IAPR Workshop on CV - Special Hardware and Industrial Applications OCT.12-14, 1988, Tokyo

MULTIRESOLUTION IMAGE DYNAMIC THRESHOLDING

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ABSTRACT

This paper presents a pyramid-based method of dynamic thresholding, in which we use the Gaussian pyramid to support our "coarse-to-fine" search strategy. At the top level of the pyramid, we divide the image into four subimages and in each subimage we analyze the gray level varince to find wether there is edge or not. We do the hierachical search until we reach the bottom of the pyramid. At the bottom level of the pyramid, the original image, we estimate the thresholding values in these subimages in which there is edge and assign zero to the thresholding values in those sub-images in which there is no edge. Finally, by subimage-wise threshold values interpolation and pixel-wise threshold values interpolation, we find the dynamic threshold values.

INTRODUCTION

Thresholding is the oldest method for image segmentation. The importance of thresholding segmentation is based on its simplisity and its wide applicability. It is useful because it is a data reduction step and produces a binary representation of an image. Wide selections of thresholding techniques use the information contained within the gray level histogram of the image. The most general method involves locating all the modes of the histogram. A popular thresholding method assumes that the gray value histogram contain two and only two prominent modes and they are both Normally (Gaussianly) distributed. The method fits the observed histogram to a sum of Gaussians with the distribution means and widths as parameters. The problem of such an analysis is the computational complexity and its sensitivity to the corrections of the underlying assumption. The authors surveyed many other methods of selecting the threshold value in the previous paper [1].

Dynamic thresholding is developed based on the fixed-value thresholding. The aim of this paper is to present a new pyramid-based method of automatically selecting the threshold values, and we use the Gaussian pyramid to support our coarse-to-fine search strategy. In the following section, we consider the multiresolution image (or pyramid) srtucture, within which many basic image operation may be performed efficiently. Section 3 presents the new method of dynamic thresholding and the final section gives the experimental result of practical cases.

MULTIRESOLUTION IMAGE (PYRAMID)

Multiresolution image[2-3] (image pyramid) is a data structure within which the input image is represented at successively reduced resolutions. As we proceed from the bottom level of the pyramid toward the top , local operations become capable of detecting globlal features in the input image. This property, as well as the small overhead in memory space relative to the input image, make the image pyramid an efficient tool in computer vision. Generally speaking, at each pyramid level the pixel array has square shape and the dimension of its sides is some power of two and the adjacent level arrays differ in size by a factor of four, the sides of the array at a given level are halved relative to the sides of the next lower level array.

The Gaussian pyramid is a sequence of images in which each is a low-pass filtered copy of its predcessor. Each level contains a representation of the original image at a scale of resolution that is twice as coarse as the level below it. Suppose the image is represented initially by the array which contains N columes and N rows of pixels. This

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image becomes the bottom or zero level of the Gaussian pyramid. Pyramid level 1 contains N/2 columes and N/2 rows of pixels, which is a reduced or low-pass filtered version of the level 0. Each value within level 1 is computed as a weighted (the weighting function is called generating kernel, being chosen subject to some constraints) average of values in level 0 within a 5X5 window. This process is repeated until, say 32X32 image is created as the apex of the Gaussian pyramid.

DYNAMIC THRESHOLDING

The dynamic threholding method proposed here is the development of [1]. In [1] we studied the gray value varince of the overlapped subimages of which the image is composed. If the varince of the subimage is greater than the given varince threshold, then we think that there is edge in the subimage and then estimate the gray level threshold value, otherwise we assign zero to the subimage gray level threshold. And by subimage-wise and pixel-wise interpolations of gray level threshold value, the dynamic thresholding is obtained. Multiresolution image dynamic thresholding is the extension of above mentioned method. We use the Gaussian pyramid to support the multiresolution image dynamic thresholding.

