CONTOUR ADAPTIVE IMAGE CODING

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ABSTRACT

This paper presents a new image coding framework that separates singularities based on their topological dimension: point singularities (0D), line singularities (1D) and plane (2D). Contours are smooth curves corresponding to line singularities and boundaries of plane singularities. We propose to directly code contour locations in the spatial domain and spatially adapt the bases to approximate various singularities conditioned on contour locations. The key to the success of our forward adaptive coding lies in the exploitation of contour geometry while achieving spatial adaptation. Preliminary experimental results are used to demonstrate the potential of our approach.

1. INTRODUCTION

The fundamental challenge with image coding arises from the diversity of singularities in natural images. Recent advances in image coding are largely due to spatially adaptive statistical modeling of wavelet coefficients [3, 15, 14]. Despite the popularity of wavelet coding, it is difficult to exploit geometric constraints of image source in the wavelet space. Although geometric wavelet bases such as contourlets [2], bandelets [6] have been proposed, they are facing the same problem as wavelets − i.e., only suitable for certain type of singularities.

An improved understanding of image source can be obtained by a geometric perspective of modeling singularities. Specifically, we propose to classify image singularities based on their topological dimension: point (0D), line (1D) and plane (2D). The topological dimension of a singularity point can be understood as the number of coordinates needed to locally specify the singularity points observing the same probability distribution function (PDF). For example, the boundary pixels of an object are line singularities because locally they form a 1D manifold. More examples of singularities with different dimensions are shown in Fig. 1.

It should be noted that the $locality$ in the definition of topological dimension of singularities is a $scale$ dependent concept [5]. Roughly speaking, the scale of an image is determined by the distance of objects to the camera (scene depth) and the camera point-spread-function (PSF). Furthermore, the source of illumination (e.g., shading or shadow), which also contributes to singularities in natural images, has not received sufficient attention so far to the best of our knowledge. Since natural scenes often consist of objects across a wide range of scales and with varying lighting conditions, natural images contain a mixture of singularities with varying dimensions.

Topological dimension of image singularities sheds new insights into the practice of image coding. Specifically, line and plane singularities represent two classes of events at the opposite ends of the spectrum: line singularities are more localized in space than frequency while plane singularities go the other way. Depending on the scale, both line and plane singularities could turn into point singularities whose localization leans towards neither space nor frequency. Therefore, wavelet bases, with good localization property in both space and frequency, represent a compromised strategy of handling the diversity of singularities in natural images. The question is: why compromise?

In this paper, we present a forward adaptive approach that spatially adapts the bases to match the dimensionality of singularities. In our approach, contours that mark the location of line and plane singularities are explicitly detected and directly coded in the spatial domain. Conditioned on contour locations, we employ 1D and (shape adaptive) 2D discrete cosine bases to approximate line and plane singularities respectively. For regions other than line or plane singularities (i.e., point singularities and smooth areas), we propose a contour adaptive (CA) wavelet transform (WT) that intelligently packs wavelet bases to avoid their support being overlapped with contours.

This work distinguishes from segmentation-based coding of arbitrary shape objects adopted by MPEG-4 [1] in the following aspects. First, line singularities represent a class of pixels satisfying 1D manifold constraint but impossible to be segmented into either object due to nonideal PSF of camera (we will elaborate on this issue in Section 3A). Realizing such pitfall with object segmentation, we propose to treat line singularities separately as a 1D coding problem. Second, object segmentation often become difficult due to interference from lighting condition variations (e.g., the boundary of objects might not form a close curve due to shading). We propose to get around such difficulty by enforcing support constraint in CA-WT (refer to Section 3B).

We also mention there exist other attacks on geometric modeling of natural images in the literature. In [4], it was proposed to decompose an image u into two additive components $v+w$, where v, w model geometric and texture components of u respectively. The weakness with such approach is the intrinsic redundancy with coding the location information. In [13], an image is structured into three classes of blocks: smooth, texture and geometry. Modest coding gain was reported over wavelet-based SFQ coder [15]. In [9], a more flexible quadtree-based image representation and Rate-Distortion optimized pruning method are developed and give good performance for piecewise smooth images.

2. SINGULARITY CLASSIFICATION

In this section, we discuss the classification of singularities based on their topological dimension and highlight the importance of contours.

