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Image Compression Based on Centipede Model

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An efficient contour based image coding scheme based on Centipede Model [1] is introduced in this paper. Unlike previous contour based models which presents discontinuities with various scales as a step edge of constant scale, the centipede model allows us to utilize the actual scales of discontinuities as well as location and contrast across them. The use of the actual scale of edges together with other properties enables us to reconstruct a better replica of the original image as compared to the algorithm lacking this feature. In this model, there is a centipede structure for each edge segment which lies along the edge segment and the gray level variation across an edge point is represented by a hybrid spline and distance between left and right feet of the centipede. The proposed model aims at reconstructing the closest intensity surface to the original one from the contour information. We first obtain edges by using the Generalized Edge Detector (GED) [2,3] which controls the scale and shape of the filter, providing edges suitable to the application in hand. Then the detected edges are traced to produce the distinct contours. These contours are ranked by assigning a priority based on the weighted sum of contour length, mean contrast, contour density and mean contour curvature. In our scheme, the compression ratio is controlled by retaining the most significant segments and by adjusting the distance between the successive foot pairs. The original image is reconstructed from this sparse information by minimizing a hybrid energy functional which spans a space called $\lambda\tau$-space, where λ represents the smoothness of the image and represents τ the continuity of the image. Since the GED filters are derived from this energy functional, we have utilized the same process both for detecting the edges and reconstructing the surface from them. The proposed model and the algorithm have been tested on both real and synthetic images. Compression ratio reaches to 180:1 for synthetic images while it ranges from 25:1 to 100:1 for real images. We have experimentally shown that the proposed model preserves perceptually important features even at the high compression ratios.

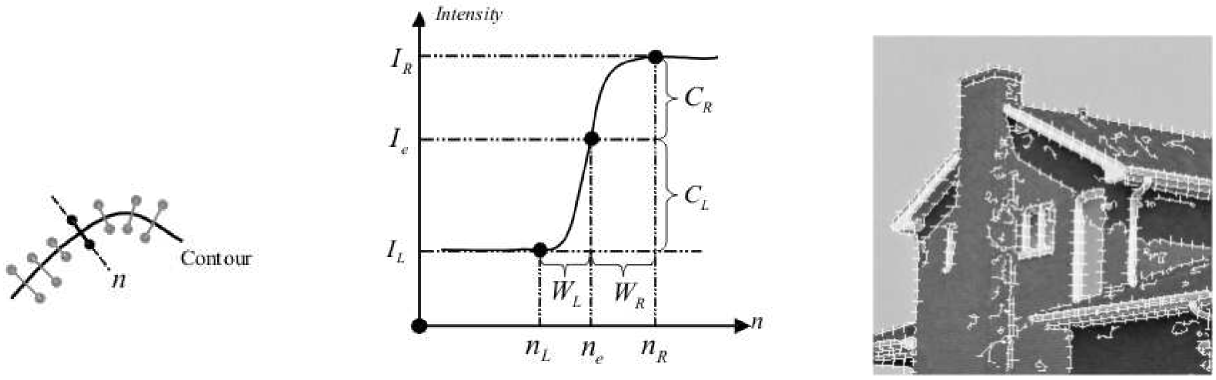
Keywords: Image compression, edge detection, surface reconstruction, image representation, scale space.

1. Introduction

The feature-based image compression has attracted great interest as an attempt to exceed the boundaries of classical coding methods such as predictive coding, information theory based methods, transform coding and vector quantization. This is due to the fact that the classical methods often treat images as a source of information the way they do text, voice, or any other type of information. Hence their performance is limited to the spatial or frequency distribution of the waveform. In general images have its own information characteristics quite different than any other type of information. Also when lossy compression is considered the final assessment is often done by human viewers, so any coding scheme should utilize the properties of human visual system (HVS).

