MORPHOLOGICAL PYRAMIDS FOR MULTISCALE EDGE DETECTION

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ABSTRACT

In this paper, we present an edge detector that is based on a morphological pyramid (MP) structure. The algorithm utilizes a multiresolution pyramidal structure created by successive morphological filtering and subsampling of the original image. The boundaries detected at coarse scale representations of the morphological pyramid (MP) are used to guide the detection of discontinuities at higher resolution levels. The segmentation and resulting edge detection yielded by the MP is particularly effective in the presence of impulse noise. We provide results that demonstrate superior solution quality over standard fixed resolution detectors and over previous multiresolution approaches. Because of the low computational cost of the MP edge detector, it is suitable for video tracking, image and video compression, and real-time object recognition.

I. INTRODUCTION

Edge detection is an important step in feature-based image analysis. The classic gradient-based edge detectors are sensitive to noise and produce more false edges than morphologically motivated methods [1]. Recently, multiresolution, multi-scale approaches have attracted attention because of their computational efficiency and their robustness in the presence of noise. In digital image processing, the most convenient multiresolution structure is the image pyramid. An image pyramid is a family of images created from an initial image by repetitive filtering and subsampling. The filtering step is used before sampling to avoid aliasing and to remove small scale features.

Typically, a linear filter is utilized to satisfy the traditional sampling constraints. However, a pyramid generated via linear filtering (and subsampling) is not well suited for edge detection due to the sacrifice of edge localization. Although the use of a nonlinear filter in pyramid construction would preclude image reconstruction for coding applications, the nonlinear substitute is appropriate for edge detection and image segmentation tasks. A *nonlinear pyramid*, the anisotropic diffusion pyramid (ADP), can be used for edge detection [2]. The nonlinear approach affords decreased edge localization error, compared to the linear Gaussian-based pyramid edge detector. In this paper, we present a nonlinear edge detector that utilizes morphological pyramids (MPs). Edge detection utilizing MPs is effectual because it can be efficiently implemented, in contrast to the ADP, while offering the same low edge localization error as the ADP.

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II. MORPHOLOGICAL PYRAMIDS

The fundamental operators in morphology are dilation, erosion, opening and closing [3]. A grayscale function, $I(x)$, dilated by a structuring element, K, is given by

$$(I \oplus K)(x) = \max_{y \in K}\{I(x-y)\} \tag{1}$$

where $x \in E^2$, and K is a subset of E^2. Similarly, the erosion is defined by

$$(I \Theta K)(x) = \min_{y \in K}\{I(x+y)\}. \tag{2}$$

The opening and closing are defined, respectively, as

$$I \circ K = (I \Theta K) \oplus K, \tag{3}$$

and

$$I \bullet K = (I \oplus K) \Theta K. \tag{4}$$

In the construction of the MP for edge detection, we can apply the open, close, open-close or close-open filters. Both open and close are increasing, translation

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invariant and idempotent. Idempotence guarantees that the result of an opening/closing is unchanged after reapplication, analogous to bandpass filters in linear signal processing.

Given an image I and a structuring element K, a morphological pyramid can be defined as a collection of images, $MP = \{I_L, L = 0, 1, \ldots, N\}$, where I_L is the image at level L, sampled from the filtered image at level L-1. $N(= \log_S P)$ is the largest integer for I_L to be non-empty, where S is the sample spacing in each row and column, and P is the height/width of the image in pixels. The procedure for constructing a pyramid with a close filter can be summarized as follows:

(1) Initialization: $I_0 = I$.

(2) $I_L = [(I_{(L-1)} \bullet K)]_{\downarrow S}$.

(3) Repeat (2) until $L = N$.

Here the notation $[.]_{\downarrow S}$ indicates the image contained within brackets is subsampled by a factor of S along each row and column.

Demonstration of the MP construction is given in Figures 1-3. The image in Figure 2 is a noisy version of Figure 1. Laplacian-distributed noise with variance of 27.8 has been added to the original 8-bit graylevel image. Levels 0 (the retinal level), 1, 2 and 3 of the MP for Figure 2 are shown in Figure 3. The structuring element used here is a 3x3 square window and the sample spacing is S = 2. Figures 4-6 allow inspection of levels 1-3. Notice that the MP in itself provides a segmentation of the image data, although the edge localization is poor at the higher pyramid levels.

