

www.icgst.com

GVIP

Efficient Edge Noise Removal and Perceptual Feature Classification

Xiaofen Zheng, Qigang Gao
Faculty of Computer Science, Dalhousie University
 6050 University Avenue, Halifax
 Nova Scotia, Canada B3H 1W5
 [xzheng, qggao]@cs.dal.ca,
<http://flame.cs.dal.ca/~IPAMI>

Abstract

Over-segmentation of edge features has been a challenging problem for many edge-based vision applications. Too many useless features are simply background noise which are costly for higher-level processing. The conventional methods of dealing with over-segmentation use various noise suppressing filters at pixel level for the entire image, and then form features by grouping identified edge points. The computation cost and lack of global heuristics are the major drawbacks.

This paper presents a perceptual organization based method for both noise suppression and perceptual feature classification of pre-tracked and partitioned edge segments. In this method, edge traces are selectively tracked and partitioned based on a previously proposed model. Each partitioned edge segment is then classified into noise or perceptual features using the continuity of gradient distribution along the segment. Noise segments can be identified by their discontinuous gradient magnitude. The remaining segments can be further classified into curve and straight line features by identifying constant or monotonic changes of gradient direction. Because its only computations are simple statistics based on a small edge data set, our method is well suited for real-time or hardware-limited applications. Experiments and analysis are provided.

Keywords: *Edge feature, Feature extraction, Over-segmentation, Noise removal, Noise depression, Feature classification, Perceptual organization.*

1 Introduction

Image features extraction is essential for computers to describe and represent the content of an image. Image features allow identification or interpretation of meaningful physical objects from images. When analyzing an image, an appropriate balance between

too many and too few features is difficult to find. Under-segmentation, too few features, will lead to inadequate hypotheses without strong evidence, while over-segmentation, too many features, will cause confusion, extra hypotheses and extra computation [5].

Low level image features include edge, color, texture and spatial attributes of the objects. High level image features, such as grouped edge structures and shapes, involve semantic interpretations of the image contents. Low level features are extracted directly from digital representations of objects and have little or nothing to do with human's perceptual organization. To bridge the gap between low level features and high level semantic meaning of objects, the simulation of some of the human functions of perception and cognition in machine vision is a promising field of research.

There are many feature extraction methods proposed for shape based image analysis. In [3], the approximation of 2D continuous functional curves were computed to extract features. This method recursively fits the candidate features with line segments or circular arcs, and decrements a segment if the fitting result is bad. The recursive processes will finally yield a good fitting. However, the computational cost increases quickly with the amount of curve data and the number of approximation segments. Hough transformation [7] is a commonly used technique for shape extraction and representation using boundary based methods. The Hough transformation parameterizes the shapes into single point representations thereby reducing the complexity of the image. A low-order polynomial descriptive language was presented in [4]. In this method, the region boundaries were partitioned and represented by a chain-code-like description. Chain code representation is useful for determining the cross correlation coefficients, but they cannot be related to the actual shape of the patterns. The Freeman chain code [1] gives each edge pixel a code based upon the direction from the previous pixel to

encode the boundary lines. It is a compact way to represent the contours of objects, but the efficiency decreases with the noise edges. In [6], planar curves were described as ordered lists of constant curvature segments. This method is to find a minimal set of pairs of composed scale to best describe the shape of the curve.

Most edge features based methods require good segmentation and are only effective for simple and clean images. Purely data driven methods increase the computation cost and reduce robustness if the data is fuzzy and full of noise.

2 Methodology

Our research focuses on using perceptual organization to extract important low level shape features as a basis for high level interpretation and other purposes.

2.1 Previous Model

Gao and Wong [2] presented a generic curve grouping and partition method which allows machines to perform curve segmentations following rules based on perceptual organization. Their edge tracker detects edge traces and locates curve partitioning points (CPPs) at the same time. As shown in Figure 1, CPPs, perceptually significant points at which transitions of monotonicity take place [8], partition edge traces from the original image into atomic edge features. These edge features are segments that human perception can not meaningfully further divide.

