Object Shape Coding Using Adaptive Beamlet

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***Abstract* — A Beamlet transform approach to compress the shapes is discussed here. Beamlets and its multiscale analysis is used to achieve compression efficiency. For entropy coding DPCM and Huffman coding is used. To demonstrate the feasibility of this approach different scales of Beamlet are used and PSNR is calculated as performance measure. The simulation result shows that this approach works well for shape coding.**

***Index Terms* — Shape coding, Beamlet transform, Multiresolution Entropy coding, Radon transform, PSNR**

I. Introduction

Extracting the redundancies in the shape or curves falls into category of shape coding and contour coding[2].It has many more applications in multimedia signal processing including content based video coding. The methods of coding the objects in the video using its shapes might turn out better in some cases.

Some of the works in this area is run length coding, chain coding shape adaptive DCT. Run length coding exploits redundancies in the relative positions in 8(or 4neighbourhood of pixels).Thereafter came the chain coding which is based on the coding the shape in eight different directions and further exploiting the run length coding

Multiresolution is famous concept which allows to analyze signal at different scales. A role similarly played by points in case of wavelet analysis is played by the line segments by Beamlets. [1] The Beamlet transform of image f(x,y) is collection of integrals of f over each segment in the Beamlet dictionary. Where Beamlet dictionary is defined as all values of points those are passed by line segments, occupying different locations and at different dyadic scales. Associated with the Beamlet pyramid there is Beamlet graph. For image with nxn pixels this graph consists of (n+1)2 vertices and 16n2 edges. We use these edges to calculate the threshold.

If g is the input image and Tg(b) the Beamlet transform of input image this is represented as

$$Tg\ (b) = \int g(x\ (l))\ dl \quad (1)$$

The digital representation for the same is given by

$$Tg(b) = \sum g(x,y) \quad (2)$$

There is similarity and difference between Multiresolution approach in wavelet family and Beamlet family. The algorithms like (i) Applying the threshold to Beamlet coefficient. (ii) Dyadic partitioning is more similar to algorithms in wavelet style analysis. The other classes of algorithms are based on local use of neigh boringness of Beamlet coefficient. We primarily use the first approach in wavelet like way.

II. Beamlet Transform And Curves

A. Constructing beamlet pyramid

We construct the Beamlet pyramid by connecting the defined vertices with the important condition that no vertices lying on horizontal or vertical line are connected.as shown in figure 1

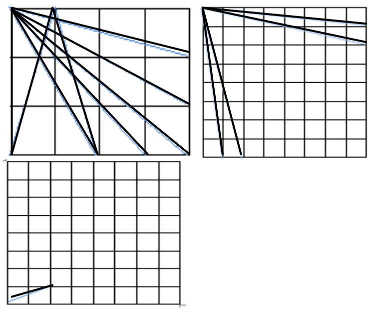


Figure 1: Beamlet at different scales

B. Retaining the approximate shape using beamlets

To approximate the shape we decompose the image into smaller parts and apply Beamlet pyramid at various scales to get the better approximation. A part of shape lying on line is examined and decided if it is to be part of coding scheme or not. Further if it is necessary and found that shape can be coded further we carry out dyadic partitioning again as shown in figure 2.

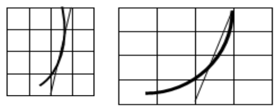


Figure 2: (a) Decomposition is not required (b) Required

III. Our Algorithm

We count the total no of pixels of shape lying on line .If Li be the line of the Beamlet pyramid at scale S, then

$$X = \sum_{t=0}^{N} Li(t) \quad (3)$$

Where X is the sum of pixels obtained on Li. If the sum obtained is greater than threshold (T) we choose the line as part of shape.

If X > T then

Li € W where W is the set of Parameters which retains such lines information

W= { {L1s,L1e},…{Lis,Lie}} (4)

Where Lis is the starting point of line Li and Le is the endpoint of line Li

Then we count the total no of regions lying on the line Li and apply the same methodology on each to calculate their respective W.Based on the no of pixels present in each line we retain their x and y positions. This would be marked as Px, Py where

Px={px1,px2..,Pxn},Py={py1,py2..,Pyn} (5)

The elements in Px and Py are differentially pulse code modulated (DPCM) by taking successive differences. This enables to remove the redundancies. Then using the magnitude of these DPCM coefficients and run length coding we apply variable length coding technique and assign them the unique Huffman code. After dyadic partitioning we apply Equation 3,4 and 5 above and use the same method to encode

IV. Results

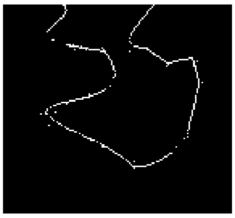
We applied above algorithm to different random shapes and decoded them Following are the results obtained on some of the random shapes chosen. Figure 3-a shows the original image and 3-b shows its decoded using above approach

a-Original shape

b-Decoded shape

Figure 3: Results obtained on standard shapes

a- Original shape



b-Decoded shape

c -original shape

d-decoded shape

Figure 4: Results obtained on random shapes

Below are the tabulated results on various shapes and compression ratio with PSNR

Table 1: Comparison of the results obtained on various shapes (vertices=5 per 100 pixels)

Shapes	PSNR db	Compression ratio(Percentage)
Shape in figure 4-a	84.29	80
Shape in figure 4-c	76.53	82
Shapes involving lines	89.48	91
Lena edges(figure 3)	72	70

Table 2: Comparison of the results obtained on various shapes (vertices=10 per 100 pixels)

Shapes	PSNR db	Compression ratio(Percentage)
Shape in figure 4-a	86.52	78
Shape in figure 4-c	80.31	77
Shapes involving lines	92.4	86
Lena edges(figure 3)	75	67

V. Conclusion

Shape coding is the technique where we encode the shape of any arbitrary object in this paper we use beamlet transform and locally adaptive beamlet based approach for coding the shapes.

It is clear from the tabulated results the compression efficiency for shapes with more no of lines is greater than the curvilinear shapes. This is obvious since if a single line covers most of the part of the shape, much of redundancy is removed. For scaling we used the fix no of vertices for making beamlet pyramid. No of vertices were 5 per 100 pixels for each decomposition. For decomposition we used 4 (fixed) tree like decompositions .Compression ratio and PSNR can be still be improved if higher no of decompositions are used with the smaller scale.

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