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A. Topological Dimension of Singularities

Singularities are important because they carry critical information about the image content. In natural images, the origin of singularities is diverse: boundaries of objects at different scene depth, reflectance variation of a rough surface, shading or shadow caused by the interaction between scene geometry and lighting conditions, and so on. We argue that such diversity of singularities is the fundamental challenge with modeling natural images.

To overcome such difficulty, we propose a geometric approach of modeling image singularities. Since the dimension of an object is a topological measure of the size of its covering properties, we propose to define topological dimension of a singularity point as follows:

Definition For any singularity point, its topological dimension is the number of coordinates needed to $locally$ specify the singularity points observing the same probability distribution function (PDF).

For example, any singularity point within a textural region has dimension of two (plane); while as the point moves to the boundary of the region, it reduces to one (line). For a non-textural region where local PDF is constantly varying, the dimensionality becomes zero (point).

One tricky issue in the above definition is $locality$ (it also affects how we define textures in the above example). When we think of a pair of physical points in the scene, their projected distance in the image is arbitrary depending on the camera distance (scale). Therefore, locality heavily depend on the scale of the image $-$ e.g., when we look at a tree in the forest from a far distance, the whole forest is local; while as we move close, only adjacent trees are qualified as local. Such scale-dependency largely contributes to the varying localization property of singularities in space and frequency.

In this work, we suggest that line singularities are more localized in space while plane singularities are more localized in frequency (point singularities lie somewhere between). We are particularly interested in $contours$ that are defined as skeletons of line singularities and boundaries of plane singularities. Contours are special because of the manifold constraint $-$ i.e., they are essentially 1D manifold embedded in the 2D space (such constraint can be viewed as the generalization of geometric constraint of edges). Resolving contour location uncertainty in the wavelet space is doomed to fail because wavelet bases are suboptimal for representing singularities. Instead, we propose to extract contours from an image and directly code their positions in the spatial domain.

B. Contour Extraction for Classification

Contour extraction deals with the detection of line/plane singularities from an image. For detecting line singularities, we propose a three-stage strategy: preprocessing by anisotropic diffusion [8] to suppress interference (e.g., noise and texture), edge detection and post-processing to remove spurious structures. A necessary condition for a collection of connected point sets to form a contour is that it has sufficient length and smoothness (manifold constraint) as well as enough number of significant coefficients after WT (singularity condition). Therefore, if an image contains objects at multiple scene depths, the boundary of some object in the background might be declared as a contour only at a coarse resolution (refer to Fig. 6).

For detecting plane singularities, we propose a Gabor-filtering approach based on the observation that textures in natural images are often localized in orientation and frequency. It is known that Gabor bases localized in space, frequency and orientation are effective on texture discrimination [12]. By decomposing an image under Gabor bases with K different orientations, we obtain a K-dim orientation selectivity vector for each pixel. Pixels with strong textureness can be detected by analyzing orientation selectivity vectors. The boundaries of textural regions can then be obtained by clustering texture pixels. Before being coded along with the locations of line singularities, we might need to process the boundaries to enforce the manifold constraint of contours.

3. CODING STRATEGIES

In the framework of forward adaptive image coding, contour locations need to be transmitted as overhead. We have found that the manifold constraint of contours can be effectively exploited by context-based adaptive arithmetic coding of either binary contour maps or its equivalent chain-code representations. Conditioned on contour locations, we divide image coding into two subproblems: nonzero dimensional (line and plane singularities) and zero dimensional (point singularities and smooth areas).

A. Coding of Line and Plane Singularities

Due to nonideal camera PSF, the width of line singularities could be wider than a single pixel. The extracted single-pixel contour can be viewed as the skeleton (zero-distance) of the 1D manifold. Using distance transform, pixels away from the contour would have positive or negative distances, as shown in Fig. 2. Based on the distance attribute, coding of line singularities boils down into a 1D problem. The 1D coding problem can be further facilitated by exploring contour geometry. If we model a contour by the concatenation of curve segments, the phase of 1D intensity profile slowly varies within each segment and only experiences large jump at corners. Since abrupt phase jump clicks with local statistics variation, it is desirable to treat each segment independently (refer to Fig. 3). Specifically, we propose to apply 1D Discrete Cosine Transform (DCT) to each segment (note that the dimension of basis is varying from segment to segment).