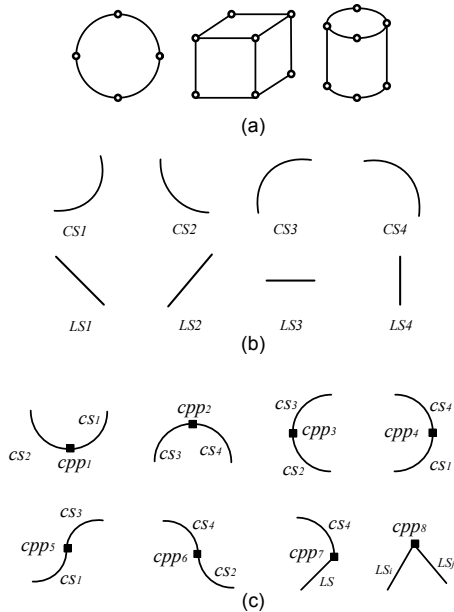


Figure 1: (a) The examples of curve partition. (b) The eight categories of generic segments. (c) The eight categories of curve partitioning points. [8]

The existing systems take all the partitioned seg-

ments as edge features for the high level processing. Many useless segmented features which are simply background noise are extracted unintentionally. Since boundary based methods often over-segment natural object dominated images, we propose our classification method to distinguish and remove this noise from the regular shape contours.

2.2 Observation

In most cases, noise edges are unwanted in boundary-based object recognition methods. The edges which have gradient changes in original image but show discontinuity in edge gradient magnitude and direction are noise. Straight lines and curves with continuous gradient change are often the true boundaries of objects.

As shown in Figure 2, the three edge features can be classified by their dx and dy properties. Figure 2(a), Figure 2(c) and Figure 2(e) show the original edge traces, Figure 2(b), Figure 2(d) and Figure 2(f) show the corresponding dy/dx of each point on the edge traces, where the edge points are sequentially mapped on the horizontal axis the dy/dx value of each point is mapped to the vertical axis. For straight lines, the dy/dx value of the points is relatively constant. For noise, the dy/dx value of the edge points change widely. For curve segments, we study the monotonicity of the dy/dx value, i.e. the statistical increasing or decreasing tendency.

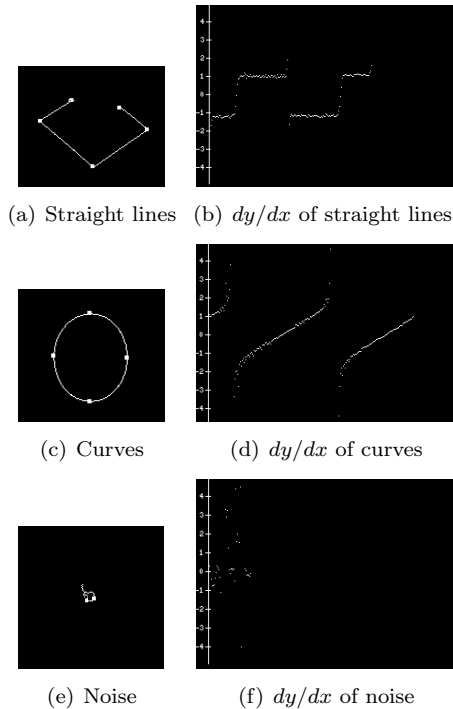


Figure 2: Image edge features and their properties.

2.3 System Architecture

This paper presents an improved system for remove noise and classify the other partitioned segments. The feature extraction and classification process is shown in Figure 3. The input is the original digital image with some objects in it. The edges of objects are tracked out from the image and partitioned into segments. Noise classification removes noise edges and keeps the other perceptually meaningful features. Then these segments are classified into straight lines and curves for the high-level processing. All the three classifications are done by estimating the likelihood and determining its significance according to our classification rules.

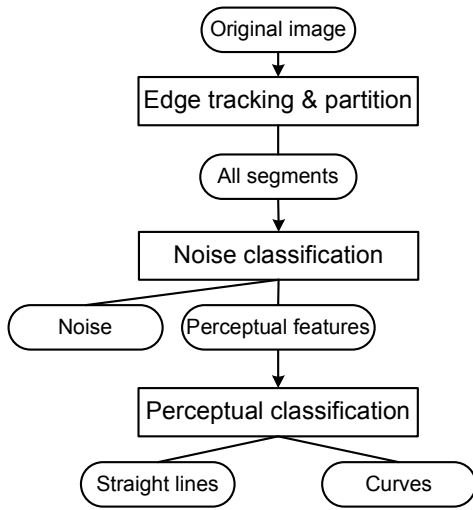


Figure 3: The perceptual edge feature classification structure.

