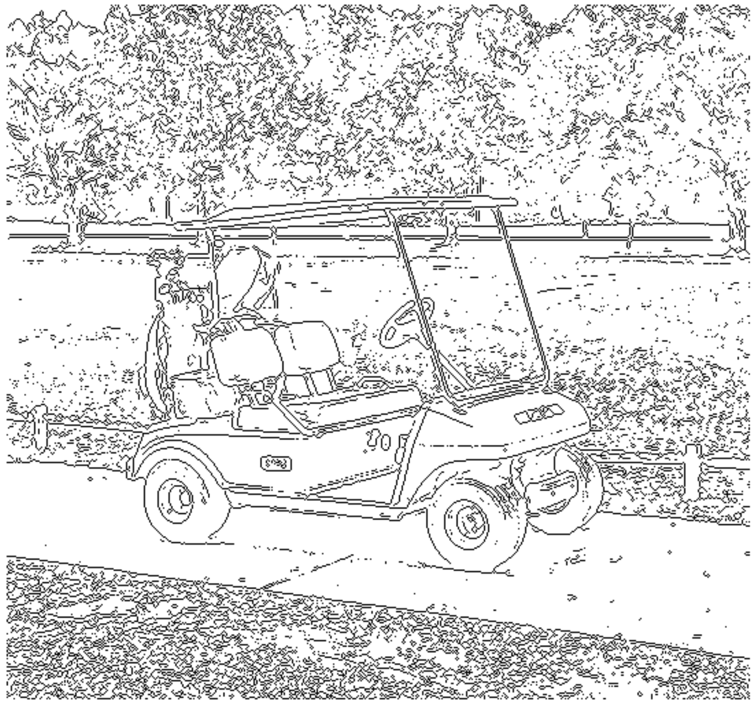


(a) Nalwa edge image (mean=5.31)

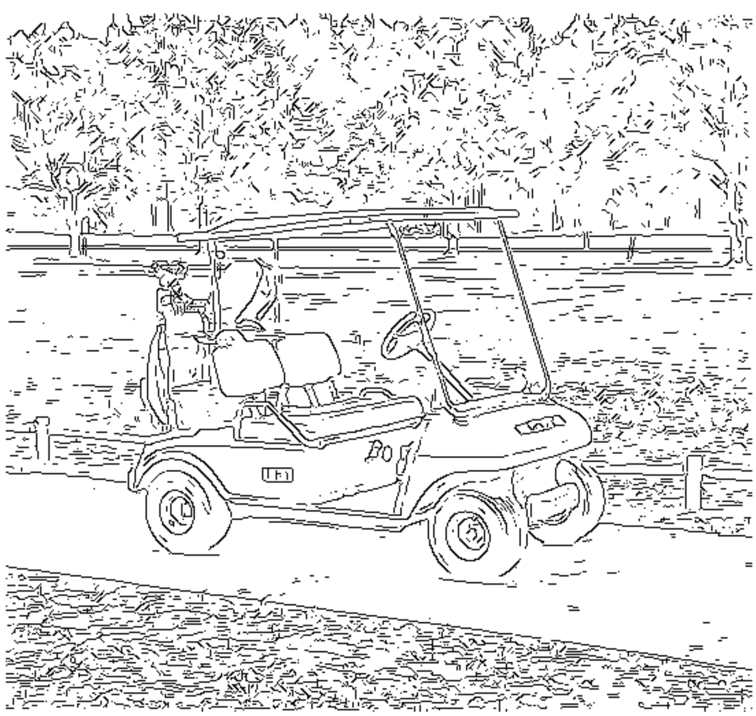
Figure 10. Edge images that had the smallest range in average ratings. Image (a) was produced by the Nalwa edge detector with input parameters *blur*=1.50, *low*=0.20 and *high*=0.60. Image (b) was produced by the Rothwell edge detector with input parameters *sigma*=0.50, *low*=18.0 and *alpha*=0.80. Image (c) was produced by the Iverson edge detector with input parameters *direction*=8, *low*=0.000 and *high*=0.00. Image (d) was produced by the Bergholm edge detector with input parameters *starting sigma*=2.00, *ending sigma*=1.00 and *threshold*=15. Image (e) was produced by the Canny edge detector with input parameters *sigma*=0.60, *low*=0.30 and *high*=0.90.

(Continued on next page)

Figure 10. (Continued)



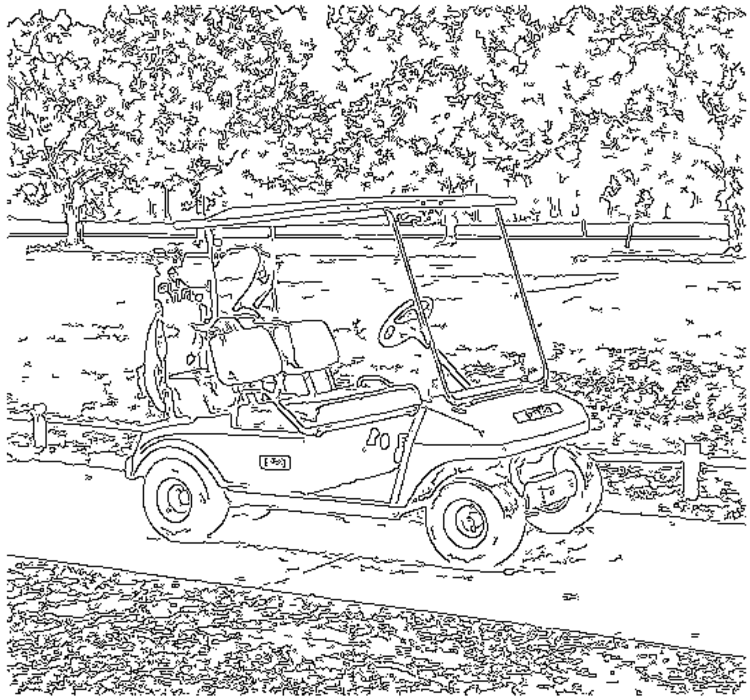
(b) Rothwell edge image (mean=5.38)



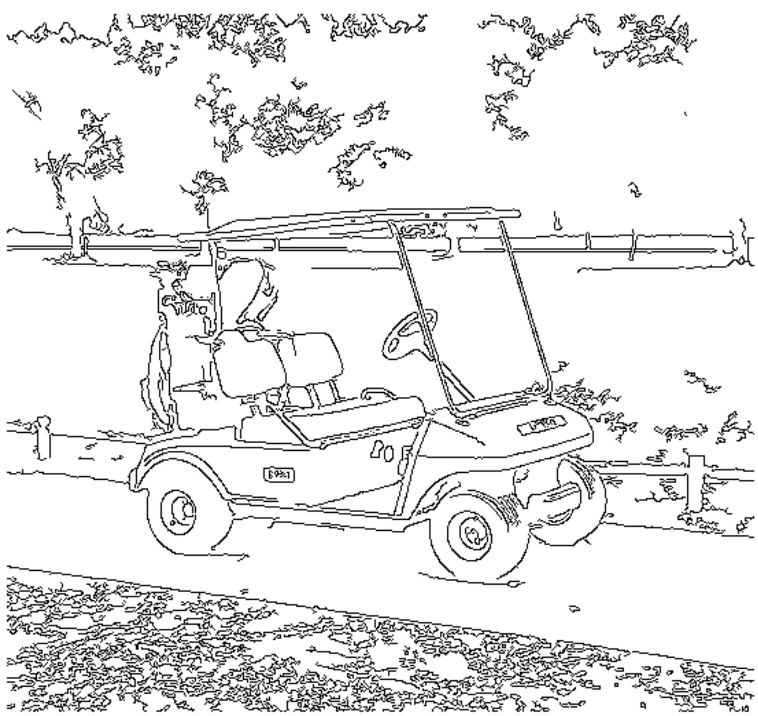
(c) Iverson edge image (mean=5.56)

(Continued on next page)

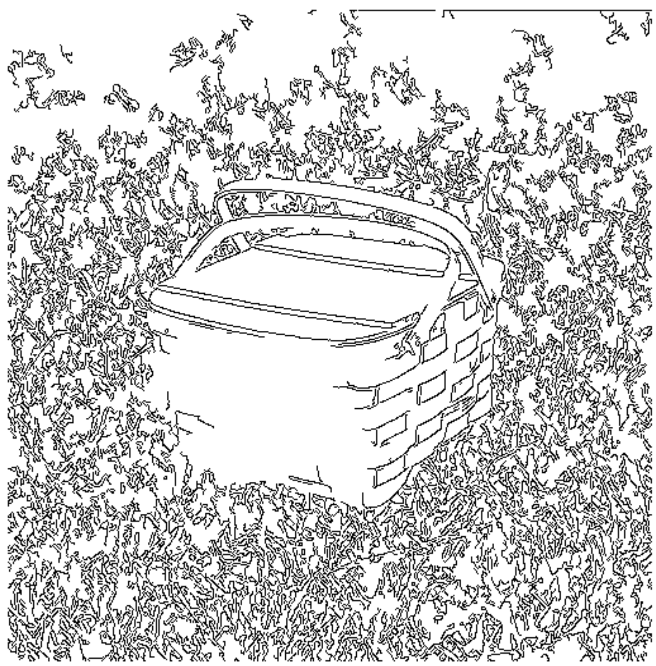
Figure 10. (Continued)



(d) Bergholm edge image (mean=5.69)



(e) Canny edge image (mean=6.13)



(a) Canny edge image (mean=3.06)

Figure 11. Edge images that had the largest range in average ratings. Image (a) was produced by the Canny edge detector with input parameters *sigma*=0.60, *low*=0.30 and *high*=0.90. Image (b) was produced by the Nalwa edge detector with input parameters *blur*=1.50, *low*=0.20 and *high*=0.60. Image (c) was produced by the Iverson edge detector with input parameters *direction*=8, *low*=0.000 and *high*=0.00. Image (d) was produced by the Bergholm edge detector with input parameters *starting sigma*=2.00, *ending sigma*=1.00 and *threshold*=15. Image (e) was produced by the Rothwell edge detector with input parameters *sigma*=0.50, *low*=18.0 and *alpha*=0.80.

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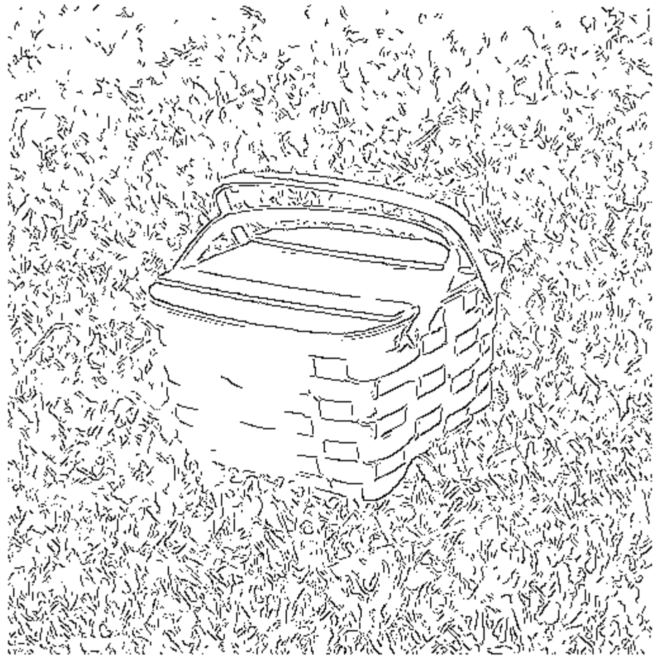
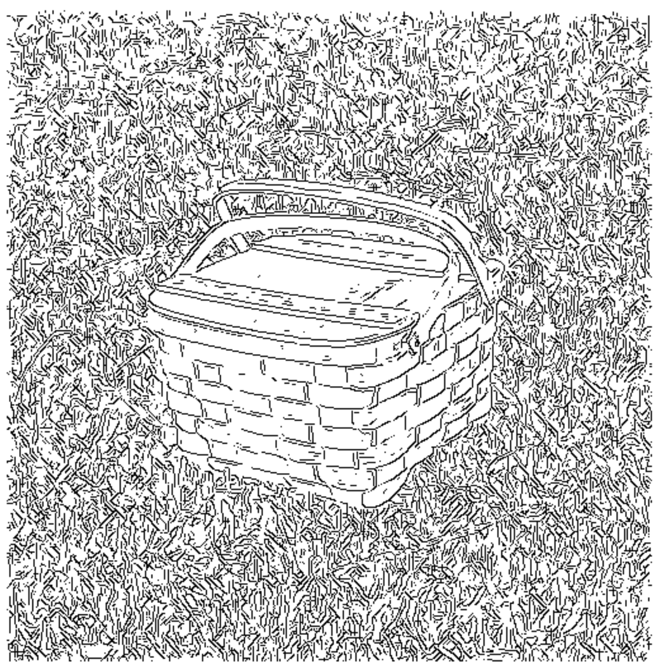
Figure 11. (Continued)



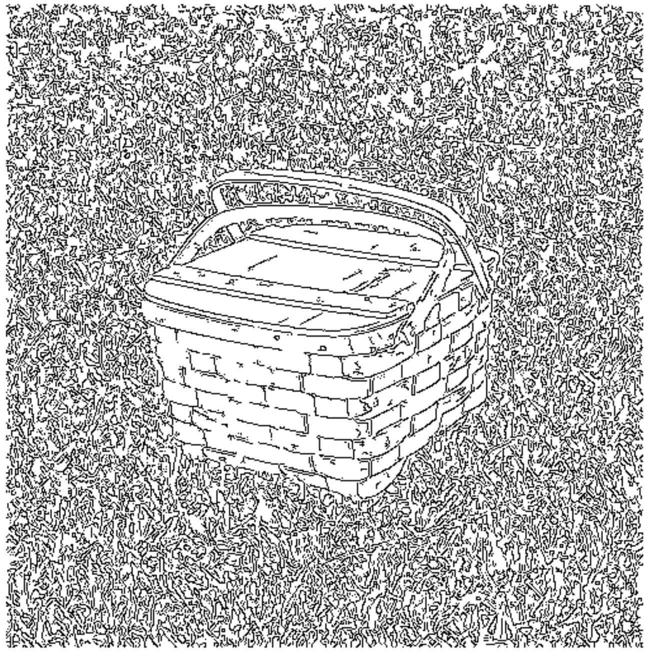
(b) Nalwa edge image (mean=3.63)



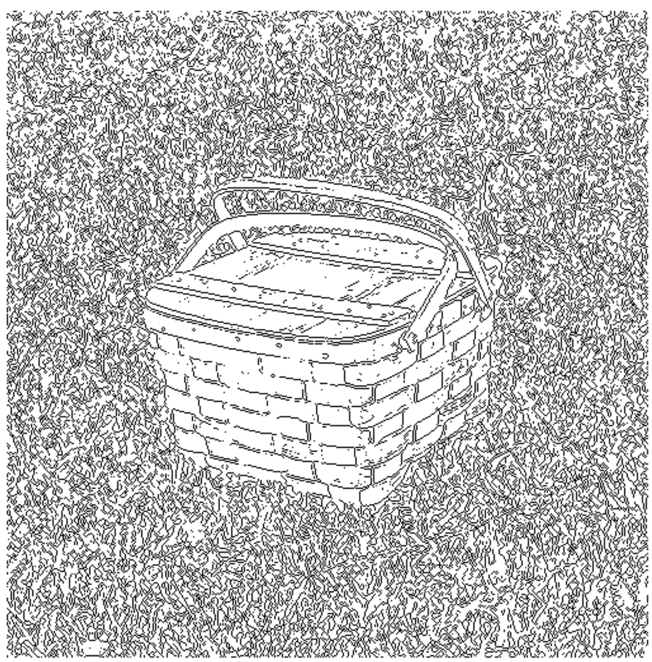
(c) Iverson edge image (mean=5.63)

(Continued on next page)

Figure 11. (Continued)



(d) Bergholm edge image (mean=5.81)



(e) Rothwell edge image (mean=6.25)

Source	DF	Anova SS	Mean Square	Pr >F
Parameter combination	1	163.81	163.81	0.0001
Parameter combination * Edge detector	8	120.06	15.01	0.0001
Parameter combination * Man-made/Natural	2	1095.70	547.85	0.0001
Parameter combination * Textured/Non-textured	2	24.35	12.17	0.0052
Parameter combination * Edge detector * Man-made/Natural	8	41.07	5.14	0.0230
Parameter combination * Edge detector * Textured/Non-textured	8	165.06	20.63	0.0001
Parameter combination * Edge detector * Man-made/Natural * Textured/Non-textured	10	115.02	11.50	0.0001
Error	3160	7209.93	2.31	

Table 8. ANOVA results for a test of the significance of the effect of fixing the input parameters across all images or adapting them for each image.

Statistically significant differences in the mean performance of the algorithms were tested for using the Bonferroni test [20]. This test applied individual tests for differences in the mean detector performance between each pair of edge detection algorithms using a one-way analysis of variance. Ten separate analyses of variance were done. Since the same data was used in multiple tests whose results were to be compared, the level of significance was adjusted from 0.05 to 0.005 for each test. This was done so the family-wise error was approximately 0.05. The analysis was the same for the adapted and fixed parameter data.

6.4.2.1 Results of the Adapted Parameter Comparison

Table 9 lists the results of the comparison of edge detectors using the parameters that were optimized and set individually for each of the twenty images. The table lists the mean performance of each edge detector and the significant differences in the mean performance between algorithms. Because the significant differences account for the distribution of scores for each edge detector, they are more accurate measures of the true difference in edge detector performance than simply the differences in the means. The statistically significant differences in the performance of the algorithms indicate that the Rothwell, Bergholm and Canny edge detectors all performed significantly better than both the Iverson and Nalwa edge detectors.

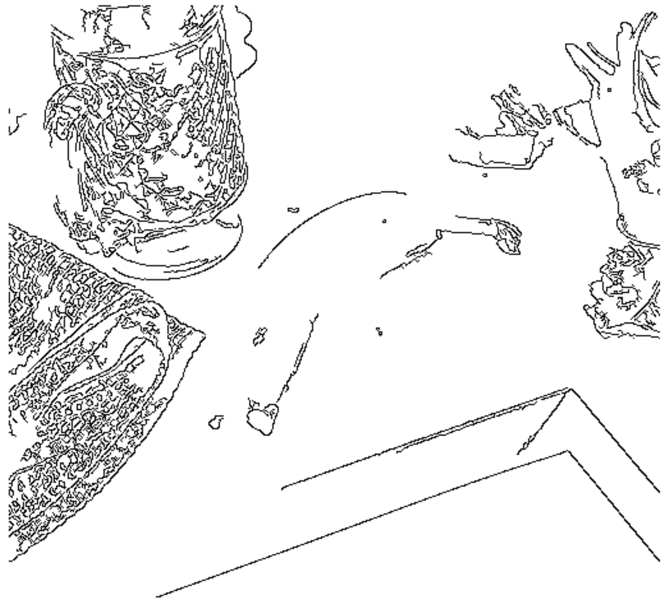
Edge Detector	Mean	Significant Differences
Canny (C)	4.80	(I,N) $<$ (R,B,C)
Bergholm (B)	4.78	
Rothwell (R)	4.76	
Nalwa (N)	4.43	
Iverson (I)	4.26	

Table 9. Relative edge detector performance using adapted parameters.

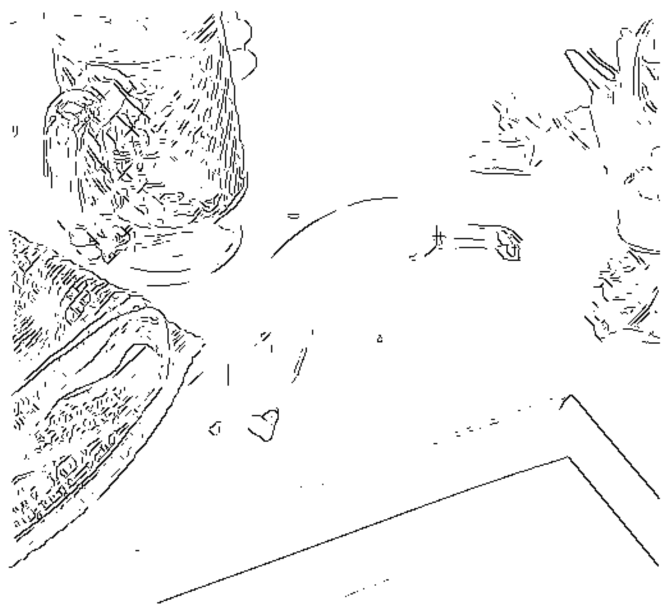
Although the Canny edge detector performed significantly better than the Iverson edge detector on average, the performance can be quite different on any particular image. Figure 12 shows the image where the Canny edge detector performed better than the Iverson edge detector by the largest amount while Figure 13 illustrates an image where the Iverson edge detector outperformed the Canny edge detector.

6.4.2.2 Results of the Fixed Parameter Comparison

Table 10 lists the results of the comparison of edge detectors using the parameters that were optimized and fixed for the set of twenty images. The statistically significant differences reveal that the Bergholm edge detector outperformed both the Canny and Nalwa edge detectors. The Iverson and Rothwell edge detectors did not perform significantly differently from any of the edge detectors in the pairwise tests.

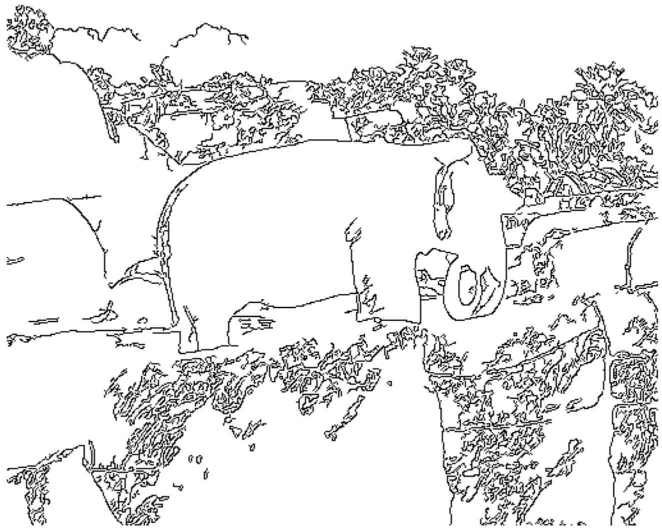


(a) Edges detected by the Canny edge detector in the banana image. (mean rating = 4.81)



(b) Edges detected by the Iverson edge detector in the banana image. (mean rating = 1.81)

Figure 12. An image where the Canny edge detector outperformed the Iverson edge detector.
Image (a) was produced by the Canny algorithm with input parameters *sigma*=0.60, *low*=0.30 and *high*=0.90. Image (b) was produced by the Iverson algorithm with input parameters *direction*=8, *low*=0.000 and *high*=0.000.



(a) Edges detected by the Canny edge detector (mean rating = 4.19)

(b) Edges detected by the Iverson edge detector (mean rating = 5.50)

Figure 13. An image where the Iverson edge detector outperformed the Canny edge detector.

Image (a) was produced by the Canny algorithm with input parameters *sigma*=0.60, *low*=0.30 and *high*=0.90. Image (b) was produced by the Iverson algorithm with input parameters *direction*=8, *low*=0.000 and *high*=0.000.

Edge Detector	Mean	Significant Differences
Bergholm (B)	4.38	(C,N) < B
Iverson (I)	4.24	
Rothwell (R)	4.21	
Nalwa (N)	3.97	
Canny (C)	3.96	

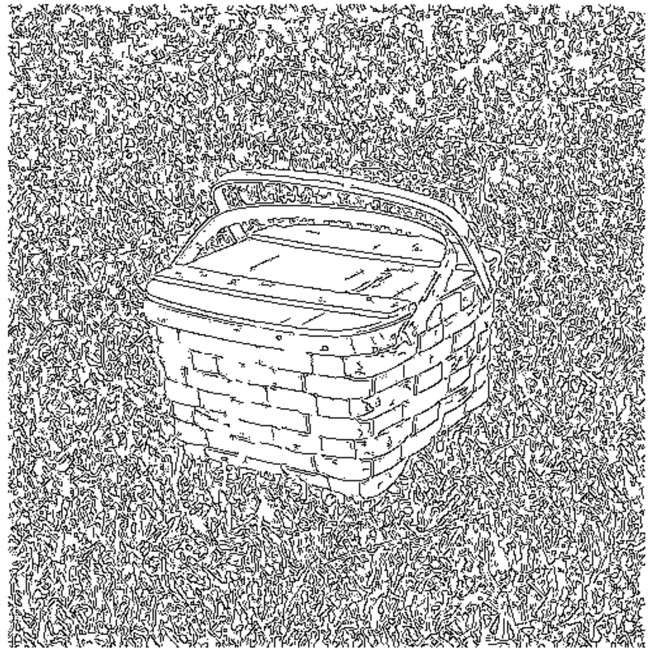
Table 10. Relative edge detector performance using fixed parameters.

Although the Bergholm edge detector performed significantly better than the Canny edge detector across the set of twenty images, the difference in performance on individual images varies. This is illustrated by Figures 14 and 15. Figure 14 shows the image where the Bergholm edge detector performed better than the Canny edge detector while Figure 15 shows an image where the Canny edge detector outperformed the Bergholm edge detector.

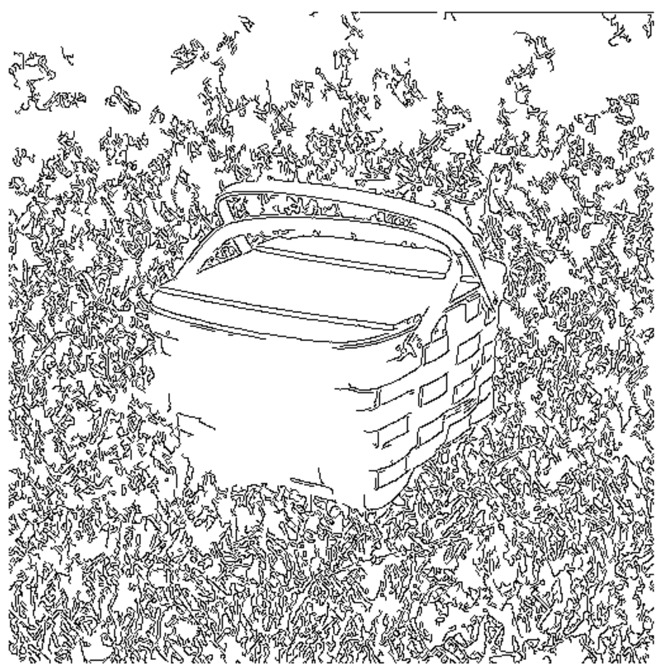
How does the measured relative performance of the edge detectors depend on the selection of images used in the evaluation?

An analysis of variance was done on the adapted parameter data to examine the interaction between the performance of the edge detectors and the image type. Results from the analysis of variance in Table 11 show that there are also significant interactions between the edge detector performance and the image type (Pr>F = 0.0023 for all the tests) in the adapted parameter data. This means that the size of the difference in the performance of the edge detectors changes with the type of images used to compare the algorithms.

Because there was an interaction between the performance of the algorithms and the image type, the relative performance of the algorithms was calculated separately for each image type. The results are displayed in Table 12. The table shows



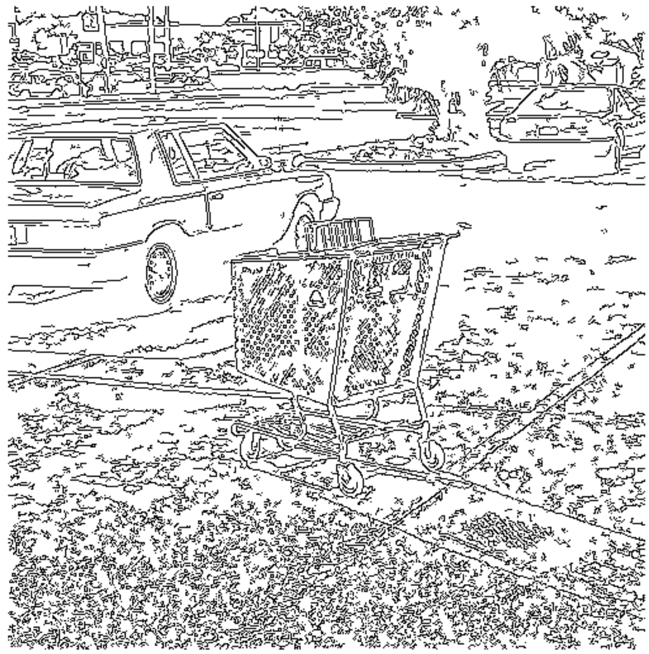
(a) Bergholm edge detector (mean rating = 5.81)



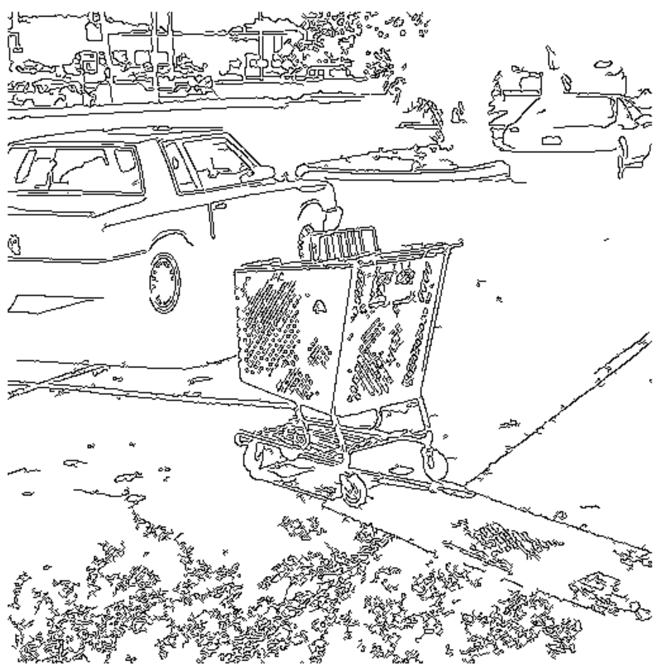
(b) Canny edge detector (mean rating = 3.06)

Figure 14. An image where the Bergholm edge detector outperformed the Canny edge detector.

Image (a) was produced by the Bergholm algorithm with input parameters *starting sigma*=2.0, *ending sigma*=1.0 and *threshold*=15. Image (b) was produced by the Canny algorithm with input parameters *sigma*=0.60, *low*=0.30 and *high*=0.90.