For plane singularities, we opt to use block discrete cosine bases for their good localization in frequency and orientation. At the region boundary where the block intersects with a contour, we propose a variant of [11] that implements shape adaptive (SA)-DCT without shifting rows and columns. The basic idea is to adaptively choose the starting point of row/column transform based on contour geometry. Specifically, we propose to select the border that mostly lies within the textural region and transform along the direction perpendicular to that border first. Our modified scheme enjoys the benefits of SA-DCT while simultaneously preserving the geometry (relative positions of pixels) by avoiding shifting any row or column. Fig. 4 shows two examples of modified SA-DCT.

B. Coding of Point Singularities and Smooth Regions

For other regions than line and plane singularities, we have developed a contour adaptive (CA)-WT. The key to the effectiveness of CA-WT is that the support of wavelet bases does not run across any contour (we call it "support constraint"). Ideally when contours separate an image into unconnected regions, existing shape-adaptive(SA)-WT [7] can be adopted. Unfortunately, for typical natural images, contours are seldom close curves (refer to Fig. 6). To overcome such difficulty, we opt to transform each horizontal (vertical) segment separated by contours respectively (symmetric extension is used at the segment boundary). To guarantee the reversibility, we suggest to implement CA-WT by the celebrated lifting scheme.

In CA-WT, contour geometry can help resolve location uncertainty of significant high-band coefficients. For example, if a contour contains any geometric singularities such as corners with large curvatures, corners will inevitably produce significant coefficients due to support constraint. Similarly, when the inter-contour distance is smaller than 2^k, the area between two contours would degenerate into a single-pixel line after k-level CA-WT (refer to Fig. 5). Again due to support constraint, transform at the next level will definitely generate significant coefficients at the ends of single-pixel line. However, since contour geometry is available at the decoder, the positions of those significant coefficients caused by support constraint do not require any overhead.

4. CODING RESULTS

In this section, we report some preliminary coding results to demonstrate the potential of contour-adaptive image coding (no effort has been put into Rate-Distortion optimization). First, we use popular test image $lena$ and $barbara$ to illustrate detection of line and plane singularities. Fig. 6a shows the extracted line singularities for $lena$ at the fine and coarse resolutions. It takes 4832 and 1880 bits respectively to code the contours at two scales (no plane singularities are found for $lena$). Fig. 6b shows the extracted line and plane singularities ($K = 16$) for $barbara$. It can be seen that Gabor-filtering strategy accurately picks out textural regions (note that the manifold constraint still need to be enforced for the boundaries to become legitimate contours).

Second, we use an experiment with synthetic 200×200 $disk$ image to shed some light on CA-WT. Fig. 7 compares the transformed images between traditional WT and CA-WT. Due to the support constraint enforced by CA-WT (wavelet bases can not cross the circle), no significant coefficients are produced in the high-frequency bands. It is estimated that around 2K bits are required for 1D DCT coding (significant coefficient positions: 800 bits, quantized values: 1200 bits) to achieve $PSNR$ of around $40dB$ (contour location takes another 700 bits). By contrast, it takes traditional wavelet coding 7K bits (significant coefficient positions: 5500 bits, quantized values: 1500 bits) to reach the same distortion level.

To demonstrate the potential of contour adaptive image coding for real-world images, we have implemented a baseline coder. Since our implementation still lacks contour smoothing for plane singularities, we opt to report coding results for a textureless image (e.g., a 512×512 subimage cut from JPEG2K test image $bike$ as shown in Fig. 3). The number of significant coefficients produced by CA-WT is about 50% less than that by traditional WT, which contributes to the large coding gain for such specific image. Further gain is possible because we have not incorporated the part for automatically locating significant coefficients caused by support constraint in CA-WT (they should cost no overhead). Fig. 8 compares the portion of decoded images by our baseline coder and by SPIHT coder [10] at the same bit rate of 0.192bpp. More extensive coding results will be reported at the conference.

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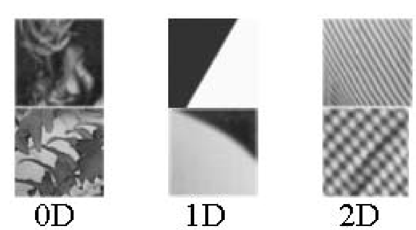

Fig. 1. Singularity classification: point (0D), line (1D) and plane (2D).