At the top level of the pyramid, we divide the image into four sub-images. The low resolution levels in the pyramid tend to blur the image and thus attenuate the gray level changes that denote edge. Thus the starting level in the pyramid must be picked up judiciously to ensure that important edges are detected. In each subimage of the top level of the Gaussian pyramid, consider:

$$f(i,j) = P_1 f_1(i,j) + P_2 f_2(i,j)$$

where P_1 and P_2 are the prior probabilities, $i,j = 0, 1, \ldots N-1$.

$$E[f] = P_1 E[f_1] + P_2 E[f_2]$$

$$= P_1 U_1 + P_2 U_2$$

$$Var[f] = E[(f - E[f])^2]$$

$$= E[(P_1 f_1 + P_2 f_2 - P_1 U_1 - P_2 U_2)^2]$$

where U_1 and U_2 are the expectation values of $f_1(i,j)$ and $f_2(i,j)$ respectively. $f_1(i,j)$ and $f_2(i,j)$ are independent of each other, then the varince can be rewrite as

$$Var[f] = P_1^2 D_1 + P_2^2 D_2 + P_1 P_2 U_1 U_2$$

where D_1 and D_2 are the v arince of $f_1(i,j)$ and $f_2(i,j)$ respectively. if

$$D_2 = D_1 + D_r$$

$$U_2 = U_1 + U_r$$

Above equations are the relation between the objects and background of image in mean and varince. Then the gray level varince of image is

$$Var[f] = D_1 + (U_r^2 + D_r)/4U_r^2 -$$

$$U_r^2 (P_2 - (0.5 + D_r/2U_r^2))^2$$

Often $D_r \ll U_r^2$, so when $P_2 = 0.5$ the varince reaches the maximum. The varince first increases and then decreases as P_2 increases and the Varince vs P_2 curve is a parabala. Because the probability P_2 is the ratio of the areas of object to the area of subimage, when P_2 is far away from 0.5 (i.e. the varince is far away from the maximum) there is no edge in the subimage. Therefor the magnitude of Var[f] can be used as a indication of wether the subimage contains edge or not. So we think that if the varince is greater than a given value, there is edge in this subimage, if the varince is not greater than the given value, there is not any edge in this subimage. The same operation as we applied to the top level image is applied to the four subimages at the next higher resolution level corresponding to the sub-image in which there is edge. In the four subimages at the next higher resolution level corresponding to the subimage in which there is not any edge, we also think there is not any edge. We repeat the above process and do the hierachical search until we reach the bottom of the pyramid.

Now we find the gray level threshold values of the subimages at bottom level of the Gaussian pyramid. For all those subimages in which there is no edge, we assign zero to the threshold values for the time beings for the convenience of the following computations. For each subimage in which there is edge, let the threshold value be T and the gray level of object and background after threholding be G_1 and G_2, then the error function is

$$F(T,G_1,G_2) =$$

$$\sum_{i,j}\sum \{[f(i,j)-G_2]^2 . U[f(i,j)-T-1]$$

$$+ [f(i,j)-G_1]^2 . U[T-f(i,j)]\}$$

where

$$U(x) = \begin{cases} 0 & \text{when } x \leq 0 \\ 1 & \text{when } x > 0 \end{cases}$$

we rewrite the error function as

$$F(T,G_1,G_2) = \sum_{i=0}^{T} P_i(i-G_1)^2 + \sum_{T+1}^{N-1} P_i(i-G_2)^2$$

where P (i = 0...255) is the gray level histogram of the subimage. we minimize the error function and obtain the T

$$G_1 = \sum_{i=0}^{T} P_i \cdot i$$

$$G_2 = \sum_{T+1}^{N-1} P_i \cdot i$$

$$T = (G_1+G_2)/2$$

For those subimages whose threshold values are assigned to zero their thresholds are estimated from the neighboring subimages having computed thresholds. Then we find all the threhold values of all the subimages on the bottom level by subimage-wise interpolation of threshold values. Let the weighting function be

$$W(r) = f(r)$$

f(0) = 1, when r increases W(r) decreases. Let

$$Q(m,n,r) = \sum_{i,j \in R(m,n)} W(r).U[T(i,j)]$$

where (m,n) is the subimage whose threhold value is to be found by interpolation. T[i,j] is the threshold value of subimage (i,j). r is the distance in subimage between subimage (i,j) and (m,n). R(m,n) is neighborhood whose center is (m,n) and radius is r in subimage. When

$$r = r_0$$

$$Q(m,n,r\ ) = Q_0$$

Q_0 is a given value, a confident measure, we obtain the threshold value of the subimage:

$$S(m,n) = \sum\sum_{i,j \in R(m,n)} W(k).T(i,j)/Q_0$$

In fact this interpolation provides a smooth operation and make one threshold value associated with each and every subimage. Finally, we apply a bilinear pixel-wise interpolation of threhold values to assure continuity in the boundary points at border of two neighboring subimages with different thresholds and then we may obtain the dynamic threshold values of the image.