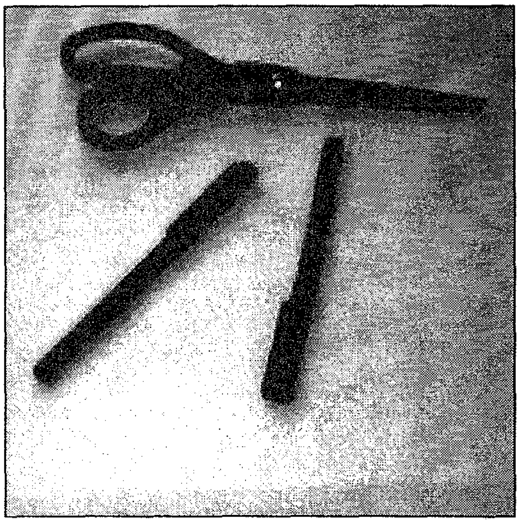

Figure 1: The original "office" image.

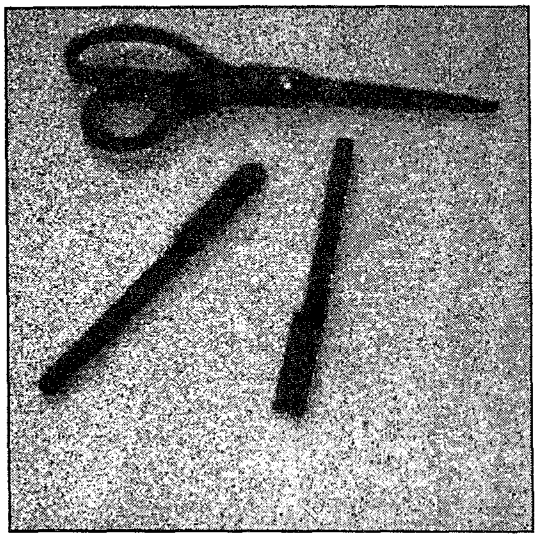

Figure 2: The noisy "office" image.

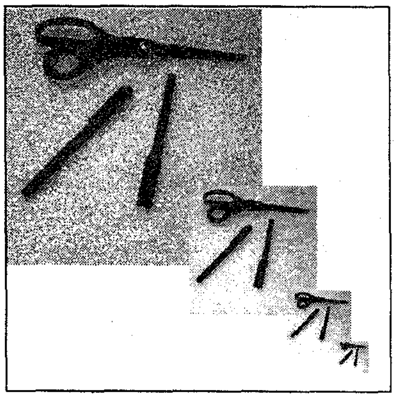

Figure 3: Levels 0-3 of the MP from Figure 2.

III. PYRAMID NODE LINKING

The segmentation and edge detection process is accomplished using a pyramid node linking technique [4] on the MP. A child-parent relationship is defined between nodes (pixels) in adjacent levels. For each node in level L there is a 4x4 region of candidate child nodes at level L-1 and 4 candidate parent nodes at level L+1. Links between adjacent levels in the pyramid are formed based on the absolute differences in intensity. Each node is linked to a single candidate parent as follows:

$$I_L(i,j) = I_{L+1}(\mathrm{int}(\frac{i}{2}) + a, \mathrm{int}(\frac{j}{2}) + b). \tag{5}$$

where

$$(a,b) = \arg_{(m,n)} \left[\inf \left| I_{L+1}(\mathrm{int}(\frac{i}{2}) + m, \mathrm{int}(\frac{j}{2}) + n) - I_L(i,j) \right| \right] \tag{6}$$

and $(m,n) \in \{(0,0),(0,1),(1,0),(1,1)\}$. This process commences at the root level (the coarsest scale used in the segmentation) and repeats until the pixel values of level 0 (the retinal level) are linked to pixels on the root level R. The choice of R determines the maximum possible number of segments and the size of the smallest region to be detected.

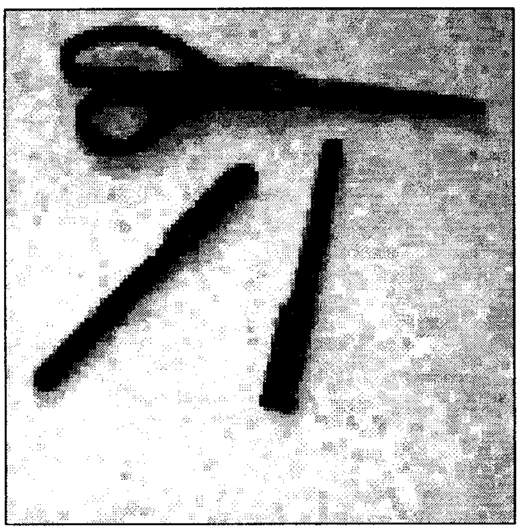

Figure 4: MP level 1 (128x128) using Figure 2 as pyramid base.