In this paper, the edge features are classified into three categories: straight line, curve, and noise. The percentage of the noise features is calculated and the correlation between noise and other features are analyzed. The noise removal process appears to be relatively uncorrelated to the straight line and curve features and instead based on the characteristics of the image. Removing this noise will increase the efficiency and reduce the complexity of following higher level processes.

3 Noise and Perceptual Feature Classification

The curve partitioning points partition the edge traces into small segments, which we called edge features. We will present a method to classify these edge features into three categories: straight line, curve, and noise, shown in Figure 2(a), Figure 2(c) and Figure 2(e). Our feature classification can be used to remove noise segments and keep the curves and straight lines for further segment classification.

3.1 Noise Removal

3.1.1 Noise Classification Rule

Based on the properties shown in Figure 2, rule 3.1 is proposed to classify noise from the edge features extracted from original image.

Classification Rule 3.1 Squared Euclidean distance of an edge segment D is computed as:

$$D = \sum_{i=1}^{n-1} (\arctan P_{i+1} - \arctan P_i)^2$$

Where P_i and P_{i+1} are two consecutive points on this edge, $\arctan P_i$ and $\arctan P_{i+1}$ are their arctangent values and n is the total number of the points on the edge segment.

The arctangent squared Euclidean distance denotes the smoothness of the edge. The higher the value is, the less smooth the edge is. Because dy/dx approaches infinity as dx approaches 0, we measure the arctangent value of each point instead of dy/dx .

3.1.2 Experiment

Figure 4 shows two examples of using noise classification rule 3.1. The noise classification simplifies the original edge traces and most importantly it distinguishes the good object traces from all the image features.

3.2 Perceptual Feature Classification

3.2.1 Feature Classification Rule

After noise is removed from the edge features, the other segments are perceptually meaningful segments which can be classified into straight line and curve using classification rules 3.2 and 3.3.

Classification Rule 3.2 Arctangent Variance of an edge segment V is computed as:

$$V = \frac{1}{n} \sum_{i=1}^n (\arctan P_i - \overline{\arctan P})^2$$

Where P_i is a point on an edge, $\arctan P_i$ is the arctangent value of point P_i , n is the total number of points on the edge segment, and $\overline{\arctan P}$ is the mean arctangent value of all points on the edge segment.

The value of arctangent variance denotes the constancy of arctangent value of the points on the edge. The higher the value is, the less constant the arctangent value is.

Classification Rule 3.3 Monotonicity of an edge segment M is computed as:

$$M = \frac{1}{n-1} \sum_{i=1}^{n-1} \begin{cases} 1 & \text{if } (\arctan P_{i+1} - \arctan P_i) > 0 \\ 0 & \text{others} \end{cases}$$