(a) Bergholm edge detector (mean=4.56)



(b) Canny edge detector (mean=5.31)

Figure 15. An image where the Canny edge detector outperformed the Bergholm edge detector.

Image (a) was produced by the Bergholm algorithm with input parameters *starting sigma*=2.0, *ending sigma*=1.0 and *threshold*=15. Image (b) was produced by the Canny algorithm with input parameters *sigma*=0.60, *low*=0.30 and *high*=0.90.

Source	DF	Anova SS	Mean Square	Pr > F
Edge detector	4	77.27	19.32	0.0001
Edge detector * Man-made/Natural	5	414.44	82.88	0.0001
Edge detector * Textured/Non-textured	5	67.12	13.42	0.0001
Edge detector * Man-made/Natural * Textured/Non-textured	5	40.99	8.20	0.0023
Error	1580	3476.95	2.20	

Table 11. ANOVA results for the ratings obtained for using adapted parameters.

that the relative ranking of the edge detectors in each image category is consistent; no two algorithms change significantly in relative performance to each other.

The low performance of the Iverson algorithm on the Natural, Non-textured images stands out. A study of the results shows that the ratings are low across four of the five images in this category. This shows that the low overall performance is not due to a "problem image" but is due to the whole set of images in this category. Currently, we are not able to conjecture a plausible explanation for this result.

A similar analysis was done on the fixed parameter data. Table 13 shows the results from an analysis of variance used to examined the significance of the interactions between the edge detector and the image type. The results indicate that there is a significant difference in the average ratings of the edge detectors (Pr>F = 0.0015) and that there are significant interactions between the edge detector and the image type (Pr>F = 0.0001 for all the tests). This means that the size of the difference in the performance of the edge detectors changes with the type of images used to compare the algorithms.

Because there was an interaction between the performance of the algorithms and the image type, separate analyses were conducted for each of the four subsets of the data. Table 14 shows the results of the analysis. The significant differences between the performance of the algorithms are generally consistent with each other.

Man-made Non-textured		
Edge Detector	Mean	Significant Difference
Canny (C)	5.54	I < C
Bergholm (B)	5.20	
Rothwell (R)	5.15	
Nalwa (N)	5.06	
Iverson (I)	4.85	

Man-made Textured		
Edge Detector	Mean	Significant Difference
Bergholm (B)	5.38	N < (R,B)
Rothwell (R)	5.33	
Canny (C)	5.03	
Iverson (I)	4.95	
Nalwa (N)	4.59	

Natural Non-textured		
Edge Detector	Mean	Significant Difference
Nalwa (N)	4.31	I < (B,C,R,N)
Rothwell (R)	4.24	
Canny (C)	4.19	
Bergholm (B)	4.13	
Iverson (I)	2.96	

Natural Textured		
Edge Detector	Mean	Significant Difference
Canny (C)	4.44	NONE
Bergholm (B)	4.41	
Rothwell (R)	4.31	
Iverson (I)	4.26	
Nalwa (N)	3.76	

Table 12. Relative performance of the edge detectors on subsets of the adapted parameter images.

Source	DF	Anova SS	Mean Square	Pr > F
Edge detector	4	42.79	10.70	0.0015
Edge detector * Man-made/Natural	5	722.33	144.47	0.0001
Edge detector * Textured/Non-textured	5	122.29	24.45	0.0001
Edge detector * Man-made/Natural * Textured/Non-textured	5	74.03	14.81	0.0001
Error	1580	3813.98	2.41	

Table 13. ANOVA results for the ratings obtained for using fixed parameters.

Man-made Non-textured		
Edge Detector	Mean	Significant Difference
Bergholm (B)	5.28	NONE
Rothwell (R)	4.86	
Iverson (I)	4.80	
Canny (C)	4.79	
Nalwa (N)	4.76	

Man-made Textured		
Edge Detector	Mean	Significant Difference
Rothwell (R)	5.13	(N,C) < (I,B,R)
Bergholm (B)	5.10	
Iverson (I)	5.04	
Canny (C)	4.30	
Nalwa (N)	4.04	

Natural Non-textured		
Edge Detector	Mean	Significant Difference
Nalwa (N)	3.61	R < N
Canny (C)	3.39	
Bergholm (B)	3.13	
Iverson (I)	2.90	
Rothwell (R)	2.84	

Natural Textured		
Edge Detector	Mean	Significant Difference
Iverson (I)	4.24	(C,N) < I
Rothwell (R)	4.03	
Bergholm (B)	4.00	
Nalwa (N)	3.46	
Canny (C)	3.35	

Table 14. Relative performance of the edge detectors on subsets of the fixed parameter images.

The only inconsistency was in the relative performance of the Rothwell and the Nalwa algorithms. The Nalwa algorithm was determined to be significantly better than the Rothwell algorithm on the Natural Non-textured objects while the Rothwell algorithm was determined to be significantly better than the Nalwa algorithm on the Man-made Textured images. This difference masked the Rothwell algorithm from being significant in the analysis based on the twenty images. This illustrates the dependence of the measured performance of an edge detector on the images that are used to evaluate them. In general, we would strongly caution against reading too much into the differences in rankings for different 5-image groups.

6.4.3 Execution Time of the Algorithms

The objective of the comparison of algorithms was to measure the performance of the algorithms by the quality of the results. As an afterthought, the execution time of the algorithms was considered.

Detector	Time (sec)
Canny	10
Nalwa	80
Iverson	1255
Rothwell	32
Bergholm	115

Table 15. Approximate average execution time of the algorithms on the 28 images.

The execution times for the algorithms were calculated from the time stamps of the edge files produced for the comparison. This means that the times reported here are only a crude approximation of the algorithm complexity. This is because the algorithms were optimized to varying degrees during compilation and may have different I/O patterns, and were run on shared SUN Sparc10 and Sparc20 computers. The times provided are therefore just estimates of the average execution time of the algorithms on 1792 images (64 runs for each of 28 images).

The estimated execution time for each algorithm is listed in Table 15. Small differences in the running times should not be considered important.

CHAPTER 7
DISCUSSION

7.1 Discussion of Results

The results in chapter 6 were used to draw conclusions about the relative performance of the algorithms compared in this evaluation. It is tempting to go one step further and draw conclusions about the field of edge detection in general. This is risky because the selection of edge detectors was designed to test a diverse set of edge detectors, not to represent all edge detection algorithms. It is safer to limit the speculation on the results to the edge detectors that were evaluated, rather than draw conclusions about the state of edge detection algorithms in general.

The results of our analysis of determining the effect of fixing or adapting the parameters of an algorithm for the image being processed showed that significantly better results are obtained when the parameters are adapted to each image.

An analysis of the relative performance of the algorithms resulting in a ranking of the algorithms as (Canny,Nalwa)<Bergholm for fixed parameters and as (Iverson,Nalwa)<(Rothwell,Bergholm,Canny) for adapted parameters. The performance increases from left to right and the parentheses group algorithms whose difference in performance was not statistically significant.

From this result, it is evident that the newer algorithms have achieved an increase in performance over the older algorithms when the parameters are fixed and are not adapted to each individual image. When the parameters are adapted for each image, however, the newer algorithms did not show the same significant increase in performance.

This performance increase for fixed parameters is a real achievement because there is no way to adapt the parameters of the algorithm for each image in most vision systems. Although some methods have been proposed for adapting the parameters for each image, it is unlikely that those techniques are as good as people are for the complex types of images used in this work.

The results indicated that the Canny algorithm had the highest performance when the parameters were adapted for each image. Although the performance was not statistically significantly better than the performance of the Rothwell or Bergholm algorithms, improving from the worst performance in fixed parameters to the best performance in adapted parameter performance is striking. This suggests that the parameters of the Canny algorithm are “good knobs to turn”.

These results suggest that the choice of the algorithm may depend on its application. For example, computer vision researchers developing higher level vision processing methods may prefer to use the Canny algorithm because it can produce better edge images if care is taken in adjusting the parameters manually. This would provide them with higher quality edges. Researchers implementing “production” vision systems that cannot manually adapt the parameters may however benefit from selecting one of the newer algorithms to incorporate into their system.

Finally, it is interesting to note that were no statistically significant differences in the performance of the five algorithms on Man-Made/Non-Textured images when the parameters were fixed. This is the type of images that the algorithms were generally designed to process.

7.2 Discussion of the Evaluation Methodology

The methodology presented in chapter 5 is novel is two ways. It relies on using real images in the evaluation and it measures the performance of edge detection algorithms by their performance in a vision system executing a task. These attributes required selecting a limited number of images, and using human vision in the evaluation process.

Measuring the performance of edge detection algorithms using a sampling of real images limits the evaluation because the results that are obtained are conditioned on the images used in the evaluation. Recall that the performance of the algorithms changed with the image properties as specified by the crude categorization of images as Man-made/Non-Textured, Man-made/Textured, Natural/Non-Textured and Natural/Textured. This means that a large number of images should be used to evaluate an edge detector. Twenty images were used in the overall evaluation. While this is not a large number of images, it does represent a diverse set of images, and it is a larger number of images than have been used in any previous comparison study. The analysis on each type of image (i.e. Man-made/Textured) was done on a set of only five images. While statistically significant differences in performance were found, the ability to generalize the results may be very limited. For example, it is unlikely that the particular five images we used adequately sample the space of all Man-made/Textured images. Therefore, no claim is made that any particular algorithm works best on any of the general image categories ("Textured", "Man-Made", etc.). The categories were only defined to test the algorithms on meaningful subsets of the images.

The requirement of using a large number of real images to measure the performance of algorithms may sound like a drawback of this method. It is not. Neither synthetic images nor a small number of real images can adequately capture the conditions under which an edge detector will need to function in a real vision system. Therefore, any evaluation method should use enough images to represent the range of input that an edge detector is expected to process. The number of input images that are "sufficient" for representing the input image domain is not well defined. Until this can be determined, I believe, the more images that are used in the evaluation process, the better.

I have argued against using synthetic images to evaluate edge detectors. While they can be used to produce a precise, repeatable measurement of the performance of an algorithm, the methods that rely on using them may "provide a more precise than accurate measure of the performance of an algorithm" [9].

To cope with the errors introduced by using a sample of real images, a moderate sized, diverse set of images were used in the evaluation. Images of man-made and natural and textured and non-textured objects were used in the evaluation because we believed that would test the algorithms over a broad range of image attributes and they could be used to examine if the relative performance of the algorithms depended on the image characteristics.

Selecting the task of object recognition to evaluate the performance of the algorithms from the edge images also places constraints on the generalizations of the results. Since the performance of the algorithms was measured using an object recognition task, the results are only directly meaningful for that task. For example, using these results to select an algorithm for isolating the features to use in stereo correspondence processing may be risky. We chose to use object recognition as the task because it is the long term goal of computer vision and a lot of research is being done in this area.

Edge detection algorithms were assessed in this work solely on their performance of detecting edges. This was done because the detected edges were represented in a binary edge image for evaluation. This format could not represent the direction and strength of the edges. We realize that both of these can be very important in many computer vision systems, but we believe they play a secondary role to the importance of accurate detection of edges.

The human vision system was used for object recognition because it was the only robust system currently able to perform general 3-dimensional object recognition. This choice introduced subjective variability in measurement process. This variability takes on two forms. First there is the variability in sampling of the participants. Second, there is the variability within the group of participants that are used in the evaluation.

Our methods did not examine the first source of variation. We used computer vision students in the experiments, so this sampling was far from a random sampling of the population at large. We did estimate the second type of variability by measuring the overall correlation of results given by the participants and by using an analysis of variance that counted this variation as noise. The high correlation coefficient between participants and the significance of the main effects in the analysis of variance support our belief that strong conclusions can be made in spite of the inherent subjective variability in the data.

The methodology we used measured the relative performance of the edge detection algorithms evaluated in this study. The conclusions about the performance of the edge detectors were drawn from statistical tests that measure a significance of the difference in means for different factors; these include edge detector, image type and the method used in setting the parameters.

It is important to note that this method did not characterize the performance of the algorithms using an absolute score. This is because of the nature of the participant ratings collected in the experiment. While we collected numerical ratings of the quality of the edge images by providing a scale for user responses, these are relative scores. Therefore, it would be a mistake to measure the performance of another algorithm by collecting data for it and comparing the numerical scores to the results collected in this experiment. Doing so would ignore many potentially significant sources of variation. The next section presents a better method of using our results in evaluating other edge detection algorithms.

7.3 Extended Application of the Evaluation Method

The goal in this work was to develop a method for evaluating edge detection algorithms and to demonstrate its use by applying it to measure a sampling of edge detection algorithms. Therefore, it is the methodology, and not only the specific results, are useful to the vision community.

My hope is that the criteria we specified for evaluating edge detection algorithms will be adopted by the vision community. This could be done by either developing new evaluation methods that meet these criteria or by applying the specific methodology developed in this work. If the latter method is pursued, this evaluation methodology could be applied in part or in full to evaluate a new algorithm.

Applying the method in its complete form would require defining a set of edge detectors to evaluate, obtaining new images, checking the naming consistency of each, categorizing the images by their properties, determining the parameters to use for each algorithm and then comparing the relative performance of the algorithms. Applying the method in part may require only doing the last two steps.

To make it easier for other researchers to compare edge detection algorithms using the method applied in this thesis, the images that were used in this evaluation are available on the world wide web

(http://marathon.csee.usf.edu/edge/edge_detection.html)

and by anonymous ftp

(ftp://figment.csee.usf.edu/pub/Edge_Comparison/images)

Using these resources, the only steps required to evaluate a new algorithm are: (1) to identify preferred parameters for the new algorithm to be compared by using the parameter selection methodology, (2) to conduct the edge detector comparison experiment with both the new algorithm and at least a few algorithms used in this study (we recommend the Canny and Bergholm) and (3) do the statistical analysis.

The steps involved in evaluating a new edge detection algorithm are to:

1) Decide which of the algorithms the new algorithm is to be compared with. In principle, one could compare a new algorithm with only the highest performance algorithm. This, however, is not the recommended approach because comparing several edge detectors is much more informative, and is little more work than comparing only two algorithms.

2) Acquire the images from the ftp site.

3) Select 64 initial parameter combinations for the new algorithm and generate the 64 edge images for each of the 20 grey-scale images. View the edge images and select the best five for each of the 20 images (12 hours time). Apply a greedy search to find a subset of 12 of the 64 parameters. At each step in the search, select the parameter set that reduces the number of best edge images (top 5/64) included across all 20 images the least number of times, by the largest amount possible. This means that one first searches for a subset of parameters that includes all images at least once, then includes each image at least twice, etc. until 12 parameter sets are included.

4) Print out evaluation sheets similar to those in Figure 2 for each of the 240 edge images (20images*12parameters). Print out the 20 grey-scale images.

Make a set of evaluation images for each participant by photocopying the prints. Have a number of participants (we used nine) evaluate all 240 edge images in one session. Note that paper is used because it allows the participants to view the whole set of edge images at once. This is not possible on a computer monitor due to its limited resolution. The experiment should take a couple of hours.

5) Type the ratings into a computer and calculate the ICC(3,k) correlation coefficient to check that the subjects shared a common rating scheme. Calculate the average ratings for each parameter set for each image. To identify the best adapted parameters, find the best average rating for each image. To find the best fixed parameters, calculate the mean of the average ratings (across images) and find the parameter set with the largest mean. Please note, that the parameters identified by this process may (and probably are not) the very best fixed or adapted parameters attainable. If someone spent more time adjusting the parameters to each image (starting with more than 64 initial parameter sets), they may get better results. Therefore, the above procedure should be used because it applies equal effort in the parameter optimization process for all of the algorithms.

6) Print out the edge images for each algorithm for each image. Also print the grey-scale images. Make a number of sets of evaluation images (we made one set for each of 16 participants) by photocopying the prints. Randomize the edge images within each of the 20 sets of images separately for each of the evaluation sets. Then randomize the order of the 20 sets of images. Have each participants evaluate all of the edge images in one session. The time required for this step will depend on the number of edge

detectors being compared. If the new edge detector is compared to all five of the edge detectors evaluated in this thesis then there will be 240 edge images for each participant to evaluate. It should take a couple of hours to rate 240 edge images.

7) Calculate the ICC(3,k) correlation coefficient to determine if the subjects shared a common rating scheme. Divide the data in half (adapted and fixed parameter data) and analyze each subset of data the same way. Perform a set of one-way analysis of variance tests using the ratings obtained for each pair of algorithms. The number of tests will depend on the number of algorithms being compared. In deciding whether each one way ANOVA test is significant, use $\alpha = \frac{0.05}{c}$, where c is the number of statistical tests being done. We used α=0.005 because c is 10 (5 choose 2). If all six algorithms are compared then there will be 15 one-way ANAOVA's and $\alpha = 0.00\overline{3}$. Calculate the means for each each detector, order them, and group the means using the results of the ANOVA tests to identify statistically significant differences in the ratings. This will provide the relative performance of the algorithms.

I estimate that the a comparison of edge detectors using the above method could realistically be conducted in three or four weeks. This is worthwhile because it clearly demonstrates the performance of an algorithm. Given the amount of time it takes to develop a new edge detection algorithm, investing one month to demonstrate its performance is, I believe, a good use of that time.

It is important to note that repeated application of this evaluation method can eventually "wear out" the image set. This is because new edge detectors might be designed to give good performance on the particular set of 20 images used in the evaluation without providing good performance on other images. This is an inherent problem with making an evaluation test public because an algorithm can be trained to perform well on the test. To minimize the possibility of this, a new set of images could occasionally be substituted for the 20 images presently used in the evaluation. The cost of doing this is that the naming experiment must be performed with the new images, and the parameter setting experiment must then be re-applied for each algorithm.

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APPENDICES

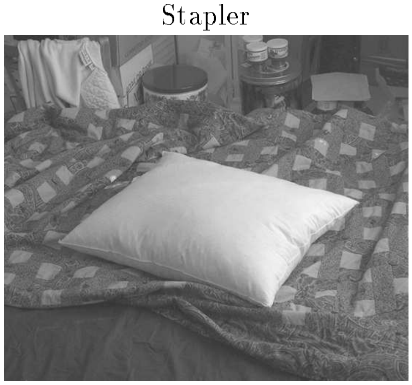
APPENDIX 1. IMAGES USED IN THE EVALUATION

Golf Cart

Pitcher

Stapler

Mailbox



Pillow

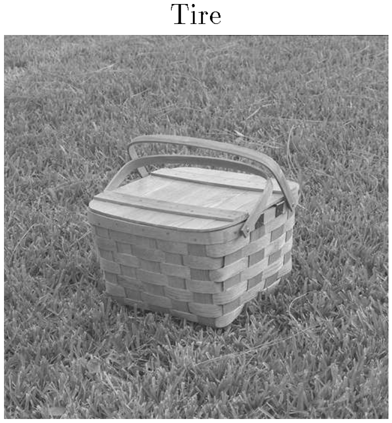
Figure 16. Man-made objects without texture.

Brush

Shopping Cart

Tire

Grater



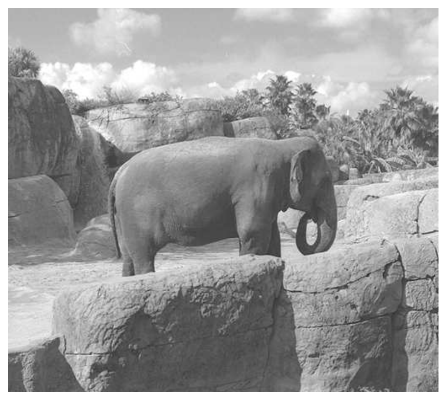
Basket

Figure 17. Man-made objects with texture.

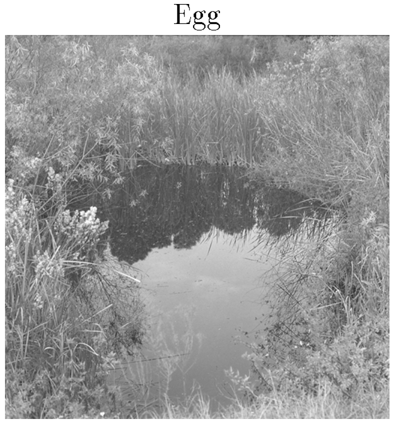
Orange

Banana

Egg



Elephant

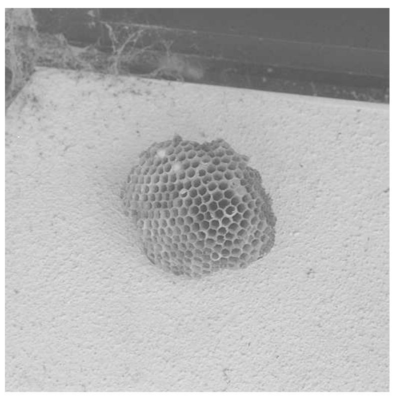


Pond

Figure 18. Natural objects without texture.

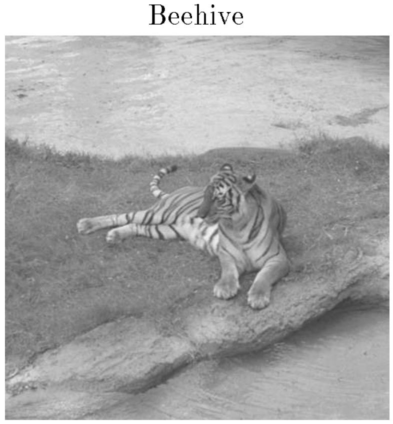
Pine Cone

Feather



Beehive

Turtle



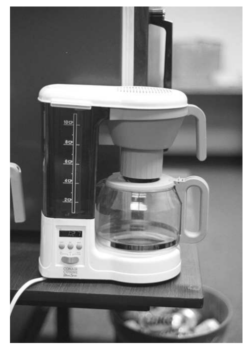
Tiger

Figure 19. Natural objects with texture.

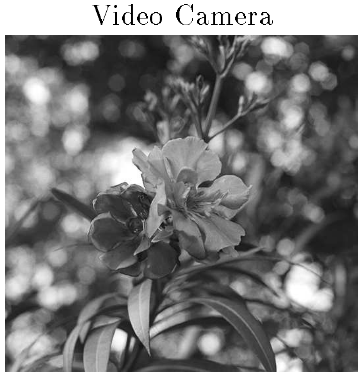
Briefcase

Trash can

Video Camera



Coffee Maker



Flower

Airplane

Traffic Cone

Stairs

Figure 20. Eight images used in a previous study.

APPENDIX 2. INITIAL PARAMETER SETTINGS

Initially selected set of 64 parameter combinations			
sigma, low, high	sigma, low, high	sigma, low, high	sigma, low, high
0.60 0.20 0.60	1.20 0.20 0.60	1.80 0.20 0.60	2.40 0.20 0.60
0.60 0.20 0.70	1.20 0.20 0.70	1.80 0.20 0.70	2.40 0.20 0.70
0.60 0.20 0.80	1.20 0.20 0.80	1.80 0.20 0.80	2.40 0.20 0.80
0.60 0.20 0.90	1.20 0.20 0.90	1.80 0.20 0.90	2.40 0.20 0.90
0.60 0.30 0.60	1.20 0.30 0.60	1.80 0.30 0.60	2.40 0.30 0.60
0.60 0.30 0.70	1.20 0.30 0.70	1.80 0.30 0.70	2.40 0.30 0.70
0.60 0.30 0.80	1.20 0.30 0.80	1.80 0.30 0.80	2.40 0.30 0.80
0.60 0.30 0.90	1.20 0.30 0.90	1.80 0.30 0.90	2.40 0.30 0.90
0.60 0.40 0.60	1.20 0.40 0.60	1.80 0.40 0.60	2.40 0.40 0.60
0.60 0.40 0.70	1.20 0.40 0.70	1.80 0.40 0.70	2.40 0.40 0.70
0.60 0.40 0.80	1.20 0.40 0.80	1.80 0.40 0.80	2.40 0.40 0.80
0.60 0.40 0.90	1.20 0.40 0.90	1.80 0.40 0.90	2.40 0.40 0.90
0.60 0.50 0.60	1.20 0.50 0.60	1.80 0.50 0.60	2.40 0.50 0.60
0.60 0.50 0.70	1.20 0.50 0.70	1.80 0.50 0.70	2.40 0.50 0.70
0.60 0.50 0.80	1.20 0.50 0.80	1.80 0.50 0.80	2.40 0.50 0.80
0.60 0.50 0.90	1.20 0.50 0.90	1.80 0.50 0.90	2.40 0.50 0.90

The top 5 of 64 parameter combinations selected with the parameter selection tool for each image.					
Image	Combination 1	Combination 2	Combination 3	Combination 4	Combination 5
golf cart	2.40 0.20 0.60	0.60 0.40 0.90	1.20 0.50 0.80	2.40 0.50 0.60	0.60 0.50 0.90
pitcher	0.60 0.20 0.80	0.60 0.40 0.80	0.60 0.30 0.80	1.80 0.40 0.70	1.80 0.20 0.70
stapler	2.40 0.20 0.70	1.80 0.50 0.70	1.20 0.50 0.80	1.20 0.20 0.80	2.40 0.40 0.70
mailbox	1.20 0.20 0.60	1.20 0.50 0.60	1.20 0.40 0.60	2.40 0.40 0.90	1.20 0.30 0.60
pillow	2.40 0.20 0.90	1.80 0.20 0.90	1.80 0.30 0.90	2.40 0.30 0.80	2.40 0.20 0.80
brush	0.60 0.50 0.80	0.60 0.20 0.90	1.20 0.50 0.80	1.20 0.30 0.80	1.20 0.40 0.80
shopping cart	1.20 0.50 0.80	1.20 0.40 0.80	0.60 0.40 0.90	0.60 0.50 0.80	0.60 0.30 0.90
tire	1.20 0.20 0.60	1.80 0.20 0.60	1.80 0.20 0.70	2.40 0.30 0.60	2.40 0.20 0.60
grater	0.60 0.40 0.90	0.60 0.30 0.90	1.20 0.50 0.80	1.20 0.40 0.80	0.60 0.20 0.90
picnic basket	0.60 0.20 0.60	0.60 0.30 0.60	0.60 0.40 0.60	1.20 0.20 0.60	1.80 0.20 0.60
orange	1.20 0.30 0.90	0.60 0.50 0.90	1.20 0.20 0.90	1.20 0.40 0.80	1.20 0.40 0.90
banana	1.80 0.20 0.80	2.40 0.30 0.70	1.20 0.20 0.70	1.80 0.20 0.70	1.20 0.20 0.80
egg	2.40 0.20 0.70	1.20 0.30 0.80	2.40 0.30 0.70	1.20 0.40 0.80	2.40 0.50 0.70
elephant	1.80 0.20 0.80	2.40 0.30 0.70	1.80 0.20 0.70	1.20 0.40 0.70	1.20 0.30 0.70
pond	1.20 0.20 0.80	1.20 0.30 0.70	0.60 0.40 0.70	0.60 0.30 0.70	0.60 0.30 0.80
pine cone	1.20 0.20 0.60	1.20 0.30 0.60	0.60 0.30 0.60	1.80 0.40 0.60	1.20 0.40 0.60
feather	1.20 0.50 0.60	0.60 0.30 0.90	1.20 0.40 0.60	1.20 0.30 0.60	1.20 0.20 0.60
beehive	1.80 0.40 0.90	1.80 0.30 0.90	2.40 0.20 0.90	1.80 0.50 0.90	1.80 0.20 0.90
turtle	1.20 0.30 0.90	1.20 0.40 0.90	1.20 0.20 0.90	0.60 0.40 0.90	0.60 0.30 0.90
tiger	1.20 0.40 0.90	1.80 0.40 0.90	1.20 0.50 0.90	1.80 0.30 0.90	2.40 0.30 0.80
briefcase	1.20 0.40 0.80	1.80 0.50 0.70	1.20 0.30 0.80	1.80 0.40 0.70	2.40 0.20 0.60
trash can	1.80 0.30 0.70	1.20 0.20 0.60	1.20 0.30 0.60	1.80 0.20 0.70	1.20 0.40 0.60
video camera	1.80 0.20 0.60	1.80 0.30 0.60	1.80 0.40 0.60	1.20 0.40 0.60	1.80 0.20 0.70
coffee maker	0.60 0.20 0.90	1.80 0.20 0.70	1.20 0.20 0.80	1.20 0.30 0.80	1.20 0.40 0.80
flower	1.20 0.30 0.80	0.60 0.20 0.90	0.60 0.40 0.90	0.60 0.50 0.90	0.60 0.30 0.90
airplane	0.60 0.20 0.90	0.60 0.30 0.90	0.60 0.50 0.90	0.60 0.40 0.90	1.20 0.20 0.90
traffic cone	2.40 0.50 0.80	2.40 0.40 0.80	2.40 0.30 0.90	1.80 0.50 0.90	0.60 0.50 0.90
stairs	0.60 0.30 0.80	0.60 0.20 0.80	1.80 0.30 0.60	2.40 0.20 0.60	1.20 0.50 0.70

(a) Canny

Table 16. Parameters initially selected for the edge detectors.
(a) Canny (b) Nalwa (c) Iverson (d) Bergholm and (e) Rothwell
(Continued on next page)

Table 16. (Continued)

Initially selected set of 64 parameter combinations			
blur, low, high	blur, low, high	blur, low, high	blur, low, high
0.60 0.05 0.15	0.90 0.05 0.15	1.20 0.05 0.15	1.50 0.05 0.15
0.60 0.05 0.30	0.90 0.05 0.30	1.20 0.05 0.30	1.50 0.05 0.30
0.60 0.05 0.45	0.90 0.05 0.45	1.20 0.05 0.45	1.50 0.05 0.45
0.60 0.05 0.60	0.90 0.05 0.60	1.20 0.05 0.60	1.50 0.05 0.60
0.60 0.10 0.15	0.90 0.10 0.15	1.20 0.10 0.15	1.50 0.10 0.15
0.60 0.10 0.30	0.90 0.10 0.30	1.20 0.10 0.30	1.50 0.10 0.30
0.60 0.10 0.45	0.90 0.10 0.45	1.20 0.10 0.45	1.50 0.10 0.45
0.60 0.10 0.60	0.90 0.10 0.60	1.20 0.10 0.60	1.50 0.10 0.60
0.60 0.15 0.15	0.90 0.15 0.15	1.20 0.15 0.15	1.50 0.15 0.15
0.60 0.15 0.30	0.90 0.15 0.30	1.20 0.15 0.30	1.50 0.15 0.30
0.60 0.15 0.45	0.90 0.15 0.45	1.20 0.15 0.45	1.50 0.15 0.45
0.60 0.15 0.60	0.90 0.15 0.60	1.20 0.15 0.60	1.50 0.15 0.60
0.60 0.20 0.15	0.90 0.20 0.15	1.20 0.20 0.15	1.50 0.20 0.15
0.60 0.20 0.30	0.90 0.20 0.30	1.20 0.20 0.30	1.50 0.20 0.30
0.60 0.20 0.45	0.90 0.20 0.45	1.20 0.20 0.45	1.50 0.20 0.45
0.60 0.20 0.60	0.90 0.20 0.60	1.20 0.20 0.60	1.50 0.20 0.60

