SEGMENTATION BASED REVERSIBLE IMAGE COMPRESSION

Krishna Ratakonda and Narendra Ahuja

Beckman Institute
405 N. Mathews Avenue
Urbana, IL 61801.
krishna@stereo.ai.uiuc.edu

ABSTRACT

Reversible compression of images has been the topic of considerable research [1-3], as it finds applications in many fields in which the deviation of the reproduced image from the original image is intolerable, however small be the deviation. This paper is concerned with the problem of reducing spatial redundancies in gray scale images, thus providing effective lossless compression, using segmentation information. We will present new edge models that deal effectively with two issues that make such models normally unsuitable for compression applications: local applicability and large number of parameters needed for representation. Segmentation information is provided by a recent transform [6], which we found to possess qualities making it especially suitable for compression. The final residual image is obtained using autocorrelation-based 2-D linear prediction. Different implementations providing lossless compression are presented along with results over a number of common test images. Results show that the proposed approach can be used to yield robust lossless compression, while providing consistently and significantly better results than the best possible JPEG lossless coder.

1. INTRODUCTION

Different methods have been proposed to achieve lossless compression, the more successful of which exploit the *local* two dimensional redundancies in the images [1-3]. The JPEG lossless coding algorithm uses a predictor to generate the residual image, the difference between the predicted image and the actual image, which is then encoded using a one dimensional entropy coder. The predictor can be any one of eight different models as proposed in the JPEG standard [3]. More sophisticated methods use complicated techniques to generate the residual, which however do not produce *significantly and consistently* better results than the simpler JPEG implementation. This can be attributed to the overhead generated by such methods accounting for any advantage accrued from obtaining a better residual.

The objective of segmentation is to partition the image into closed regions which are intrinsically similar and extrinsically dissimilar (with respect to all adjacent regions) in terms of gray level homogeneity. It has been used as a tool for lossy image compression by Kunt [4]. However it's effectiveness in providing lossless compression has not received much attention. In this paper we shall first use segmentation information in order to form a smoothly varying residual image, which will be devoid of edges, and then use an autocorrelation model to further decorrelate the residual. A recent transform [6], possessing desirable properties for multiscale segmentation, forms the basic segmentation algorithm. Each region generated by segmentation, can be further subdivided into the interior sub-region and the edge sub-region; the distribution of grey level values in the sub-regions being distinctly different (fig. 1(a)). The pels in the edge sub-regions, which have a higher standard deviation (with respect to the interior sub-regions), can be modelled explicitly using edge models. This is feasible because the 2-D variation of the grey level values within the edge sub-regions follow very specific distributions (fig. 1(b)-(c)). The interior sub-region for each region can be, as a first approximation, modelled by a constant. Specifying the models for the interior and edge sub-regions of each region models the entire image. Subtracting this model from the original image we obtain a smoothly varying residual, which can be then modelled by autocorrelation based minimum variance prediction.

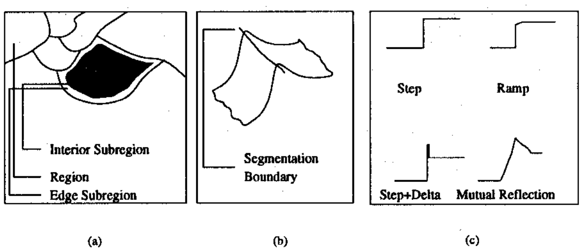

Figure 1: (a) Segmentation : a region, interior sub-region and edge sub-region (b) a segmentation boundary along an edge (with grey values represented by height) (c) some common 1-D profiles of grey values across edges.

2. EDGE MODELS

Real image edges are typically composed of a combination of steps, peaks and roof profiles (see fig. 1(c)). This has been experimentally demonstrated by Herskovits and Binford in 1970. Quantitative analysis of the associated physical phenomena has been provided by Forsyth and Zisserman [7]. Over the years many edge models have been developed [8, 9]. But as far as application to image compression

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goes, there seems to be no notable headway, which can be attributed to two main reasons :

1. *Local Applicability* : Commonly used edge models either explicitly [9, 10] or implicitly [8] model the curvature across the edge. Explicit models are of particular interest to us, as the local grey value distribution near the edges can be reconstructed from the model parameters. However such models are only applicable in small windows; for example [9] uses a 5x5 window. This results in a large storage space requirement, making edge modelling unattractive for compression.
2. *Representation* : We observe that polynomial modelling would result in a large number of parameters (since we are modelling across discontinuities) and a general nonlinear model [9] would result in a large number of models (with relatively small parameters per model). Either way, representation of the edge model requires large storage space.