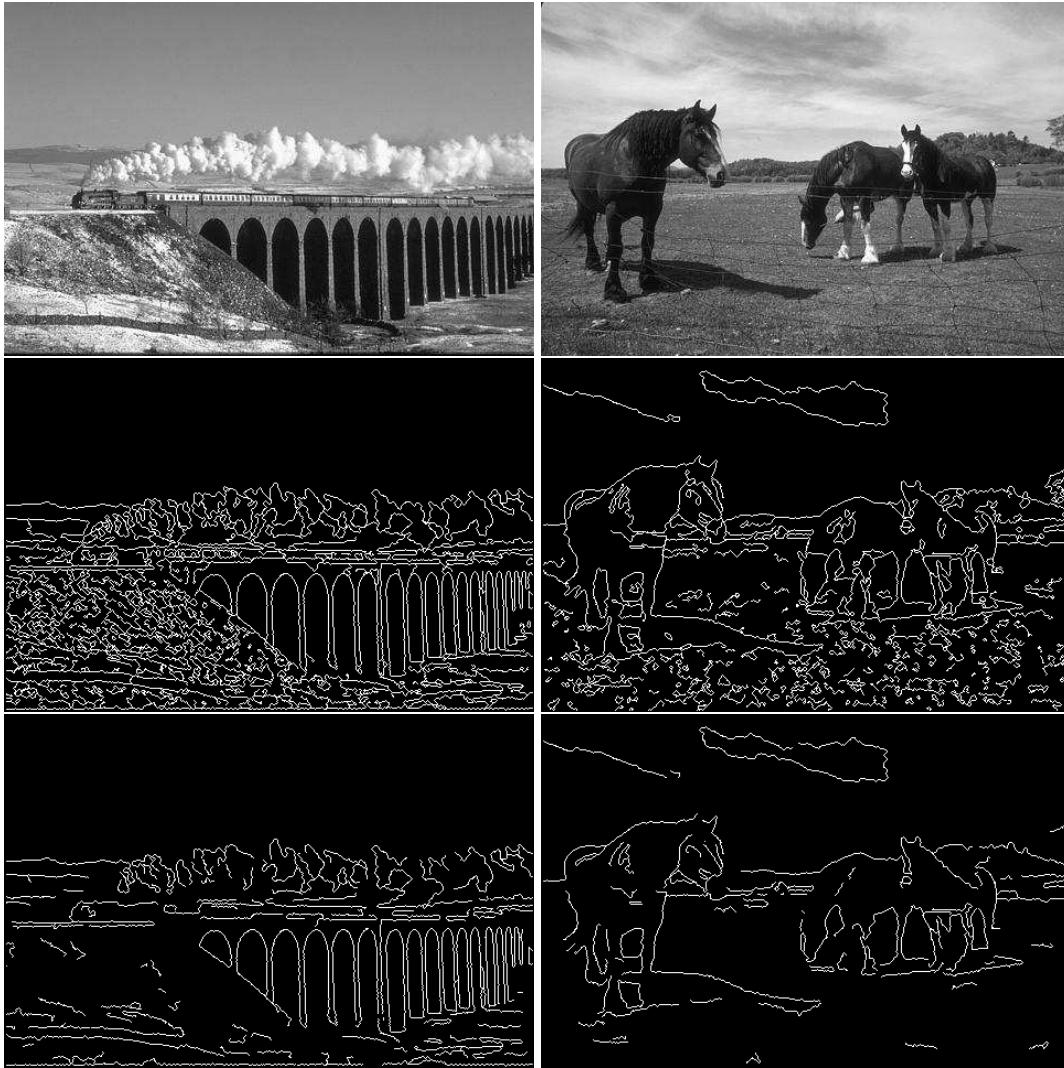


Figure 4: Noise removal examples. Upper: the original images; Middle: the extracted edges; Bottom: the results after noise removal.

Where P_i and P_{i+1} are two consecutive points on an edge, $\arctan P_i$ and $\arctan P_{i+1}$ are their arctangent values and n is the total of the points on the edge segment.

Higher values of monotonicity indicate edges whose arctangents are consistently increasing or consistently decreasing.

3.2.2 Experiment

Figure 5 shows the results of using rule 3.2 and rule 3.3 to distinguish straight lines and curves from the remaining edge segments .

The classification process is based solely on the edge data, which greatly reduces the computation cost compared with other methods which use the whole images. These noise removal results are purely based on the features data by the squared Euclidean distance classification rule proposed above. This feature level

classification and noise removal process is important for the overall efficiency of the system and can reduce the complexity and confusion of the grouping process.

4 Results Analysis

4.1 Noise Percentage

The noise percentage was calculated as the number of noise segments divided by the number of all edge features detected in a image. This does not reflect the quality of the original image. Instead, the lower the percentage is, the more significant manmade objects are in the original images, i.e., images with low noise percentage are primarily composed of manmade objects.

Table 1 and Table 2 show the noise percentage in 30 images we tested. Images primarily composed