One general image model often used characterizes the image in terms of contours and regions surrounded by them. In this framework, one class of algorithm requires an accurate partitioning of image into homogeneous closed regions [4–6] (region based), whereas the other class of algorithms attempt to reconstruct the image from edge segments (contour based) and their neighborhood [4, 7, 8]. The former approach utilizes the uniformity of the each segmented region while the latter utilizes the differences between two regions. Even though much of the research efforts have been devoted to the region based approaches, it is more practical and efficient to extract edges by using high performance edge detectors instead of costly region segmentation. The use of contours for coding goes back to the late sixties [7]. The idea was to separate an image into low-pass and high-pass components where the low-pass component can already be compressed successfully by waveform coding techniques (e.g., subsampling, transform coding). The high-pass component conveys the details and perceptual information (e.g., edges, corners, contours, lines, ridges etc.) about the image.

Feature-based coding algorithms have focused



(a) (b) (c)

Figure 1. Centipede Model: Centipede Backbone on an edge segment, Model Parameters, Model superimposed on the House image (from left to right).

on the extraction and modeling of some set of these features to efficiently code the high-pass component. Kunt et al. [4] decomposed the zero-crossing edges into different directions by using the Laplacian of Gaussian (LoG) operator. Then the edges are modeled by their location and zero-crossing magnitude. The locations are coded by run-length coding with Huffman coding while magnitude are first modeled by a wavelet and its parameters are coded. Carlsson [8] proposed another contour based image coding technique in which edges are detected by LoG operator and gray level values on both sides of the edges are modeled by polynomials. Then the polynomial coefficients are computed and quantized. Salembier et al. [9] studied the morphological operators such as edge/region detector, edge simplification, surface interpolator for image and video compression. Acar and Gökmen [10] utilized the weak membrane model of image in an attempt to carry out the edge detection and surface reconstruction by using the same process. This unification enables to use the same minimization process for both edge detection and surface reconstruction, and simplifies the coding scheme. However, the reconstructed images look somewhat artificial due to treating each edge as a step function by disregarding its actual scale. As known, the boundaries of physical structures in the world give rise to blurred transitions in image intensities instead of step discontinuities. Elder and Zucker [11] suggested a method to estimate the scale of edge by modeling it as a step function blurred by a Gaussian kernel with varying scale obtained by solving the heat equation in which the diffusion occurs over the scale. Lindeberg [12] introduced another scheme to select the scale from a scale-space edge representation.

Another interesting and propitious feature is ridges/valleys. Robinson [13] devised a model based on ridges and valleys as perceptual image features instead of edges and regions. Ridge and valley type of features are inherent properties of fingerprint images. Gökmen et al. [14] developed a model based coding of fingerprint images using these features.

Another direction in feature-based coding of images is to benefit the advantages of both feature-based and transform-based approaches, which is called hybrid coding. Dijk and Martens [15] combined the contour based approach and transform coding and expressed the local edge parameters in terms of the Hermite Transform coefficients. Ran and Farvardin [16, 17] decomposed an image into three components. The primary component is called strong brim edges and coded separately by N-ring code. The other two components are called smooth and texture components. Two alternative methods (i.e., entropy-coded adaptive DCT and entropy-coded subband coding) were studied in their paper for coding of these components.

In this study, we have been interested in developing a contour-based model which allows us to utilize the estimated scale of edge in an efficient way. We are also interested in using a scheme in

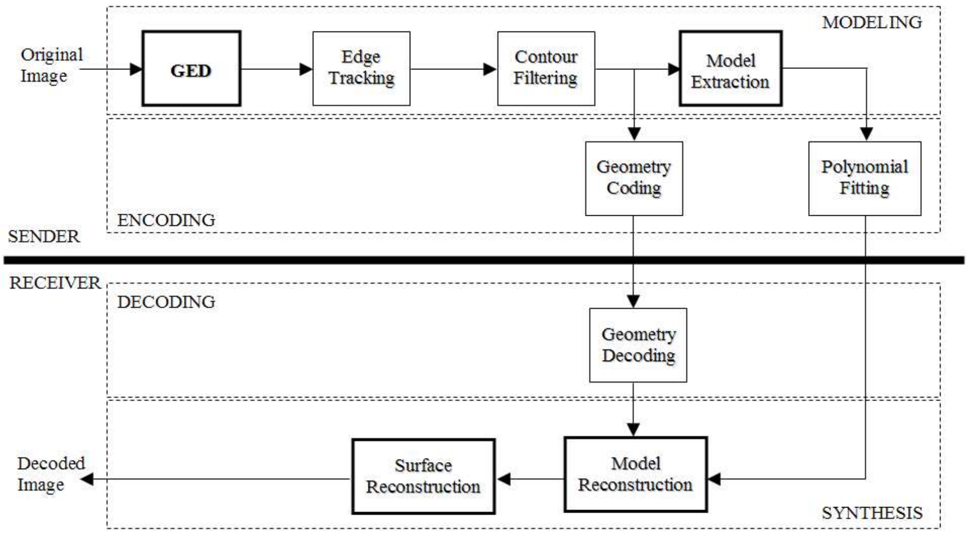


Figure 2. The generic architecture of the codec system.

