Automatic Reference Color Selection for Adaptive Mathematical Morphology

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Abstract – This paper proposes the automatic reference color selection. The automatic reference color selection mechanism which enables the management of diverse color models. Both 1D and 2D histograms are used in this model. The histogram can be applied on a per- pixel basis where the resulting information is used to determine the most frequent color for the pixel location. Here, RGB and HSI technique is used to determine the most reference color. The main advantage is to avoid the ambiguity problem .The work to be implemented is to determine the dominant color using Kernel Density Estimation. The color image is segmented and the reference color is determined.

Index Terms – Adaptive mathematical morphology; Color image segmentation; Kernel density estimation; Reference color selection.

1. INTRODUCTION

In the past decade, mathematical morphology (MM) has been widely applied in image processing such as image retrieval, satellite imagery, template matching, aerial surveillance, and image segmentation. Such high-dimensional image data have facilitated the extension of MM from binary and gray-scale to color images, and even higher dimensions of visual features. This is crucial for the continual development of image processing, which tends to consider only the illumination information of pixels. However, the task of MM typically neglects the details of the image content. Because acquisition techniques for color images continue to advance and mature, their compatibility with extent algorithms should be extended, and must be as concrete as possible.

Managing a color image implies that the dimension increment of a feature vector and the computational complexity result in a longer execution time compared with manipulating a gray-scale image. In high-dimensional space, the interchannel correlation increases, reducing the computational cost and severing the correlation between channels challenging. MM has recently become widely used in image processing because of the advantage presented by set theory. Adaptive MM facilitates the application of high-dimensional image data, which can be extended from binary and gray-scale images to color images, and even to higher dimensions of visual features. The MM process is an application based on lattice theory in spatial structures. Understanding the relationship between pixels and sorting them according to their characteristics becomes crucial. However, ranking higher-dimensional vectors in a direct manner remains a challenge. Compared with a single-dimensional image (e.g., binary and grayscale), no standard ordering mechanism exists for color feature vectors. Color ordering for color morphological processing can typically be divided into two approaches: marginal-oriented and vector-oriented methods. The marginal-oriented approach involves operating each color component independently. In other words, the ordering method does not consider the marginal correlation between components, and treats each color component as a gray-scale image. By contrast, the vector-oriented approach performs color morphology as a vectorized ordering mechanism including reduced ordering, conditional ordering, and partial ordering. Numerous recent studies have proposed sequential ordering approaches of color.

Image processing is processing of images using mathematical operations by using any form of signal processing for which the input is an image, a series of images, or a video, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Images are also processed as three-dimensional signals with the third-dimension being time or the z-axis.

Computers are indispensable for the analysis of large amounts of data, for tasks that require complex computation, or for the extraction of quantitative information. On the other hand, the human visual cortex is an excellent image analysis apparatus, especially for extracting higher-level information, and for many applications including medicine, security, and remote sensing human analysts still cannot be replaced by computers. For this reason, many important image analysis tools such as edge detectors and neural networks are inspired by human visual perception models.

A.MORPHOLOGY

Morphology is a theory and technique for the analysis and processing of geometrical structures, based on set theory, lattice theory, topology, and random functions. MM is most commonly applied to digital images, but it can be employed as well on graphs, surface meshes, solids, and many other spatial structures.

Topological and geometrical continuous-space concepts such as size, shape, convexity, connectivity, and geodesic distance, were introduced by MM on both continuous and discrete spaces. MM is also the foundation of morphological image processing, which consists of a set of operators that transform images according to the above characterizations.

The basic morphological operators are erosion, dilation, opening and closing. MM was originally developed for binary images, and was later extended to grayscalefunctions and images. The subsequent generalization is widely accepted today as MM's theoretical foundation to complete lattices.

B.BINARY MORPHOLOGY

In binary morphology, an image is viewed as a subset of an Euclidean space or the integer grid, for some dimension d.

i. STRUCTURING ELEMENT

The basic idea in binary morphology is to probe an image with a simple, pre-defined shape, drawing conclusions on how this shape fits or misses the shapes in the image. This simple "probe" is called the structuring element, and is itself a binary image (i.e., a subset of the space or grid).

ii.BASIC OPERATORS

The basic operations are shift-invariant (translation invariant) operators strongly related to Minkowski addition. Let E be a Euclidean space or an integer grid, and A binary image in E.