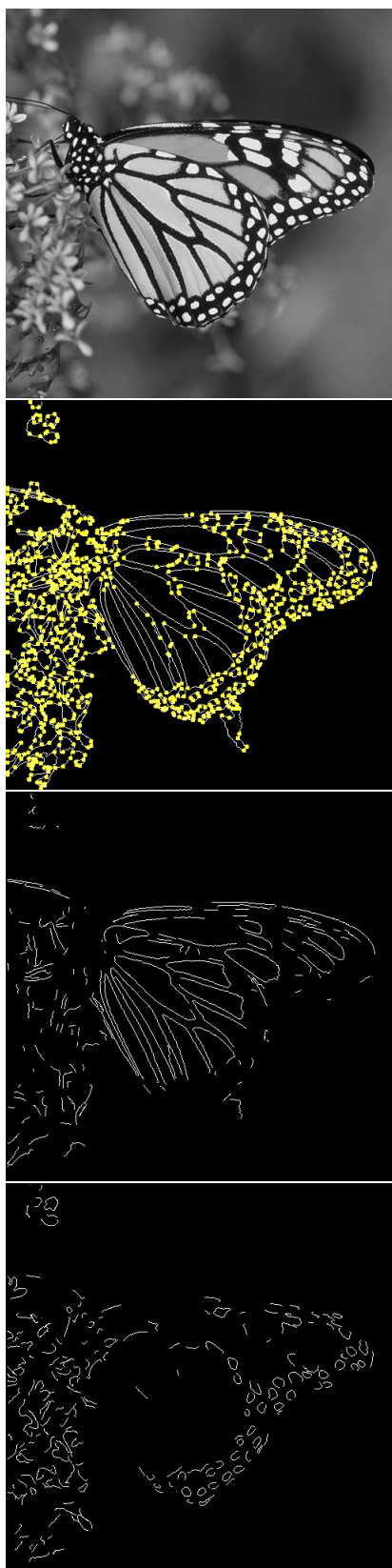


Figure 5: Edge feature classification examples. Upper: original image; Second: the extracted edges and CPPs; Third: straight lines; Bottom: curves.

of manmade objects appear to have lower noise percentage than images primarily composed of natural objects.

From these tables, it is obvious that noise features would cost expensive computation if not removed before grouping process. The noise removal process reduces over-segmentation problem caused by the characteristics natural images.

Images	All features	Noise	Noise percentage
blox.im	92	3	3.3
cheque.im	691	74	10.7
term.im	185	20	10.8
circle.im	117	19	16.2
part.im	109	18	16.5
plane.im	75	15	20
hotel.im	1745	414	23.7
cross.im	186	51	27.4
build.im	1066	345	32.4
airport.im	453	172	38

Table 1: The Noise Percentage of images primarily composed of manmade objects (Refer to appendix for images).

Images	All features	Noise	Noise percentage
kid.im	1183	439	37.1
wface.im	830	312	37.6
bldboat.im	866	357	41.2
pepper.im	1321	570	43.1
person.im	978	445	45.5
window.ppm	715	364	50.9
car.im	906	486	53.6
eye.im	1326	712	53.7
manbuilding.im	1378	747	54.2
woman.im	1328	754	56.8
girls.im	2079	1254	60.3
mushroom.im	2049	1290	63
panther.im	1171	785	67
river.im	1932	1393	72.1
church.im	1504	1085	72.1
viewbridge.im	1320	974	73.8
elephant.im	1288	977	75.9
horse.im	1667	1273	76.4
sail.im	1334	1076	80.7
stone.im	2647	2205	83.3

Table 2: The Noise Percentage of images primarily composed of natural objects (Refer to appendix for images).

4.2 Edge Features Correlation

Correlation can be used to describe the relationship between instances of two events. In each of our 30 images, we find the numbers of curve partition point, all edge features, curve segments, straight line segments and noise. The correlation of two variables is defined

Image Features	CPP	Edge Features	Noise	Straight Line	Curve
CPP	1.000	0.998	0.927	0.582	0.642
Edge Features		1.000	0.917	0.609	0.659
Noise			1.000	0.247	0.321
Straight Line				1.000	0.920
Curve					1.000

Table 3: The correlation value of the number of different image features in 30 image samples.

by

$$r^2 = \frac{(\sum xy - n\bar{x}\bar{y})^2}{(\sum x^2 - n\bar{x}^2)(\sum y^2 - n\bar{y}^2)}$$

where x and y are the two dimensional data point of a set of n data points, and \bar{x} and \bar{y} are the average values of the two dimensions.

Table 3 shows the correlations between different types of image features in the 30 image samples. Because CPPs partition the edges into segments, the number of CPPs and the number of edges have almost perfect correlation. The number of noise segments has a relatively low correlation values with the number of straight lines and the number of curves. This suggests that noise classification is an independent process from straight lines classification and curve classification and mainly relates with characteristics of the image. For comparison, Figure 6 is a scatter plot of the numbers of different types of image features extracted in the 30 images.