The top 5 of 64 parameter combinations selected with the parameter selection tool for each image.					
Image	Combination 1	Combination 2	Combination 3	Combination 4	Combination 5
golf cart	1.50 0.05 0.60	1.50 0.20 0.60	1.50 0.15 0.45	1.50 0.10 0.60	1.50 0.15 0.60
pitcher	1.50 0.20 0.60	1.50 0.05 0.45	0.60 0.15 0.60	0.60 0.05 0.60	0.60 0.20 0.60
stapler	1.50 0.05 0.60	1.50 0.15 0.60	1.50 0.10 0.60	1.50 0.20 0.60	1.50 0.15 0.45
mailbox	1.50 0.05 0.15	0.90 0.20 0.15	0.60 0.10 0.15	0.90 0.10 0.15	1.50 0.15 0.15
pillow	1.20 0.10 0.60	1.50 0.20 0.60	1.50 0.10 0.60	1.50 0.15 0.60	1.20 0.20 0.60
brush	0.60 0.05 0.60	0.60 0.15 0.60	0.60 0.20 0.60	0.60 0.10 0.60	0.90 0.10 0.60
shopping cart	0.90 0.05 0.60	0.90 0.15 0.60	0.60 0.15 0.60	1.50 0.10 0.45	0.60 0.10 0.60
tire	1.20 0.05 0.15	1.50 0.10 0.15	1.20 0.10 0.15	1.50 0.15 0.15	0.90 0.05 0.15
grater	0.60 0.15 0.60	0.60 0.05 0.60	0.60 0.10 0.60	0.60 0.20 0.60	0.90 0.05 0.60
picnic basket	1.50 0.15 0.15	1.20 0.15 0.15	0.60 0.05 0.15	1.20 0.05 0.15	1.20 0.20 0.15
orange	1.50 0.20 0.60	1.50 0.05 0.60	1.50 0.15 0.60	1.50 0.10 0.60	1.20 0.15 0.60
banana	1.50 0.15 0.30	1.20 0.05 0.30	1.50 0.20 0.30	0.60 0.20 0.30	0.60 0.05 0.30
egg	1.50 0.20 0.45	1.50 0.05 0.45	1.50 0.10 0.45	1.50 0.15 0.45	1.20 0.15 0.45
elephant	1.20 0.05 0.60	1.20 0.10 0.60	1.20 0.15 0.60	1.20 0.20 0.60	0.60 0.15 0.60
pond	0.90 0.05 0.15	0.60 0.20 0.15	0.60 0.10 0.15	1.20 0.05 0.15	1.50 0.15 0.15
pine cone	1.50 0.05 0.15	1.50 0.20 0.15	1.50 0.15 0.15	1.50 0.10 0.15	1.20 0.10 0.15
feather	0.60 0.20 0.30	1.20 0.05 0.30	0.60 0.15 0.30	0.60 0.05 0.30	1.20 0.10 0.30
beehive	1.50 0.05 0.60	1.50 0.20 0.60	1.50 0.15 0.60	1.50 0.10 0.60	1.20 0.10 0.60
turtle	1.50 0.20 0.60	1.50 0.10 0.60	1.50 0.05 0.60	1.50 0.15 0.60	1.20 0.05 0.60
tiger	1.50 0.20 0.60	1.50 0.15 0.60	1.50 0.05 0.60	1.50 0.10 0.60	1.20 0.20 0.60
briefcase	1.50 0.15 0.60	1.50 0.20 0.60	1.50 0.05 0.60	1.50 0.10 0.60	1.20 0.15 0.60
trash can	1.20 0.05 0.30	1.20 0.20 0.30	1.20 0.15 0.30	1.50 0.15 0.30	1.20 0.10 0.45
video camera	1.50 0.15 0.45	1.50 0.20 0.45	1.50 0.05 0.45	1.20 0.05 0.45	1.50 0.10 0.45
coffee maker	1.20 0.10 0.60	1.50 0.10 0.60	1.50 0.15 0.60	1.20 0.05 0.60	0.90 0.20 0.60
flower	1.50 0.10 0.60	1.50 0.20 0.60	1.50 0.15 0.60	1.50 0.05 0.60	1.20 0.20 0.60
airplane	1.50 0.15 0.60	1.50 0.10 0.60	1.50 0.20 0.60	1.50 0.05 0.60	1.20 0.10 0.60
traffic cone	1.20 0.10 0.60	1.50 0.10 0.60	1.20 0.15 0.60	1.50 0.20 0.60	1.50 0.05 0.60
stairs	0.60 0.10 0.60	0.60 0.15 0.60	0.60 0.05 0.60	0.90 0.15 0.60	0.90 0.05 0.60

(b) Nalwa

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Table 16. (Continued)

Initially selected set of 64 parameter combinations			
directions, low, high	directions, low, high	directions, low, high	directions, low, high
4 0.00 0.00	6 0.00 0.00	8 0.00 0.00	10 0.00 0.00
4 0.00 0.05	6 0.00 0.05	8 0.00 0.05	10 0.00 0.05
4 0.00 0.30	6 0.00 0.30	8 0.00 0.30	10 0.00 0.30
4 0.00 0.55	6 0.00 0.55	8 0.00 0.55	10 0.00 0.55
4 0.00 0.80	6 0.00 0.80	8 0.00 0.80	10 0.00 0.80
4 0.20 0.05	6 0.20 0.05	8 0.20 0.05	10 0.20 0.05
4 0.20 0.30	6 0.20 0.30	8 0.20 0.30	10 0.20 0.30
4 0.20 0.55	6 0.20 0.55	8 0.20 0.55	10 0.20 0.55
4 0.20 0.80	6 0.20 0.80	8 0.20 0.80	10 0.20 0.80
4 0.40 0.05	6 0.40 0.05	8 0.40 0.05	10 0.40 0.05
4 0.40 0.30	6 0.40 0.30	8 0.40 0.30	10 0.40 0.30
4 0.40 0.55	6 0.40 0.55	8 0.40 0.55	10 0.40 0.55
4 0.40 0.80	6 0.40 0.80	8 0.40 0.80	10 0.40 0.80
4 0.60 0.05	6 0.60 0.05	8 0.60 0.05	10 0.60 0.05
4 0.60 0.30	6 0.60 0.30	8 0.60 0.30	10 0.60 0.30
4 0.60 0.55	6 0.60 0.55	8 0.60 0.55	10 0.60 0.55

The top 5 of 64 parameter combinations selected with the parameter selection tool for each image.					
Image	Combination 1	Combination 2	Combination 3	Combination 4	Combination 5
golf cart	10 0.00 0.05	10 0.20 0.05	8 0.40 0.55	8 0.20 0.55	8 0.60 0.55
pitcher	6 0.60 0.30	6 0.00 0.30	6 0.20 0.05	6 0.60 0.05	6 0.00 0.00
stapler	6 0.00 0.00	8 0.00 0.05	4 0.40 0.05	4 0.60 0.30	4 0.20 0.30
mailbox	10 0.00 0.05	4 0.00 0.05	4 0.20 0.05	4 0.60 0.05	8 0.00 0.05
pillow	8 0.00 0.00	8 0.60 0.05	8 0.20 0.05	8 0.40 0.05	8 0.20 0.30
brush	4 0.60 0.55	4 0.00 0.55	4 0.20 0.55	4 0.40 0.55	8 0.00 0.55
shopping cart	10 0.00 0.80	4 0.00 0.80	4 0.20 0.80	10 0.40 0.55	8 0.20 0.55
tire	8 0.00 0.00	8 0.20 0.05	8 0.40 0.05	8 0.60 0.05	8 0.00 0.30
grater	4 0.00 0.05	4 0.40 0.05	4 0.20 0.05	4 0.60 0.05	8 0.20 0.30
picnic basket	4 0.20 0.55	6 0.00 0.05	10 0.00 0.05	4 0.40 0.05	6 0.60 0.05
orange	8 0.00 0.00	4 0.20 0.05	4 0.40 0.05	8 0.20 0.05	4 0.20 0.30
banana	8 0.00 0.00	8 0.20 0.05	4 0.60 0.05	4 0.40 0.05	4 0.00 0.30
egg	4 0.00 0.05	4 0.20 0.05	8 0.00 0.30	6 0.40 0.05	4 0.40 0.05
elephant	6 0.60 0.05	6 0.00 0.30	10 0.00 0.00	10 0.40 0.05	10 0.00 0.05
pond	4 0.00 0.05	4 0.00 0.00	4 0.20 0.30	8 0.40 0.05	8 0.00 0.00
pine cone	8 0.20 0.05	10 0.00 0.00	8 0.60 0.05	8 0.00 0.30	4 0.00 0.30
feather	8 0.60 0.55	8 0.20 0.55	8 0.00 0.55	8 0.20 0.30	8 0.00 0.00
beehive	8 0.00 0.55	4 0.40 0.30	8 0.60 0.05	8 0.00 0.05	8 0.20 0.30
turtle	8 0.00 0.05	4 0.00 0.05	4 0.00 0.00	4 0.00 0.30	4 0.20 0.30
tiger	10 0.00 0.00	6 0.60 0.30	8 0.00 0.30	6 0.00 0.00	6 0.40 0.30
briefcase	8 0.20 0.30	6 0.00 0.30	8 0.00 0.30	6 0.20 0.30	8 0.60 0.30
trash can	6 0.00 0.00	8 0.00 0.05	8 0.40 0.05	8 0.20 0.05	8 0.20 0.30
video camera	8 0.00 0.05	8 0.20 0.05	8 0.00 0.00	8 0.40 0.05	8 0.60 0.05
coffee maker	6 0.00 0.00	6 0.40 0.30	6 0.00 0.30	6 0.40 0.05	6 0.60 0.05
flower	8 0.60 0.55	4 0.20 0.55	8 0.20 0.55	8 0.40 0.55	8 0.00 0.55
airplane	8 0.00 0.55	8 0.20 0.55	8 0.40 0.50	4 0.20 0.50	4 0.00 0.55
traffic cone	4 0.20 0.55	8 0.00 0.55	4 0.60 0.55	6 0.40 0.55	6 0.60 0.55
stairs	8 0.00 0.55	4 0.20 0.55	10 0.00 0.55	8 0.40 0.55	4 0.00 0.55

(c) Iverson

(continued on next page)

Table 16. (Continued)

Initially selected set of 64 parameter combinations			
start sigma, end sigma, high	start sigma, end sigma, high	start sigma, end sigma, high	start sigma, end sigma, high
2.0 0.5 5.0	3.0 0.5 5.0	4.0 0.5 5.0	5.0 0.5 5.0
2.0 0.5 10.0	3.0 0.5 10.0	4.0 0.5 10.0	5.0 0.5 10.0
2.0 0.5 15.0	3.0 0.5 15.0	4.0 0.5 15.0	5.0 0.5 15.0
2.0 0.5 20.0	3.0 0.5 20.0	4.0 0.5 20.0	5.0 0.5 20.0
2.0 1.0 5.0	3.0 1.0 10.0	4.0 1.0 5.0	5.0 1.0 5.0
2.0 1.0 10.0	3.0 1.0 15.0	4.0 1.0 10.0	5.0 1.0 10.0
2.0 1.0 15.0	3.0 1.0 20.0	4.0 1.0 15.0	5.0 1.0 15.0
2.0 1.0 20.0	3.0 1.0 5.0	4.0 1.0 20.0	5.0 1.0 20.0
2.0 1.5 5.0	3.0 1.5 5.0	4.0 1.5 5.0	5.0 1.5 5.0
2.0 1.5 10.0	3.0 1.5 10.0	4.0 1.5 10.0	5.0 1.5 10.0
2.0 1.5 15.0	3.0 1.5 15.0	4.0 1.5 15.0	5.0 1.5 15.0
2.0 1.5 20.0	3.0 1.5 20.0	4.0 1.5 20.0	5.0 1.5 20.0
2.0 2.0 5.0	3.0 2.0 5.0	4.0 2.0 5.0	5.0 2.0 5.0
2.0 2.0 10.0	3.0 2.0 10.0	4.0 2.0 10.0	5.0 2.0 10.0
2.0 2.0 15.0	3.0 2.0 15.0	4.0 2.0 15.0	5.0 2.0 15.0
2.0 2.0 20.0	3.0 2.0 20.0	4.0 2.0 20.0	5.0 2.0 20.0

The top 5 of 64 parameter combinations selected with the parameter selection tool for each image.					
Image	Combination 1	Combination 2	Combination 3	Combination 4	Combination 5
golf cart	2.0 1.0 20.0	3.0 2.0 20.0	5.0 1.5 15.0	2.0 2.0 20.0	2.0 1.5 20.0
pitcher	2.0 2.0 15.0	2.0 1.0 15.0	2.0 0.5 15.0	2.0 1.5 15.0	4.0 2.0 15.0
stapler	4.0 1.5 10.0	3.0 2.0 5.0	3.0 2.0 10.0	3.0 1.5 10.0	4.0 2.0 10.0
mailbox	4.0 1.5 5.0	4.0 2.0 5.0	4.0 1.0 5.0	3.0 2.0 5.0	5.0 1.5 5.0
pillow	4.0 2.0 15.0	4.0 1.5 15.0	5.0 2.0 15.0	3.0 2.0 15.0	4.0 1.5 20.0
brush	2.0 1.5 15.0	2.0 2.0 10.0	4.0 1.0 15.0	2.0 1.0 15.0	3.0 1.0 15.0
shopping cart	2.0 2.0 20.0	2.0 1.5 20.0	2.0 1.0 20.0	2.0 2.0 15.0	3.0 2.0 15.0
tire	2.0 2.0 5.0	3.0 1.5 5.0	3.0 2.0 5.0	2.0 1.5 5.0	2.0 1.0 5.0
grater	2.0 1.5 15.0	2.0 1.0 15.0	2.0 1.0 20.0	2.0 0.5 20.0	2.0 1.5 20.0
picnic basket	2.0 1.5 10.0	3.0 1.5 10.0	4.0 1.5 10.0	2.0 1.0 15.0	3.0 1.0 10.0
orange	2.0 1.5 10.0	5.0 1.5 10.0	2.0 2.0 10.0	5.0 1.5 15.0	3.0 1.5 10.0
banana	5.0 2.0 5.0	2.0 2.0 5.0	4.0 1.5 5.0	3.0 2.0 5.0	5.0 1.5 5.0
egg	5.0 2.0 10.0	5.0 2.0 5.0	5.0 1.5 10.0	4.0 2.0 10.0	4.0 1.5 10.0
elephant	3.0 2.0 20.0	2.0 1.5 20.0	2.0 2.0 20.0	4.0 2.0 20.0	5.0 2.0 20.0
pond	2.0 2.0 10.0	3.0 1.5 10.0	3.0 1.0 10.0	2.0 1.0 15.0	2.0 0.5 15.0
pine cone	3.0 1.0 15.0	4.0 1.5 15.0	5.0 1.5 10.0	2.0 1.5 15.0	4.0 2.0 15.0
feather	3.0 2.0 10.0	3.0 2.0 15.0	2.0 2.0 15.0	3.0 1.0 15.0	3.0 1.5 15.0
beehive	3.0 1.5 20.0	3.0 2.0 20.0	4.0 1.5 15.0	4.0 2.0 15.0	2.0 2.0 20.0
turtle	3.0 1.5 15.0	2.0 1.5 15.0	2.0 1.5 20.0	4.0 1.5 20.0	2.0 2.0 15.0
tiger	2.0 2.0 20.0	4.0 1.5 20.0	3.0 2.0 20.0	3.0 1.5 20.0	5.0 1.5 20.0
briefcase	2.0 2.0 15.0	3.0 2.0 10.0	3.0 1.5 10.0	2.0 1.5 15.0	2.0 1.5 20.0
trash can	4.0 2.0 5.0	5.0 2.0 5.0	5.0 1.5 5.0	3.0 2.0 5.0	4.0 1.5 5.0
video camera	2.0 2.0 10.0	4.0 2.0 10.0	2.0 1.5 10.0	3.0 1.5 10.0	3.0 2.0 10.0
coffee maker	2.0 2.0 10.0	4.0 2.0 10.0	3.0 1.5 10.0	3.0 2.0 10.0	2.0 1.5 15.0
flower	5.0 1.5 20.0	4.0 2.0 20.0	5.0 2.0 20.0	2.0 2.0 20.0	4.0 1.5 20.0
airplane	3.0 1.0 20.0	4.0 1.0 20.0	4.0 1.5 20.0	4.0 0.5 20.0	5.0 1.0 15.0
traffic cone	4.0 2.0 20.0	2.0 2.0 20.0	5.0 1.5 20.0	5.0 2.0 20.0	3.0 2.0 20.0
stairs	5.0 2.0 20.0	2.0 2.0 20.0	3.0 2.0 20.0	4.0 2.0 15.0	2.0 1.5 20.0

(d) Bergholm

(continued on next page)

Table 16. (Continued)

Initially selected set of 64 parameter combinations			
sigma, threshold, alpha	sigma, threshold, alpha	sigma, threshold, alpha	sigma, threshold, alpha
0.50 3.0 0.80	1.00 3.0 0.80	1.50 3.0 0.80	2.00 3.0 0.80
0.50 3.0 0.85	1.00 3.0 0.85	1.50 3.0 0.85	2.00 3.0 0.85
0.50 3.0 0.90	1.00 3.0 0.90	1.50 3.0 0.90	2.00 3.0 0.90
0.50 3.0 0.95	1.00 3.0 0.95	1.50 3.0 0.95	2.00 3.0 0.95
0.50 8.0 0.80	1.00 8.0 0.80	1.50 8.0 0.80	2.00 8.0 0.80
0.50 8.0 0.85	1.00 8.0 0.85	1.50 8.0 0.85	2.00 8.0 0.85
0.50 8.0 0.90	1.00 8.0 0.90	1.50 8.0 0.90	2.00 8.0 0.90
0.50 8.0 0.95	1.00 8.0 0.95	1.50 8.0 0.95	2.00 8.0 0.95
0.50 13.0 0.80	1.00 13.0 0.80	1.50 13.0 0.80	2.00 13.0 0.80
0.50 13.0 0.85	1.00 13.0 0.85	1.50 13.0 0.85	2.00 13.0 0.85
0.50 13.0 0.90	1.00 13.0 0.90	1.50 13.0 0.90	2.00 13.0 0.90
0.50 13.0 0.95	1.00 13.0 0.95	1.50 13.0 0.95	2.00 13.0 0.95
0.50 18.0 0.80	1.00 18.0 0.80	1.50 18.0 0.80	2.00 18.0 0.80
0.50 18.0 0.85	1.00 18.0 0.85	1.50 18.0 0.85	2.00 18.0 0.85
0.50 18.0 0.90	1.00 18.0 0.90	1.50 18.0 0.90	2.00 18.0 0.90
0.50 18.0 0.95	1.00 18.0 0.95	1.50 18.0 0.95	2.00 18.0 0.95

The top 5 of 64 parameter combinations selected with the parameter selection tool for each image.					
Image	Combination 1	Combination 2	Combination 3	Combination 4	Combination 5
golf cart	1.50 8.0 0.85	1.00 13.0 0.90	1.00 13.0 0.80	1.50 8.0 0.80	1.00 13.0 0.85
pitcher	1.00 8.0 0.85	1.00 8.0 0.90	1.50 8.0 0.85	1.50 8.0 0.95	1.50 8.0 0.90
stapler	2.00 3.0 0.95	2.00 3.0 0.85	2.00 3.0 0.90	2.00 3.0 0.80	1.50 3.0 0.80
mailbox	1.00 8.0 0.90	1.00 8.0 0.85	1.00 8.0 0.80	1.00 8.0 0.95	1.00 3.0 0.95
pillow	1.50 8.0 0.90	1.00 13.0 0.90	1.50 8.0 0.85	1.50 8.0 0.95	1.00 13.0 0.85
brush	0.50 18.0 0.90	0.50 18.0 0.80	0.50 18.0 0.85	0.50 18.0 0.95	0.50 13.0 0.85
shopping cart	1.00 13.0 0.95	1.00 13.0 0.85	1.00 13.0 0.90	1.00 13.0 0.80	1.00 18.0 0.90
tire	1.00 3.0 0.95	1.00 3.0 0.90	1.00 3.0 0.85	1.00 3.0 0.80	1.50 3.0 0.90
grater	0.50 18.0 0.90	0.50 18.0 0.95	0.50 18.0 0.85	0.50 18.0 0.80	1.00 13.0 0.85
picnic basket	1.00 8.0 0.85	1.00 8.0 0.90	0.50 18.0 0.80	1.00 8.0 0.80	1.00 8.0 0.95
orange	2.00 3.0 0.95	1.50 3.0 0.90	1.50 3.0 0.95	2.00 3.0 0.80	1.50 3.0 0.80
banana	1.50 3.0 0.90	1.50 3.0 0.85	1.50 3.0 0.95	1.50 3.0 0.80	1.00 3.0 0.85
egg	1.50 3.0 0.90	2.00 3.0 0.90	2.00 3.0 0.85	2.00 3.0 0.80	2.00 3.0 0.95
elephant	1.50 13.0 0.80	2.00 8.0 0.80	2.00 8.0 0.85	1.00 13.0 0.80	2.00 8.0 0.95
pond	0.50 18.0 0.90	1.00 8.0 0.95	1.00 8.0 0.85	1.00 8.0 0.80	1.00 8.0 0.90
pine cone	1.00 8.0 0.90	1.00 13.0 0.95	1.00 13.0 0.85	1.00 18.0 0.80	1.00 13.0 0.90
feather	1.00 8.0 0.90	1.00 8.0 0.85	1.00 8.0 0.80	0.50 18.0 0.95	1.00 8.0 0.95
beehive	1.00 13.0 0.80	1.50 8.0 0.80	1.50 8.0 0.90	1.50 8.0 0.85	1.00 13.0 0.95
turtle	1.00 8.0 0.90	1.00 8.0 0.95	1.50 8.0 0.85	1.00 13.0 0.85	1.00 13.0 0.95
tiger	1.00 18.0 0.85	1.50 13.0 0.95	1.50 13.0 0.80	2.00 8.0 0.90	1.00 18.0 0.90
briefcase	1.00 13.0 0.80	1.00 13.0 0.90	1.00 13.0 0.85	1.00 13.0 0.95	1.00 8.0 0.95
trash can	2.00 3.0 0.95	1.50 3.0 0.95	1.50 3.0 0.80	1.50 3.0 0.85	1.50 3.0 0.90
video camera	1.00 8.0 0.80	1.00 8.0 0.85	1.00 8.0 0.95	1.00 8.0 0.90	1.50 8.0 0.80
coffee maker	1.00 13.0 0.80	0.50 18.0 0.85	1.00 8.0 0.80	1.50 8.0 0.80	1.00 8.0 0.95
flower	1.00 13.0 0.95	1.50 8.0 0.90	1.50 8.0 0.85	1.50 13.0 0.95	1.00 18.0 0.85
airplane	1.00 18.0 0.90	1.00 18.0 0.95	1.00 18.0 0.85	1.00 18.0 0.80	1.00 13.0 0.90
traffic cone	1.00 18.0 0.80	2.00 8.0 0.80	1.50 13.0 0.90	1.50 13.0 0.85	2.00 8.0 0.85
stairs	1.00 13.0 0.90	1.50 8.0 0.80	1.50 8.0 0.85	1.50 8.0 0.90	1.00 13.0 0.85

(e) Rothwell

APPENDIX 3. PARAMETER SETTING DATA

golf cart			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	7 5 5 6 4 6 5 6 4
1.80	0.20	0.70	6 4 4 4 3 6 3 6 3
0.60	0.30	0.90	7 6 4 6 7 7 7 7 4
1.20	0.20	0.60	7 2 4 3 4 6 4 4 4
0.60	0.50	0.90	7 7 5 5 7 7 6 7 3
1.20	0.30	0.80	7 4 5 4 6 7 5 6 4
1.20	0.40	0.60	7 2 6 3 4 5 4 6 6
1.20	0.20	0.80	7 5 6 4 4 7 4 7 5
2.40	0.20	0.60	6 3 2 3 3 5 2 6 3
0.60	0.30	0.80	7 4 7 3 5 6 6 6 6
1.20	0.40	0.90	7 7 3 4 4 6 5 7 3
1.80	0.30	0.90	6 5 2 2 4 2 4 6 2

pitcher			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	6 6 4 4 4 5 2 6 3
1.80	0.20	0.70	7 7 4 5 4 6 3 6 5
0.60	0.30	0.90	6 4 3 3 3 3 2 5 2
1.20	0.20	0.60	7 3 6 3 3 4 4 7 5
0.60	0.50	0.90	5 4 2 2 2 3 1 2 1
1.20	0.30	0.80	6 6 4 4 3 5 3 4 3
1.20	0.40	0.60	7 3 7 3 3 4 3 5 5
1.20	0.20	0.80	6 6 4 6 3 6 1 5 3
2.40	0.20	0.60	6 5 4 3 4 4 3 2 4
0.60	0.30	0.80	7 7 5 5 6 7 4 7 6
1.20	0.40	0.90	5 1 2 1 2 2 1 4 1
1.80	0.30	0.90	4 1 1 1 1 1 1 1 1

stapler			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	7 3 3 6 6 5 4 5 5
1.80	0.20	0.70	6 3 3 5 6 6 3 5 5
0.60	0.30	0.90	7 6 6 7 6 7 3 5 4
1.20	0.20	0.60	6 3 5 3 5 5 3 4 4
0.60	0.50	0.90	7 6 7 4 6 6 4 4 3
1.20	0.30	0.80	7 5 4 5 6 5 3 5 4
1.20	0.40	0.60	6 4 5 3 4 5 3 4 4
1.20	0.20	0.80	7 5 4 5 5 6 3 4 5
2.40	0.20	0.60	6 2 4 5 4 5 2 3 4
0.60	0.30	0.80	6 4 7 4 5 5 3 4 5
1.20	0.40	0.90	5 2 1 4 2 3 2 4 3
1.80	0.30	0.90	5 2 1 2 2 2 1 3 2

mailbox			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	6 4 3 4 5 6 2 4 3
1.80	0.20	0.70	6 3 3 4 5 5 2 4 3
0.60	0.30	0.90	6 7 4 4 4 5 4 5 4
1.20	0.20	0.60	7 6 7 3 6 6 4 5 6
0.60	0.50	0.90	6 7 4 4 4 3 4 4 1
1.20	0.30	0.80	7 6 3 4 5 6 2 4 4
1.20	0.40	0.60	7 6 6 5 6 6 4 4 6
1.20	0.20	0.80	6 5 5 3 5 6 2 4 4
2.40	0.20	0.60	5 3 2 4 3 2 3 3 2
0.60	0.30	0.80	7 5 5 3 5 5 4 5 3
1.20	0.40	0.90	5 2 2 4 2 2 1 4 1
1.80	0.30	0.90	5 1 1 5 2 1 1 5 1

pillow			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	6 7 4 5 6 5 4 7 6
1.80	0.20	0.70	6 7 3 6 5 2 2 7 3
0.60	0.30	0.90	5 3 5 5 7 4 5 5 3
1.20	0.20	0.60	7 2 6 3 5 6 3 6 2
0.60	0.50	0.90	6 4 4 5 7 5 7 7 2
1.20	0.30	0.80	6 4 4 7 7 6 4 7 3
1.20	0.40	0.60	7 2 6 5 5 6 3 7 3
1.20	0.20	0.80	7 5 5 6 6 6 4 5 3
2.40	0.20	0.60	5 4 3 3 5 2 2 6 3
0.60	0.30	0.80	6 5 7 3 7 7 7 4 6
1.20	0.40	0.90	5 7 2 3 6 3 4 7 3
1.80	0.30	0.90	5 6 1 3 6 3 4 7 2

brush			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	6 6 7 5 6 3 6 3 4
1.80	0.20	0.70	5 5 2 3 4 4 4 3 2
0.60	0.30	0.90	6 7 3 4 3 7 7 6 5
1.20	0.20	0.60	5 1 5 2 2 3 3 1 1
0.60	0.50	0.90	6 7 3 4 4 6 7 6 3
1.20	0.30	0.80	5 6 7 7 6 3 5 4 3
1.20	0.40	0.60	5 2 5 3 2 3 3 2 2
1.20	0.20	0.80	5 5 7 5 4 4 3 5 3
2.40	0.20	0.60	4 1 1 2 2 2 2 2 1
0.60	0.30	0.80	5 2 6 2 3 6 3 1 2
1.20	0.40	0.90	6 4 3 4 4 3 5 6 4
1.80	0.30	0.90	4 4 1 3 4 2 3 6 1

shopping cart			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	7 6 4 4 4 6 4 6 5
1.80	0.20	0.70	6 4 3 4 3 3 2 4 4
0.60	0.30	0.90	6 6 5 6 6 7 4 6 7
1.20	0.20	0.60	6 3 7 3 5 5 5 2 3
0.60	0.50	0.90	7 7 3 5 4 5 4 7 3
1.20	0.30	0.80	6 5 4 5 4 5 4 5 5
1.20	0.40	0.60	6 3 7 4 5 6 5 4 6
1.20	0.20	0.80	6 5 4 5 6 6 6 5 5
2.40	0.20	0.60	5 1 2 3 2 2 1 2 3
0.60	0.30	0.80	6 4 4 4 6 5 6 4 6
1.20	0.40	0.90	5 2 2 4 3 3 1 7 2
1.80	0.30	0.90	4 2 1 4 2 2 1 6 1

tire			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	5 3 3 3 3 4 4 2 3
1.80	0.20	0.70	6 7 3 6 6 6 6 6 6
0.60	0.30	0.90	5 2 4 2 2 3 2 2 2
1.20	0.20	0.60	7 7 7 7 7 7 7 7 7
0.60	0.50	0.90	5 2 3 2 2 3 2 2 2
1.20	0.30	0.80	5 3 6 4 3 4 4 2 3
1.20	0.40	0.60	6 5 6 3 4 5 4 2 4
1.20	0.20	0.80	5 3 5 3 3 4 3 2 3
2.40	0.20	0.60	6 7 2 6 6 6 6 5 5
0.60	0.30	0.80	6 5 5 3 3 4 5 3 4
1.20	0.40	0.90	5 2 2 3 2 1 2 2 1
1.80	0.30	0.90	3 1 1 1 1 1 1 2 1

Table 17. Parameter settings raw scores for the Canny detector.