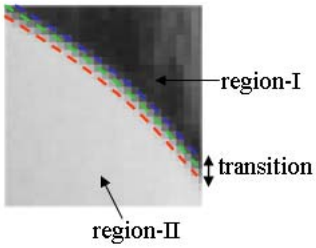

Fig. 2. 1D manifold constraint of line singularities: red, green and blue colors denote positive, zero and negative distances from the contour respectively.

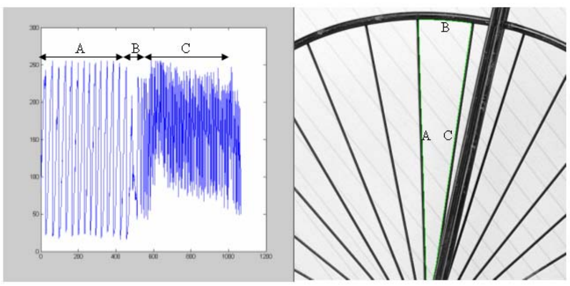

Fig. 3. Intensity function (left) and the corresponding contour geometry (right) of line singularities.

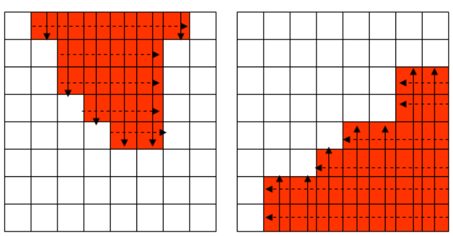

Fig. 4. Modified SA-DCT without row/column shifting (transform goes along solid lines first and then dashed).

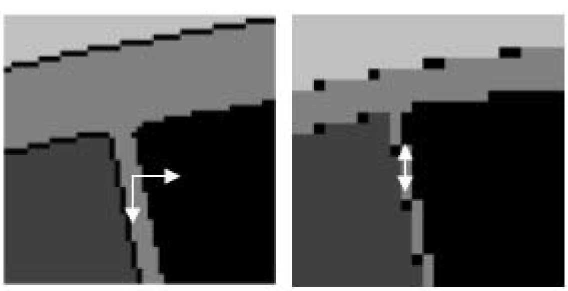

Fig. 5. At the marked area, the dimension of local support is two at the high resolution (left) but reduces to one at the coarse resolution (right).

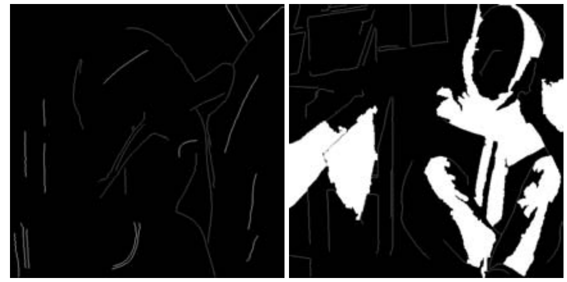

Fig. 6. Left: detected line singularities at fine (gray) and coarse (white) resolutions; right: detected line (gray) vs. plane (white) singularities.

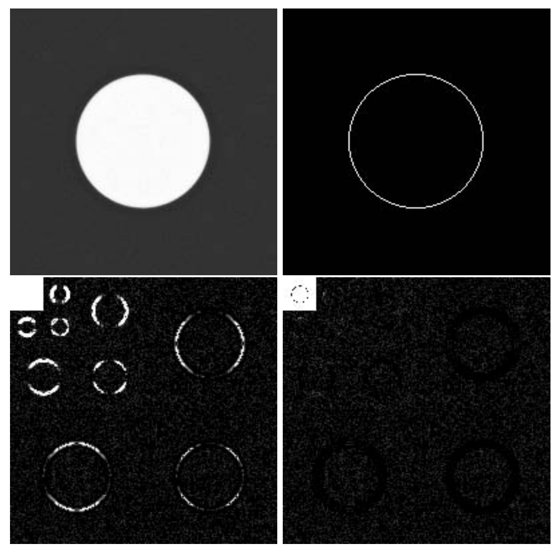

Fig. 7. a) original *disk* image; b) contour map; c) image after traditional WT; d) image after CA-WT.

Fig. 8. Comparison of portions of decoded *bike* images by SPIHT (left,PSNR=25.05dB) and our baseline coder (right, PSNR=28.69dB) at the same bit rate of 0.192bpp.