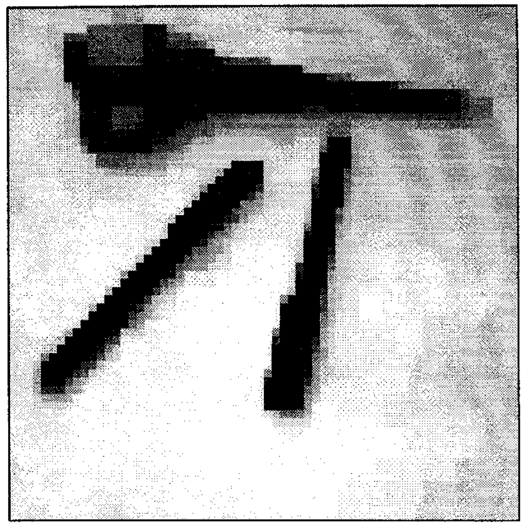

Figure 5: MP level 2 (64x64) using Figure 2 as pyramid base.

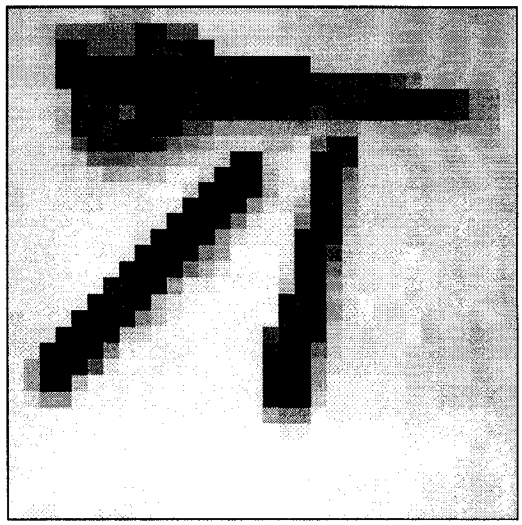

Figure 6: MP level 3 (32x32) using Figure 2 as pyramid base.

Given that the smallest region desired in the segmentation has a minimal width of d,

$$R = \max\{L : L < \log_S d - 1\} \tag{7}$$

Here S denotes the sampling spacing and d may be considered the minor axis of the smallest segment.

Through linking, segments are formed in level 0 from the coarse-to-fine segmentation originating at level R. From the segmented image, an edge map is generated by simply locating the boundaries between the segments. A threshold is not needed with this approach.

IV. RESULTS

The performance of MP-based edge detector is compared to another multiresolution edge detector – the ADP-based edge detector reported in [2]. Using Figure 2 as the input image, the MP with R=3 yields the edge map shown in Figure 7. The edge map created by the ADP edge detector (using R=3) is shown in Figure 8. Both methods yield excellent edge localization, and create continuous, thin edge contours that reflect the structurally significant objects in the scene. Note that the MP created connected regions for both the scissors and the pens while the ADP generated false gaps in these objects.

The MP also outperforms the traditional gradient-based edge detectors in the presence of noise. A noisy infrared (IR) image is shown in Figure 9. By simply thresholding the gradient magnitude of the image in Figure 9, no suitable edge map may be achieved (see Figure 10). However, the MP-based method provides a clear delineation of the aircraft and of the clouds (see Figure 11). One drawback of the MP technique may be observed in Figure 11 – the contours lack the smoothness given by linear methods such as the Laplacian-of-a-Gaussian.

Because the MP is constructed using simple morphological operations, it is an efficient vehicle for real-time applications. The computational complexity of the MP and that of the ADP are in stark contrast. For one level of the MP, the number of comparisons (adds) for the closing is $2M^2P^2$, where M is the size of structuring element (=3 typically), and P x P is the image size. For one level of the ADP, there are $8kP^2$ floating point (f.p.) addition operations, $8kP^2$ f.p. multiplication operations and $4kP^2$ f.p. exponential operations involved, where k is the number of diffusion iterations. Clearly, the construction of the ADP is more expensive than creation of the MP.

Although many analytical questions remain open, we can conclude that the MP provides a viable, efficient structure for multiscale edge detection.