(Continued on next page)

Table 17. (Continued)

grater			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	6	7	4	5	7	7	5	3	6
1.80	0.20	0.70	4	3	3	3	3	5	3	3	4
0.60	0.30	0.90	6	7	5	5	7	6	5	7	6
1.20	0.20	0.60	6	2	6	6	5	6	3	4	3
0.60	0.50	0.90	6	5	3	4	6	6	5	6	6
1.20	0.30	0.80	6	6	4	4	7	6	5	6	6
1.20	0.40	0.60	7	4	6	4	6	6	3	4	3
1.20	0.20	0.80	6	6	5	4	7	6	5	5	6
2.40	0.20	0.60	4	2	2	3	3	3	1	3	2
0.60	0.30	0.80	7	4	7	5	6	7	5	6	3
1.20	0.40	0.90	3	3	3	2	4	3	1	3	3
1.80	0.30	0.90	2	1	1	1	1	1	1	1	1

picnic basket			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	5	4	4	3	5	6	3	2	4
1.80	0.20	0.70	4	4	3	4	4	5	3	2	4
0.60	0.30	0.90	5	4	6	3	4	5	2	1	3
1.20	0.20	0.60	6	6	4	6	6	7	6	3	5
0.60	0.50	0.90	4	3	3	1	5	2	1	1	2
1.20	0.30	0.80	5	4	4	4	4	6	3	2	5
1.20	0.40	0.60	6	6	5	5	6	6	6	5	6
1.20	0.20	0.80	5	5	5	4	5	5	6	4	5
2.40	0.20	0.60	3	2	2	4	3	4	1	1	3
0.60	0.30	0.80	6	5	7	4	5	6	6	4	4
1.20	0.40	0.90	4	3	2	2	3	2	1	1	2
1.80	0.30	0.90	4	3	1	1	2	2	1	1	2

orange			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	5	7	6	6	5	6	5	4	4
1.80	0.20	0.70	5	3	2	4	5	6	1	3	3
0.60	0.30	0.90	4	4	6	4	3	4	6	5	4
1.20	0.20	0.60	4	4	3	4	2	4	4	3	3
0.60	0.50	0.90	5	7	3	5	5	6	5	5	4
1.20	0.30	0.80	5	5	7	4	4	6	3	5	5
1.20	0.40	0.60	4	4	3	4	3	4	4	3	3
1.20	0.20	0.80	4	5	3	5	4	2	4	4	4
2.40	0.20	0.60	4	3	2	5	5	2	1	2	3
0.60	0.30	0.80	4	4	7	3	2	1	6	4	3
1.20	0.40	0.90	6	6	2	6	7	6	2	4	4
1.80	0.30	0.90	6	2	2	3	6	3	1	3	4

banana			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	4	5	4	3	3	5	5	3	5
1.80	0.20	0.70	4	6	4	6	4	6	6	3	5
0.60	0.30	0.90	2	2	3	1	2	2	4	1	2
1.20	0.20	0.60	4	4	6	4	2	4	4	3	4
0.60	0.50	0.90	1	1	3	1	1	1	1	1	1
1.20	0.30	0.80	5	7	5	5	3	5	4	3	6
1.20	0.40	0.60	5	4	6	4	2	5	4	3	4
1.20	0.20	0.80	6	7	5	5	3	6	5	3	6
2.40	0.20	0.60	4	6	5	5	3	4	1	3	4
0.60	0.30	0.80	5	7	7	5	3	6	6	4	5
1.20	0.40	0.90	1	1	2	1	1	1	1	1	1
1.80	0.30	0.90	1	1	1	1	1	2	1	1	1

egg			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	6	7	5	6	7	5	4	1	6
1.80	0.20	0.70	4	7	5	6	6	4	5	2	5
0.60	0.30	0.90	3	2	6	3	2	6	1	1	3
1.20	0.20	0.60	4	1	2	2	3	1	1	1	2
0.60	0.50	0.90	3	2	6	2	2	5	1	1	3
1.20	0.30	0.80	6	6	5	6	6	4	4	2	6
1.20	0.40	0.60	4	1	2	3	3	2	1	2	3
1.20	0.20	0.80	6	6	3	7	7	4	4	2	5
2.40	0.20	0.60	4	5	5	5	6	3	1	1	3
0.60	0.30	0.80	4	3	3	3	6	3	4	3	4
1.20	0.40	0.90	3	2	7	1	1	6	1	1	2
1.80	0.30	0.90	3	2	7	2	1	6	1	1	2

elephant			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	6	5	3	4	6	5	6	2	4
1.80	0.20	0.70	6	4	2	2	3	4	1	2	3
0.60	0.30	0.90	6	6	5	5	6	6	6	3	6
1.20	0.20	0.60	6	2	3	2	3	3	1	1	2
0.60	0.50	0.90	6	6	4	5	6	7	2	2	6
1.20	0.30	0.80	6	4	7	6	3	7	2	2	4
1.20	0.40	0.60	5	4	4	3	5	3	3	2	2
1.20	0.20	0.80	6	4	3	2	4	7	5	2	4
2.40	0.20	0.60	3	1	1	2	3	5	1	1	2
0.60	0.30	0.80	6	3	3	3	4	7	6	2	4
1.20	0.40	0.90	5	5	6	4	5	7	1	2	3
1.80	0.30	0.90	5	3	6	1	3	6	1	2	3

pond			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	1	3	3	4	4	2	2	1	4
1.80	0.20	0.70	1	2	3	4	4	1	1	1	2
0.60	0.30	0.90	1	3	5	3	5	2	3	1	4
1.20	0.20	0.60	1	1	6	2	4	2	5	1	2
0.60	0.50	0.90	1	1	2	1	1	1	2	1	2
1.20	0.30	0.80	1	1	4	3	5	2	5	1	4
1.20	0.40	0.60	1	3	7	3	5	3	5	1	4
1.20	0.20	0.80	1	2	6	3	5	2	5	1	3
2.40	0.20	0.60	1	2	2	2	2	1	1	1	2
0.60	0.30	0.80	1	3	7	3	6	3	5	1	5
1.20	0.40	0.90	1	1	2	1	3	1	1	1	3
1.80	0.30	0.90	1	1	1	1	1	1	1	1	3

pine cone			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	3	4	3	4	3	4	2	2	4
1.80	0.20	0.70	4	2	3	4	2	2	2	2	3
0.60	0.30	0.90	2	1	3	2	1	3	1	2	1
1.20	0.20	0.60	4	2	7	3	4	6	4	2	4
0.60	0.50	0.90	2	1	1	1	1	2	1	2	1
1.20	0.30	0.80	4	3	4	3	3	3	3	2	5
1.20	0.40	0.60	4	3	7	4	4	5	4	2	4
1.20	0.20	0.80	4	3	6	3	3	5	3	2	5
2.40	0.20	0.60	3	1	3	3	1	2	1	2	2
0.60	0.30	0.80	4	2	6	4	3	5	3	2	2
1.20	0.40	0.90	2	1	1	1	1	1	1	2	1
1.80	0.30	0.90	2	1	2	2	1	1	1	2	1

(Continued on next page)

Table 17. (Continued)

feather			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	4 3 4 2 2 3 3 2 4
1.80	0.20	0.70	5 3 4 3 2 4 2 3 4
0.60	0.30	0.90	6 7 5 5 3 5 6 3 5
1.20	0.20	0.60	7 6 7 6 4 6 5 3 6
0.60	0.50	0.90	2 1 2 1 1 3 1 1 2
1.20	0.30	0.80	5 4 5 2 2 4 4 2 4
1.20	0.40	0.60	7 6 7 6 3 6 6 3 6
1.20	0.20	0.80	6 5 6 3 3 4 4 2 3
2.40	0.20	0.60	3 2 3 2 2 2 1 2 3
0.60	0.30	0.80	7 6 7 6 4 6 6 4 6
1.20	0.40	0.90	3 1 1 1 1 2 1 2 2
1.80	0.30	0.90	2 1 1 1 1 1 1 1 1

beehive			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	7 3 5 2 2 4 6 3 5
1.80	0.20	0.70	6 4 4 2 3 4 2 2 3
0.60	0.30	0.90	6 3 5 3 3 4 6 3 5
1.20	0.20	0.60	6 1 3 1 1 1 3 2 2
0.60	0.50	0.90	7 6 6 4 4 5 6 5 6
1.20	0.30	0.80	7 4 4 2 3 3 2 3 3
1.20	0.40	0.60	6 1 3 1 1 2 2 2 2
1.20	0.20	0.80	6 2 4 1 2 2 2 3 3
2.40	0.20	0.60	7 5 2 2 3 3 1 3 4
0.60	0.30	0.80	4 1 2 1 1 2 1 1 1
1.20	0.40	0.90	7 7 6 6 4 6 6 6 7
1.80	0.30	0.90	7 7 7 4 4 7 7 7 6

turtle			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	7 4 4 5 6 6 7 6 6
1.80	0.20	0.70	6 3 4 5 5 6 3 3 4
0.60	0.30	0.90	6 6 6 6 7 6 7 7 6
1.20	0.20	0.60	2 1 1 3 2 2 2 2 3
0.60	0.50	0.90	6 6 7 7 7 6 7 7 6
1.20	0.30	0.80	7 5 5 7 7 6 6 7 6
1.20	0.40	0.60	4 1 1 3 2 2 4 2 2
1.20	0.20	0.80	6 5 5 5 7 6 6 6 6
2.40	0.20	0.60	3 2 3 3 3 4 2 3 4
0.60	0.30	0.80	6 2 3 5 3 5 4 2 2
1.20	0.40	0.90	7 6 6 6 6 6 5 7 5
1.80	0.30	0.90	5 1 7 4 5 5 4 7 5

tiger			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	5 3 3 4 2 5 3 2 3
1.80	0.20	0.70	4 3 2 2 1 2 1 1 3
0.60	0.30	0.90	6 4 2 5 2 6 3 3 4
1.20	0.20	0.60	3 2 1 1 1 2 1 2 1
0.60	0.50	0.90	6 4 4 6 3 5 5 5 5
1.20	0.30	0.80	4 2 2 4 2 4 2 2 2
1.20	0.40	0.60	3 1 1 1 1 2 1 1 1
1.20	0.20	0.80	4 3 2 3 2 3 1 2 2
2.40	0.20	0.60	2 1 1 2 1 1 1 1 3
0.60	0.30	0.80	3 1 1 3 1 3 1 2 1
1.20	0.40	0.90	6 5 4 6 3 6 3 3 5
1.80	0.30	0.90	5 5 5 4 3 5 3 3 5

briefcase			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	6 7 7 5 5 6 1 6 4
1.80	0.20	0.70	6 6 5 4 4 6 1 5 4
0.60	0.30	0.90	4 5 4 3 2 4 1 5 3
1.20	0.20	0.60	6 3 3 3 6 5 6 5 6
0.60	0.50	0.90	3 5 4 2 2 4 2 4 2
1.20	0.30	0.80	5 7 7 6 7 5 2 4 4
1.20	0.40	0.60	5 3 3 4 6 5 5 6 6
1.20	0.20	0.80	5 7 6 7 5 5 4 6 4
2.40	0.20	0.60	4 2 2 3 5 5 1 4 3
0.60	0.30	0.80	5 4 3 2 6 4 5 5 5
1.20	0.40	0.90	1 1 1 1 1 2 1 1 1
1.80	0.30	0.90	1 1 1 1 1 2 1 1 1

trash can			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	6 4 5 5 3 5 4 2 2
1.80	0.20	0.70	7 7 7 6 7 6 5 7 5
0.60	0.30	0.90	1 1 4 1 1 1 2 1 1
1.20	0.20	0.60	7 3 1 4 6 6 5 7 6
0.60	0.50	0.90	1 1 4 1 1 3 1 2 1
1.20	0.30	0.80	7 6 6 5 4 6 5 6 2
1.20	0.40	0.60	7 3 1 4 6 6 7 6 6
1.20	0.20	0.80	7 6 6 2 4 6 6 6 3
2.40	0.20	0.60	6 5 7 6 5 5 5 4 5
0.60	0.30	0.80	6 2 2 2 4 4 6 5 2
1.20	0.40	0.90	1 1 3 1 1 1 1 1 1
1.80	0.30	0.90	1 1 3 1 1 1 1 1 1

video camera			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	6 2 4 5 6 6 5 6 3
1.80	0.20	0.70	7 7 5 7 7 6 5 6 4
0.60	0.30	0.90	5 2 3 3 4 4 5 5 2
1.20	0.20	0.60	6 4 7 4 6 5 7 6 6
0.60	0.50	0.90	4 2 2 3 3 3 3 5 2
1.20	0.30	0.80	7 6 5 5 5 6 6 6 3
1.20	0.40	0.60	6 4 5 5 7 6 7 6 6
1.20	0.20	0.80	7 7 5 5 7 7 6 6 3
2.40	0.20	0.60	5 3 4 3 5 4 3 4 5
0.60	0.30	0.80	6 3 6 6 5 7 7 7 5
1.20	0.40	0.90	5 1 2 2 2 2 2 1 1
1.80	0.30	0.90	3 1 1 1 1 1 1 1 1

coffee maker			Participant
parameters			1 2 3 4 5 6 7 8 9
1.20	0.40	0.80	7 5 4 5 5 6 6 7 6
1.80	0.20	0.70	7 4 3 5 4 5 6 7 5
0.60	0.30	0.90	6 6 4 7 5 5 6 7 4
1.20	0.20	0.60	7 1 4 3 3 3 5 6 4
0.60	0.50	0.90	6 6 5 3 5 4 4 6 4
1.20	0.30	0.80	7 5 4 6 6 5 7 7 6
1.20	0.40	0.60	7 1 5 3 3 3 5 6 6
1.20	0.20	0.80	7 4 3 7 6 6 6 7 5
2.40	0.20	0.60	6 2 2 4 3 5 3 6 4
0.60	0.30	0.80	7 1 6 4 5 6 7 7 6
1.20	0.40	0.90	5 3 2 2 2 3 2 3 2
1.80	0.30	0.90	4 2 1 1 2 3 2 4 1

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Table 17. (Continued)

flower			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	4	3	3	5	3	5	1	3	2
1.80	0.20	0.70	2	2	3	2	2	3	1	2	2
0.60	0.30	0.90	4	3	6	6	3	6	4	2	4
1.20	0.20	0.60	4	2	3	3	2	5	1	1	4
0.60	0.50	0.90	2	4	4	4	3	4	3	1	5
1.20	0.30	0.80	5	4	4	2	3	4	1	2	5
1.20	0.40	0.60	4	1	4	3	2	5	2	1	4
1.20	0.20	0.80	5	3	3	5	3	5	1	3	4
2.40	0.20	0.60	1	1	3	3	2	1	1	1	3
0.60	0.30	0.80	3	1	7	3	3	6	3	2	5
1.20	0.40	0.90	1	2	2	1	2	1	1	1	2
1.80	0.30	0.90	1	2	1	1	1	1	1	1	1

airplane			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	6	5	4	5	3	4	3	4	5
1.80	0.20	0.70	6	1	1	2	2	4	1	2	2
0.60	0.30	0.90	7	7	7	6	6	7	6	6	6
1.20	0.20	0.60	6	3	2	2	3	3	2	2	4
0.60	0.50	0.90	7	7	6	7	6	7	6	7	6
1.20	0.30	0.80	7	4	4	4	4	6	3	2	5
1.20	0.40	0.60	6	3	2	2	2	3	3	2	2
1.20	0.20	0.80	6	5	4	4	3	4	3	3	5
2.40	0.20	0.60	4	1	1	2	1	2	1	1	2
0.60	0.30	0.80	6	3	2	3	3	4	3	3	4
1.20	0.40	0.90	6	6	3	4	5	7	3	3	6
1.80	0.30	0.90	4	2	1	1	1	5	1	1	2

traffic cone			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	7	5	5	5	5	7	4	6	3
1.80	0.20	0.70	7	5	4	5	4	6	5	6	3
0.60	0.30	0.90	7	4	6	7	7	7	6	5	5
1.20	0.20	0.60	6	3	4	5	5	6	6	4	5
0.60	0.50	0.90	7	6	7	4	7	7	6	5	4
1.20	0.30	0.80	6	5	5	6	6	7	5	6	3
1.20	0.40	0.60	6	3	4	5	4	7	4	6	5
1.20	0.20	0.80	6	4	4	6	5	7	4	5	4
2.40	0.20	0.60	6	2	2	6	5	5	4	5	3
0.60	0.30	0.80	6	2	6	5	5	7	6	5	3
1.20	0.40	0.90	7	6	3	6	7	7	5	5	4
1.80	0.30	0.90	7	4	2	6	5	7	5	5	4

stairs			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.20	0.40	0.80	6	7	5	4	3	6	3	4	3
1.80	0.20	0.70	7	6	5	3	3	6	3	4	3
0.60	0.30	0.90	6	4	6	3	3	5	5	3	5
1.20	0.20	0.60	5	4	4	5	2	5	6	2	2
0.60	0.50	0.90	6	3	5	3	3	6	3	2	3
1.20	0.30	0.80	7	6	3	3	4	6	5	4	5
1.20	0.40	0.60	6	3	4	5	3	5	6	3	2
1.20	0.20	0.80	6	7	3	4	4	6	4	4	3
2.40	0.20	0.60	6	2	2	3	3	3	1	3	3
0.60	0.30	0.80	7	6	7	5	4	7	4	4	4
1.20	0.40	0.90	5	2	2	3	2	5	1	2	3
1.80	0.30	0.90	5	1	1	2	2	2	1	1	1

golf cart			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	7 6 7 6 7 6 6 7 7
1.50	0.20	0.60	7 6 7 6 7 7 5 6 7
0.60	0.15	0.60	7 7 7 7 6 5 6 6 4
1.20	0.10	0.60	7 7 7 7 7 6 6 6 6
1.50	0.15	0.15	6 1 5 5 4 2 3 4 3
0.60	0.10	0.60	7 7 7 6 6 6 6 5 5
1.50	0.15	0.45	7 6 6 6 6 6 5 6 4
1.20	0.05	0.15	6 1 4 4 4 3 3 3 3
1.20	0.05	0.30	7 5 5 4 5 4 3 4 4
1.50	0.05	0.45	7 5 6 5 6 5 5 5 4
0.60	0.05	0.30	7 2 5 3 5 2 3 4 2
1.50	0.05	0.15	6 3 5 5 4 2 3 3 2

pitcher			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	6 3 5 5 5 5 4 7 6
1.50	0.20	0.60	6 6 5 6 5 5 4 7 5
0.60	0.15	0.60	6 6 5 6 6 6 4 7 6
1.20	0.10	0.60	6 6 5 6 4 6 4 7 4
1.50	0.15	0.15	7 1 6 4 5 3 4 6 2
0.60	0.10	0.60	6 4 5 6 6 7 4 7 6
1.50	0.15	0.45	6 4 5 6 6 7 4 7 5
1.20	0.05	0.15	6 1 6 4 5 4 4 6 2
1.20	0.05	0.30	7 2 7 7 6 5 5 7 3
1.50	0.05	0.45	7 5 6 6 6 7 3 7 4
0.60	0.05	0.30	6 2 7 4 5 5 4 6 3
1.50	0.05	0.15	6 1 7 3 5 3 3 6 2

stapler			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	6 6 7 6 7 5 2 7 2
1.50	0.20	0.60	6 6 7 7 7 6 4 7 4
0.60	0.15	0.60	5 2 6 3 5 4 4 5 2
1.20	0.10	0.60	6 3 7 5 6 4 4 7 3
1.50	0.15	0.15	6 2 5 4 4 2 2 5 2
0.60	0.10	0.60	5 2 6 3 5 5 3 5 2
1.50	0.15	0.45	6 4 7 5 6 5 3 6 2
1.20	0.05	0.15	5 1 5 4 4 1 2 5 2
1.20	0.05	0.30	6 2 5 4 4 2 2 5 3
1.50	0.05	0.45	6 4 7 5 6 3 2 6 4
0.60	0.05	0.30	5 1 5 2 5 2 2 4 1
1.50	0.05	0.15	5 2 5 3 4 2 2 5 2

mailbox			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	5 5 6 6 6 7 5 5 2
1.50	0.20	0.60	5 5 6 6 6 7 5 5 2
0.60	0.15	0.60	6 4 7 5 7 6 5 6 3
1.20	0.10	0.60	5 3 7 6 6 5 5 5 2
1.50	0.15	0.15	7 1 6 4 4 2 5 5 5
0.60	0.10	0.60	6 4 7 4 7 5 4 6 2
1.50	0.15	0.45	6 4 7 5 6 5 4 6 4
1.20	0.05	0.15	7 1 6 4 4 2 3 6 5
1.20	0.05	0.30	7 2 6 5 5 2 5 5 4
1.50	0.05	0.45	7 3 7 6 5 5 5 5 4
0.60	0.05	0.30	7 2 6 6 5 3 5 5 4
1.50	0.05	0.15	7 1 6 4 4 2 3 5 5

pillow			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	7 6 7 7 7 6 5 6 7
1.50	0.20	0.60	7 6 7 7 7 7 5 6 7
0.60	0.15	0.60	7 5 7 7 7 5 6 6 6
1.20	0.10	0.60	7 4 6 7 7 7 6 5 7
1.50	0.15	0.15	5 1 4 4 4 2 3 3 2
0.60	0.10	0.60	7 5 6 6 7 6 5 6 6
1.50	0.15	0.45	7 3 6 5 6 6 5 5 4
1.20	0.05	0.15	3 1 4 3 4 2 2 2 2
1.20	0.05	0.30	4 2 5 4 5 3 3 4 3
1.50	0.05	0.45	6 3 6 5 6 7 3 5 6
0.60	0.05	0.30	3 2 5 4 5 4 3 4 3
1.50	0.05	0.15	4 1 4 2 4 3 3 4 2

brush			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	5 5 6 5 7 6 5 6 4
1.50	0.20	0.60	4 5 6 5 7 6 5 6 5
0.60	0.15	0.60	5 6 7 7 7 5 6 6 6
1.20	0.10	0.60	4 5 7 6 7 6 6 6 4
1.50	0.15	0.15	2 1 5 4 4 3 2 5 2
0.60	0.10	0.60	5 6 7 4 6 6 5 6 3
1.50	0.15	0.45	4 3 7 4 6 4 4 6 2
1.20	0.05	0.15	3 1 5 3 4 3 2 4 2
1.20	0.05	0.30	4 2 5 4 5 4 3 4 2
1.50	0.05	0.45	4 4 6 4 6 6 3 6 2
0.60	0.05	0.30	5 2 5 4 5 2 2 5 2
1.50	0.05	0.15	4 1 5 3 4 2 2 5 2

shopping cart			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	5 5 5 4 5 7 6 5 4
1.50	0.20	0.60	5 5 5 4 5 7 6 5 5
0.60	0.15	0.60	6 4 6 6 6 5 6 3 4
1.20	0.10	0.60	5 5 6 5 5 6 6 4 5
1.50	0.15	0.15	6 2 5 4 4 2 2 2 2
0.60	0.10	0.60	6 4 6 5 6 6 5 4 5
1.50	0.15	0.45	6 3 6 6 5 5 4 4 3
1.20	0.05	0.15	5 1 5 4 4 2 2 2 2
1.20	0.05	0.30	5 2 5 5 4 3 3 2 3
1.50	0.05	0.45	6 4 6 5 5 5 4 4 4
0.60	0.05	0.30	5 1 5 5 4 4 4 2 3
1.50	0.05	0.15	5 1 5 4 4 2 2 2 2

tire			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	5 7 5 3 4 4 5 5 3
1.50	0.20	0.60	5 7 4 4 4 4 5 5 2
0.60	0.15	0.60	5 5 5 2 4 3 3 4 1
1.20	0.10	0.60	5 5 5 2 4 3 4 5 2
1.50	0.15	0.15	7 1 7 5 6 6 4 5 6
0.60	0.10	0.60	5 6 5 3 4 3 3 4 1
1.50	0.15	0.45	6 6 5 5 5 7 4 5 5
1.20	0.05	0.15	7 2 7 6 6 5 4 6 6
1.20	0.05	0.30	6 3 6 5 5 7 4 6 5
1.50	0.05	0.45	6 5 5 6 5 7 3 5 5
0.60	0.05	0.30	6 3 5 4 5 4 2 5 4
1.50	0.05	0.15	6 1 7 6 6 6 4 6 6

Table 18. Parameter settings raw scores for the Nalwa detector.

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Table 18. (Continued)

grater			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	6 6 7 6 5 7 6 5 6
1.50	0.20	0.60	5 6 6 6 5 7 6 5 6
0.60	0.15	0.60	6 5 6 5 6 6 6 4 6
1.20	0.10	0.60	6 6 6 5 5 7 6 4 6
1.50	0.15	0.15	6 1 4 4 4 2 2 2 2
0.60	0.10	0.60	6 7 6 6 6 7 4 4 6
1.50	0.15	0.45	6 2 6 5 5 7 4 4 5
1.20	0.05	0.15	5 2 4 5 4 2 2 3 1
1.20	0.05	0.30	6 4 5 5 4 2 3 2 3
1.50	0.05	0.45	6 4 6 6 6 5 4 4 5
0.60	0.05	0.30	6 2 5 6 4 4 3 3 3
1.50	0.05	0.15	5 1 4 4 4 3 2 2 2

picnic basket			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	6 3 2 4 6 3 3 5 4
1.50	0.20	0.60	5 3 2 4 6 3 3 5 3
0.60	0.15	0.60	6 3 4 5 5 4 4 5 3
1.20	0.10	0.60	6 3 4 5 6 4 4 5 4
1.50	0.15	0.15	6 3 5 6 4 4 7 4 2
0.60	0.10	0.60	6 3 3 4 5 5 5 4 4
1.50	0.15	0.45	6 4 3 5 5 5 5 4 5
1.20	0.05	0.15	6 5 6 6 4 6 5 5 3
1.20	0.05	0.30	7 4 7 6 4 6 6 4 3
1.50	0.05	0.45	7 4 5 6 5 5 5 5 4
0.60	0.05	0.30	7 5 6 7 4 7 7 5 5
1.50	0.05	0.15	6 5 7 6 4 6 6 5 4

orange			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	5 6 6 5 6 5 5 5 5
1.50	0.20	0.60	6 5 3 5 6 6 5 5 6
0.60	0.15	0.60	5 4 2 4 5 5 6 5 4
1.20	0.10	0.60	6 5 6 6 6 6 5 5 6
1.50	0.15	0.15	4 1 5 4 4 2 2 3 2
0.60	0.10	0.60	6 4 2 4 5 5 6 5 4
1.50	0.15	0.45	6 3 7 5 6 5 3 5 6
1.20	0.05	0.15	4 2 5 4 4 2 2 3 2
1.20	0.05	0.30	5 2 5 5 5 4 2 3 3
1.50	0.05	0.45	6 3 6 5 5 5 3 4 6
0.60	0.05	0.30	4 1 2 3 4 3 4 2 2
1.50	0.05	0.15	4 1 5 2 4 2 2 2 2

banana			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	2 2 3 2 2 1 1 1 1
1.50	0.20	0.60	2 2 3 2 2 1 1 1 1
0.60	0.15	0.60	2 1 1 1 2 1 1 1 1
1.20	0.10	0.60	1 1 3 1 2 1 1 1 1
1.50	0.15	0.15	4 3 7 4 6 5 3 4 4
0.60	0.10	0.60	3 2 3 2 2 2 1 1 1
1.50	0.15	0.45	5 3 4 3 4 4 5 3 3
1.20	0.05	0.15	5 3 7 5 6 6 4 5 4
1.20	0.05	0.30	5 6 6 4 6 6 5 6 5
1.50	0.05	0.45	5 5 4 4 4 4 3 3 3
0.60	0.05	0.30	6 6 6 6 5 5 5 4 5
1.50	0.05	0.15	6 3 7 5 6 6 4 4 4

egg			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	6 7 2 6 5 6 2 3 4
1.50	0.20	0.60	6 7 2 6 5 6 2 3 4
0.60	0.15	0.60	6 6 2 5 4 5 3 3 5
1.20	0.10	0.60	6 7 4 6 5 6 3 3 4
1.50	0.15	0.15	6 3 6 5 4 3 1 2 3
0.60	0.10	0.60	5 5 2 4 4 6 3 3 5
1.50	0.15	0.45	6 5 4 5 6 6 3 3 4
1.20	0.05	0.15	5 2 6 4 5 2 1 2 2
1.20	0.05	0.30	6 3 6 4 5 2 1 3 3
1.50	0.05	0.45	6 4 4 5 6 5 3 3 4
0.60	0.05	0.30	6 3 5 4 3 2 1 2 2
1.50	0.05	0.15	6 3 6 4 4 2 1 2 2

elephant			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	7 7 7 5 5 6 3 4 5
1.50	0.20	0.60	7 7 6 5 5 6 3 5 5
0.60	0.15	0.60	7 5 4 5 4 5 4 5 6
1.20	0.10	0.60	7 5 6 5 5 6 3 5 5
1.50	0.15	0.15	6 2 1 2 2 2 2 2 3
0.60	0.10	0.60	7 6 5 6 4 6 3 4 5
1.50	0.15	0.45	7 4 4 4 4 4 3 3 5
1.20	0.05	0.15	6 1 1 2 2 1 1 2 2
1.20	0.05	0.30	6 2 2 4 3 3 2 2 3
1.50	0.05	0.45	6 4 3 6 4 4 2 3 4
0.60	0.05	0.30	5 1 2 2 1 2 1 2 1
1.50	0.05	0.15	6 2 2 1 2 1 1 2 2

pond			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	2 1 1 4 5 3 2 1 3
1.50	0.20	0.60	2 2 1 4 5 2 2 1 3
0.60	0.15	0.60	2 4 2 6 6 2 4 1 3
1.20	0.10	0.60	2 3 1 5 6 2 3 1 3
1.50	0.15	0.15	1 1 2 3 4 1 2 1 2
0.60	0.10	0.60	2 4 3 7 6 2 4 1 5
1.50	0.15	0.45	2 2 3 4 6 2 2 1 4
1.20	0.05	0.15	1 1 2 1 4 1 2 1 3
1.20	0.05	0.30	2 2 3 3 5 1 3 1 5
1.50	0.05	0.45	2 3 3 4 5 2 3 1 4
0.60	0.05	0.30	2 1 3 3 5 1 3 1 3
1.50	0.05	0.15	1 1 2 2 4 1 2 1 2

pine cone			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	4 4 5 6 2 6 3 2 4
1.50	0.20	0.60	2 4 6 5 2 6 3 2 3
0.60	0.15	0.60	2 3 5 5 2 4 3 2 3
1.20	0.10	0.60	4 3 7 4 2 4 3 2 3
1.50	0.15	0.15	2 1 1 2 1 2 2 1 2
0.60	0.10	0.60	2 2 6 4 2 5 3 2 2
1.50	0.15	0.45	3 3 6 5 2 5 3 2 4
1.20	0.05	0.15	2 1 2 2 1 1 2 1 1
1.20	0.05	0.30	2 2 2 4 2 4 2 1 2
1.50	0.05	0.45	2 3 4 4 2 5 3 2 3
0.60	0.05	0.30	2 2 2 3 2 3 2 1 1
1.50	0.05	0.15	1 1 1 2 1 3 2 1 1