EXPERIMENTAL RESULT

Figure 1 is the Gaussian pyramid whose bottom level size is 256X256 and top level size is 32X32. we use the optimal generating kernel proposed by P.Meer, E.Baugher and A.Rosenfeld [4] to establish the Gaussian pyramid. The optimal kernel is better at preserving contrast, shape, and gray level detail and assures minimal information loss after the resolution reduction. Figure 2a-c are the results segmented with different fixed threshold values and Figure 3 is the segmented result using dynamic thresholding method proposed in this paper. It can be seen that the dynamic thresholding performs better than the ordinary thresholding method in detecting the bandtype of the human chromosome.

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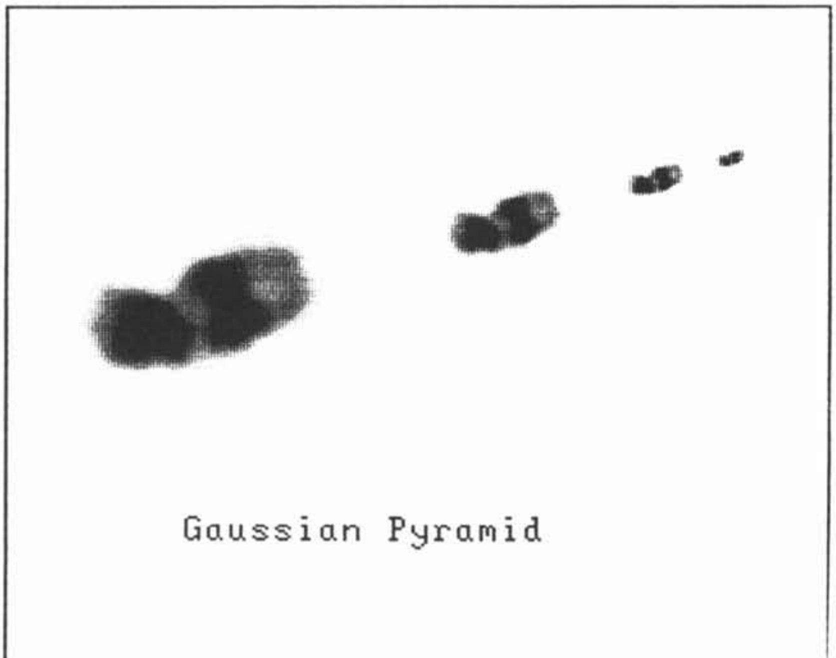

Fig. 1

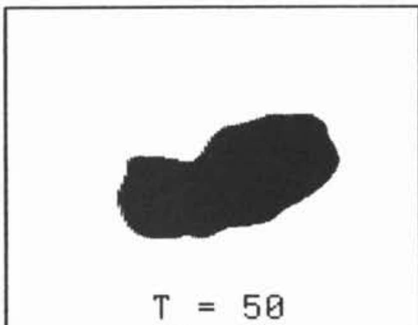

Fig. 2a

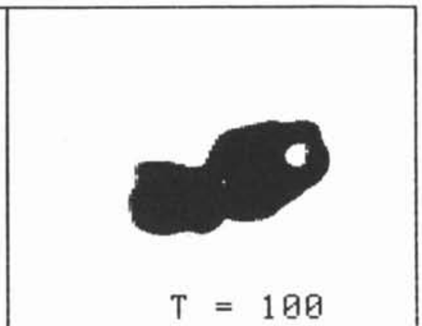

Fig. 2b

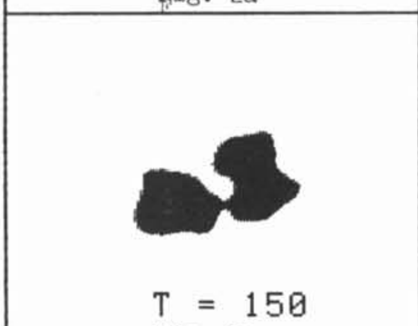

Fig. 2c

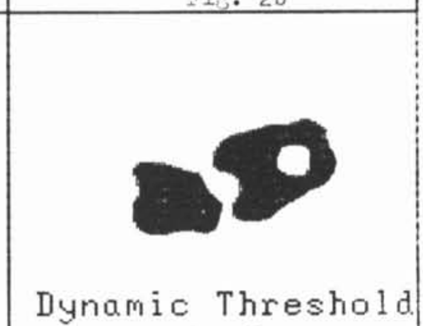

Fig. 3