which the process of detecting discontinuities is related to the way we reconstruct original image from these discontinuities. Furthermore we would like to preserve the intelligibility of the image even for the high compression ratios by keeping the most important features in the image. The organization of the paper is as follows. In the following section, we introduce a coding scheme which combines all of these features by utilizing a novel model called centipede model. In section 3, we also describe how to encode the model parameters, together with ranking the edge segments and modeling the gray level variation along a segment by fitting polynomial curves. Section 3 also studies the optimal extraction of the model parameters. Section 3 includes the reconstruction of original image from encoded model parameters by minimizing a hybrid energy functional. In Section 4 the performance of the algorithm on synthetic and real images are quantitatively and qualitatively analyzed. Finally we conclude with Section 5.

2. Centipede Model

In our coding scheme, each connected edge segment as well as its intensity variations around segment is described by a generic model called *centipede*. A centipede, depicted in Fig.1, consists of a backbone along the edge segment and a number of legs approximately parallel to each other and normal to the backbone at the intersection points. The lengths of the legs may vary along the backbone and the length of the left leg may be different from that of the right leg. Our centipede model consists of four parameters. Representing the position of ith centipede parametrically by $\Gamma_i(j) = (x(j), y(j))$, the model can be described by the set $\{\Phi_i\}_{i=1}^{n}$ defined as

$$\begin{aligned} \Phi_i &= \{\Gamma_i(j), \Psi_i(j), \Upsilon_i(j))\}_{j=1}^{L_i} \\ \Psi_i(j) &= (W_L(j), W_R(j)) = (n_L - n_e, n_R - n_e) \\ \Upsilon_i(j) &= (C_L(j), C_R(j)) = (I_L - I_e, I_R - I_e) \end{aligned} \tag{1}$$

where n is the number of contours and L_i is the length of ith contour. Thus, the model consists of the geometry of the edge segments Γ, the lengths of left and right legs $\Psi = (W_L, W_R)$ capturing an estimate of the scale, and finally Υ corresponding to the reconstruction model of the contour profile. The length of a leg, namely Ψ, corresponding to the scale of an edge, is determined along the direction normal to the contour at the corresponding edge point. The reconstruction model, Υ, consists of the contrast across an edge pixel corresponds to the footholds of centipede in the model, which are denoted as (C_L, C_R).

The entire image is modeled as a family of centipedes placed on edge segments. In Fig. 1, centipedes superimposed on the original House image for the selected region (Fig. 1(a)) are shown.

Table 1
G-filter along x direction : $G^{(x)}(x, y; \lambda, \tau)$ where $\Delta = Q^2 - 4P$, $P = \lambda\tau$, $Q = \lambda(1-\tau)$

Case	$G^{(x)}(x, y)$	
I	$\Delta > 0$	$\frac{2P}{\sqrt{\Delta}} sgn(x)\ a\ b\ [\exp(-a(\lvert x\rvert + \lvert y\rvert)) - \exp(-b(\lvert x\rvert + \lvert y\rvert))]$
II	$\Delta < 0$	$K\ sgn(x)\ \exp(-\frac{1}{\sqrt[4]{4P}}\cos(\theta)(\lvert x\rvert + \lvert y\rvert)) \times$ $[(\sin(\theta)\varphi - \cos(\theta)\frac{1}{\sqrt[4]{4P}})\cos(\varphi(\lvert x\rvert + \lvert y\rvert)) -$ $(\cos(\theta)\varphi + \sin(\theta)\frac{1}{\sqrt[4]{4P}})\sin(\varphi(\lvert x\rvert + \lvert y\rvert))]$
III	$\Delta = 0$	$\frac{-1}{4Q^2}\lvert x\rvert\ sgn(x)\ (\frac{1}{\sqrt{Q}}\lvert y\rvert + 1)\exp(-\sqrt{\frac{1}{Q}}(\lvert x\rvert + \lvert y\rvert))$
IV	$P = 0$	$-\sqrt{2Q}\ sgn(x)\ \exp(-\sqrt{\frac{1}{2Q}}(\lvert x\rvert + \lvert y\rvert))$