We need to split the region into an edge sub-region and interior sub-region as a first step. This is done using a simple standard deviation based criterson. First observe that the edge pels by definition should be at the edges of the region. An *outer tier* of pels in this context may be defined as all the pels within a subregion that are adjacent to pels from other regions/subregions. If the region is initially assumed to have no edge pels (i.e., the region is equivalent to the interior subregion), the following algorithm may be used:

1. Find the standard deviations of the outer tier of pels, and the rest of the pels (excluding the outer tier) of the interior subregion.
2. If the ratio of the standard deviations of the outer tier and the rest of the pels is greater than a constant factor (thresholding factor)
   - declare the outer tier to be edge pels. Assuming that the edge pels now belong to the edge subregion (and hence do not belong to the interior subregion), go to step 1.
   - else exit loop.

The standard deviation of the outer tier of pels reduces as we move inward into the region, by definition (a region cannot have edges in its interior). This ensures that the algorithm stops eventually. The thresholding factor can be any number greater than 1.0. In all the results it is assumed to be 1.5.

In order to solve the *Representation Problem*, we need to find an edge model for the curvature across the edge, that can be represented in a compression wise efficient sense. We observe that the segmentation boundary should cut the edge in the "middle" of the discontinuity across the edge, in order to form regions (see fig. 1(b)). If the segmentation boundary cuts the discontinuity at any other place, then one of the detected regions towards which a greater portion of the discontinuity lies, would suffer in terms of gray level homogeneity. For the edges in fig. 1(c), this would mean that the cut portions should, in nearly all cases, be well approximated by a lower order polynomial. Thus in order to represent a single edge we could use two lower order polynomials; the segmentation boundary representing the line where the two polynomials should meet in order to form the complete edge.

In order to solve the *Local Applicability Problem*, we need to find a way to vary the same edge model to fit a local area. In the following discussion, we shall consider only half of the edge discontinuity (as the discontinuity is split in the "middle" by the segmentation boundary), and observe it's variation within a region. Solving the Representation Problem enabled us to represent this half edge discontinuity by a lower order polynomial (linear suffices in practice).

One result of using the definition of the region (as we move inside a region it should be homogeneous, with constant or smoothly varying gray levels), is that a lower order polynomial can be used to represent the inner (with respect to the region) starting point for the linear model. [11] suggests that another lower order polynomial can be used to represent the outer (again with respect to the region) ending point for the linear model (fig. 2(b)). Since we are using a linear model, defining the inner and outer points through which the model passes, completely defines the model.

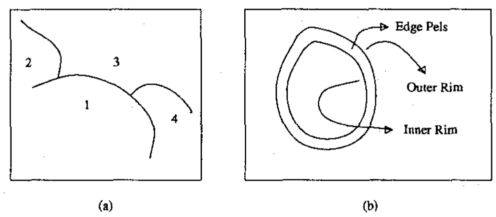

Figure 2: *Local Applicability Problem* : (a) adjoining regions (1,2,3) have different mean gray levels (b) modelling the outer and inner rims of a region separately, models the edge.

However it is found that using the same lower order polynomial for the entire region, on the outer rim, produces bad results. This could be explained theoretically, considering that a single region has many adjacent regions (typically 3-4). In fig. 2(a), regions 1,2,3 have different mean gray levels *necessarily*, by the definition of the region. This suggests that there might be a discontinuity in the gray levels at the points where these regions come together. We found that using a lower order polynomial on the outer rim is only valid *as long as it is between the same two regions*; thus pointing towards a piece-wise lower order approximation on the outer rim (see fig. 3).

3. FORMING AND STORING THE RESIDUAL IMAGE

Once we obtain a model for the edge sub-region and assuming a constant model for the interior, we can subtract the model from the original image, thus forming the initial smoothly varying residual image. However we still need to identify the grey level homogenity scale (which defines the coarseness of a multiscale segmentation algorithm), at which the optimum (compression wise) amount of segmentation information is stored. We find this by considering a number of scales from the finest to the coarsest (usually 10) and evaluating the performance at each region at each scale. This still leaves us with two choices of implementation :

1. By finding the optimal scale for each region individually. This is possible because there is a continuity of representation, the regions obtained at a coarser scale being exactly reproduced at all finer scales.
2. By finding a single optimal scale for all regions globally. This is computationally much simpler and faster to implement.

We found that the latter choice does not produce significantly different results, especially when the range of scales is large. The smoothly varying residual obtained from the structure based processing can be further decorrelated using 2-D linear prediction [1, 2]. The rationale behind such processing is that in the first step we remove edges that cause large errors in the linear prediction model to be applied in the second step.

The overhead information that needs to be stored is in two parts : segmentation information and model information. The former is stored efficiently using contour coding [5], since most of the pels are connected while the latter is stored using an entropy constrained uniform scalar quantizer for the model parameters.

4. RESULTS AND CONCLUSION

Results show a consistent 15-20% improvement over the best possible JPEG lossless standard (see table 1). Moreover they are invariant to the amount of detail and noise in the image. It is also found that the typical probability distribution of the residual image values is not Laplacian, as is the case with other methods [1], which do not use explicit edge modelling. It's more Gaussian in shape, thus suggesting that the residual is mostly random noise. To conclude, we have proposed a theoretically sound lossless compression method, which makes no crude approximations to the structure in the image, for the first time ever. We have also proposed ways to represent edge models, which makes coding them compression wise a viable proposition.

