ASSIGNMENT-10

10.1 What is image segmentation and why might one want to segment an image? Describe an image segmentation algorithm and explain its advantages and disadvantages.

Ans. The division of a digital image into many pieces is known as image segmentation (sets of pixels, also known as image objects). The purpose of segmentation is to make an image more intelligible and easier to examine by simplifying and/or changing its representation. In most cases, image segmentation is used to locate objects and boundaries (lines, curves, and so on) in images. Image segmentation, to put it another way, is the process of giving a label to each pixel in an image so that pixels with the same label share certain properties.

One of the Image Segmentation Algorithm is "Thresholding Segmentation".

In image processing, the threshold approach is the simplest way of segmentation. It divides an image's pixels by comparing the intensity of each pixel to a predetermined value (threshold). When the required object has a higher intensity than the background, this technique comes in handy (unnecessary parts).

The threshold value (T) can be thought of as a constant, but only if the image has very low noise (unnecessary information and data). Depending on your needs, you can make the threshold value fixed or dynamic.

By separating a grayscale image into two segments, the thresholding approach converts it to a binary image (required and not required sections).

The significance threshold is determined during the design stages of an A/B test and relates to the risk of making a type I error (registering a false positive) that is regarded acceptable in the given conditions. The sample size required for a uniformly most powerful test at that threshold, as well as the stated minimum effect of interest and statistical power against a composite hypothesis with a lower bound at the MEI, is calculated using the threshold.

The measured p-value is compared to the threshold once the test is finished, and if it is lower, the null hypothesis is rejected.

Threshold-based techniques have the major disadvantage of lacking the sensitivity and specificity required for accurate categorization. The true positive rate (TPR) of a function or test that must detect the presence or absence of some intrinsic attribute is referred to as sensitivity (for example, tissue type). As a result, the test's goal is to establish whether this inherent quality exists as precisely as feasible. A binary test's sensitivity is defined as follows in formal terms:

$$Sensitivity = TPR = \frac{\sum True+}{\sum Intrinsic+}, \tag{2.1}$$

where *True+* is defined as the number of samples that have the intrinsic property *and* were categorized by the test as positive, and *Intrinsic+* is defined as the *total* number of elements that have the intrinsic property (regardless of the outcome of the test).

10.2 Explain the basis for optimal segmentation using the Otsu method.

Ans. Automatic image thresholding is performed using Otsu's approach, named after Nobuyuki Otsu. The method returns a single intensity threshold that divides pixels into two classes: foreground and background in its most basic form. This limit is set by limiting intra-class intensity variance, or, in other words, maximizing inter-class variation. Otsu's approach is a one-dimensional discrete version of Fisher's Discriminant Analysis, is connected to Jenks optimization, and is comparable to a globally optimal k-means on the intensity histogram.

Otsu’s Method:

The algorithm looks for the lowest threshold that minimizes intra-class variation, which is defined as the weighted sum of the two classes' variances:

$$\sigma_w^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t)$$

Weights ω_0 and ω_1 are the probabilities of the two classes separated by a threshold t ,and σ_0^2 and σ_1^2 are variances of these two classes.

The class probability is computed from the bins of the histogram:

$$\omega_0(t) = \sum_{i=0}^{t-1} p(i)$$

$$\omega_1(t) = \sum_{i=t}^{L-1} p(i)$$

Algorithm:

1. Compute histogram and probabilities of each intensity level
2. Set up initial $\omega_i(0)$ and $\mu_i(0)$
3. Step through all possible thresholds $t = 1, \ldots$ maximum intensity
    1. Update ω_i and μ_i
    2. Compute $\sigma_b^2(t)$
4. Desired threshold corresponds to the maximum $\sigma_b^2(t)$

10.3 Explain the difference between contextual and non-contextual segmentation methods.
Ans.

10.4 What segmentation method is particularly useful for segmenting images that contain a variable background? Explain the basis of the method and why it works.
Ans.

10.5 Distinguish between automatic and semi-automatic methods of segmentation, giving examples of each.
Ans.

10.6 Design an energy term for a snake to track lines of constant gray value.
Ans.

10.7 Illustrate the use of the distance transform and morphological watershed for separating objects that touch each other.