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Table 18. (Continued)

feather			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.50	0.10	0.60	3	5	1	3	3	2	3	2	2
1.50	0.20	0.60	5	5	1	3	3	2	3	2	2
0.60	0.15	0.60	5	4	2	4	4	5	4	3	2
1.20	0.10	0.60	5	3	2	4	3	5	3	3	2
1.50	0.15	0.15	6	2	5	3	6	6	6	4	5
0.60	0.10	0.60	5	3	3	4	4	3	3	4	4
1.50	0.15	0.45	6	4	4	5	4	4	4	4	4
1.20	0.05	0.15	5	1	6	5	6	6	5	4	5
1.20	0.05	0.30	6	2	6	6	5	6	6	3	6
1.50	0.05	0.45	5	3	3	6	4	5	5	3	4
0.60	0.05	0.30	6	2	7	4	6	6	5	3	2
1.50	0.05	0.15	6	1	7	5	6	5	5	2	3

beehive			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.50	0.10	0.60	6	7	6	6	5	5	7	4	5
1.50	0.20	0.60	6	7	7	7	5	5	7	4	5
0.60	0.15	0.60	5	4	2	6	4	5	4	3	4
1.20	0.10	0.60	6	6	5	5	4	5	5	3	4
1.50	0.15	0.15	5	1	1	4	2	1	2	2	3
0.60	0.10	0.60	5	3	3	4	3	5	3	3	4
1.50	0.15	0.45	5	4	4	5	4	5	3	3	4
1.20	0.05	0.15	4	2	1	3	1	1	1	2	2
1.20	0.05	0.30	5	2	1	2	2	2	2	2	3
1.50	0.05	0.45	6	4	5	4	4	3	4	3	5
0.60	0.05	0.30	3	1	1	3	1	1	1	2	2
1.50	0.05	0.15	5	2	2	2	2	1	2	2	3

turtle			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.50	0.10	0.60	7	6	6	7	7	7	7	7	7
1.50	0.20	0.60	7	6	6	7	7	7	7	7	7
0.60	0.15	0.60	7	7	7	6	7	7	7	7	7
1.20	0.10	0.60	7	6	6	5	7	7	7	7	7
1.50	0.15	0.15	6	2	3	3	5	2	4	5	3
0.60	0.10	0.60	7	7	7	5	7	7	7	7	7
1.50	0.15	0.45	7	5	5	5	7	6	6	6	4
1.20	0.05	0.15	6	2	3	3	5	3	4	6	2
1.20	0.05	0.30	7	3	4	4	6	4	4	6	3
1.50	0.05	0.45	7	4	5	5	6	6	6	6	4
0.60	0.05	0.30	7	3	4	5	6	5	5	7	3
1.50	0.05	0.15	6	2	3	3	5	3	4	6	3

tiger			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.50	0.10	0.60	3	3	4	6	3	4	3	2	4
1.50	0.20	0.60	3	4	4	6	3	4	3	2	4
0.60	0.15	0.60	2	2	3	5	2	3	1	2	2
1.20	0.10	0.60	3	2	3	5	2	3	2	1	3
1.50	0.15	0.15	2	1	1	2	1	1	1	2	2
0.60	0.10	0.60	2	1	2	4	2	3	2	1	2
1.50	0.15	0.45	3	3	4	4	2	2	2	1	2
1.20	0.05	0.15	2	1	1	1	1	1	1	2	1
1.20	0.05	0.30	3	1	1	3	2	1	1	2	2
1.50	0.05	0.45	3	2	2	4	2	2	2	1	2
0.60	0.05	0.30	2	1	1	2	1	1	1	2	1
1.50	0.05	0.15	2	1	1	1	1	1	1	2	2

briefcase			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.50	0.10	0.60	6	7	3	4	5	7	4	7	2
1.50	0.20	0.60	6	6	3	4	5	7	4	7	2
0.60	0.15	0.60	6	4	4	5	5	6	5	6	3
1.20	0.10	0.60	6	6	3	5	5	7	4	7	3
1.50	0.15	0.15	6	3	6	5	6	4	3	5	5
0.60	0.10	0.60	6	5	4	4	6	6	5	6	4
1.50	0.15	0.45	6	4	5	5	6	6	5	6	6
1.20	0.05	0.15	6	2	7	6	5	3	3	5	3
1.20	0.05	0.30	6	3	6	6	6	3	3	5	4
1.50	0.05	0.45	6	7	5	5	6	4	5	7	4
0.60	0.05	0.30	6	2	7	5	5	3	4	6	2
1.50	0.05	0.15	6	2	6	5	5	3	3	6	3

trash can			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.50	0.10	0.60	5	3	2	1	4	3	3	2	2
1.50	0.20	0.60	5	3	2	1	4	2	3	2	2
0.60	0.15	0.60	5	4	5	3	4	3	5	2	3
1.20	0.10	0.60	5	4	4	2	4	2	5	2	2
1.50	0.15	0.15	6	2	7	4	6	3	3	2	3
0.60	0.10	0.60	5	5	5	3	5	4	5	2	3
1.50	0.15	0.45	6	5	4	4	6	5	5	3	5
1.20	0.05	0.15	6	1	7	4	5	2	3	3	3
1.20	0.05	0.30	6	3	6	5	6	3	4	3	4
1.50	0.05	0.45	6	5	5	5	6	6	5	3	5
0.60	0.05	0.30	5	2	6	4	6	3	4	3	3
1.50	0.05	0.15	6	2	7	3	5	2	3	4	3

video camera			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.50	0.10	0.60	7	7	4	7	7	5	6	5	6
1.50	0.20	0.60	6	7	4	7	7	5	6	5	6
0.60	0.15	0.60	6	4	3	4	5	5	6	4	3
1.20	0.10	0.60	6	7	4	5	7	5	6	5	7
1.50	0.15	0.15	7	2	7	5	5	2	3	4	3
0.60	0.10	0.60	6	4	3	3	6	5	4	3	3
1.50	0.15	0.45	7	5	5	6	6	5	6	4	5
1.20	0.05	0.15	6	1	7	5	5	1	4	4	3
1.20	0.05	0.30	6	2	6	4	5	3	5	5	4
1.50	0.05	0.45	7	4	5	6	6	5	6	5	5
0.60	0.05	0.30	6	1	2	3	4	2	3	4	2
1.50	0.05	0.15	6	1	7	4	5	2	4	5	3

coffee maker			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.50	0.10	0.60	7	6	7	6	7	7	7	7	7
1.50	0.20	0.60	6	6	7	6	7	6	7	7	7
0.60	0.15	0.60	7	4	6	5	6	6	7	7	6
1.20	0.10	0.60	7	5	7	7	7	7	7	7	6
1.50	0.15	0.15	6	1	4	4	5	3	4	4	3
0.60	0.10	0.60	7	5	6	5	6	5	6	7	6
1.50	0.15	0.45	7	3	6	7	6	5	6	7	4
1.20	0.05	0.15	6	1	4	4	5	2	3	5	3
1.20	0.05	0.30	7	1	5	4	5	3	5	6	3
1.50	0.05	0.45	7	3	5	4	6	4	6	7	4
0.60	0.05	0.30	6	2	4	4	5	3	4	5	3
1.50	0.05	0.15	6	2	4	5	5	3	4	4	3

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Table 18. (Continued)

flower			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	4 6 7 6 5 6 3 6 4
1.50	0.20	0.60	5 6 7 6 5 5 3 6 3
0.60	0.15	0.60	5 5 5 5 6 4 5 6 6
1.20	0.10	0.60	5 6 7 6 5 6 3 5 4
1.50	0.15	0.15	2 1 3 5 2 1 2 3 2
0.60	0.10	0.60	6 5 5 6 6 3 5 5 6
1.50	0.15	0.45	3 4 6 5 4 5 4 6 3
1.20	0.05	0.15	2 1 3 4 2 1 2 3 2
1.20	0.05	0.30	2 2 3 4 3 1 2 3 3
1.50	0.05	0.45	3 4 6 5 4 4 2 4 3
0.60	0.05	0.30	2 3 2 3 4 3 3 4 3
1.50	0.05	0.15	1 2 3 2 2 2 2 3 2

airplane			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	5 4 6 5 5 5 3 3 5
1.50	0.20	0.60	5 4 6 5 5 5 3 3 5
0.60	0.15	0.60	4 2 4 4 4 4 3 3 2
1.20	0.10	0.60	5 3 6 6 4 5 3 3 3
1.50	0.15	0.15	5 1 2 3 2 3 2 2 3
0.60	0.10	0.60	5 2 4 4 3 4 2 3 2
1.50	0.15	0.45	5 2 4 5 3 3 2 3 3
1.20	0.05	0.15	4 1 2 2 2 1 1 2 2
1.20	0.05	0.30	5 1 2 3 2 2 1 2 2
1.50	0.05	0.45	5 2 4 4 3 4 2 3 3
0.60	0.05	0.30	4 1 2 3 2 1 1 2 1
1.50	0.05	0.15	4 1 2 2 2 2 1 2 2

traffic cone			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	7 5 7 7 7 7 5 4 4
1.50	0.20	0.60	7 5 6 7 7 7 6 4 6
0.60	0.15	0.60	6 4 6 7 6 6 7 4 3
1.20	0.10	0.60	7 5 6 7 7 7 7 4 6
1.50	0.15	0.15	6 1 5 5 5 2 4 3 3
0.60	0.10	0.60	7 4 6 6 6 5 6 4 3
1.50	0.15	0.45	7 4 6 6 7 6 6 4 4
1.20	0.05	0.15	6 2 5 4 5 3 5 2 2
1.20	0.05	0.30	7 3 5 4 6 5 6 2 4
1.50	0.05	0.45	7 5 7 5 6 5 6 3 6
0.60	0.05	0.30	6 3 5 4 5 4 5 2 2
1.50	0.05	0.15	5 2 5 3 5 4 4 2 4

stairs			Participant
parameters			1 2 3 4 5 6 7 8 9
1.50	0.10	0.60	5 7 6 4 5 7 5 5 5
1.50	0.20	0.60	5 7 6 4 5 6 5 5 5
0.60	0.15	0.60	6 6 7 5 6 6 6 5 6
1.20	0.10	0.60	6 7 7 5 6 7 6 5 6
1.50	0.15	0.15	5 3 3 5 3 2 2 2 2
0.60	0.10	0.60	6 6 7 5 6 7 6 5 5
1.50	0.15	0.45	5 5 5 5 5 6 4 4 4
1.20	0.05	0.15	5 2 3 4 3 2 2 2 2
1.20	0.05	0.30	5 3 3 5 4 3 3 4 3
1.50	0.05	0.45	5 4 5 6 5 5 4 3 3
0.60	0.05	0.30	5 2 3 3 4 2 2 2 2
1.50	0.05	0.15	5 1 2 2 3 2 2 2 2

golf cart			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	6 5 6 6 6 7 6 7 4
8	0.20	0.05	6 7 7 6 5 6 7 6 5
8	0.00	0.00	6 7 7 6 5 6 7 5 5
4	0.20	0.55	6 5 6 6 6 7 6 7 6
8	0.00	0.05	7 6 7 5 5 6 6 6 5
8	0.20	0.30	6 6 7 5 5 6 7 6 5
4	0.00	0.05	6 7 7 5 5 6 7 5 5
6	0.00	0.00	6 7 7 5 5 6 6 5 5
8	0.00	0.30	6 7 7 6 5 6 7 5 5
8	0.20	0.55	6 6 6 6 6 7 6 7 6
6	0.00	0.30	6 4 7 5 5 6 6 6 4
10	0.00	0.05	6 4 7 5 5 6 6 6 4

pitcher			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	5 3 5 4 2 4 2 5 4
8	0.20	0.05	6 7 7 4 3 6 4 6 6
8	0.00	0.00	5 6 7 5 3 6 4 6 6
4	0.20	0.55	5 3 5 4 2 4 2 5 4
8	0.00	0.05	5 6 7 6 3 5 4 6 6
8	0.20	0.30	5 7 6 5 3 6 4 6 5
4	0.00	0.05	6 7 7 5 3 6 4 6 6
6	0.00	0.00	6 7 7 5 3 6 3 6 6
8	0.00	0.30	6 7 6 5 3 6 3 6 5
8	0.20	0.55	5 3 5 4 2 5 2 5 4
6	0.00	0.30	6 5 6 5 3 5 3 6 5
10	0.00	0.05	5 5 7 6 3 6 3 6 6

stapler			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	5 1 3 3 3 2 3 5 4
8	0.20	0.05	6 3 5 4 4 4 4 5 5
8	0.00	0.00	5 3 5 4 4 5 4 5 5
4	0.20	0.55	5 1 3 3 3 2 2 4 4
8	0.00	0.05	5 6 5 5 4 5 4 5 5
8	0.20	0.30	6 6 5 5 4 5 4 6 5
4	0.00	0.05	6 5 5 4 4 4 4 5 5
6	0.00	0.00	6 6 4 4 4 4 4 6 5
8	0.00	0.30	6 6 5 5 4 4 4 6 5
8	0.20	0.55	5 2 3 3 3 2 2 5 4
6	0.00	0.30	6 5 4 4 4 5 4 5 5
10	0.00	0.05	6 6 4 5 4 5 3 5 5

mailbox			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	6 7 6 4 6 6 5 5 4
8	0.20	0.05	7 6 7 5 6 5 6 4 5
8	0.00	0.00	7 6 7 5 6 5 6 4 5
4	0.20	0.55	6 7 6 4 6 5 4 5 4
8	0.00	0.05	7 6 7 5 6 5 6 4 5
8	0.20	0.30	7 6 7 5 6 5 6 5 5
4	0.00	0.05	7 6 7 6 6 5 6 4 5
6	0.00	0.00	7 6 7 6 6 5 6 4 5
8	0.00	0.30	7 6 7 6 6 5 6 5 5
8	0.20	0.55	6 7 6 4 6 6 4 5 4
6	0.00	0.30	7 6 7 5 6 5 6 4 5
10	0.00	0.05	7 7 7 5 6 5 6 4 5

pillow			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	5 2 6 4 5 2 5 5 3
8	0.20	0.05	6 5 7 5 6 4 6 5 5
8	0.00	0.00	6 5 7 5 6 4 6 5 5
4	0.20	0.55	5 2 6 5 5 2 4 5 3
8	0.00	0.05	6 3 7 6 6 4 6 5 3
8	0.20	0.30	6 7 7 6 6 4 6 5 5
4	0.00	0.05	5 4 7 6 5 4 6 5 3
6	0.00	0.00	6 6 7 6 6 4 6 5 3
8	0.00	0.30	6 6 7 6 6 4 6 5 4
8	0.20	0.55	6 2 6 4 5 3 5 5 3
6	0.00	0.30	6 7 7 4 6 4 5 5 4
10	0.00	0.05	6 5 7 4 5 4 6 5 4

brush			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	7 7 5 6 6 6 6 7 6
8	0.20	0.05	6 6 7 5 6 5 6 7 5
8	0.00	0.00	6 6 7 5 6 5 7 7 5
4	0.20	0.55	6 7 6 4 6 6 6 7 5
8	0.00	0.05	6 6 7 6 6 5 7 7 5
8	0.20	0.30	6 6 7 6 5 5 7 7 4
4	0.00	0.05	6 6 7 5 6 5 7 7 5
6	0.00	0.00	6 6 7 4 5 5 5 6 4
8	0.00	0.30	6 6 7 5 5 5 7 7 5
8	0.20	0.55	6 7 5 6 6 6 5 7 3
6	0.00	0.30	6 6 6 6 5 5 5 6 2
10	0.00	0.05	6 6 6 5 5 5 5 6 3

shopping cart			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	5 6 6 4 6 6 6 6 4
8	0.20	0.05	5 2 7 3 5 4 6 5 3
8	0.00	0.00	5 4 7 3 5 4 5 5 2
4	0.20	0.55	5 6 6 4 6 5 6 6 3
8	0.00	0.05	5 3 7 4 5 4 5 5 2
8	0.20	0.30	5 2 7 4 5 4 5 5 2
4	0.00	0.05	5 2 7 4 5 4 5 6 2
6	0.00	0.00	5 5 7 5 5 4 6 6 4
8	0.00	0.30	5 3 7 4 5 4 5 6 3
8	0.20	0.55	5 6 6 5 6 6 6 7 5
6	0.00	0.30	6 4 7 4 5 4 6 6 3
10	0.00	0.05	6 5 7 4 5 5 6 6 3

tire			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	5 4 6 3 4 5 2 5 3
8	0.20	0.05	5 2 7 3 5 5 4 5 3
8	0.00	0.00	5 2 7 4 5 5 5 5 4
4	0.20	0.55	5 3 6 2 3 5 3 4 2
8	0.00	0.05	5 2 7 4 5 5 5 4 4
8	0.20	0.30	5 2 7 2 5 5 5 5 4
4	0.00	0.05	5 3 7 3 4 5 3 5 3
6	0.00	0.00	5 3 7 3 4 5 2 4 3
8	0.00	0.30	5 3 7 3 4 5 5 4 4
8	0.20	0.55	5 4 6 2 3 5 4 5 3
6	0.00	0.30	5 2 7 4 5 5 4 4 3
10	0.00	0.05	5 2 7 3 5 5 2 5 4

Table 19. Parameter settings raw scores for the Iverson detector.

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Table 19. (Continued)

grater			Participant								
parameters			1	2	3	4	5	6	7	8	9
8	0.00	0.55	5	3	5	4	6	5	4	7	5
8	0.20	0.05	6	4	7	5	5	6	5	5	4
8	0.00	0.00	6	4	7	5	5	6	5	6	3
4	0.20	0.55	5	3	5	4	6	6	3	6	4
8	0.00	0.05	6	5	7	7	5	6	5	6	3
8	0.20	0.30	6	5	7	7	5	6	5	5	4
4	0.00	0.05	6	4	7	6	5	6	5	5	4
6	0.00	0.00	6	5	6	6	5	6	5	5	3
8	0.00	0.30	6	5	7	7	5	6	5	5	3
8	0.20	0.55	6	3	5	4	6	7	3	6	5
6	0.00	0.30	6	4	6	6	5	6	4	5	3
10	0.00	0.05	6	4	6	6	5	6	5	5	3

picnic basket			Participant								
parameters			1	2	3	4	5	6	7	8	9
8	0.00	0.55	7	4	6	4	5	6	5	6	3
8	0.20	0.05	7	6	7	6	7	7	7	7	3
8	0.00	0.00	7	5	7	6	7	7	7	7	3
4	0.20	0.55	7	3	7	6	6	7	6	6	4
8	0.00	0.05	7	4	7	7	7	7	7	7	4
8	0.20	0.30	7	4	7	7	7	7	7	7	4
4	0.00	0.05	7	7	7	6	6	7	7	7	3
6	0.00	0.00	7	7	7	6	6	7	7	7	5
8	0.00	0.30	7	4	7	5	6	7	7	7	4
8	0.20	0.55	7	3	6	4	5	6	5	6	5
6	0.00	0.30	7	5	7	7	7	7	7	7	4
10	0.00	0.05	7	5	7	5	7	7	6	7	4

orange			Participant								
parameters			1	2	3	4	5	6	7	8	9
8	0.00	0.55	2	3	3	3	2	2	3	6	4
8	0.20	0.05	2	4	3	4	2	2	3	6	4
8	0.00	0.00	2	4	3	4	2	2	4	6	4
4	0.20	0.55	2	3	3	5	2	2	4	6	4
8	0.00	0.05	2	1	3	3	2	2	3	6	4
8	0.20	0.30	2	2	3	4	2	1	3	6	4
4	0.00	0.05	2	2	3	4	2	2	3	6	4
6	0.00	0.00	2	3	3	3	1	2	3	6	2
8	0.00	0.30	2	2	3	3	2	2	4	6	4
8	0.20	0.55	2	3	3	4	2	2	4	6	4
6	0.00	0.30	2	1	3	3	2	2	3	6	2
10	0.00	0.05	2	1	3	3	1	1	3	6	2

banana			Participant								
parameters			1	2	3	4	5	6	7	8	9
8	0.00	0.55	2	1	4	1	2	1	4	2	3
8	0.20	0.05	2	2	6	1	2	2	5	2	4
8	0.00	0.00	2	2	6	2	2	2	5	2	4
4	0.20	0.55	2	1	4	1	2	2	4	2	2
8	0.00	0.05	2	2	5	2	2	2	5	2	4
8	0.20	0.30	2	2	5	2	2	1	5	2	4
4	0.00	0.05	2	2	5	3	2	2	4	2	4
6	0.00	0.00	2	1	4	2	1	2	2	2	3
8	0.00	0.30	2	2	5	2	2	2	5	2	4
8	0.20	0.55	2	1	4	2	2	1	4	2	3
6	0.00	0.30	2	1	4	2	2	2	3	2	3
10	0.00	0.05	2	1	3	1	1	1	1	2	3

egg			Participant								
parameters			1	2	3	4	5	6	7	8	9
8	0.00	0.55	3	3	4	1	1	1	4	2	2
8	0.20	0.05	4	4	6	3	3	3	5	2	4
8	0.00	0.00	4	4	6	3	3	3	4	2	4
4	0.20	0.55	3	2	4	1	2	1	2	2	2
8	0.00	0.05	4	5	6	2	3	4	5	2	4
8	0.20	0.30	4	4	6	3	3	4	5	2	4
4	0.00	0.05	4	5	6	4	3	4	5	2	4
6	0.00	0.00	4	5	6	2	3	4	5	2	3
8	0.00	0.30	4	4	6	2	3	4	5	2	4
8	0.20	0.55	3	2	4	1	2	1	3	2	2
6	0.00	0.30	4	3	5	2	2	3	4	2	3
10	0.00	0.05	4	3	5	2	1	3	3	2	3

elephant			Participant								
parameters			1	2	3	4	5	6	7	8	9
8	0.00	0.55	6	7	6	4	7	7	3	7	5
8	0.20	0.05	6	4	7	5	6	6	5	6	5
8	0.00	0.00	6	6	7	6	6	6	5	6	4
4	0.20	0.55	5	7	6	4	7	6	4	7	4
8	0.00	0.05	6	3	7	5	6	6	5	6	5
8	0.20	0.30	6	3	7	6	6	6	5	6	4
4	0.00	0.05	6	5	7	5	6	6	5	6	4
6	0.00	0.00	6	5	7	6	6	6	4	6	5
8	0.00	0.30	6	4	7	5	6	6	5	6	4
8	0.20	0.55	5	7	6	4	7	7	3	7	4
6	0.00	0.30	6	6	7	5	6	6	4	6	5
10	0.00	0.05	6	6	7	5	6	6	4	6	5

pond			Participant								
parameters			1	2	3	4	5	6	7	8	9
8	0.00	0.55	3	1	4	6	7	1	4	2	4
8	0.20	0.05	3	2	4	4	7	1	3	2	2
8	0.00	0.00	3	3	4	3	7	1	3	2	3
4	0.20	0.55	3	2	4	4	7	1	4	2	3
8	0.00	0.05	3	2	4	3	7	1	3	2	3
8	0.20	0.30	3	2	4	2	7	1	4	2	3
4	0.00	0.05	3	3	4	2	7	1	4	2	4
6	0.00	0.00	3	4	4	3	7	1	4	2	2
8	0.00	0.30	3	3	4	3	7	1	3	2	3
8	0.20	0.55	3	1	4	6	7	1	4	2	4
6	0.00	0.30	3	4	4	4	7	1	3	2	2
10	0.00	0.05	3	4	4	4	7	1	3	2	2

pine cone			Participant								
parameters			1	2	3	4	5	6	7	8	9
8	0.00	0.55	2	2	4	5	2	5	4	3	2
8	0.20	0.05	3	5	5	3	2	4	5	2	3
8	0.00	0.00	3	5	6	4	2	3	5	2	3
4	0.20	0.55	2	1	4	5	2	5	4	3	2
8	0.00	0.05	3	4	6	4	2	3	5	2	2
8	0.20	0.30	2	3	5	3	2	4	5	2	2
4	0.00	0.05	3	1	6	3	2	3	5	2	2
6	0.00	0.00	3	4	6	4	2	4	4	2	4
8	0.00	0.30	3	4	5	4	2	5	5	3	3
8	0.20	0.55	2	3	4	5	2	5	5	3	3
6	0.00	0.30	2	3	5	5	2	5	5	3	4
10	0.00	0.05	3	4	5	4	2	4	5	2	4

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Table 19. (Continued)

feather			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	6 4 5 5 3 6 6 4 4
8	0.20	0.05	6 4 6 5 4 6 6 3 5
8	0.00	0.00	6 4 7 6 4 6 6 3 4
4	0.20	0.55	6 2 5 4 3 6 6 4 3
8	0.00	0.05	6 4 6 4 3 6 6 4 4
8	0.20	0.30	6 3 7 5 4 6 6 4 3
4	0.00	0.05	6 5 7 4 3 6 5 4 4
6	0.00	0.00	6 5 7 5 3 6 5 3 4
8	0.00	0.30	6 5 7 4 4 6 6 4 5
8	0.20	0.55	6 6 5 5 3 6 5 4 4
6	0.00	0.30	6 6 6 5 3 6 5 4 4
10	0.00	0.05	6 3 7 4 2 6 4 3 4

beehive			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	5 3 6 5 7 5 5 6 4
8	0.20	0.05	6 5 6 4 7 5 5 6 4
8	0.00	0.00	6 5 6 4 7 5 6 6 4
4	0.20	0.55	6 4 6 4 7 6 4 6 4
8	0.00	0.05	6 4 6 3 7 5 6 6 4
8	0.20	0.30	5 4 6 3 7 5 6 6 4
4	0.00	0.05	6 4 6 4 7 5 6 5 4
6	0.00	0.00	5 2 5 5 7 5 4 6 3
8	0.00	0.30	6 4 6 5 7 5 6 5 4
8	0.20	0.55	4 4 6 5 7 5 5 5 4
6	0.00	0.30	5 2 6 5 7 5 4 6 3
10	0.00	0.05	6 1 5 5 7 5 4 6 3

turtle			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	7 4 5 5 6 7 5 7 3
8	0.20	0.05	7 7 7 7 7 7 7 7 5
8	0.00	0.00	7 6 7 6 7 7 7 7 5
4	0.20	0.55	7 3 5 4 6 7 6 7 3
8	0.00	0.05	7 5 7 7 7 7 7 7 5
8	0.20	0.30	7 6 7 7 7 7 7 7 5
4	0.00	0.05	7 7 7 7 7 7 7 7 5
6	0.00	0.00	7 7 6 7 6 7 7 7 4
8	0.00	0.30	7 7 7 7 7 7 7 7 5
8	0.20	0.55	7 2 5 5 6 7 5 7 3
6	0.00	0.30	7 2 5 4 6 7 6 7 2
10	0.00	0.05	7 3 6 5 6 7 6 7 4

tiger			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	5 6 4 5 4 5 6 4 5
8	0.20	0.05	5 6 7 4 4 5 6 3 5
8	0.00	0.00	5 7 7 3 4 5 5 4 5
4	0.20	0.55	5 5 6 4 4 5 5 3 5
8	0.00	0.05	5 6 6 4 4 5 6 3 5
8	0.20	0.30	5 5 6 5 4 5 6 4 5
4	0.00	0.05	5 7 4 5 4 5 6 3 5
6	0.00	0.00	5 6 3 4 5 6 5 4 4
8	0.00	0.30	5 7 5 4 4 5 5 3 5
8	0.20	0.55	5 7 5 4 4 5 6 4 5
6	0.00	0.30	5 4 3 3 5 6 5 4 4
10	0.00	0.05	5 3 3 3 5 6 5 4 3

briefcase			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	4 5 4 4 4 6 3 6 3
8	0.20	0.05	6 6 7 4 6 7 5 6 5
8	0.00	0.00	5 7 7 4 6 7 5 6 5
4	0.20	0.55	5 4 5 5 4 5 4 6 4
8	0.00	0.05	6 7 7 5 6 7 5 7 5
8	0.20	0.30	5 7 6 6 5 6 5 7 5
4	0.00	0.05	6 6 7 5 6 7 5 7 5
6	0.00	0.00	5 7 7 5 6 7 5 7 5
8	0.00	0.30	5 7 6 5 5 6 4 7 5
8	0.20	0.55	5 3 4 4 4 5 3 6 3
6	0.00	0.30	6 7 6 5 5 6 4 6 5
10	0.00	0.05	6 7 7 6 6 7 4 6 5

trash can			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	4 3 4 1 3 2 3 2 2
8	0.20	0.05	5 6 7 4 5 6 6 4 4
8	0.00	0.00	6 6 7 4 5 6 6 3 4
4	0.20	0.55	4 2 5 1 3 3 3 1 2
8	0.00	0.05	6 6 7 4 5 6 5 2 4
8	0.20	0.30	6 6 7 4 5 6 5 4 4
4	0.00	0.05	6 6 7 4 5 6 5 4 3
6	0.00	0.00	5 6 7 4 5 6 6 4 5
8	0.00	0.30	6 5 7 4 5 6 5 4 4
8	0.20	0.55	4 3 4 1 3 2 3 1 2
6	0.00	0.30	6 6 7 3 5 6 4 4 5
10	0.00	0.05	5 6 7 3 5 6 4 4 3

video camera			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	5 3 4 3 3 5 4 6 2
8	0.20	0.05	6 7 7 7 5 6 6 7 6
8	0.00	0.00	6 7 7 7 5 6 6 7 6
4	0.20	0.55	5 3 5 5 3 5 4 5 2
8	0.00	0.05	6 7 7 5 5 5 6 7 6
8	0.20	0.30	6 6 6 5 4 6 5 7 4
4	0.00	0.05	6 7 7 4 4 5 6 7 5
6	0.00	0.00	6 7 7 4 4 6 6 7 6
8	0.00	0.30	6 7 6 4 5 5 5 7 4
8	0.20	0.55	5 3 4 4 3 5 4 5 2
6	0.00	0.30	6 4 6 4 5 5 5 6 4
10	0.00	0.05	6 4 7 4 4 5 6 7 6

coffee maker			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	6 2 4 4 4 6 4 6 3
8	0.20	0.05	7 5 6 7 6 7 5 7 5
8	0.00	0.00	7 4 6 7 6 7 5 7 5
4	0.20	0.55	6 2 4 4 4 6 4 6 3
8	0.00	0.05	7 4 7 6 6 7 5 7 5
8	0.20	0.30	7 6 5 6 5 7 5 7 4
4	0.00	0.05	7 3 7 6 5 7 5 7 5
6	0.00	0.00	7 5 6 6 6 7 5 7 6
8	0.00	0.30	7 6 5 5 5 7 5 7 4
8	0.20	0.55	6 3 4 4 4 6 4 7 3
6	0.00	0.30	7 5 5 7 5 7 5 7 5
10	0.00	0.05	7 5 6 5 5 7 5 7 4