iii.EROSION

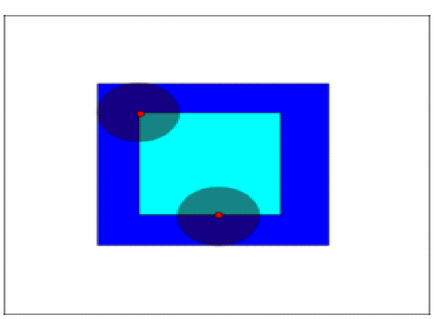

Fig.1 Erosion

The erosion of the dark-blue square by a disk, resulting in the light-blue square. When the structuring element B has a center (e.g., B is a disk or a square), and this center is located on the origin of E, then the erosion of A by B can be understood as the locus of points reached by the center of B when B moves inside A. For example, the erosion of a square of side 10, centered at the origin, by a disc of radius 2, also centered at the origin, is a square of side 6 centered at the origin.

Example application: Assume we have received a fax of a dark photocopy. Everything looks like it was written with a pen that is bleeding. Erosion process will allow thicker lines to get skinny and detect the hole inside the letter "o".

iv.DILATION

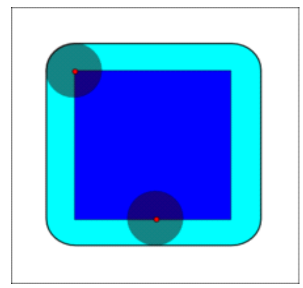

Fig.2 Dilation

The dilation of the dark-blue square by a disk, resulting in the light-blue square with rounded corners. If B has a center on the origin, as before, then the dilation of A by B can be understood as the locus of the points covered by B when the center of B moves inside A. In the above example, the dilation of the square of side 10 by the disk of radius 2 is a square of side 14, with rounded corners, centered at the origin. The radius of the rounded corners is 2.

Example application: Dilation is the dual operation of the erosion. Figures that are very lightly drawn get thick when "dilated". Easiest way to describe it is to imagine the same fax/text is written with a thicker pen.

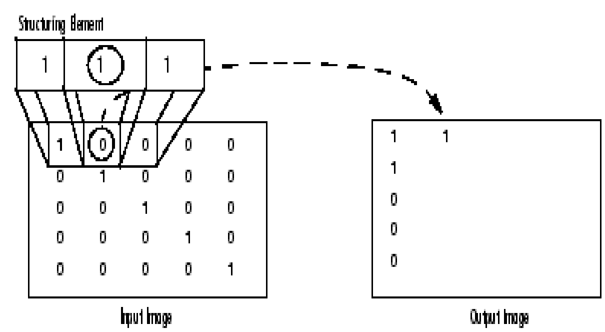

Fig.3 Morphological Dilation of a Binary Image

The following figure illustrates this processing for a grayscale image. The figure shows the processing of a particular pixel in the input image. Note how the function applies the rule to the input pixel's neighborhood and uses the highest value of all the pixels in the neighborhood as the value of the corresponding pixel in the output image.

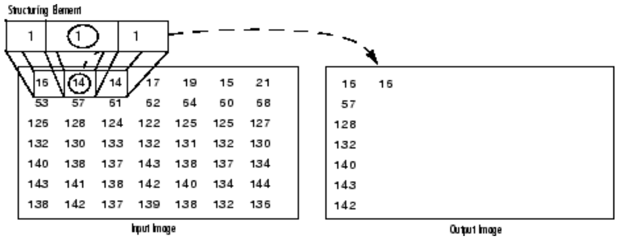

Fig.4 Morphological Dilation of a Grayscale Image

V.OPENING

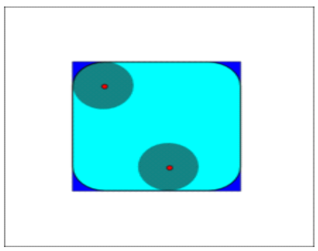

Fig.5 Opening

The opening of the dark-blue square by a disk, resulting in the light-blue square with round corners. Example application: Let's assume someone has written a note on a non-soaking paper and that the writing looks as if it is growing tiny hairy roots all over. Opening essentially removes the outer tiny "hairline" leaks and restores the text. The side effect is that it rounds off things. The sharp edges start to disappear.

vi.CLOSING

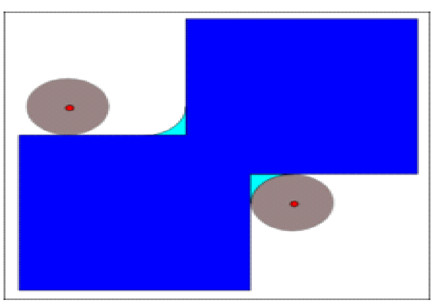

Fig.6 Closing

The closing of the dark-blue shape (union of two squares) by a disk, resulting in the union of the dark-blue shape and the light-blue areas

C.SEGMENTATION

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like Marching cubes.