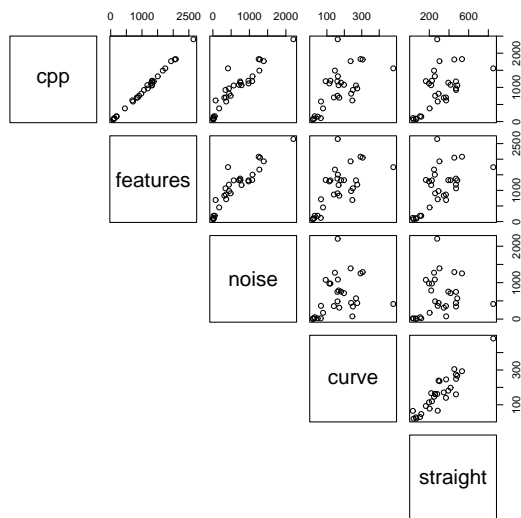


Figure 6: Scatter plot of the numbers of image features in 30 image samples.

In Figure 6, each dot denotes an image, and the inputs are the number of CPPs, features, noise, straight lines and curves in those 30 images. The less scattered the spots in each subgraph are, i.e., the more concentrated the data are on a line in each subgraph, the more correlated the two variables are. From Figure 6, we can also observe that noise are not correlated with straight lines or curves.

5 Conclusion

We presented an edge feature classification method based on the rules of human perception. The main advantage of this method is that, since the only computations are simple statistics based on a small subset of the image data, it is well suited for real-time or hardware-limited applications.

The classification allowed us to remove noise and reduce over-segmentation in image feature extraction. This process will benefit the higher level processes on the path to object recognition. Not only does it reduce the computation cost of future work, but it also greatly reduces the complexity and confusion caused by over-segmentation.

Several branches of future research appear promising. Our quantification of the classification confidence will allow a multi-scale representation of images. Combining this multi-scale representation with fuzzy logic techniques may bring more robustness. These additions will allow multi-scale grouping of significant forms in images and provide a powerful tool to image retrieval and higher level object recognition.

Acknowledgement

We thank both NSERC and Deep Vision Inc. for their funding support. Deep Vision Inc. also provided their edge tracker software, which was used to produce original edge trace data. We would also like to thank Scott Sherrill-Mix for his constructive suggestions and revisions.

Appendix

All 30 original images: Figure 7 (From <http://www.cs.berkeley.edu/projects/vision/grouping/segbench/BSDS300/html/dataset/images/gray> and <http://flame.cs.dal.ca/~IPAMI>).

References

- [1] H. Freeman. Boundary encoding and processing. In *Picture Processing and Psychopictorics*, pages 241–266, 1970.
- [2] Qigang Gao and A.K.C. Wong. Curve detection based on perceptual organization. *Pattern Recognition*, 26(1):1039–1046, 1993.



Figure 7: Images.

- [3] C. Ichoku, B. Deffontains, and J. Chorowicz. Segmentation of digital plane curves: a dynamic focusing approach. *IPattern Recognition Letters*, 17:741–750, 1996.
- [4] Yvan G. Leclerc. Constructing simple stable descriptions for image partitioning. *International Journal of Computer Vision*, 3(1):73–102, 1994.
- [5] M. Mirmehdi, P.L. Palmer, J.V. Kittler, and H. Dabis. Feedback control strategies for object recognition. *Image Processing*, 8(8):1084–1101, August 1999.
- [6] Marielle Mokhtari and Robert Bergevin. Generic multi-scale segmentation and curve approximation method. In *LNCS 2106: Scale-Space and Morphology in Computer Vision, Third International Conference, Scale-Space 2001*, pages 227–235, Vancouver, Canada, July 2001.
- [7] D.W.C. Pao, H.F. Li, and R. Jayakumar. Shapes recognition using the straight line Hough transform: theory and generalization. *IEEE Transactions On Pattern Analysis and Machine Intelligence*, 14(11):1076–1082, 1992.
- [8] Xiaofen Zheng and Qigang Gao. Generic Edge Tokens: Representation, Segmentation and Grouping. In *16th International Conference on Vision Interface*, pages 423–430, Halifax, Canada, June 2003.