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Table 19. (Continued)

flower			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	6 7 5 5 7 6 6 6 4
8	0.20	0.05	6 5 7 6 6 6 5 6 5
8	0.00	0.00	6 5 7 6 6 5 5 6 5
4	0.20	0.55	5 3 5 5 7 6 6 5 4
8	0.00	0.05	7 7 7 6 6 6 5 5 5
8	0.20	0.30	7 7 7 6 6 6 5 6 5
4	0.00	0.05	7 7 7 6 6 6 4 6 3
6	0.00	0.00	6 6 6 5 6 6 5 6 4
8	0.00	0.30	6 6 6 6 6 6 5 5 5
8	0.20	0.55	7 7 5 4 7 6 6 6 4
6	0.00	0.30	6 7 6 3 6 6 4 5 3
10	0.00	0.05	7 4 6 3 6 5 4 6 3

airplane			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	6 7 6 5 4 7 6 6 6
8	0.20	0.05	5 5 7 4 3 5 5 4 4
8	0.00	0.00	5 5 7 4 3 5 5 4 3
4	0.20	0.55	6 7 6 5 4 7 6 6 6
8	0.00	0.05	5 5 7 4 3 5 5 4 3
8	0.20	0.30	5 5 7 4 3 5 4 4 3
4	0.00	0.05	5 2 7 3 3 5 4 4 3
6	0.00	0.00	5 5 7 3 3 5 5 4 4
8	0.00	0.30	5 5 7 3 3 5 4 4 3
8	0.20	0.55	6 7 6 4 4 7 6 6 6
6	0.00	0.30	5 5 7 3 3 5 5 4 3
10	0.00	0.05	5 5 7 3 3 5 5 4 3

traffic cone			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	7 4 6 7 7 7 7 7 6
8	0.20	0.05	7 5 7 5 7 7 7 7 5
8	0.00	0.00	7 5 7 6 7 7 7 7 5
4	0.20	0.55	7 4 6 7 7 7 6 7 6
8	0.00	0.05	7 6 7 5 7 7 7 7 5
8	0.20	0.30	7 6 7 6 7 7 7 7 5
4	0.00	0.05	7 4 7 6 7 7 7 7 5
6	0.00	0.00	7 7 7 7 7 7 6 7 5
8	0.00	0.30	7 6 7 7 7 7 7 7 5
8	0.20	0.55	7 5 6 6 7 7 7 7 6
6	0.00	0.30	7 7 7 5 7 7 7 7 4
10	0.00	0.05	7 6 7 5 7 7 7 7 4

stairs			Participant
parameters			1 2 3 4 5 6 7 8 9
8	0.00	0.55	6 7 5 4 6 6 5 5 6
8	0.20	0.05	5 4 7 6 4 4 5 4 4
8	0.00	0.00	5 4 7 6 4 4 5 3 4
4	0.20	0.55	6 7 5 3 6 6 6 6 6
8	0.00	0.05	5 4 7 6 4 4 6 3 4
8	0.20	0.30	5 6 6 6 4 5 6 4 5
4	0.00	0.05	5 4 7 6 4 4 6 3 4
6	0.00	0.00	5 4 7 6 4 4 6 3 4
8	0.00	0.30	5 6 6 5 4 5 6 3 5
8	0.20	0.55	6 7 5 4 6 6 5 6 6
6	0.00	0.30	5 5 6 5 4 6 6 5 5
10	0.00	0.05	5 5 7 5 4 5 6 3 4

golf cart			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	5 7 5 6 6 7 6 7 6
2.0	1.5	15	6 5 6 5 4 6 6 5 4
3.0	1.5	10	5 5 6 6 4 6 6 5 4
3.0	2.0	20	5 6 5 5 7 7 5 7 5
2.0	1.0	15	6 5 7 5 4 4 7 5 4
2.0	2.0	15	6 7 5 5 5 5 5 6 5
3.0	2.0	5	5 3 4 3 3 4 3 4 3
4.0	1.5	20	5 6 4 4 7 7 5 7 6
4.0	2.0	10	5 5 4 4 4 6 4 6 5
3.0	2.0	15	6 6 4 4 6 6 4 6 5
4.0	1.5	5	6 2 4 3 3 4 3 5 3
5.0	1.5	10	6 5 5 4 5 6 4 6 5

pitcher			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	6 6 4 4 4 6 3 5 4
2.0	1.5	15	6 7 6 5 4 7 5 7 5
3.0	1.5	10	5 7 7 3 4 7 5 7 3
3.0	2.0	20	5 6 3 4 5 6 2 6 4
2.0	1.0	15	6 7 7 3 4 7 6 5 3
2.0	2.0	15	6 7 6 5 4 7 5 5 5
3.0	2.0	5	4 5 4 2 3 6 4 6 3
4.0	1.5	20	4 3 3 4 5 5 2 5 4
4.0	2.0	10	5 4 5 3 4 6 3 6 5
3.0	2.0	15	6 6 4 4 5 7 3 7 5
4.0	1.5	5	4 5 5 2 3 6 4 5 3
5.0	1.5	10	5 4 5 3 4 7 4 6 5

stapler			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	4 4 2 3 4 4 3 6 2
2.0	1.5	15	6 6 4 4 5 5 4 7 4
3.0	1.5	10	5 4 7 5 5 5 5 7 6
3.0	2.0	20	4 6 4 3 4 3 3 7 2
2.0	1.0	15	6 7 6 4 5 5 4 7 4
2.0	2.0	15	6 7 4 3 5 5 4 7 3
3.0	2.0	5	4 3 6 7 3 6 5 6 5
4.0	1.5	20	4 6 3 3 4 5 3 7 2
4.0	2.0	10	5 5 5 5 5 6 4 7 6
3.0	2.0	15	5 7 5 4 4 6 4 7 3
4.0	1.5	5	3 2 6 6 3 6 5 6 5
5.0	1.5	10	5 7 7 5 5 5 4 7 6

mailbox			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	4 7 4 6 6 7 4 6 2
2.0	1.5	15	5 5 6 7 4 7 6 6 4
3.0	1.5	10	5 5 6 6 4 7 6 5 6
3.0	2.0	20	4 6 3 5 6 6 5 5 2
2.0	1.0	15	5 5 7 6 4 7 6 6 5
2.0	2.0	15	5 7 5 4 4 7 5 5 5
3.0	2.0	5	4 4 5 3 2 7 5 5 5
4.0	1.5	20	4 6 3 3 5 6 5 6 2
4.0	2.0	10	5 7 4 4 5 7 4 5 4
3.0	2.0	15	5 7 4 3 5 7 4 5 4
4.0	1.5	5	4 5 5 4 3 7 5 4 6
5.0	1.5	10	5 7 5 5 4 7 5 5 3

pillow			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	6 7 4 5 7 6 6 6 5
2.0	1.5	15	7 6 6 4 5 6 6 6 5
3.0	1.5	10	5 3 6 3 4 5 7 5 4
3.0	2.0	20	5 7 4 6 7 3 6 6 5
2.0	1.0	15	7 5 7 3 5 6 7 6 4
2.0	2.0	15	7 7 5 5 6 6 6 6 5
3.0	2.0	5	4 2 4 2 3 3 4 5 3
4.0	1.5	20	6 7 4 5 7 4 6 7 4
4.0	2.0	10	6 4 4 4 4 5 6 6 4
3.0	2.0	15	7 7 5 5 6 6 6 6 6
4.0	1.5	5	4 2 4 2 3 3 4 4 3
5.0	1.5	10	5 6 5 3 4 6 7 6 3

brush			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	4 7 5 6 7 6 6 6 4
2.0	1.5	15	6 7 6 5 4 6 7 7 5
3.0	1.5	10	7 5 7 3 4 4 7 5 5
3.0	2.0	20	4 6 3 4 5 6 6 6 3
2.0	1.0	15	6 5 7 4 6 6 7 6 5
2.0	2.0	15	6 7 5 4 6 6 6 7 4
3.0	2.0	5	6 2 3 3 3 2 5 4 2
4.0	1.5	20	3 6 3 2 3 5 4 6 3
4.0	2.0	10	6 5 2 4 5 5 5 5 3
3.0	2.0	15	5 6 5 5 6 6 6 7 4
4.0	1.5	5	6 2 4 3 3 2 5 4 2
5.0	1.5	10	5 2 5 4 5 5 5 5 3

shopping cart			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	4 6 4 5 6 6 6 6 6
2.0	1.5	15	5 5 7 3 4 5 6 5 3
3.0	1.5	10	4 5 6 4 4 4 6 5 3
3.0	2.0	20	3 7 2 6 4 5 4 5 3
2.0	1.0	15	5 3 7 3 4 3 6 5 2
2.0	2.0	15	4 5 5 4 6 4 6 6 5
3.0	2.0	5	5 5 5 2 3 3 4 4 3
4.0	1.5	20	4 7 2 6 4 5 4 5 4
4.0	2.0	10	4 4 4 4 5 4 3 6 4
3.0	2.0	15	5 4 3 5 5 5 4 6 4
4.0	1.5	5	5 2 7 3 3 3 4 5 3
5.0	1.5	10	4 6 4 5 5 6 4 6 4

tire			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	4 7 4 2 3 3 3 5 2
2.0	1.5	15	5 4 6 2 5 4 5 5 4
3.0	1.5	10	5 4 6 4 5 5 5 5 4
3.0	2.0	20	2 2 2 1 2 1 2 4 1
2.0	1.0	15	5 3 6 3 5 5 5 6 4
2.0	2.0	15	5 5 5 4 5 5 5 5 3
3.0	2.0	5	6 4 7 6 6 7 6 6 6
4.0	1.5	20	2 2 2 1 1 1 2 5 1
4.0	2.0	10	5 7 4 3 4 3 4 5 4
3.0	2.0	15	4 6 4 2 3 2 3 5 3
4.0	1.5	5	6 5 7 3 6 6 6 7 6
5.0	1.5	10	4 5 3 3 4 3 3 6 3

Table 20. Parameter settings raw scores for the Bergholm detector.
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Table 20. (Continued)

grater			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	5	3	4	4	7	5	5	7	4
2.0	1.5	15	6	7	7	5	6	6	6	7	5
3.0	1.5	10	5	6	6	4	5	4	5	6	4
3.0	2.0	20	4	2	3	2	3	4	4	5	3
2.0	1.0	15	6	7	7	4	6	6	6	7	6
2.0	2.0	15	5	7	6	5	6	6	6	7	5
3.0	2.0	5	5	3	6	3	3	4	4	4	4
4.0	1.5	20	3	3	3	2	2	2	2	5	2
4.0	2.0	10	5	5	5	3	4	5	4	6	3
3.0	2.0	15	4	3	5	4	4	5	3	6	3
4.0	1.5	5	5	5	6	5	3	4	4	6	4
5.0	1.5	10	3	3	4	3	2	3	3	4	3

picnic basket			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	4	4	4	3	4	5	4	4	3
2.0	1.5	15	6	7	6	5	6	7	7	6	5
3.0	1.5	10	6	7	7	5	6	7	7	6	5
3.0	2.0	20	4	3	3	3	4	5	5	4	3
2.0	1.0	15	5	6	7	5	7	7	7	5	6
2.0	2.0	15	5	7	5	3	5	7	6	5	6
3.0	2.0	5	4	6	6	3	3	4	4	3	5
4.0	1.5	20	4	3	3	3	4	5	5	4	3
4.0	2.0	10	5	6	5	5	4	7	4	5	4
3.0	2.0	15	5	6	4	4	4	6	4	5	4
4.0	1.5	5	5	5	6	3	7	5	5	5	5
5.0	1.5	10	5	7	5	4	5	6	6	5	3

orange			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	3	3	1	1	3	1	2	4	2
2.0	1.5	15	3	7	3	4	4	3	4	5	3
3.0	1.5	10	4	5	4	3	6	4	5	4	6
3.0	2.0	20	3	6	1	1	3	1	1	5	3
2.0	1.0	15	4	7	3	5	5	3	4	5	4
2.0	2.0	15	3	7	3	4	4	2	2	5	5
3.0	2.0	5	6	2	5	3	2	3	3	3	4
4.0	1.5	20	3	3	2	2	3	2	1	4	3
4.0	2.0	10	5	4	4	3	6	3	2	5	4
3.0	2.0	15	4	6	3	4	4	2	2	5	3
4.0	1.5	5	6	2	5	2	3	2	3	4	5
5.0	1.5	10	5	5	4	3	6	4	4	5	5

banana			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	1	1	3	1	1	1	3	1	1
2.0	1.5	15	2	1	4	1	1	1	4	1	2
3.0	1.5	10	4	7	5	4	4	5	5	5	5
3.0	2.0	20	2	1	2	1	1	1	2	1	2
2.0	1.0	15	2	4	4	1	2	2	4	1	2
2.0	2.0	15	2	4	4	1	2	2	4	1	2
3.0	2.0	5	5	7	6	3	5	6	5	6	4
4.0	1.5	20	1	1	2	1	1	2	2	1	1
4.0	2.0	10	4	7	5	4	4	4	3	5	5
3.0	2.0	15	1	4	4	2	2	3	3	1	2
4.0	1.5	5	5	7	7	3	5	6	5	7	4
5.0	1.5	10	4	7	5	4	4	5	5	5	5

egg			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	1	4	3	2	3	1	2	1	2
2.0	1.5	15	2	7	5	3	4	2	3	2	3
3.0	1.5	10	2	5	6	4	5	2	4	3	3
3.0	2.0	20	1	7	3	2	3	1	2	2	2
2.0	1.0	15	2	7	5	3	4	2	3	3	3
2.0	2.0	15	2	6	5	2	4	2	2	2	2
3.0	2.0	5	5	3	7	3	6	3	5	4	3
4.0	1.5	20	2	7	3	2	3	2	2	2	2
4.0	2.0	10	4	6	5	4	5	3	4	2	2
3.0	2.0	15	2	7	4	2	4	2	2	1	2
4.0	1.5	5	6	3	7	3	6	3	5	4	3
5.0	1.5	10	4	5	6	5	5	3	5	3	3

elephant			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	6	7	6	4	7	6	4	7	5
2.0	1.5	15	6	4	6	3	5	3	5	6	5
3.0	1.5	10	5	3	5	2	3	2	3	4	2
3.0	2.0	20	6	7	4	4	7	6	4	6	3
2.0	1.0	15	5	5	7	2	5	6	6	6	3
2.0	2.0	15	6	7	6	3	6	6	4	6	5
3.0	2.0	5	3	1	4	1	2	2	1	2	2
4.0	1.5	20	6	6	5	4	6	6	4	5	4
4.0	2.0	10	5	3	4	3	4	4	2	4	3
3.0	2.0	15	6	6	4	4	6	6	3	5	4
4.0	1.5	5	4	3	4	1	3	2	2	2	2
5.0	1.5	10	4	4	4	3	4	4	2	4	3

pond			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	3	5	3	3	5	1	5	1	3
2.0	1.5	15	3	4	7	1	4	1	6	1	4
3.0	1.5	10	3	3	6	1	4	1	6	1	4
3.0	2.0	20	1	5	1	2	3	1	4	1	3
2.0	1.0	15	3	3	7	3	4	1	6	1	4
2.0	2.0	15	2	5	6	3	6	1	3	1	3
3.0	2.0	5	1	1	2	1	2	1	2	1	1
4.0	1.5	20	1	5	1	2	3	1	4	1	2
4.0	2.0	10	2	5	3	1	3	1	3	1	3
3.0	2.0	15	3	5	3	2	5	1	3	1	3
4.0	1.5	5	1	1	2	1	2	1	2	1	1
5.0	1.5	10	3	4	3	3	3	1	5	1	3

pine cone			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	2	6	5	3	3	6	3	2	3
2.0	1.5	15	2	4	2	1	2	4	2	2	2
3.0	1.5	10	1	5	3	1	2	5	2	1	2
3.0	2.0	20	2	6	5	4	4	6	2	3	4
2.0	1.0	15	1	4	2	1	2	6	2	1	1
2.0	2.0	15	2	6	4	2	3	5	2	1	3
3.0	2.0	5	2	5	2	2	2	3	1	1	2
4.0	1.5	20	3	6	4	4	4	5	3	2	3
4.0	2.0	10	2	6	4	3	3	6	1	2	3
3.0	2.0	15	2	6	4	2	3	5	1	2	3
4.0	1.5	5	2	5	4	2	3	5	2	2	3
5.0	1.5	10	2	5	5	4	3	5	1	2	2

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Table 20. (Continued)

feather			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	2 3 3 3 3 4 2 2 5
2.0	1.5	15	3 4 6 5 5 6 5 3 4
3.0	1.5	10	4 4 5 4 3 6 5 3 3
3.0	2.0	20	2 3 2 2 2 3 2 4 3
2.0	1.0	15	5 2 7 4 5 7 6 4 4
2.0	2.0	15	3 4 5 3 4 6 4 4 5
3.0	2.0	5	3 1 4 2 2 4 2 2 3
4.0	1.5	20	3 3 2 2 2 3 2 4 2
4.0	2.0	10	2 7 3 2 3 4 2 3 3
3.0	2.0	15	3 7 2 3 3 4 2 4 5
4.0	1.5	5	3 4 4 1 2 2 2 2 2
5.0	1.5	10	3 7 3 2 3 4 3 3 3

beehive			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	5 7 5 5 6 7 4 6 4
2.0	1.5	15	6 6 5 3 5 7 7 6 5
3.0	1.5	10	5 6 4 3 5 7 7 6 4
3.0	2.0	20	6 7 4 4 7 7 5 7 5
2.0	1.0	15	5 5 5 3 5 7 7 6 5
2.0	2.0	15	6 6 6 4 6 7 6 6 4
3.0	2.0	5	4 5 2 1 3 4 4 4 3
4.0	1.5	20	5 7 3 2 7 7 4 7 6
4.0	2.0	10	6 6 4 3 6 7 5 6 4
3.0	2.0	15	6 7 5 3 6 7 5 6 4
4.0	1.5	5	4 5 2 2 4 6 4 5 2
5.0	1.5	10	7 7 4 4 7 7 5 7 6

turtle			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	5 7 7 4 7 7 6 7 5
2.0	1.5	15	5 7 7 6 7 7 7 7 5
3.0	1.5	10	5 6 6 4 6 7 6 6 3
3.0	2.0	20	6 6 5 5 7 7 5 7 5
2.0	1.0	15	5 7 7 6 7 7 7 7 5
2.0	2.0	15	6 7 6 5 7 7 6 7 5
3.0	2.0	5	6 5 4 3 5 6 4 6 2
4.0	1.5	20	5 7 5 4 7 7 5 7 5
4.0	2.0	10	5 5 5 4 6 7 4 7 3
3.0	2.0	15	6 7 7 4 7 7 5 7 5
4.0	1.5	5	5 4 4 2 5 6 4 6 2
5.0	1.5	10	5 6 5 2 6 6 4 7 3

tiger			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	5 7 5 4 6 5 5 7 4
2.0	1.5	15	3 4 3 3 4 3 4 3 2
3.0	1.5	10	3 3 2 2 2 2 3 2 2
3.0	2.0	20	5 7 6 4 6 6 4 6 4
2.0	1.0	15	2 3 3 3 3 2 5 3 2
2.0	2.0	15	4 6 4 3 4 4 5 3 3
3.0	2.0	5	2 2 1 1 2 1 2 2 1
4.0	1.5	20	5 7 5 3 6 7 4 6 5
4.0	2.0	10	4 4 4 2 2 4 2 3 3
3.0	2.0	15	4 6 4 2 4 5 3 5 4
4.0	1.5	5	2 2 1 1 2 3 2 2 1
5.0	1.5	10	4 4 4 3 2 4 3 3 2

briefcase			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	4 7 4 4 4 4 4 7 4
2.0	1.5	15	5 7 5 5 6 6 5 7 4
3.0	1.5	10	5 7 6 3 6 5 6 6 5
3.0	2.0	20	4 5 5 3 4 6 3 7 4
2.0	1.0	15	5 7 6 4 6 7 6 6 5
2.0	2.0	15	5 7 5 5 5 6 5 6 4
3.0	2.0	5	6 4 6 2 7 5 4 5 6
4.0	1.5	20	4 5 4 2 4 5 3 7 3
4.0	2.0	10	5 5 4 3 5 6 4 7 4
3.0	2.0	15	4 5 4 3 4 5 4 6 4
4.0	1.5	5	6 4 7 2 7 5 5 5 5
5.0	1.5	10	5 5 4 3 4 6 4 6 4

trash can			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	3 2 3 1 3 1 4 3 2
2.0	1.5	15	4 3 6 3 4 5 6 4 2
3.0	1.5	10	5 7 6 4 7 6 6 6 4
3.0	2.0	20	3 2 3 1 3 2 3 4 2
2.0	1.0	15	5 4 6 2 7 4 6 4 3
2.0	2.0	15	4 4 5 2 4 4 6 5 2
3.0	2.0	5	6 3 7 5 6 7 4 6 6
4.0	1.5	20	3 3 4 1 3 3 3 4 2
4.0	2.0	10	5 7 4 6 5 5 4 6 4
3.0	2.0	15	4 4 3 3 4 4 4 5 2
4.0	1.5	5	6 3 7 3 6 6 5 6 5
5.0	1.5	10	5 7 4 5 5 6 5 6 4

video camera			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	5 4 3 3 4 3 3 4 3
2.0	1.5	15	5 6 5 5 7 6 4 5 4
3.0	1.5	10	5 6 6 4 7 7 5 5 5
3.0	2.0	20	4 7 3 3 4 5 3 4 3
2.0	1.0	15	5 5 5 6 5 6 6 4 4
2.0	2.0	15	5 7 5 5 5 6 4 5 4
3.0	2.0	5	5 3 7 3 6 6 4 3 4
4.0	1.5	20	4 7 3 2 5 3 2 4 3
4.0	2.0	10	6 7 4 2 6 6 3 5 5
3.0	2.0	15	6 7 3 4 5 6 3 5 4
4.0	1.5	5	5 3 6 3 5 4 4 4 6
5.0	1.5	10	6 5 4 3 4 6 4 4 5

coffee maker			Participant
parameters			1 2 3 4 5 6 7 8 9
2.0	2.0	20	5 6 4 6 6 6 3 5 3
2.0	1.5	15	6 3 5 5 7 6 5 6 6
3.0	1.5	10	7 2 5 3 5 6 4 5 4
3.0	2.0	20	4 6 4 5 6 7 3 6 3
2.0	1.0	15	7 2 7 6 6 7 6 5 7
2.0	2.0	15	6 4 5 5 7 7 4 5 4
3.0	2.0	5	7 1 7 3 5 4 3 4 3
4.0	1.5	20	4 5 4 3 6 6 3 6 2
4.0	2.0	10	6 3 5 4 7 6 4 5 3
3.0	2.0	15	5 4 5 3 5 6 3 6 3
4.0	1.5	5	7 2 6 3 5 6 4 5 3
5.0	1.5	10	6 3 5 4 5 6 3 5 4

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Table 20. (Continued)

flower			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	1	6	4	3	3	3	4	2	3
2.0	1.5	15	3	6	5	6	5	2	5	3	3
3.0	1.5	10	1	5	3	2	2	1	3	2	1
3.0	2.0	20	2	7	4	3	4	3	3	4	3
2.0	1.0	15	3	6	6	4	4	4	6	3	2
2.0	2.0	15	2	6	4	4	3	3	3	4	4
3.0	2.0	5	1	5	2	2	1	1	2	2	1
4.0	1.5	20	3	7	4	4	4	2	4	3	3
4.0	2.0	10	1	5	3	2	1	2	2	2	3
3.0	2.0	15	2	6	4	3	2	2	2	3	4
4.0	1.5	5	2	5	2	2	2	1	3	2	1
5.0	1.5	10	3	5	5	3	1	2	2	2	2

airplane			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	5	7	5	3	5	5	5	6	6
2.0	1.5	15	4	6	5	3	4	4	4	5	4
3.0	1.5	10	4	5	5	4	3	4	3	5	4
3.0	2.0	20	5	7	4	3	6	6	4	6	6
2.0	1.0	15	5	5	6	2	4	4	5	5	4
2.0	2.0	15	4	6	5	3	4	5	4	5	4
3.0	2.0	5	3	2	3	1	2	1	2	3	3
4.0	1.5	20	5	7	4	5	6	7	4	6	6
4.0	2.0	10	4	3	4	4	4	5	3	6	4
3.0	2.0	15	4	7	4	4	5	5	3	5	5
4.0	1.5	5	4	2	3	2	2	2	2	3	3
5.0	1.5	10	4	4	4	2	5	5	2	6	4

traffic cone			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	6	7	4	6	5	7	4	7	5
2.0	1.5	15	5	5	5	4	3	7	6	5	5
3.0	1.5	10	5	4	5	4	4	7	6	4	4
3.0	2.0	20	6	7	4	6	6	7	4	5	6
2.0	1.0	15	5	3	6	3	3	6	7	4	5
2.0	2.0	15	5	5	5	4	4	7	5	6	5
3.0	2.0	5	4	1	4	3	3	5	3	4	2
4.0	1.5	20	6	7	4	5	6	7	4	7	5
4.0	2.0	10	5	6	5	4	5	7	4	6	4
3.0	2.0	15	6	6	5	5	5	6	4	6	6
4.0	1.5	5	4	1	4	3	3	4	3	5	2
5.0	1.5	10	5	5	5	5	4	7	5	6	4

stairs			Participant								
parameters			1	2	3	4	5	6	7	8	9
2.0	2.0	20	5	7	5	4	5	7	5	7	6
2.0	1.5	15	5	6	6	4	3	7	6	6	3
3.0	1.5	10	4	5	5	5	3	6	5	4	2
3.0	2.0	20	4	7	4	4	4	7	5	5	5
2.0	1.0	15	5	5	7	6	3	7	6	5	4
2.0	2.0	15	5	7	6	6	4	7	5	4	4
3.0	2.0	5	3	2	3	2	2	4	2	3	2
4.0	1.5	20	4	7	4	2	4	6	4	6	5
4.0	2.0	10	4	4	5	3	4	7	4	5	3
3.0	2.0	15	5	7	5	3	5	7	5	6	4
4.0	1.5	5	4	3	4	2	2	4	2	5	2
5.0	1.5	10	5	6	5	3	4	6	4	6	3

golf cart			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 5 6 6 4 5 6 2 5
1.0	8	0.95	5 5 6 6 4 6 6 2 2
1.0	13	0.85	5 7 5 5 6 7 5 4 5
1.5	8	0.85	5 7 5 4 5 7 5 5 5
1.0	13	0.80	5 7 5 5 6 7 5 4 4
1.5	3	0.90	5 2 4 3 3 4 4 3 2
1.5	3	0.80	5 2 4 3 3 3 4 3 2
2.0	3	0.95	5 2 4 4 3 4 3 2 2
0.5	18	0.80	7 6 7 6 5 7 7 5 2
1.0	18	0.80	6 7 3 4 7 5 4 6 5
1.0	18	0.85	5 7 3 4 7 5 4 6 3
1.5	13	0.80	5 4 2 3 5 5 3 6 2

pitcher			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 6 6 7 6 7 6 6 5
1.0	8	0.95	6 6 6 6 6 7 6 6 5
1.0	13	0.85	5 7 4 5 5 6 5 5 4
1.5	8	0.85	5 7 4 5 5 6 5 5 4
1.0	13	0.80	5 7 4 4 5 6 5 6 4
1.5	3	0.90	5 5 5 2 3 7 4 4 5
1.5	3	0.80	5 3 5 2 3 7 4 4 3
2.0	3	0.95	5 5 4 4 3 7 4 6 3
0.5	18	0.80	6 7 7 6 6 7 7 5 5
1.0	18	0.80	4 4 3 3 4 5 4 5 2
1.0	18	0.85	5 4 3 3 4 5 3 5 2
1.5	13	0.80	4 4 1 3 4 5 3 5 3

stapler			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 7 5 4 5 5 5 7 5
1.0	8	0.95	6 7 5 4 5 6 5 7 5
1.0	13	0.85	4 7 3 3 4 5 3 6 2
1.5	8	0.85	4 6 3 3 4 4 3 6 2
1.0	13	0.80	3 6 3 3 4 4 3 6 3
1.5	3	0.90	5 3 6 6 3 6 4 6 4
1.5	3	0.80	5 3 7 6 3 6 4 6 4
2.0	3	0.95	6 3 4 5 3 4 4 7 4
0.5	18	0.80	3 7 6 4 7 4 4 6 3
1.0	18	0.80	3 5 2 3 6 4 2 6 2
1.0	18	0.85	3 5 2 3 6 4 2 6 2
1.5	13	0.80	3 5 2 2 4 4 2 6 3

mailbox			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	7 6 6 6 5 7 7 6 6
1.0	8	0.95	6 6 6 6 5 7 7 5 5
1.0	13	0.85	5 7 5 5 6 6 6 6 4
1.5	8	0.85	5 5 5 5 6 6 5 6 4
1.0	13	0.80	5 7 5 5 7 6 6 6 4
1.5	3	0.90	5 3 4 2 2 5 4 4 5
1.5	3	0.80	6 3 4 2 2 5 4 5 5
2.0	3	0.95	5 3 4 2 2 6 3 5 4
0.5	18	0.80	6 6 7 6 6 7 7 5 4
1.0	18	0.80	4 7 3 4 4 5 4 5 2
1.0	18	0.85	5 7 3 3 4 5 4 5 2
1.5	13	0.80	5 7 3 3 4 5 2 6 2

pillow			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	7 4 6 4 7 6 7 6 6
1.0	8	0.95	7 4 6 4 7 6 7 6 6
1.0	13	0.85	6 5 5 5 6 6 6 6 4
1.5	8	0.85	6 6 5 5 6 6 6 7 4
1.0	13	0.80	6 6 5 5 6 6 6 6 3
1.5	3	0.90	5 2 4 2 4 4 4 5 3
1.5	3	0.80	5 1 4 2 4 4 4 5 3
2.0	3	0.95	5 3 3 3 4 5 5 5 3
0.5	18	0.80	7 4 7 6 7 6 7 6 5
1.0	18	0.80	4 6 2 3 5 5 5 6 2
1.0	18	0.85	4 4 2 3 5 5 5 7 2
1.5	13	0.80	4 2 1 3 5 5 4 6 2

brush			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	5 5 6 6 4 6 7 5 5
1.0	8	0.95	5 5 6 6 4 5 7 5 4
1.0	13	0.85	5 6 5 5 6 6 6 7 5
1.5	8	0.85	4 6 4 4 5 5 4 6 3
1.0	13	0.80	5 6 5 5 5 6 6 6 5
1.5	3	0.90	5 4 3 3 3 3 5 4 4
1.5	3	0.80	5 3 3 3 3 3 5 5 2
2.0	3	0.95	5 3 2 2 2 3 4 5 2
0.5	18	0.80	6 6 7 5 7 7 7 6 6
1.0	18	0.80	4 7 4 4 5 5 5 6 4
1.0	18	0.85	4 7 2 4 5 5 5 6 4
1.5	13	0.80	3 6 1 2 4 2 3 5 2

shopping cart			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 3 6 6 3 2 6 4 2
1.0	8	0.95	6 3 6 6 3 3 6 3 3
1.0	13	0.85	6 5 5 5 5 6 6 5 4
1.5	8	0.85	5 6 3 3 4 6 4 6 4
1.0	13	0.80	6 5 5 4 5 6 4 6 5
1.5	3	0.90	5 1 2 3 2 1 2 3 3
1.5	3	0.80	6 2 2 3 2 2 3 4 2
2.0	3	0.95	5 1 1 2 2 4 2 4 2
0.5	18	0.80	5 3 7 4 3 4 3 4 2
1.0	18	0.80	6 7 4 3 6 6 4 6 6
1.0	18	0.85	6 7 4 3 6 6 4 6 6
1.5	13	0.80	4 6 1 2 4 5 3 5 3

tire			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 4 6 5 4 5 6 4 4
1.0	8	0.95	6 4 6 5 4 5 6 5 4
1.0	13	0.85	5 7 4 4 3 4 4 4 3
1.5	8	0.85	5 7 3 3 3 4 3 4 3
1.0	13	0.80	5 7 4 3 3 4 4 4 2
1.5	3	0.90	6 5 5 4 6 6 6 4 5
1.5	3	0.80	6 4 5 5 6 6 5 4 5
2.0	3	0.95	4 5 3 3 5 5 3 3 4
0.5	18	0.80	6 7 7 6 4 4 5 4 4
1.0	18	0.80	3 7 2 2 2 2 2 3 2
1.0	18	0.85	3 6 2 2 2 2 2 3 2
1.5	13	0.80	2 4 1 1 1 1 2 2 2

Table 21. Parameter settings raw scores for the Rothwell detector.