When a centipede is placed over an edge segment, the transition of gray values can be captured by the parameters. The image is compressed by efficiently encoding the parameters of the centipede, and the original image is formed by reconstructing a surface from these model parameters through minimizing a hybrid energy functional.

3. Encoding and Decoding Images

The generic architecture of coding and decoding system as outlined above can be described in a more general way by the block diagram given in Fig. 2. The first stage at the sender side is the edge detection. The goal of edge detection is to obtain powerful and complete description from an image by characterizing intensity changes. By using this representation, it would be possible to reconstruct a good replica of the original image. An edge detector extracting and locating object boundaries in an image from intensity data is a crucial step of contour-based coding system. Since accuracy of model parameters are highly dependent on the accuracy of the detected edges, edge detection is the most important part of the algorithm. We have used generalized edge detector which provides a description of an image in a plane called $\lambda\tau$-space where τ controls the shape and λ controls the scale of the edge detection filter. These filters are summarized in Table 1. One can obtain most of the well-known edge detector such as Canny's, Deriche's, Sarkar and Boyer's, Shen and Kastan's edge detectors by setting the space parameters appropriately.

Edges are then traced to detect the distinct contours. These contours are coded by differential chain coding. Edge tracing algorithm forces the edge segments being as smooth as possible so that the gain of the compression of binary image with differential chain code followed by Huffman coding is maximized.

The second part of the compression algorithm is to select the perceptually most important edge segments among these contours obtained by tracing the edge segments. This is achieved by first assigning a priority to each edge segment simply by calculating the weighted sum of normalized set of contour length, average contrast along normal direction and average curvature evaluated directly from the differential chain code representation of the curve. Priority assigned to the contour C_i is given by (2).

$$\begin{aligned} Priority(C_i) &= w_{len} \cdot Length(C_i) \\ &+ w_{con} \cdot Contrast(C_i) \\ &+ w_{cur} \cdot Curvature(C_i) \end{aligned} \quad (2)$$

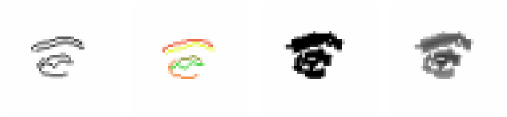
The model parameters along a contour are modeled by polynomials widely used procedure for curve fitting. Let $P_n(x)$ be the nth order polynomial with the coefficients $(c_0,c_1,\cdots,c_n)$ as given in (3).

$$P_n(x) = c_0 + c_1x^1 + c_2x^2 + \cdots + c_nx^n \quad (3)$$

M data pair is given in the form $(y_0, y_1, \cdots, y_M)$. We want such a polynomial with the coefficients $(c_0,c_1,\cdots,c_n)$ that minimizes the quantity denoted by Q :

$$Q = \sum_{i=1}^{M}(P(x_i) - y_i)^2 \quad (4)$$

(a)



(b) (c) (d) (e)

Figure 3. Optimal extraction model parameters: (a) Original Akiyo image and the selected region to be modeled, (b) detected edges in the selected region, (c) traced distinct contours (d) centipede structure, (e) modeled edge profiles.

The polynomial coefficients (c_i) are quantized and encoded.