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. There is also a balanced histogram thresholding.

Texture is encoded by lossy compression in a way similar to minimum description length(MDL) principle, but here the length of the data given the model is approximated by the number of samples times the entropy of the model. The texture in each region is modeled by a multivariate normal distribution whose entropy has a closed form expression. An interesting property of this model is that the estimated entropy bounds the true entropy of the data from above. This is because among all distributions with a given mean and covariance, normal distribution has the largest entropy. Thus, the true coding length cannot be more than what the algorithm tries to minimize.

The distortion in the lossy compression determines the coarseness of the segmentation and its optimal value may differ for each image. This parameter can be estimated heuristically from the contrast of textures in an image. For example, when the textures in an image are similar, such as in camouflage images, stronger sensitivity and thus lower quantization is required.

Histogram-based methods are very efficient compared to other image segmentation methods because they typically require only one pass through the pixels. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable.

This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in video tracking.

2. ACTIVE SYSTEM

A. COLOR REPRESENTATION AND COLOR DISTANCES

A typical color model used in image processing is the red–green–blue (RGB) representation. However, the RGB model has from an intrinsic disadvantage: a high correlation between color channels. In addition, it cannot be used to obtain the original intensity information of the image for reducing the computational burden during image acquisition. To overcome this limitation, we used color models that decouple the intensity component from the color-carrying information such as HSI and YCbCr. In color representation, we adopted a 1D histogram-based model from 3D color space such as RGB and HSI, and also used a 2D color model such as (H, S), (Cb, Cr), and (I, By). The statistical histogram of image f is obtained by solving (1), as follows: (1)The Kronecker delta function denotes the binning function for pixel in color model z, which enables the 3D HSI color model to transform as a -bit value, totaling bins, and denotes the bin index of the color histogram. In this study, we used 8 bits, where 4 bits were from the H component, and 2 bits were each from the S and I components. Otherwise, when $z = \{(H, S), (Cb, Cr), (I, By)\}$, we employed a 2D histogram with 256-by-256 bins. Because the dimension of the color space is mostly larger than 1, it is critical to determine the actual relationship between the value of the color distance and the awareness of the human eye. The International Commission on Illumination (CIE) defines a distance metric Delta-E (dE), which is a single number that represents the distance between two colors. When a dE of 1.0 is the smallest color difference discerned by the human eye, a dE less than 1.0 is imperceptible. However, certain color differences greater than 1 are acceptable, despite perhaps being unnoticeable. The major problem of dE involves resolving the perceptual uniformity issue inadequately. A certain dE that may be meaningless between two colors because it cannot be perceived may be conspicuous in another part of the spectrum. The CIE constantly corrects and modifies this benchmark. dE2000 is the first major revision of the dE94 equation. Unlike dE94, which assumes that L* (where the L*a*b* color space) correctly reflects the perceived differences in lightness, dE2000 varies the weighting of L* depending on where in the lightness range the color falls. The dE2000 equation is still under consideration and does not seem to be widely supported in graphical arts applications. The equation is also useful for dE measurements when an image includes many layered colors such as the fading effect. This is a rare condition for natural images. Consequently, the use of the dE color distance for image segmentation is negligible.

3. BLOCK DIAGRAM

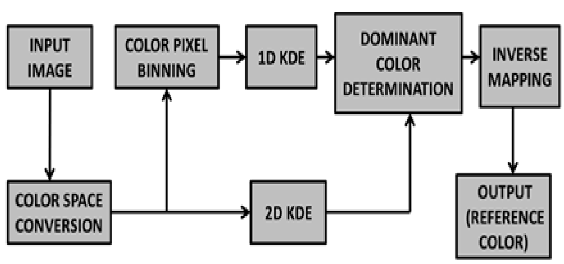

Fig.7 Block diagram

A.AUTOMATIC REFERENCE COLOR SELECTION SCHEME

The major criterion for color selection theoretically entails selecting the pixel that is most distant from the tested color pixel. It represents the distinguishing ability between two color pixels. Numerous researchers have simply employed black as the reference color. T he efficiency of ordering depends heavily on the distribution of the image color. The most appropriate reference color is selected using the complementary color of the dominant color. This method evidently yields the distance measure for achieving the highest discriminative ability. histograms are a common strategy for representing medium-size color distributions in 1D or 2D space. Because of the limited image size, it is possible to form sparse bins and few pixels per bin for the histogram. Consequently, the peak of the histogram is dominated by noise. A hybrid color-ordering (HC ordering) method, which takes advantage of R- and C-ordering. This method sustains the advantages of R-ordering by reducing the dimension of the feature vector to lower the computational cost, but also avoids the ambiguous condition generated by C-ordering when measuring the importance of the color vector. In addition, the reference color can be determined using the proposed ARCS scheme.