Ans. Watershed segmentation transforms an image into a topographic landscape with hills and valleys. To determine the elevation values of the terrain, the gray values of the appropriate pixels or their gradient magnitude are frequently employed. On the basis of this 3D representation, the watershed transform divides a picture into catchment basins. All sites whose steepest fall route finishes at the local minimum form a catchment basin. Watersheds divide basins. The watershed transform decomposes an image completely, assigning each pixel to one of two sections, or watersheds. When medical image data is noisy, a massive number of little patches arise. The "over-segmentation" problem is what this is known as. Two common approaches for distinguishing touching items in binary images are the distance transform and the watershed approach. The purpose is to create a barrier as far away from the overlapping objects' center as possible. The Distance Transform Watershed approach is ideal for spherical structures. The procedures needed are calculating the distance transform of the binary image, inverting it (so the darkest portions of the image are the centers of the objects), and then applying watershed to it using the original image as a mask. In our solution, we provide the option of using watershed with extended minima so that the user can control the number of object splits and merges. In its most basic form, the Distance Transform Watershed technique. A confocal laser scanning microscope sample image of touching DAPI stained cell nuclei, a binary mask calculated after filtering and thresholding the input image, the inverse of the distance transform applied to the binary mask (Chamfer distance map using normalized Chessknight weights and 32-bit output), and the resulting labeled image after applying watershed to the inverse distance image using the binary mask, and the resulting labeled image after applying watershed to the inverse distance image using the (dynamic of 1 and 4-connectivity).

Distance map options

Distances: allows you to choose from a pre-defined set of weights that may be used to compute the distance transform using Euclidean metric Chamfer approximations. They have an impact on the final result's position, as well as the form of the border. The choices are as follows:
Chessboard (1,1): all neighbors have the same weight.

Weights 1 for orthogonal neighbors and 2 for diagonal neighbors in City-Block (1,2).
Weights 1 for orthogonal neighbors and 2- for diagonal neighbors in the quasi-Euclidean (1,1.41) model.
Borgefors (3,4): weights 3 and 4 for orthogonal and diagonal neighbors, respectively (best approximation of Euclidean distance for 3-by-3 masks).
Weights (2,3): weights 2 and 3 for orthogonal and diagonal neighbors, respectively.
Weights (5,7): weights 5 and 7 for orthogonal and diagonal neighbors, respectively.
Weights 5 for orthogonal neighbors, 7 for diagonal neighbors, and 11 for chess-knight movements in.

10.8 Explain why the watershed lines of a binary image correspond to the "skiz" lines.

Ans. The watershed algorithm is a well-known segmentation method for identifying different items in a photograph. Starting with user-defined markers, the watershed approach considers pixel values as a local topography (elevation). Watershed lines connect basins assigned to distinct markers as the algorithm floods basins from the markers. Local minima from which basins are inundated are commonly depicted using markers. It's time to divide two circles that are overlapping. To do so, one must first draw an image that depicts the distance between the foreground and the background. The distance's maxima (i.e., the polar opposite of the distance's minima) are used as markers, and the flooding of basins from these markers separates the two circles along a watershed line. Segmentation using the watershed transform works better if you can identify or "mark" foreground objects and background locations. The following is the basic methodology for segmenting watersheds using markers:

Using the data you've acquired, create a segmentation function. The things you're seeking to segment in this image are the black areas.

Make a list of the markers that will be visible in the foreground. There are connected blobs of pixels inside each of the items.

Make a list of all the markers you want to use as a background. This is a collection of unattached pixels.

By adjusting the segmentation function, you can only have minima at foreground and background marker positions.

Determine the watershed transform for the modified segmentation function.

To begin segmenting the data, the algorithm must first identify starting points. A typical method for selecting markers is the gradient local minimum. Seed sites can be chosen in a number of ways. A user-controlled marker selection is included in our HTML5 demo app. Use your left and right mouse buttons to select foreground and background areas. Some studies discuss automatic seed selection strategies such as binarization, morphological opening, distance transform, and other techniques.