	Air	Bab	Lena	Sail	Tiff
interior entropy	3.40	4.40	3.91	4.10	3.78
edge entropy	4.35	4.31	4.48	4.39	4.51
total entropy	3.94	5.10	4.37	4.49	4.08

(a)

	Air	Bab	Lena	Sail	Tiff
interior entropy	3.43	4.47	3.96	4.15	3.81
edge entropy	4.25	4.21	4.33	4.29	4.32
total entropy	3.89	5.07	4.27	4.40	3.97

(b)

	Air	Bab	Lena	Sail	Tiff
interior entropy	3.47	4.52	4.03	4.23	3.86
edge entropy	4.01	4.13	4.17	4.17	4.18
total entropy	3.75	4.95	4.11	4.29	3.89

(c)

Airplane	Baboon	Lena	Sailboat	Tiffany
4.12	6.45	4.61	5.25	4.32

(d)

Table 1: Results from applying the various implementations: (a) piecewise constant model (b) piecewise linear model (c) linear prediction model and (d) best JPEG implementation (all results in bits/pel). In (a)-(c), interior (of a region) residual entropy and edge residual entropy are also provided. Total entropy in all cases includes the overhead storage space.

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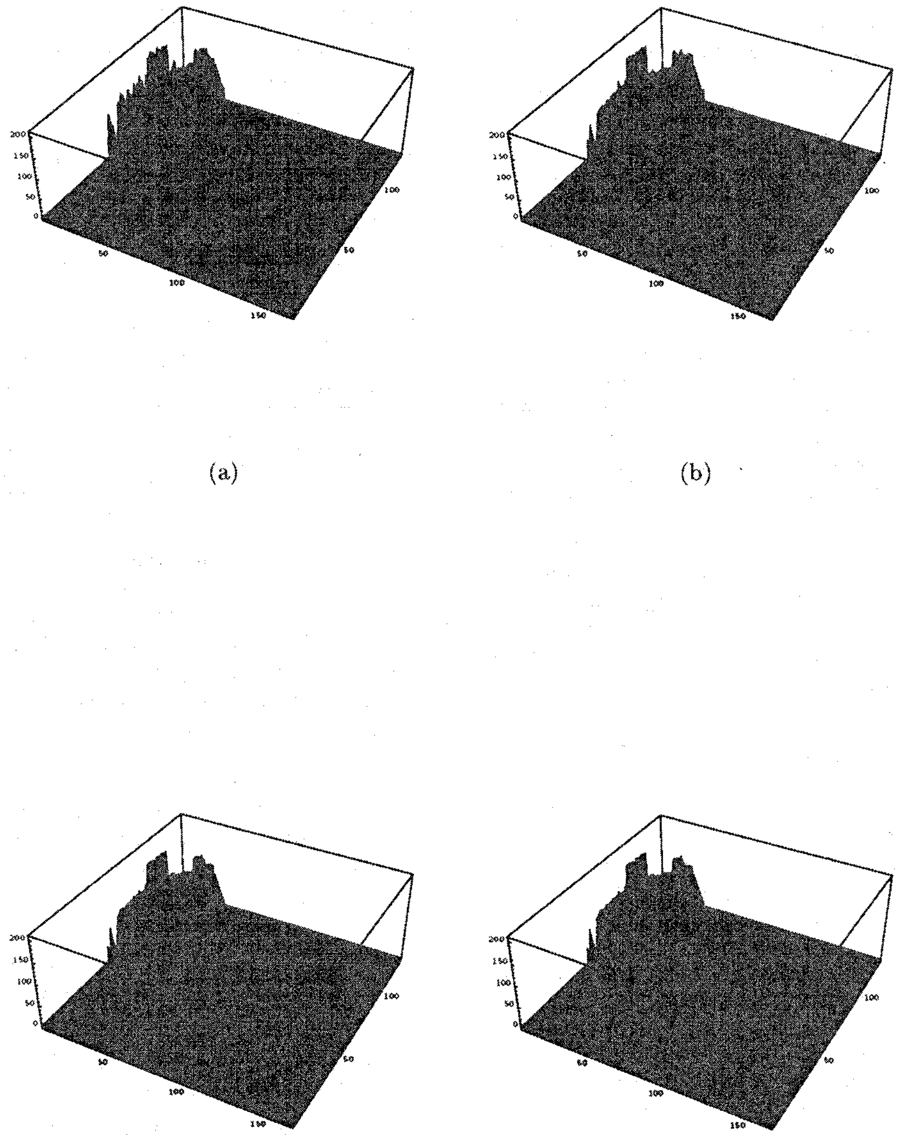

(a) (b)

(c) (d)

Figure 3: Edge models (grey values are represented by height): (a) region represented apart from the rest of the image. Outer rim of the edge subregion modeled with (b) the piecewise mean model, (c) the piecewise linear model, (d) the autocorrelation model (the interior subregion being faithfully reproduced).