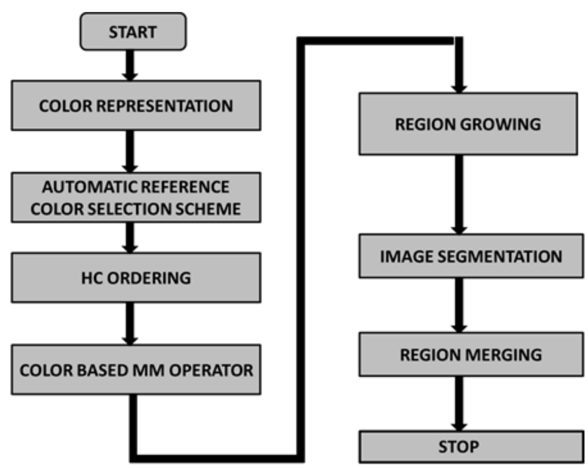

Fig.8 Flow Chart

B.2D-KDE

A KDE is a nonparametric graph that can reconstruct an unknown population from a random data sample. The KDE does not use regression for fitting a distribution to the data. The simple concept underlying kernel estimates is that each bin, w=1, 2, …, n is drawn from an unknown density histogram , which is replaced by a specified distribution (e.g., normal), centered on the point, and with a standard deviation designated by a smoothing parameter (called the bandwidth, and >0). We were interested in estimating the shape of this function . Its kernel density estimator can be expressed as

$\hat{h}(s) = 1/nhs \ \ \Sigma w=1 \Phi hs(j-jw/hs)$ for $0 \le j \le n$

4. RESULTS OF SIMULATION

The image given as input is analysed. The algorithm developed in the MATLAB environment gives the following results as shown in Fig. The parameters of the image is found out and the preferred colour is determined.

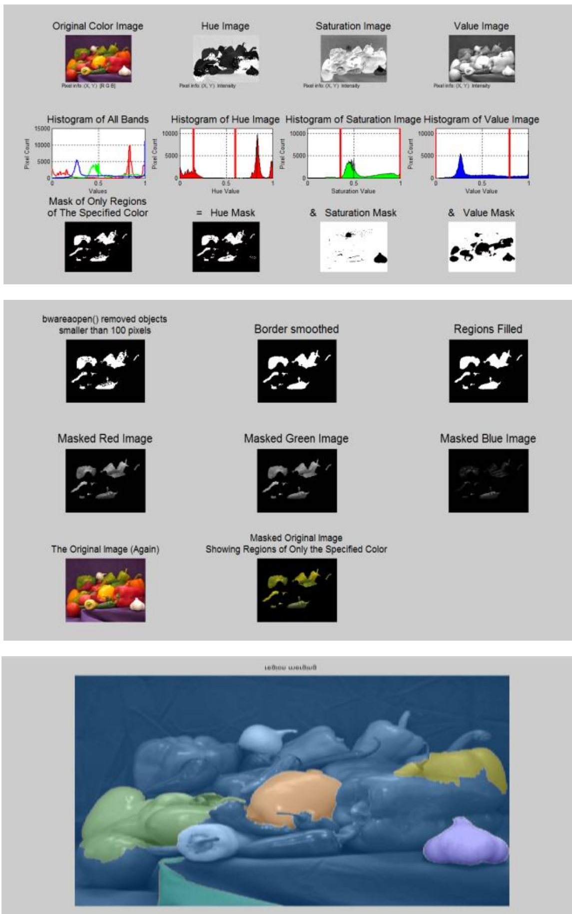

Fig.9 Simulated Output

5. CONCLUSION

The ARCS scheme was used to determine the optimal reference color for MM and color image segmentation application. We also used 1D histogram-based modeling scheme binning from 3D color spaces such as RGB and HSI, and adopted 2D color models such as (H, S), (Cb, Cr), and (I, By). The experiments revealed that the segmentation result obtained using the (I, By) color model more accurately reflected subjective human perception. The presented adaptive merging algorithm with the ARCS scheme and HC-ordering algorithm used for MM-based image segmentation outperformed typical segmentation methods. We proposed an alternative method based on quartile analysis, and successfully avoided the HC-ordering method for an additional threshold determination step. This approach rendered region merging simpler and more practical.

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