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Table 21. (Continued)

grater			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.0	8	0.90	7	7	6	5	4	6	6	6	6
1.0	8	0.95	6	7	6	5	4	4	6	6	5
1.0	13	0.85	6	7	5	4	5	5	5	7	5
1.5	8	0.85	4	6	2	3	3	4	4	6	3
1.0	13	0.80	6	7	5	4	7	6	6	7	5
1.5	3	0.90	6	4	4	3	3	3	3	5	4
1.5	3	0.80	6	4	4	3	3	4	3	4	5
2.0	3	0.95	5	3	2	2	3	2	2	3	3
0.5	18	0.80	6	7	7	4	7	6	6	6	6
1.0	18	0.80	4	6	4	2	6	3	4	6	4
1.0	18	0.85	4	6	3	2	6	3	4	7	3
1.5	13	0.80	3	3	1	1	2	2	2	6	2

picnic basket			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.0	8	0.90	6	7	6	6	7	7	7	5	6
1.0	8	0.95	6	7	6	5	7	7	7	4	5
1.0	13	0.85	5	5	5	4	6	6	6	5	4
1.5	8	0.85	5	5	4	3	5	6	3	5	4
1.0	13	0.80	5	5	5	4	6	6	6	4	4
1.5	3	0.90	6	2	4	4	3	4	4	2	3
1.5	3	0.80	5	2	4	3	3	3	4	3	2
2.0	3	0.95	4	1	3	3	2	3	2	2	3
0.5	18	0.80	7	6	7	6	7	7	7	4	6
1.0	18	0.80	5	4	3	2	4	5	4	3	3
1.0	18	0.85	5	4	2	2	4	3	3	3	3
1.5	13	0.80	4	2	2	2	3	2	2	2	2

orange			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.0	8	0.90	4	7	3	5	6	5	5	6	4
1.0	8	0.95	4	7	4	5	6	5	5	4	5
1.0	13	0.85	3	5	2	3	2	2	2	2	3
1.5	8	0.85	3	5	2	4	3	2	4	2	4
1.0	13	0.80	3	3	2	3	2	2	3	2	4
1.5	3	0.90	4	4	5	3	4	4	5	3	5
1.5	3	0.80	4	4	4	3	4	4	5	3	4
2.0	3	0.95	5	4	4	3	5	4	4	3	4
0.5	18	0.80	4	7	2	2	3	2	4	5	3
1.0	18	0.80	1	1	1	1	1	1	1	1	2
1.0	18	0.85	1	1	1	1	1	1	1	1	2
1.5	13	0.80	1	1	1	1	1	1	1	1	2

banana			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.0	8	0.90	2	4	4	2	2	1	5	1	2
1.0	8	0.95	2	4	4	2	2	1	5	1	2
1.0	13	0.85	1	3	3	2	1	1	4	1	2
1.5	8	0.85	2	3	3	2	1	1	4	1	2
1.0	13	0.80	2	3	3	2	1	1	4	1	2
1.5	3	0.90	5	7	5	5	5	5	5	4	4
1.5	3	0.80	5	7	5	4	5	5	4	4	4
2.0	3	0.95	4	7	5	3	4	4	3	4	3
0.5	18	0.80	2	3	4	1	1	1	5	1	1
1.0	18	0.80	1	1	3	1	1	1	2	1	1
1.0	18	0.85	1	1	2	1	1	1	2	1	1
1.5	13	0.80	1	1	2	1	1	1	1	1	1

egg			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.0	8	0.90	3	7	5	3	4	3	3	4	4
1.0	8	0.95	3	7	5	3	4	3	4	2	3
1.0	13	0.85	2	5	4	3	3	1	2	1	4
1.5	8	0.85	2	5	4	2	3	3	2	1	3
1.0	13	0.80	3	5	4	2	3	1	3	1	3
1.5	3	0.90	5	6	6	4	6	4	5	4	3
1.5	3	0.80	5	6	6	4	6	4	5	4	3
2.0	3	0.95	5	7	5	3	5	4	4	4	3
0.5	18	0.80	3	5	4	2	4	2	3	3	3
1.0	18	0.80	2	4	3	1	2	1	2	1	1
1.0	18	0.85	2	4	3	1	2	1	2	1	2
1.5	13	0.80	2	4	2	1	2	1	2	1	2

elephant			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.0	8	0.90	5	4	7	5	5	4	5	4	4
1.0	8	0.95	5	4	7	5	5	4	5	4	4
1.0	13	0.85	6	6	5	5	7	7	6	5	5
1.5	8	0.85	6	6	5	4	4	5	5	5	3
1.0	13	0.80	6	7	5	6	7	6	6	5	5
1.5	3	0.90	3	2	4	2	2	2	3	2	2
1.5	3	0.80	3	2	4	2	2	1	3	2	2
2.0	3	0.95	3	3	3	3	2	2	2	2	2
0.5	18	0.80	5	5	6	5	6	5	7	5	5
1.0	18	0.80	5	7	4	3	5	5	4	6	3
1.0	18	0.85	5	7	2	3	5	5	4	6	3
1.5	13	0.80	5	7	3	2	4	5	3	6	3

pond			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.0	8	0.90	3	3	5	2	5	1	5	2	4
1.0	8	0.95	3	3	6	2	5	1	5	2	4
1.0	13	0.85	3	5	4	4	7	1	4	2	4
1.5	8	0.85	3	3	2	3	6	1	3	2	2
1.0	13	0.80	3	5	4	4	7	1	5	2	3
1.5	3	0.90	2	1	3	2	3	1	1	1	3
1.5	3	0.80	2	1	2	2	3	1	1	1	3
2.0	3	0.95	2	1	2	2	3	1	1	1	3
0.5	18	0.80	3	4	7	3	5	1	5	2	4
1.0	18	0.80	3	5	2	4	6	1	4	2	2
1.0	18	0.85	2	5	2	4	6	1	4	1	2
1.5	13	0.80	1	2	1	1	4	1	3	1	2

pine cone			Participant								
parameters			1	2	3	4	5	6	7	8	9
1.0	8	0.90	2	3	2	3	1	1	4	1	3
1.0	8	0.95	2	3	3	4	1	1	4	1	2
1.0	13	0.85	2	5	4	3	3	3	4	2	4
1.5	8	0.85	2	5	4	3	3	2	4	2	4
1.0	13	0.80	3	5	4	3	3	3	4	2	3
1.5	3	0.90	2	1	2	2	1	1	2	1	2
1.5	3	0.80	2	1	2	1	1	1	2	1	2
2.0	3	0.95	2	1	2	2	2	1	2	1	1
0.5	18	0.80	3	5	5	4	3	4	5	2	2
1.0	18	0.80	3	4	2	4	4	4	4	2	3
1.0	18	0.85	3	4	2	4	4	4	3	3	2
1.5	13	0.80	3	4	1	2	3	5	3	2	2

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Table 21. (Continued)

feather			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	7 6 6 5 6 7 6 6 5
1.0	8	0.95	7 6 6 5 6 7 6 5 5
1.0	13	0.85	6 6 5 6 5 7 5 5 4
1.5	8	0.85	4 5 4 4 4 5 5 4 3
1.0	13	0.80	6 5 5 4 5 5 5 5 5
1.5	3	0.90	4 2 4 3 4 3 4 3 2
1.5	3	0.80	4 2 4 4 4 4 4 3 3
2.0	3	0.95	4 2 4 3 4 4 3 2 2
0.5	18	0.80	7 6 7 5 6 7 7 6 5
1.0	18	0.80	4 2 3 2 3 2 3 3 2
1.0	18	0.85	4 2 3 3 3 2 3 4 2
1.5	13	0.80	4 2 2 2 3 2 2 2 2

beehive			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 5 5 3 5 4 6 5 5
1.0	8	0.95	6 5 5 3 5 4 6 6 5
1.0	13	0.85	5 7 4 5 7 5 6 6 3
1.5	8	0.85	5 7 4 6 7 5 6 6 3
1.0	13	0.80	5 7 3 5 7 5 7 6 4
1.5	3	0.90	6 3 4 2 4 2 4 3 2
1.5	3	0.80	6 3 3 2 4 2 4 3 2
2.0	3	0.95	5 6 4 3 6 5 5 6 4
0.5	18	0.80	6 6 6 3 5 4 7 6 5
1.0	18	0.80	5 7 2 4 7 6 4 6 3
1.0	18	0.85	4 7 2 4 7 6 4 6 2
1.5	13	0.80	4 7 1 3 6 6 3 6 2

turtle			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 7 6 6 7 7 7 7 5
1.0	8	0.95	6 7 6 6 7 7 7 7 5
1.0	13	0.85	6 7 5 4 6 7 6 7 4
1.5	8	0.85	5 7 4 4 6 7 6 7 4
1.0	13	0.80	5 7 5 5 7 7 6 7 5
1.5	3	0.90	6 6 6 5 5 6 5 6 4
1.5	3	0.80	6 6 6 5 5 6 5 6 4
2.0	3	0.95	5 6 4 4 5 6 4 6 3
0.5	18	0.80	6 7 7 7 7 6 5 7 5
1.0	18	0.80	4 7 3 4 5 7 7 7 4
1.0	18	0.85	4 7 3 4 5 7 5 7 4
1.5	13	0.80	4 7 2 3 5 7 4 7 4

tiger			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	4 3 1 3 2 2 4 3 3
1.0	8	0.95	4 4 2 3 2 2 4 3 3
1.0	13	0.85	5 7 3 4 4 6 5 4 4
1.5	8	0.85	4 7 3 3 4 6 5 4 4
1.0	13	0.80	5 7 3 4 4 6 6 3 4
1.5	3	0.90	3 1 1 2 1 1 1 1 2
1.5	3	0.80	3 1 1 1 1 1 1 1 2
2.0	3	0.95	4 1 1 2 1 1 2 1 2
0.5	18	0.80	5 6 5 3 3 6 6 4 4
1.0	18	0.80	5 6 3 3 5 5 5 3 4
1.0	18	0.85	5 6 3 2 5 6 5 3 4
1.5	13	0.80	5 7 2 1 4 5 5 3 4

briefcase			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 7 6 5 6 6 6 6 4
1.0	8	0.95	6 7 6 6 6 6 6 6 6
1.0	13	0.85	6 7 5 6 4 6 3 6 3
1.5	8	0.85	5 6 4 4 5 6 3 7 2
1.0	13	0.80	6 7 5 5 5 6 4 5 3
1.5	3	0.90	5 4 4 4 3 5 3 6 4
1.5	3	0.80	6 6 4 3 3 5 3 5 4
2.0	3	0.95	5 4 5 3 3 5 3 5 4
0.5	18	0.80	6 7 7 5 6 6 7 6 6
1.0	18	0.80	4 5 3 5 4 3 2 5 3
1.0	18	0.85	3 5 3 5 4 3 2 5 3
1.5	13	0.80	4 5 2 3 3 3 2 5 2

trash can			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	5 5 6 5 6 6 7 5 4
1.0	8	0.95	5 7 6 4 6 6 7 5 4
1.0	13	0.85	4 7 5 3 4 5 5 2 3
1.5	8	0.85	4 6 4 4 4 5 5 2 3
1.0	13	0.80	4 5 5 3 4 4 5 2 2
1.5	3	0.90	6 6 4 3 7 7 6 6 5
1.5	3	0.80	6 6 4 4 7 7 5 5 5
2.0	3	0.95	5 6 5 5 6 6 4 5 5
0.5	18	0.80	5 6 7 2 5 5 7 4 3
1.0	18	0.80	3 3 3 1 3 1 3 1 1
1.0	18	0.85	3 3 3 2 3 1 3 1 2
1.5	13	0.80	2 3 2 1 3 1 4 1 2

video camera			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 7 7 3 4 6 7 5 4
1.0	8	0.95	6 7 7 3 4 6 7 4 4
1.0	13	0.85	5 7 4 6 3 5 5 4 4
1.5	8	0.85	5 6 4 5 4 5 4 6 3
1.0	13	0.80	5 6 4 4 5 5 6 4 2
1.5	3	0.90	5 4 6 3 4 5 5 3 5
1.5	3	0.80	6 4 6 3 4 5 5 3 5
2.0	3	0.95	4 4 5 3 3 6 5 3 4
0.5	18	0.80	5 6 7 3 5 3 6 4 3
1.0	18	0.80	3 3 3 2 3 2 4 3 1
1.0	18	0.85	4 3 3 2 3 2 4 3 1
1.5	13	0.80	3 3 1 1 2 2 3 2 1

coffee maker			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 5 6 4 6 7 7 6 6
1.0	8	0.95	6 5 6 4 6 7 7 6 6
1.0	13	0.85	5 7 5 5 5 6 6 5 5
1.5	8	0.85	4 7 4 5 5 6 6 7 5
1.0	13	0.80	5 7 5 5 6 6 6 5 4
1.5	3	0.90	6 2 4 3 4 6 5 5 4
1.5	3	0.80	6 3 5 2 4 6 5 5 5
2.0	3	0.95	6 3 3 4 4 4 5 6 5
0.5	18	0.80	5 7 7 6 7 7 7 6 6
1.0	18	0.80	5 7 2 3 3 5 5 6 3
1.0	18	0.85	5 7 1 3 3 5 4 6 3
1.5	13	0.80	4 7 2 3 3 5 4 6 3

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Table 21. (Continued)

flower			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	4 5 6 4 3 5 5 3 5
1.0	8	0.95	3 5 6 4 3 5 5 4 5
1.0	13	0.85	4 6 4 6 3 6 6 4 5
1.5	8	0.85	3 5 5 5 3 4 5 3 3
1.0	13	0.80	4 6 4 6 3 4 6 3 5
1.5	3	0.90	2 1 2 2 1 1 3 1 2
1.5	3	0.80	4 1 2 2 1 1 3 1 1
2.0	3	0.95	3 1 2 3 1 1 2 1 1
0.5	18	0.80	7 6 7 6 5 6 7 5 6
1.0	18	0.80	4 4 2 5 4 3 4 3 3
1.0	18	0.85	4 4 2 5 4 2 4 2 3
1.5	13	0.80	3 3 1 4 1 1 3 2 2

airplane			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	4 4 4 3 3 4 4 3 4
1.0	8	0.95	4 4 3 3 3 4 4 5 3
1.0	13	0.85	5 7 5 5 5 5 5 6 4
1.5	8	0.85	4 7 5 3 4 5 5 5 4
1.0	13	0.80	5 7 6 4 5 5 5 6 4
1.5	3	0.90	3 2 2 3 2 2 3 2 2
1.5	3	0.80	3 2 2 2 2 2 3 2 2
2.0	3	0.95	3 1 1 3 1 3 2 2 3
0.5	18	0.80	6 6 7 6 4 6 6 6 4
1.0	18	0.80	4 7 6 6 5 7 5 7 5
1.0	18	0.85	5 7 6 6 5 7 5 6 5
1.5	13	0.80	4 7 4 5 4 7 4 7 5

traffic cone			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 5 6 3 4 7 7 4 4
1.0	8	0.95	6 6 6 3 4 7 7 4 4
1.0	13	0.85	5 7 5 6 5 7 6 5 4
1.5	8	0.85	5 7 5 5 5 7 6 5 4
1.0	13	0.80	5 7 5 5 5 7 6 5 3
1.5	3	0.90	5 3 4 5 3 5 5 4 3
1.5	3	0.80	5 3 4 5 3 5 5 3 3
2.0	3	0.95	5 4 4 4 3 5 4 3 3
0.5	18	0.80	6 4 7 6 4 7 7 4 5
1.0	18	0.80	6 7 2 5 6 6 5 6 4
1.0	18	0.85	6 7 2 4 6 6 5 6 4
1.5	13	0.80	5 7 1 4 6 6 5 6 3

stairs			Participant
parameters			1 2 3 4 5 6 7 8 9
1.0	8	0.90	6 5 6 3 6 6 5 4 4
1.0	8	0.95	6 5 6 3 6 6 5 4 3
1.0	13	0.85	5 7 5 4 7 7 6 5 5
1.5	8	0.85	5 7 4 5 5 7 6 5 4
1.0	13	0.80	5 7 5 5 7 7 6 5 4
1.5	3	0.90	5 3 3 2 3 2 3 2 2
1.5	3	0.80	6 3 3 3 3 2 3 2 2
2.0	3	0.95	6 3 4 3 3 3 4 3 3
0.5	18	0.80	7 5 7 5 6 7 6 6 5
1.0	18	0.80	5 7 5 4 6 7 5 6 4
1.0	18	0.85	5 7 5 4 6 7 5 6 4
1.5	13	0.80	5 7 2 4 5 6 4 6 3

APPENDIX 4. PARAMETER SETTING RESULTS

sigma	1.2	1.8	*0.6*	1.2	0.6	1.2	1.2	1.2	2.4	0.6	1.2	1.8
low	0.4	0.2	*0.3*	0.2	0.5	0.3	0.4	0.2	0.2	0.3	0.4	0.3
high	0.8	0.7	*0.9*	0.6	0.9	0.8	0.6	0.8	0.6	0.8	0.9	0.9
golf cart	48	39	*55*	38	54	48	43	49	33	50	46	33
pitcher	40	47	31	42	22	38	40	40	35	*54*	19	12
stapler	44	42	*51*	38	47	44	38	44	35	43	26	20
mailbox	37	35	43	50	37	41	*50*	40	27	42	23	22
pillow	50	41	42	40	47	48	44	47	33	*52*	40	37
brush	46	32	*48*	23	46	46	27	41	17	30	39	28
shopping cart	46	33	*53*	39	45	43	46	48	21	45	29	23
tire	30	52	24	*63*	23	34	39	31	49	38	20	12
grater	50	31	*54*	41	47	50	43	50	23	50	25	10
basket	36	33	33	49	22	37	*51*	44	23	47	20	17
orange	*48*	32	40	31	45	44	32	35	27	34	43	30
banana	37	44	19	35	11	43	37	46	35	*48*	10	10
egg	*47*	44	27	17	25	45	21	44	33	33	24	25
elephant	41	27	*49*	23	44	41	31	37	19	38	38	30
pond	24	19	27	24	12	26	32	28	14	*34*	14	11
pine cone	29	24	16	36	12	30	*37*	34	18	31	11	13
feather	27	30	45	50	14	32	50	36	20	*52*	14	10
beehive	37	30	38	20	49	31	20	25	30	14	55	*56*
turtle	51	39	57	18	*59*	56	21	52	27	32	54	43
tiger	30	19	35	14	*43*	24	12	22	13	16	41	38
briefcase	47	41	31	43	28	47	43	*49*	29	39	10	10
trash can	36	*57*	13	45	15	47	46	46	48	33	11	11
video camera	43	*54*	33	51	27	49	52	53	36	52	18	11
coffee maker	51	46	50	36	43	*53*	39	51	35	49	24	20
flower	29	19	*38*	25	30	30	26	32	16	33	13	10
airplane	39	21	58	27	*59*	39	25	37	15	31	43	18
traffic cone	47	45	*54*	44	53	49	44	45	38	45	50	45
stairs	41	40	40	35	34	43	37	41	26	*48*	25	16

(a) Canny edge detector

Table 22. Parameter setting results summed across participants.
The table contains the summed edge ratings (across participants) from the parameter setting experiments. Italics indicate the parameter combinations that produced the best edge images. Thus, the italics in the top row indicate the best fixed parameters and the italics in each subsequent row indicate the best adapted parameters for each image. The underlined entries indicate the parameters that produced edge images that were among the best five of the original 64 edge images as selected by the parameter screener. (a) Canny (b) Nalwa (c) Iverson (d) Bergholm and (e) Rothwell

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Table 22. (Continued)

blur	1.50	1.50	0.60	1.20	1.50	0.60	1.50	1.20	1.20	1.50	0.60	1.50
low	0.10	0.20	0.15	0.10	0.15	0.10	0.15	0.05	0.05	0.05	0.05	0.05
high	0.60	0.60	0.60	0.60	0.15	0.60	0.45	0.15	0.30	0.45	0.30	0.15
golf cart	59	58	55	59	33	55	52	31	41	48	33	33
pitcher	46	49	52	48	38	51	50	38	49	51	42	36
stapler	48	54	36	45	32	36	44	29	33	43	27	30
mailbox	47	47	49	44	39	45	47	38	41	47	43	37
pillow	58	59	56	56	28	54	47	23	33	47	33	27
brush	49	49	55	51	28	48	40	27	33	41	32	28
shopping cart	46	47	46	47	29	47	42	27	32	43	33	27
tire	41	40	32	35	47	34	48	49	47	47	38	48
grater	54	52	50	51	27	52	44	28	34	46	36	27
basket	36	34	39	41	41	39	42	46	47	46	53	49
orange	48	47	40	51	27	41	46	28	34	43	25	24
banana	15	15	11	12	40	17	34	45	49	35	48	45
egg	41	41	39	44	33	37	42	29	33	40	28	30
elephant	49	49	45	47	22	46	38	18	27	36	17	19
pond	22	22	30	26	17	34	26	16	25	27	22	16
pine cone	36	33	29	32	14	28	33	13	21	28	18	13
feather	24	26	33	30	43	33	39	43	46	38	41	40
beehive	51	53	37	43	21	33	37	17	21	38	15	21
turtle	61	61	62	59	33	61	51	34	41	49	45	35
tiger	32	33	22	24	13	19	23	11	16	20	12	12
briefcase	45	44	44	46	43	46	49	40	42	49	40	39
trash can	25	24	34	30	36	37	43	34	40	46	36	35
video camera	54	53	40	52	38	37	49	36	40	49	27	37
coffee maker	61	59	54	60	34	53	51	33	39	46	36	36
flower	47	46	47	47	21	47	40	20	23	35	27	19
airplane	41	41	30	38	23	29	30	17	20	30	17	18
traffic cone	53	55	49	56	34	47	50	34	42	50	36	34
stairs	49	48	53	55	27	53	43	25	33	40	25	21

(b) Nalwa edge detector

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Table 22. (Continued)

directions	8	8	8	4	8	8	4	6	8	8	6	10
low	0.00	0.20	0.00	0.20	0.00	0.20	0.00	0.00	0.00	0.20	0.00	0.00
high	0.55	0.05	0.00	0.55	0.05	0.30	0.05	0.00	0.30	0.55	0.30	0.05
golf cart	53	55	54	55	53	53	53	52	54	56	49	49
pitcher	34	49	48	34	48	47	50	49	47	35	44	47
stapler	29	40	40	27	44	46	42	43	45	29	42	43
mailbox	49	51	51	47	51	52	52	52	53	48	51	52
pillow	37	49	49	37	46	52	45	49	50	39	48	46
brush	56	53	54	53	55	53	54	48	53	51	47	47
shopping cart	49	40	40	47	40	39	40	47	42	52	45	47
tire	37	39	42	33	41	40	38	36	40	37	39	38
grater	44	47	47	42	50	50	48	47	49	45	45	46
basket	46	57	56	52	57	57	57	59	54	47	58	55
orange	28	30	31	31	26	27	28	25	28	30	24	22
banana	20	26	27	20	26	25	26	19	26	21	21	15
egg	21	34	33	19	35	35	37	34	34	20	28	26
elephant	52	50	52	50	49	49	50	51	49	50	51	51
pond	32	28	29	30	28	28	30	30	29	32	30	30
pine cone	29	32	33	28	31	28	27	33	34	32	34	33
feather	43	45	46	39	43	44	44	44	47	44	45	39
beehive	46	48	49	47	47	46	47	42	48	45	43	42
turtle	49	61	59	48	59	60	61	58	61	47	46	51
tiger	44	45	45	42	44	45	44	42	43	45	39	37
briefcase	39	52	52	42	55	52	54	54	50	37	50	54
trash can	24	47	47	24	45	47	46	48	46	23	46	43
video camera	35	57	57	37	54	49	51	53	49	35	45	49
coffee maker	39	55	54	39	54	52	52	55	51	41	53	51
flower	52	52	51	46	54	55	52	50	51	52	46	44
airplane	53	42	41	53	41	40	36	41	39	52	40	40
traffic cone	58	57	58	57	58	59	57	60	60	58	58	57
stairs	50	43	42	51	43	47	43	43	45	51	47	44

(c) Iverson edge detector

(Continued on next page)

Table 22. (Continued)

start sigma	2.0	2.0	3.0	3.0	*2.0*	2.0	3.0	4.0	4.0	3.0	4.0	5.0
end sigma	2.0	1.5	1.5	2.0	*1.0*	2.0	2.0	1.5	2.0	2.0	1.5	1.5
threshold	20	15	10	20	*15*	15	5	20	10	15	5	10
golf cart	*55*	47	47	52	47	49	32	51	43	47	33	46
pitcher	42	*52*	48	41	48	50	37	35	41	47	37	43
stapler	32	45	49	36	48	44	45	37	48	45	42	*51*
mailbox	46	50	50	42	*51*	47	40	40	45	44	43	46
pillow	52	51	42	49	50	53	30	50	43	*54*	29	45
brush	51	*53*	47	43	52	51	30	35	40	50	31	39
shopping cart	*49*	43	41	39	38	45	34	41	38	41	35	44
tire	33	40	43	17	42	42	*54*	17	39	32	52	34
grater	44	55	45	30	*55*	53	36	24	40	37	42	28
basket	35	55	*56*	34	55	49	38	34	45	42	46	46
orange	20	36	*41*	24	40	35	31	23	36	33	32	41
banana	13	17	44	13	22	22	47	12	41	22	*49*	44
egg	19	31	34	23	32	27	39	25	35	26	*40*	39
elephant	*52*	43	29	47	45	49	18	46	32	44	23	32
pond	29	31	29	21	*32*	30	12	20	22	26	12	26
pine cone	33	21	22	*36*	20	28	20	34	30	28	28	29
feather	27	41	37	23	*44*	38	23	23	29	33	22	31
beehive	49	50	47	52	48	51	30	48	47	49	34	*54*
turtle	55	58	49	53	*58*	56	41	52	46	55	38	44
tiger	*48*	29	21	48	26	36	14	48	28	37	16	29
briefcase	42	50	49	41	*52*	48	45	37	43	39	46	41
trash can	22	37	*51*	23	41	36	50	26	46	33	47	47
video camera	32	47	*50*	36	46	46	41	33	44	43	40	41
coffee maker	44	49	41	44	*53*	47	37	39	43	40	41	41
flower	29	38	20	33	*38*	33	17	34	21	28	20	25
airplane	47	39	37	47	40	40	20	*50*	37	42	23	36
traffic cone	*51*	45	43	51	42	46	29	51	46	49	29	46
stairs	*51*	46	39	45	48	48	23	42	39	47	28	42

(d) Bergholm edge detector

(Continued on next page)