Given the edge points on a contour and normal direction, we need a mechanism for finding the optimal centipede model parameters in the sense that the error between the reconstructed edge profile and the original one is minimum. Consider $f(x)$ as the original edge profile and $g(x)$ as the reconstructed edge profile. Given the centipede footholds, namely n_L and n_R, $g(x)$ will be the minimizer of the one dimensional hybrid functional given by:

$$\begin{aligned} E(g;\lambda,\tau) &= \sum_{i=0}^{2}(g(n_i)-y_i)^2 \\ &+ \lambda\int_{\mathcal{N}}(1-\tau)(\frac{df}{dn})^2+\tau(\frac{d^2f}{dn^2})^2dn \end{aligned} \tag{5}$$

The minimizing function, $g(x)$, might be explicitly written as

$$\begin{aligned} g(n) &= h_0+h_1h(|n-n_L|)+h_2h(|n-n_e|) \\ &+ h_3h(|n-n_R|)h(|n-n_R|) \end{aligned} \tag{6}$$

where

$$h(n)=\begin{cases} |n| & ;\text{if } \tau=0 \\ \frac{|n|}{1-\tau}+\frac{e^{(-\sqrt{\frac{1-\tau}{\tau}}|n|)}}{\sqrt{\tau(1-\tau)}} & ;\text{if } 0<\tau<1 \\ |n|^3 & ;\text{if } \tau=1 \end{cases} \tag{7}$$

The centipede footholds, n_L and n_R, are determined in such a way that they minimize the mean square error as

$$\begin{aligned} MSE(f,g) &= \sum_i(f(n_i)-g(n_i)) \\ (n_L^*,n_R^*) &= \arg\min_{n_L,n_R} MSE(f,g) \end{aligned} \tag{8}$$

Fig. 3 shows optimal model parameters in a selected region (Fig. 3(a)) obtained by using (8).

At the receiver, the decoder reconstructs two images, which are binary edge map and intensity image, simply by evaluating the polynomial at each edge point. Since both images are sparse, we use hybrid energy functional to span a surface through these points. For this purpose, the surface reconstruction problem is set as finding a

Table 2
Contour selection results for House image.

Contour	Edge	Threshold	NMSE	SNR(dB)	PSNR
635	6626	100	13.91	39.44	69.91
475	6094	75	13.78	39.63	70.10
317	5336	50	14.31	38.88	69.35
160	4150	25	14.95	38.00	68.48

Table 3
Contour selection results for Lenna image.

Contour	Edge	Threshold	NMSE	SNR(dB)	PSNR
232	2754	100	21.10	31.03	63.04
165	2494	75	23.19	29.22	61.23
110	2199	50	25.10	27.64	59.65
56	1872	20	29.19	24.62	56.63

Figure 4. Original House and Lenna Images.

function $f(x,y)$ which minimizes

$$\begin{aligned} E(f;\lambda,\tau) &= \iint_{\Omega} \beta(x,y)(f(x,y)-d(x,y))^2 \\ &+ \lambda(1-\tau)(f_x^2(x,y)+f_y^2(x,y)) \\ &+ \lambda\tau(f_{xx}^2(x,y)+2f_{xy}^2(x,y) \\ &+ f_{yy}^2(x,y))\ dx\ dy \qquad (9) \end{aligned}$$

where λ controls the smoothness of the surface and τ controls the continuity of the surface. In the functional, the first term on the right hand side is a measure of the closeness of the solution $f(x,y)$ to the data $d(x,y)$, and the second and the third terms are stabilizers on the solution including the first and second order derivatives. Properties of the hybrid model is explained in [2]. Minimization of functional given by (9) is obtained by Successive Over-Relaxation (SOR). In order to eliminate a possible blurring across discontinuities, we defined the centipede footholds, i.e. W_L and W_R, as crease points and vanish the last term in (9) including the second derivatives at these points. As described in [2], GED is derived from the functional (9), the scale and the shape of the GED filter is controlled by the parameters, λ and τ in the hybrid functional. Thus we utilize the same process for both detecting edges, extracting the optimal model parameters, and reconstructing images from them, unlike unrelated processes such Canny edge detection and surface interpolation.