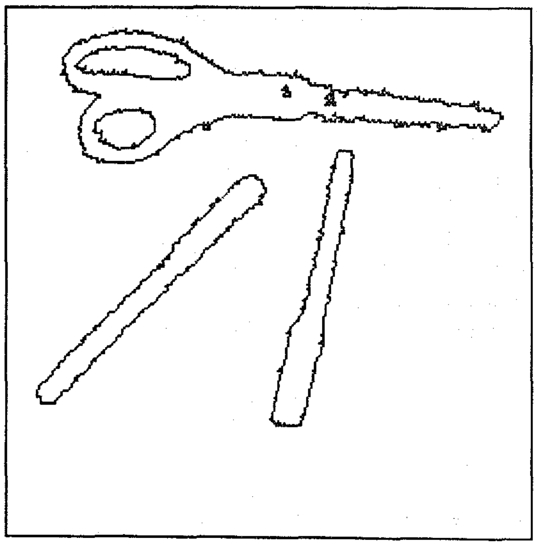

Figure 7: Edges from the MP of Figure 2.

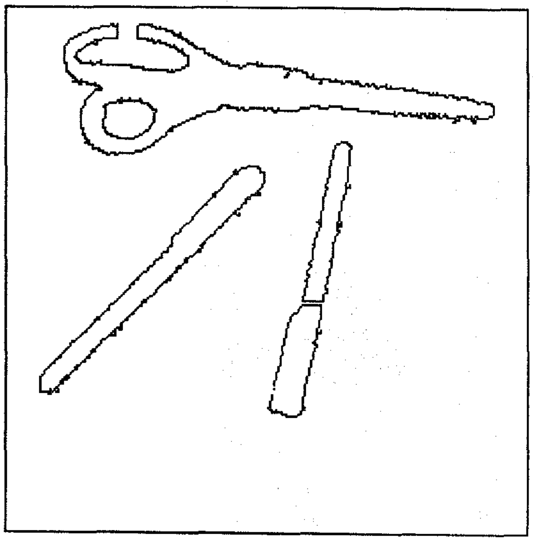

Figure 8: Edges from the ADP of Figure 2.

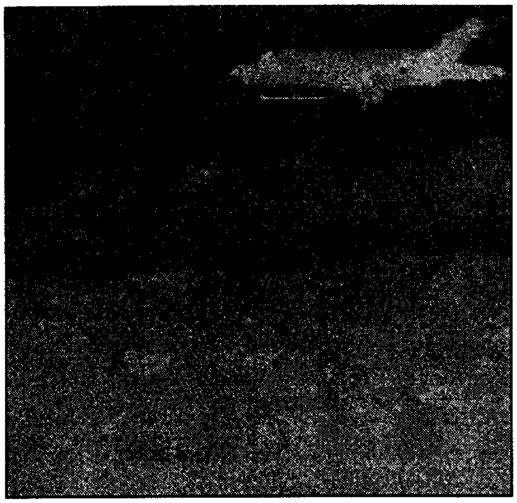

Figure 9: Noisy IR image.

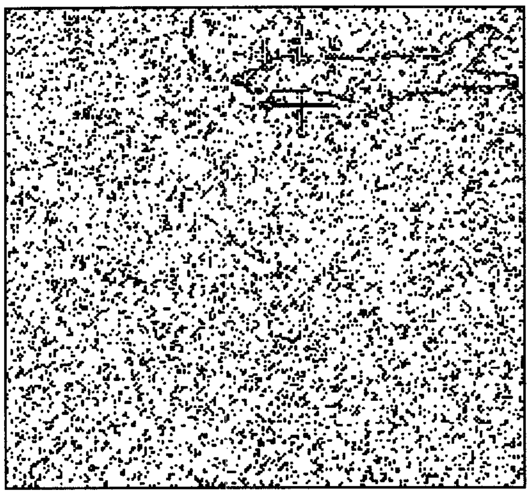

Figure 10: Edges from the gradient magnitude of Figure 9.

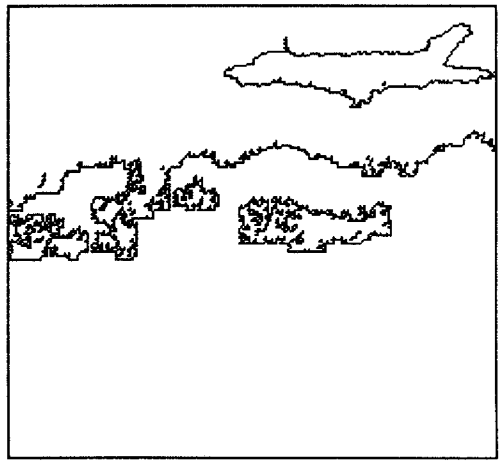

Figure 11: Edges from the MP of Figure 9.

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