Table 22. (Continued)

sigma	1.0	1.0	1.0	1.5	1.0	1.5	1.5	2.0	*0.5*	1.0	1.0	1.5
	8	8	13	8	13	3	3	3	*18*	18	18	13
alpha	0.90	0.95	0.85	0.85	0.80	0.90	0.80	0.95	*0.80*	0.80	0.85	0.80
golf cart	45	42	49	48	48	30	29	29	*52*	47	44	35
pitcher	55	54	46	46	46	40	36	41	*56*	34	34	32
stapler	49	*50*	37	35	35	43	44	40	44	33	33	31
mailbox	*56*	53	50	47	51	34	36	34	54	38	38	37
pillow	53	53	49	51	49	33	32	36	*55*	38	37	32
brush	49	47	51	41	49	34	32	28	*57*	44	42	28
shopping cart	38	39	47	41	46	22	26	23	35	*48*	48	33
tire	44	45	38	35	36	47	46	35	*47*	25	24	16
grater	53	49	49	35	53	35	36	25	*55*	39	38	22
basket	57	54	46	40	45	32	29	23	*57*	33	29	21
orange	*45*	45	24	29	24	37	35	36	32	10	10	10
banana	23	23	18	19	19	*45*	43	37	19	12	11	10
egg	36	34	25	25	25	*43*	43	40	29	17	18	17
elephant	43	43	52	43	*53*	22	21	22	49	42	40	38
pond	30	31	34	25	34	17	16	16	*34*	29	27	16
pine cone	20	21	30	29	30	14	13	14	*33*	30	29	25
feather	54	53	49	38	45	29	32	28	*56*	24	26	21
beehive	44	45	48	49	*49*	30	29	44	48	44	42	38
turtle	*58*	58	52	50	54	49	49	43	57	48	46	43
tiger	25	27	42	40	42	13	12	15	*42*	39	39	36
briefcase	52	55	46	42	46	38	39	37	*56*	34	33	29
trash can	49	*50*	38	37	34	50	49	47	44	19	21	19
video camera	*49*	48	43	42	41	40	41	37	42	24	25	18
coffee maker	53	53	49	49	49	39	41	40	*58*	39	37	37
flower	40	40	44	36	41	15	16	15	*55*	32	30	20
airplane	33	33	47	42	47	21	20	19	51	*52*	52	47
traffic cone	46	47	50	49	48	37	36	35	*50*	47	46	43
stairs	45	44	51	48	51	25	27	32	*54*	49	49	42

(e) Rothwell edge detector

APPENDIX 5. EDGE DETECTOR EVALUATION DATA

Image	Fixed Parameter Data Ratings for each participant
golf cart	6 6 4 6 7 4 7 6 6 7 7 7 6 5 7 7
pitcher	2 4 3 3 3 2 4 5 4 2 6 6 2 1 2 4
stapler	6 6 6 6 3 3 7 6 6 7 6 7 4 5 4 7
mailbox	4 4 3 4 3 4 6 6 4 3 7 7 1 3 2 3
pillow	3 4 7 4 3 4 7 6 7 6 4 7 4 6 3 4
brush	4 3 5 5 4 4 7 6 4 5 6 6 4 4 4 5
shopping cart	6 4 6 5 3 2 7 6 6 7 6 7 3 5 6 6
tire	1 3 2 6 2 1 6 5 2 3 5 5 2 2 2 1
grater	3 4 6 6 4 6 7 6 5 6 7 7 2 5 7 5
picnic	1 3 2 4 2 1 3 5 3 2 4 7 3 3 2 4
orange	3 3 3 4 2 4 5 4 4 7 4 7 2 5 5 7
banana	1 3 1 2 2 1 4 3 1 4 3 2 2 4 2 2
egg	2 3 3 3 6 1 5 4 2 3 6 4 4 5 3 3
elephant	2 3 3 4 1 5 6 4 5 7 7 4 2 4 4 5
pond	3 2 6 2 2 1 5 1 2 7 5 1 1 2 1 1
pine cone	1 1 2 3 1 1 1 2 1 2 3 1 1 1 2 1
feather	3 2 3 4 4 2 6 3 3 4 7 6 3 3 4 3
beehive	3 4 2 5 3 2 4 4 4 6 5 2 1 3 2 2
turtle	4 4 5 5 4 5 7 6 7 7 6 6 3 7 5 4
tiger	2 3 4 3 3 2 4 5 3 5 1 2 2 2 3 3
briefcase	1 3 3 4 4 3 5 5 3 2 7 4 2 2 3 2
trash can	1 4 1 4 2 1 3 4 2 3 3 4 3 2 1 2
video camera	1 3 3 3 2 2 5 4 3 2 3 5 3 3 2 2
coffee maker	3 4 7 7 4 6 7 6 6 4 6 7 4 4 4 7
flower	3 5 6 4 6 4 7 4 2 5 5 4 3 3 3 4
airplane	5 5 5 4 5 5 7 6 7 6 7 7 6 5 7 6
traffic cone	6 2 5 4 3 3 7 6 5 6 5 7 2 4 4 6
stairs	1 2 3 3 3 4 7 5 5 3 5 4 2 4 3 6

Image	Adapted Parameter Data Ratings for each participant
golf cart	6 6 6 5 7 3 7 6 6 7 7 7 7 5 7 7
pitcher	4 5 6 7 5 3 7 6 6 6 7 7 5 7 5 6
stapler	6 4 7 6 4 4 7 7 5 7 6 7 3 5 5 7
mailbox	5 5 7 5 5 5 7 6 5 3 6 7 4 4 4 4
pillow	4 4 5 4 2 2 7 7 7 7 3 7 3 7 6 5
brush	4 3 5 4 5 5 7 5 5 5 6 6 3 4 4 5
shopping cart	6 4 6 5 2 2 7 6 6 7 6 6 3 5 6 6
tire	5 6 7 7 3 2 6 7 6 7 6 5 4 6 5 6
grater	3 5 6 5 3 5 6 6 5 7 7 7 3 5 7 6
picnic	2 5 4 5 3 2 6 6 5 3 6 7 3 5 3 4
orange	4 3 4 6 2 2 5 4 4 5 5 6 2 4 6 6
banana	4 4 7 4 3 5 7 6 3 7 4 4 4 5 5 5
egg	3 4 6 6 4 2 7 5 3 5 7 5 5 6 4 5
elephant	2 3 3 4 1 5 6 3 5 7 7 5 3 4 4 5
pond	3 3 5 3 1 1 5 1 3 7 5 1 1 4 2 1
pine cone	3 1 6 3 2 1 3 3 2 6 7 2 2 2 4 2
feather	5 3 5 4 5 2 5 5 5 6 4 6 2 6 6 4
beehive	5 6 6 4 5 6 7 4 7 5 7 5 1 2 4 6
turtle	4 4 5 6 4 5 7 5 5 7 6 6 1 7 5 4
tiger	4 4 5 6 4 5 5 6 4 6 5 2 3 4 5 4
briefcase	3 4 6 4 6 6 6 6 5 3 7 4 4 3 3 2
trash can	6 7 5 5 4 7 7 6 7 6 7 7 5 6 6 5
video camera	4 6 5 5 3 3 7 7 6 6 7 6 4 4 7 3
coffee maker	3 5 6 6 6 4 6 6 6 5 7 7 3 5 4 7
flower	3 4 5 4 4 3 7 4 3 5 4 4 3 3 2 3
airplane	5 5 6 5 3 5 7 7 6 5 7 7 5 5 6 6
traffic cone	6 3 7 5 5 3 7 6 6 5 6 7 4 4 5 6
stairs	4 4 4 4 5 5 7 6 6 7 6 5 4 5 4 5

(a) Canny edge detector

Table 23. Raw scores for the comparison of edge detectors experiment.
(a) Canny (b) Nalwa (c) Iverson (d) Bergholm and (e) Rothwell
(Continued on next page)

Table 23. (Continued)

	Fixed Parameter Data
Image	Ratings for each participant
golf cart	5 5 4 5 5 6 6 7 5 4 4 7 6 4 6 6
pitcher	3 4 3 5 4 4 6 6 5 3 7 6 3 2 3 5
stapler	5 5 4 6 4 3 5 7 6 6 5 7 3 4 5 7
mailbox	4 4 3 4 4 3 7 6 5 2 6 7 2 3 2 3
pillow	5 4 5 5 5 3 7 6 5 4 5 7 4 4 5 6
brush	2 5 3 4 4 4 5 6 5 3 5 5 3 3 3 4
shopping cart	3 4 3 5 2 1 5 5 4 3 4 7 4 4 4 4
tire	3 4 5 5 1 1 7 6 3 5 6 6 5 5 3 3
grater	2 5 3 6 4 4 6 6 4 4 6 7 3 3 4 4
picnic	2 3 3 5 1 2 5 6 4 3 5 7 3 3 3 3
orange	3 3 3 6 3 4 5 5 5 5 4 6 3 5 5 6
banana	1 3 2 3 2 2 3 4 2 4 3 2 2 3 3 3
egg	3 4 4 5 3 5 7 5 3 5 7 4 5 6 4 5
elephant	4 5 2 6 5 4 7 6 6 3 6 5 4 5 6 4
pond	1 1 1 1 1 1 1 1 1 2 4 1 1 1 4 1
pine cone	3 1 5 4 2 1 3 3 1 5 4 2 2 2 3 2
feather	3 2 2 3 4 1 4 3 3 3 4 5 4 1 2 1
beehive	3 3 3 6 3 2 3 5 5 5 5 2 2 5 3 4
turtle	4 5 4 6 5 5 7 6 6 5 6 6 2 6 6 4
tiger	1 3 4 6 3 3 4 5 2 3 2 2 2 2 3 2
briefcase	3 4 2 4 4 5 6 6 5 3 6 4 3 4 4 3
trash can	2 5 2 5 6 2 5 6 4 5 4 4 4 3 2 3
video camera	4 6 4 4 6 4 7 6 5 5 5 7 4 4 4 4
coffee maker	4 6 3 6 5 3 5 7 5 5 5 7 4 6 6 6
flower	2 4 4 5 4 5 2 4 3 3 7 5 2 5 4 2
airplane	2 4 2 5 2 1 5 6 4 2 3 7 2 3 3 2
traffic cone	6 6 4 5 7 5 7 7 5 3 7 7 3 7 5 5
stairs	2 3 2 4 2 5 7 6 5 4 5 4 3 5 5 4

	Adapted Parameter Data
Image	Ratings for each participant
golf cart	4 6 4 5 6 6 6 6 5 4 4 7 5 4 6 6
pitcher	3 5 4 6 7 3 6 7 6 5 6 7 4 4 4 5
stapler	5 5 4 7 4 3 5 7 6 6 5 7 4 4 6 7
mailbox	4 5 6 4 3 4 7 6 5 3 5 7 3 4 3 4
pillow	5 4 5 5 5 3 7 7 5 4 6 7 3 4 5 6
brush	2 4 4 5 5 3 5 6 6 6 6 5 5 3 3 4
shopping cart	3 4 2 5 2 2 5 6 4 3 4 6 4 4 4 3
tire	4 5 5 7 1 3 4 7 6 2 4 7 6 7 6 7
grater	2 5 4 6 3 4 7 6 4 4 5 6 3 3 4 4
picnic	3 4 5 6 6 3 7 6 6 4 6 7 5 7 5 3
orange	3 3 3 6 3 4 5 5 5 5 4 6 3 5 5 7
banana	5 4 5 7 4 5 7 6 4 6 4 6 3 7 5 5
egg	3 4 7 6 4 5 7 5 3 5 6 5 6 6 4 5
elephant	4 4 2 5 7 3 7 6 7 2 5 5 3 5 6 6
pond	1 2 4 2 2 1 3 1 1 3 5 1 2 1 2 1
pine cone	2 1 6 3 3 1 3 2 1 5 6 2 2 2 3 2
feather	5 4 5 5 7 2 5 5 5 5 4 6 2 5 4 3
beehive	3 4 3 6 3 3 3 6 5 4 5 3 3 5 4 3
turtle	4 3 4 4 6 5 7 6 6 4 6 6 2 6 6 4
tiger	1 3 3 4 3 3 4 5 2 2 2 2 2 2 3 2
briefcase	3 4 4 5 5 3 6 6 5 5 6 6 6 5 5 5
trash can	5 5 4 7 5 2 6 7 6 4 3 5 3 5 4 4
video camera	4 5 4 5 4 4 7 6 5 5 4 6 3 5 4 4
coffee maker	4 6 4 7 2 3 5 7 5 3 6 7 4 6 6 6
flower	2 4 4 5 5 4 4 5 3 4 7 5 3 5 4 1
airplane	2 6 2 4 2 2 5 6 4 3 3 7 3 3 3 4
traffic cone	6 5 4 5 7 5 7 7 5 5 7 7 3 7 5 4
stairs	3 3 4 5 4 3 7 6 5 5 6 6 3 5 4 5

(b) Nalwa edge detector

(Continued on next page)

Table 23. (Continued)

Image	Fixed Parameter Data Ratings for each participant
golf cart	5 6 5 6 6 4 6 7 5 6 4 7 6 5 5 6
pitcher	3 5 6 6 3 2 6 6 5 4 6 6 4 4 4 5
stapler	3 2 3 3 3 3 6 4 3 3 4 7 2 2 3 5
mailbox	6 5 6 7 7 5 6 7 7 5 5 7 6 5 6 7
pillow	3 4 3 4 5 2 6 5 4 4 5 7 3 4 4 4
brush	4 4 6 6 6 3 6 7 5 7 6 5 6 5 4 6
shopping cart	4 5 5 5 5 4 4 7 5 6 4 7 6 6 4 4
tire	3 4 3 6 4 2 6 6 4 5 6 6 3 5 3 3
grater	2 4 4 5 4 5 6 7 5 5 6 7 3 4 5 5
picnic	4 4 6 7 7 3 7 7 6 5 6 7 5 6 4 6
orange	1 1 2 3 1 1 3 3 2 3 5 5 1 1 2 1
banana	1 3 2 2 3 1 3 2 1 3 3 3 2 2 2 1
egg	1 3 1 3 3 1 5 3 1 2 4 2 3 4 3 3
elephant	4 4 6 6 4 4 7 6 7 4 5 6 3 6 6 5
pond	2 3 3 1 1 1 3 2 2 5 5 1 2 3 3 1
pine cone	2 2 4 5 2 1 5 4 3 6 6 2 2 4 5 2
feather	4 3 5 5 7 2 5 4 5 5 5 7 3 5 5 4
beehive	4 4 6 7 5 4 4 5 5 6 5 4 2 3 4 3
turtle	3 3 6 4 4 4 7 5 5 3 6 5 3 5 5 4
tiger	4 2 4 5 5 4 6 6 3 4 5 2 3 4 5 5
briefcase	2 4 6 5 5 3 7 6 5 4 6 6 5 5 5 4
trash can	3 6 6 6 6 4 5 6 5 5 4 4 6 6 3 4
video camera	2 5 5 5 3 3 6 5 4 3 3 6 4 4 4 5
coffee maker	3 4 5 6 3 4 7 6 5 5 6 7 4 3 4 7
flower	3 5 3 6 6 5 7 4 3 7 3 6 5 3 6 4
airplane	3 6 4 5 5 3 6 6 5 4 4 7 4 3 4 3
traffic cone	6 5 6 5 4 5 7 7 6 4 7 7 4 5 6 5
stairs	1 4 3 6 4 1 5 6 3 4 1 4 3 6 4 5

Image	Adapted Parameter Data Ratings for each participant
golf cart	5 6 6 6 4 4 6 6 7 6 7 7 5 5 6 6
pitcher	3 5 4 5 5 2 6 6 5 5 6 7 4 4 4 5
stapler	3 3 3 2 2 2 4 5 3 3 4 7 3 2 3 5
mailbox	6 5 6 7 5 4 7 7 7 5 6 7 5 5 6 6
pillow	3 4 5 5 4 3 6 6 5 4 5 7 3 4 4 4
brush	4 4 5 5 5 4 7 6 5 6 6 5 4 4 4 6
shopping cart	5 5 5 6 4 2 6 7 5 7 5 7 6 5 6 5
tire	3 4 4 6 4 2 7 6 3 5 6 6 4 5 3 2
grater	2 5 4 6 5 4 6 6 5 5 5 7 3 4 5 5
picnic	4 4 5 6 3 3 7 7 6 5 7 7 4 6 3 6
orange	1 1 2 2 1 1 3 3 2 3 3 5 1 1 2 1
banana	1 3 1 2 2 1 2 2 1 3 3 2 2 1 2 1
egg	1 3 1 3 3 1 5 3 1 2 4 4 6 4 3 3
elephant	4 4 5 6 7 4 7 6 7 4 5 6 5 6 6 6
pond	2 2 4 2 3 1 3 2 2 5 5 1 2 3 3 1
pine cone	2 2 6 5 4 1 5 4 2 5 6 2 3 3 3 2
feather	4 3 5 4 7 3 6 5 4 5 5 6 4 5 5 4
beehive	4 4 5 6 5 3 5 5 5 6 5 3 4 3 4 3
turtle	3 3 6 5 4 4 7 5 5 4 6 6 3 5 6 4
tiger	4 3 2 5 4 4 6 6 3 4 5 2 3 4 5 5
briefcase	2 4 6 5 5 5 7 6 4 5 6 5 6 5 5 4
trash can	3 6 3 6 6 4 5 6 4 5 4 5 4 4 3 3
video camera	2 4 6 4 4 3 5 5 4 4 4 7 5 5 3 5
coffee maker	3 5 6 5 3 4 7 5 5 4 6 7 4 4 4 7
flower	3 5 3 6 3 4 7 4 3 7 3 5 4 3 6 4
airplane	5 5 7 6 5 5 7 7 6 6 7 7 4 5 5 6
traffic cone	6 4 7 7 6 5 7 7 6 4 5 7 4 5 7 5
stairs	4 4 6 4 3 5 7 6 6 5 7 4 5 5 6 5

(c) Iverson edge detector

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Table 23. (Continued)

Image	Fixed Parameter Data Ratings for each participant
golf cart	5 6 7 7 4 4 6 7 5 6 5 7 6 6 5 5
pitcher	4 6 5 7 4 4 6 6 6 6 7 7 5 5 5 5
stapler	5 4 4 4 4 3 7 6 5 5 7 7 3 2 4 6
mailbox	6 5 6 7 4 4 6 7 6 6 5 7 4 7 5 6
pillow	5 4 4 4 3 2 7 7 5 6 4 7 3 6 4 5
brush	4 4 6 6 6 4 6 6 5 7 6 5 4 6 5 6
shopping cart	3 5 5 6 4 3 4 6 4 5 4 6 4 7 4 3
tire	4 4 3 6 2 1 7 6 3 5 6 6 4 5 3 3
grater	4 5 5 7 4 5 7 7 5 6 7 7 3 6 4 6
picnic	4 6 5 7 5 5 7 7 7 6 5 7 5 7 4 6
orange	2 3 4 5 2 2 7 4 3 4 7 5 2 3 4 4
banana	1 3 1 1 1 1 4 2 2 4 3 2 2 3 2 1
egg	2 3 2 4 5 1 6 4 2 3 6 5 4 4 3 3
elephant	3 3 3 5 2 2 5 4 5 6 3 6 3 7 4 3
pond	2 3 2 2 1 1 4 1 2 4 4 1 1 4 2 1
pine cone	1 1 3 4 2 1 5 3 2 3 5 2 2 5 2 1
feather	5 3 4 5 5 1 6 4 6 6 4 6 3 7 5 2
beehive	4 6 4 5 5 3 6 5 5 7 6 3 4 4 5 4
turtle	3 4 4 5 5 5 7 5 5 6 6 5 2 7 5 4
tiger	2 3 4 6 4 3 4 5 3 4 2 2 2 2 3 3
briefcase	3 4 4 6 5 4 7 6 5 6 6 6 6 6 5 4
trash can	4 6 3 6 3 4 6 6 5 7 4 5 3 5 3 3
video camera	4 6 4 5 6 3 6 6 5 7 6 5 4 7 5 4
coffee maker	4 5 3 7 5 4 5 7 7 6 6 7 4 7 5 7
flower	2 3 7 5 3 3 2 3 2 3 5 5 2 4 3 1
airplane	3 5 4 6 3 3 5 6 5 4 4 7 4 5 4 4
traffic cone	4 5 4 6 3 2 6 7 4 7 5 7 2 6 4 3
stairs	2 4 5 5 3 2 6 6 3 6 3 3 3 7 4 4

Image	Adapted Parameter Data Ratings for each participant
golf cart	5 5 4 6 5 6 7 6 6 5 7 7 5 4 5 6
pitcher	4 5 6 7 5 5 6 6 6 5 7 7 5 5 5 6
stapler	5 5 4 5 4 4 7 5 4 4 7 7 3 2 4 4
mailbox	6 6 5 6 5 5 6 7 6 6 5 7 5 7 5 5
pillow	2 3 4 4 4 3 7 6 6 3 7 7 3 4 5 3
brush	4 3 6 6 6 6 6 6 5 6 6 5 5 6 5 6
shopping cart	5 5 3 6 3 3 6 5 5 3 6 6 5 4 5 5
tire	5 5 6 7 6 5 5 7 6 6 5 7 4 6 4 6
grater	4 5 5 6 4 4 7 7 5 7 7 7 4 6 4 6
picnic	3 4 5 6 5 4 7 7 7 6 6 7 5 6 5 7
orange	4 3 5 6 2 3 6 4 4 5 6 6 2 4 4 5
banana	4 5 5 5 3 4 7 5 4 5 5 5 2 6 4 4
egg	2 4 6 5 1 3 6 6 4 6 5 5 4 6 4 4
elephant	4 4 4 5 4 4 7 5 7 3 6 5 4 5 6 4
pond	2 4 2 2 1 1 4 1 3 6 4 1 2 4 2 1
pine cone	2 2 4 5 4 1 5 3 3 5 6 3 2 3 3 1
feather	5 3 6 5 5 2 5 4 5 6 4 5 3 7 4 2
beehive	5 5 7 4 4 6 7 4 6 5 7 3 2 2 4 5
turtle	3 4 5 5 5 5 7 5 5 7 6 6 3 7 5 4
tiger	5 4 3 3 2 5 7 6 4 5 6 2 4 4 6 6
briefcase	3 4 6 6 6 4 7 6 4 6 7 7 4 6 5 4
trash can	6 5 6 6 3 5 7 7 6 6 6 4 5 5 4 5
video camera	4 5 4 6 5 3 6 6 6 6 6 7 5 4 5 3
coffee maker	4 6 4 7 4 4 6 7 7 7 6 7 5 7 5 6
flower	2 3 6 5 3 3 2 3 4 4 5 6 1 4 3 1
airplane	3 5 5 5 3 5 7 5 5 3 5 7 3 4 6 5
traffic cone	6 5 7 5 4 5 7 7 6 4 6 7 4 4 4 4
stairs	3 4 4 4 2 6 6 5 6 4 7 6 4 5 5 5

(d) Bergholm edge detector

(Continued on next page)

Table 23. (Continued)

Image	Fixed Parameter Data Ratings for each participant
golf cart	5 5 5 6 5 4 6 7 5 5 4 7 4 7 5 6
pitcher	3 5 5 6 7 5 7 7 6 5 7 7 5 6 6 6
stapler	3 3 3 4 2 2 4 4 3 3 4 7 1 2 3 5
mailbox	6 5 5 5 6 4 6 7 6 6 5 7 5 6 4 5
pillow	4 4 3 3 4 2 6 6 5 5 4 7 2 5 4 5
brush	4 4 7 5 6 5 6 7 5 7 6 5 5 7 6 6
shopping cart	2 5 4 5 5 2 3 6 4 4 4 5 3 7 3 2
tire	4 3 4 5 7 1 7 6 3 4 5 6 3 4 2 3
grater	4 4 5 6 5 4 7 7 6 5 6 7 5 6 5 6
picnic	5 6 6 6 7 5 7 7 6 7 7 7 5 7 5 7
orange	1 2 2 3 2 1 3 3 2 3 6 5 2 1 3 2
banana	1 3 1 2 1 1 2 2 1 3 2 1 2 1 1 1
egg	2 3 1 2 2 1 5 3 2 2 4 5 4 4 3 2
elephant	5 4 3 5 5 3 5 6 5 5 4 6 5 7 5 4
pond	2 4 1 2 1 1 4 1 2 6 4 1 2 4 3 1
pine cone	2 2 3 4 1 1 4 4 2 4 5 2 2 4 3 1
feather	5 3 6 6 5 3 6 6 5 7 4 7 3 7 4 2
beehive	3 5 3 5 2 3 3 5 4 4 5 3 4 5 5 3
turtle	3 4 3 4 5 5 7 5 4 3 6 6 3 6 4 4
tiger	3 3 6 3 3 3 7 6 3 3 5 3 3 4 5 5
briefcase	4 5 5 5 7 4 6 6 5 7 6 7 4 7 6 5
trash can	2 6 1 5 6 3 5 5 5 5 3 4 3 7 3 4
video camera	3 4 3 3 4 3 6 5 4 5 3 7 3 6 3 6
coffee maker	5 5 4 5 6 3 6 7 7 6 6 7 4 6 5 7
flower	2 4 6 5 4 4 6 5 4 6 5 5 3 6 5 2
airplane	4 6 3 6 2 3 6 7 5 5 3 7 2 7 4 5
traffic cone	5 3 5 6 4 2 6 7 5 7 6 7 3 5 4 4
stairs	2 4 6 5 4 3 5 7 4 5 2 3 6 7 6 6

Image	Adapted Parameter Data Ratings for each participant
golf cart	5 5 5 6 4 4 6 7 5 5 4 7 5 7 5 6
pitcher	3 5 5 6 5 4 7 7 6 5 6 7 5 6 6 6
stapler	4 4 5 4 4 3 7 6 4 5 6 7 4 2 4 6
mailbox	6 5 6 6 4 5 5 7 7 4 4 7 5 5 5 7
pillow	4 3 5 5 3 2 6 7 5 5 4 7 4 5 4 5
brush	4 3 7 5 7 4 6 7 5 7 6 5 7 7 6 6
shopping cart	5 5 4 5 2 3 7 5 6 6 5 6 3 4 5 6
tire	4 4 4 5 4 1 7 6 5 5 5 6 3 4 2 3
grater	4 5 5 5 5 5 7 7 6 5 6 7 5 5 5 6
picnic	5 6 6 7 6 5 7 7 7 7 7 7 5 7 5 7
orange	2 3 6 4 2 3 7 3 3 4 7 6 5 3 6 5
banana	3 4 4 4 4 4 6 5 4 5 6 5 2 5 4 4
egg	3 4 5 6 4 4 7 6 3 4 6 5 7 6 5 5
elephant	4 4 4 5 6 4 6 6 7 4 6 5 4 6 6 5
pond	3 3 2 2 1 1 3 1 2 6 4 1 2 4 3 1
pine cone	2 2 3 3 3 1 5 4 2 4 5 2 1 4 3 1
feather	5 4 4 7 6 2 6 6 5 6 4 7 3 7 6 4
beehive	4 5 6 5 4 4 6 4 5 3 5 3 5 3 3 4
turtle	3 5 6 6 4 5 7 6 5 4 6 6 2 7 5 4
tiger	3 3 6 4 6 4 7 6 3 4 4 2 3 4 5 4
briefcase	4 5 7 7 5 3 7 6 4 7 6 5 4 7 6 5
trash can	5 5 6 7 4 3 7 7 5 7 4 4 4 7 4 4
video camera	5 6 4 5 6 4 7 6 6 6 6 5 2 5 5 6
coffee maker	5 5 5 5 5 4 6 7 6 7 6 7 4 6 5 7
flower	2 4 6 5 3 4 3 6 4 6 3 5 3 6 5 2
airplane	5 4 4 6 5 5 7 6 5 4 6 7 7 5 6 6
traffic cone	5 4 3 6 3 3 6 7 5 4 5 7 5 5 4 4
stairs	2 5 5 5 3 4 5 7 5 6 2 3 6 7 6 5

(e) Rothwell edge detector

APPENDIX 6. INTRODUCTION TO ANALYSIS OF VARIANCE

Analysis of variance (ANOVA) is a general method for analyzing experimental data. Many texts on statistics describe analysis of variance methods. For example, see [42] for an introduction to the subject.

The calculations that must be performed in an analysis of variance are often cumbersome and are typically carried out on a computer. Because of this, many software packages include utilities for applying analysis of variance. All of the ANOVA analysis in this thesis was done using the ANOVA procedure in the SAS/STAT[1] software package.

Below, a short description of analysis of variance is provided for readers unfamiliar with the subject. The description is given in terms of the experimental data analyzed in this thesis.

In the edge detector evaluation experiment, a dependent response variable (the edge image quality) was measured under experimental conditions identified by independent classification variables (edge detection algorithm, parameter selection method and image type). The experiment was designed to determine the performance difference of the algorithms using the edge quality ratings. Analysis of variance methods were used in the analysis of this data because they can explain the variation in the response variable in terms of the effects of the independent variables and random variation.

Analysis of variance methods are generally classified by the number of independent variables. The effect of a single independent variable can be analyzed in a one-way analysis of variance, the effects of two independent variables can be analyzed in a two-way analysis of variance, and so on.

[1]SAS is a registered trademark of SAS Institute Inc.

In general, a one-way analysis of variance is used to test whether the means of two or more populations are equal. This was done in the analysis of the data collected in the comparison of edge detectors experiment. A one-way analysis of variance was done to determine if the mean edge detector rating was equal for every pair of algorithms. In each of these tests, the ratings were samples of the dependent response variable which was measured for two levels of the independent (edge detector classification) variable. The result from the test (Pr>F) is the probability that the observed difference in the means occurred by chance.

A two-way (or higher order) analysis of variance can be used to test for interactions between the independent variables. That is, whether or not the value of the response variable changes with combinations of the independent variables. More specifically, if there were two independent variables A and B, each with two levels, the value of the response variable may increase with variable A at one level of variable B and decrease with the other level of variable B.

Both three-way and four-way analysis of variance tests were used in the analysis to determine if the edge detector ratings changed with the image type or with the method used in setting the parameters. The result from the test (Pr>F) is the probability that observed ratings exhibit interaction due to chance.

APPENDIX 7. EVALUATION SHEETS

Figure 21. All of the evaluation sheets used in the experiments.
This image shows all of the evaluation sheets used in both the parameter setting and edge detector evaluation experiments. All together there were 19,600 evaluation sheets because there were 12 parameters sets evaluated for 28 images for 5 edge detectors by 9 participants in the parameter setting experiments and there were 10 edge images for each of 28 images evaluated by 16 participants in the edge detector evaluation experiment.