4. Results and Discussion

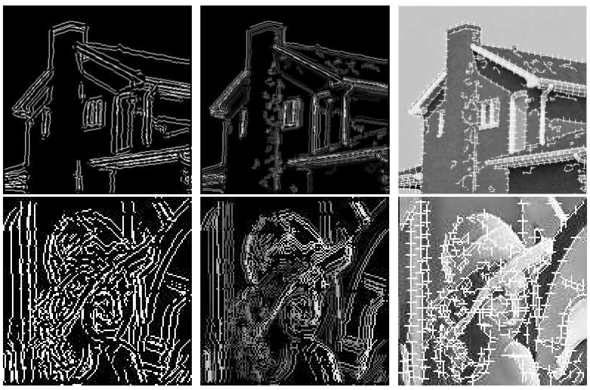
The proposed model-based image coding has been applied to various synthetic and real images. We first consider the effect of ranking the edge segments and selecting only most significant segments on the reconstructed image quality. Fig. 4 shows the original House and Lenna images. Fig. 5 shows the selected edges from a complete edge map obtained by the GED (with $\lambda = 0.5$ and $\tau = 0.5$) from edge map, 100%, 75%, 50% and 25% of edges are retained and these edges together with the reconstructed images are shown in Fig. 5 a, b, c, and d, respectively.

The quantitative results for this test are shown in Table 2 and 3. The qualitative and quantitative evaluation of results indicates that the selection scheme works quite successfully. Even if very large portion of the edge segments are removed, the reconstructed image still contains most of the perceptually pertinent features.

When we code the centipede parameters, we divided the each edge segment into blocks and approximate the parameters $I(s)$,$C_L(s)$,$C_R(s)$,$W_L(s)$, and $W_R(s)$ over a block by fit ting curves of order n. Thus in our coding scheme, the compression ratio and the quality of reconstructed image can be controlled by the following parameters: the ratio of selected edge segments, block size and orders of polynomials used in approximations for the intensity op_I, the contrast op_C, and the edge width op_W over the block. We also investigated the effects of these parameter values on the reconstructed images.

Fig. 6 shows the detected edges, the intensities and estimated scales of edges and also the centipede model superimposed on the original House and Lenna images.

Figure 5. The selected edges and reconstructed images for House and Lenna images. From top to bottom, 100, 75, 50 and 25% of edges are retained.



(a) (b) (c)

Figure 6. Representation of detected edge scales.(a) Centipede Footholds, (b) Intensities on edges and footholds, (c) Centipede Model superimposed on the original House and Lenna images.

To reveal the coding performance of the proposed model, we considered various synthetic and real images. Fig. 8 shows the results on the synthetic checkerboard and bar images, for which a compression ratios of 127 : 1 and 157 : 1 are achieved, respectively. Fig. 9 shows the original image, edge map and reconstructed images, from left to right, for House and Cameraman images. Compression ratios are 44 : 1 and 29 : 1, respectively.

As seen from these results, relatively high compression ratios can be achieved by the proposed scheme. One of the advantageous of this contour based approach as compared to transform based coding is that this scheme does not cause excessively blurred image or blocking artifacts as the compression ratio increases. It retains the most important features even for the very high compression ratios.

Compression Ratio : 44 : 1

Compression Ratio : 29 : 1

Figure 7. Original image, Edge Map and Reconstructed image for House and Cameraman images.

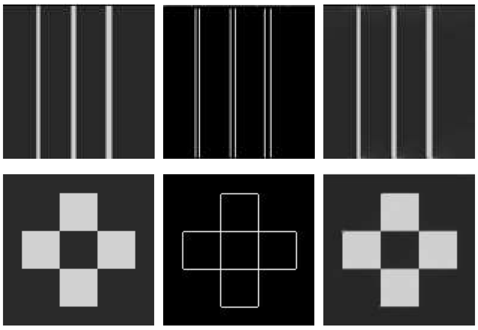


Figure 8. Compression Results for checkerboard (127 : 1) image and bars (157 : 1) image.

CR = 37 : 1 CR=22 : 1

CR = 48 : 1 CR=29 : 1

CR = 74 : 1 CR=35 : 1

Figure 9. The reconstructed House and Cameraman images for the specified compression ratios (CR).

5. Conclusion

We presented a new model for contour based image compression. This model enables us to utilize the scale, brightness and contrast of edges. We developed a ranking scheme for edge segments so that the most significant edge segments can be kept after the removal of the edge segments to increase the compression ratio. We utilized an efficient way of encoding the model parameters by means of curve fitting, differential chain coding and Huffman coding. We used the similar process controlled by the same parameters, λ and τ, for both detecting edges and reconstructing original image from edges. All these combined features make the proposed centipede model very attractive alternative to the existing model based schemes.

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