Advanced Digital Signal Processing
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Analysis on various techniques for Signal Estimation from a set of Mixtures in Images

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***Abstract*—An image is a complex signal, consisting of a number of different features contained within. The image, hence, can be presented as a number of different signals present within one image signal. In this project, we have tried different methods for identifying and extracting these individual signals from an image. For identifying the individual features, we may either use the discontinuity based approach, that is, identifying discontinuities and using them to define the boundaries between features, or the similarity based approach, where the image is divided into regions based on their similarity. Discontinuity based approach for image segmentation is manifested in the form of edge detection techniques like gradient-based edge detection and gaussian-based edge detection. On the other hand, similarity based approach for image segmentation is demonstrated in the form of thresholding and region-growing.**

Fig. 1: Image Edge Detection

I. Introduction

In an image, an edge refers to a locality where a significant change in intensity occurs. An edge is generally a line of pixels, and acts as the division between two regions of differing intensities. Edge detection, fundamentally, involves the detection of a rapid change in intensity of pixels over a lateral region. The greater the extent of the change, higher is the visibility of the edge in the image. Edge detection helps in picking out significant features of the image, recognizing patterns and in general morphological analysis of the images. As it involves recognizing changes, it mainly depends upon calculating the derivative of intensity. On the basis of the degree of derivative, they are divided into Gradient-based and Gaussian-based edge detection. We use a kernel, essentially a matrix, as a tool to identify pixels which fall on borders between two dissimilar regions. The value derived from the mask allows us to notice a sharp rise or fall in the value of intensity, and hence detect the edges.

II. State of the art survey

For the last few decades, image processing has been widely used. Image segmentation is one of the most important parts of image analysis. Most of the major applications which use image-based application need segmentation either at pre-processor level or at advanced level. Mass application like Object Recognition, Scene Understanding, Automatic Traffic control systems, Locating Objects in satellite images like roads, maps etc.need image segmentation as a major step.

A. Segmentation Techniques

Segmentation is a pre-processing step which partitions images into multiple unique regions, where a region is a set of pixels.

1) Threshold-based techniques: Threshold-based techniques are generally used for gray scale images. It is one of the popular techniques as it is very simple to implement. But additional tools and techniques are required if we want to use it for colour and synthetic images.

2) Histogram-based techniques: In this techniques first histogram of all the pixels are calculated and according to peaks and valleys, different clusters are formed. Refinement techniques are applied on these cluster for further processing.

3) Edge detection techniques: Edge detection till now is the most common approach for detecting meaningful discontinuities in gray level. First and second order derivatives like gradient and laplacian are used for detection of edges in an image.

4) Region-based techniques: It includes Region growing and Region splitting-merging procedures.

5) Watershed Transformation techniques: The Watershed transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities correspond to watershed lines, which represent the region boundaries. The watershed placed on any pixel is enclosed by a common watershed. Lines flow downhill to a common local intensity minima. Pixels draining to a common minimum form a catchment basin, which represent the watershed regions. Direct application of this segmentation algorithm generally leads to over segmentation due to noise and other local irregularities of the gradient.

6) Graph Partitioning techniques: In this method, the image being segmented is modeled as a weighted undirected graph. Each pixel is a node in the graph, and an edge is formed between every pair of pixels. The weight of an edge is a measure of the similarity between the pixels. The image is partitioned into disjoint sets by removing the edges connecting the segments.

7) Ontology: Ontology is an "explicit specification of a conceptualization". Formally An ontology structure O is defined as : $O = \{C, R, A°\}$, Where

- C is a set of elements , called concepts.
- $R \subseteq CXC$ is a set whose elements are called relations.For $r = (c1, c2) \in R$, one can write $r(c1) = c2$.
- A° is a set of axioms on O.

III. Pre-Processing

Before applying edge detection techniques, it becomes imperative to remove any kind of noise or uneven illumination from the image, to avoid errors from cropping up when edge detection is carried out.

A. Noise Removal

- **Averaging Filter:** In this method, a pixel's value is taken as the average of the value of its surrounding pixel, creating a smoother transition between pixels and suppressing abrupt noises. The average can be weighted to give more value to those pixels closer to the centre to provide a better averaging.
- **Median Filter:** In this method, the centre pixel is the median of the surrounding pixels around it.

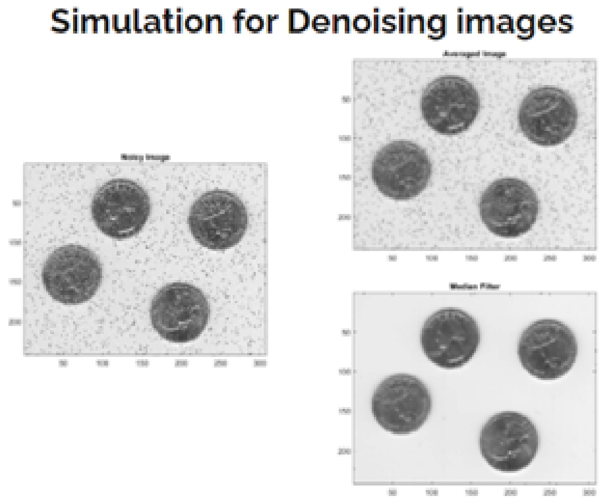

Fig. 2: Denoising Images

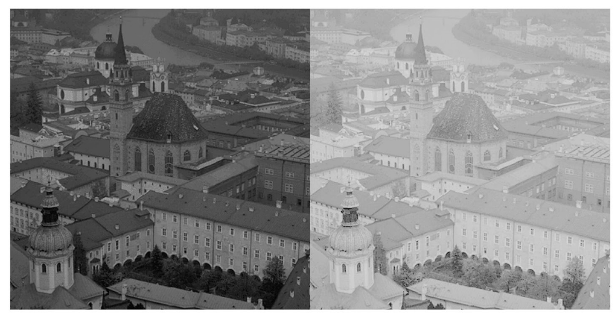

Fig. 3: Homomorphic Filtering for Removing Non-uniform Illumination

B. Illumination Correction

Generally, homomorphic filtering is used to rectify non-uniform illumination in the image. In spatial domain, Illumination and reflectance are in a multiplicative relation in the image, and it is not easy to correct just one of the two. It involves mapping the image into a non-linear domain like logarithm space to a domain in which linear filters are applicable and then, the higher-frequency i.e., the reflectance component and the lower-frequency i.e., the illumination component can be separated, and suppressing one of them before applying a filter to remove the contribution of illuminance part and get a uniformly illuminated version. Finally, the rectified image is mapped back to the original domain.

IV. Gradient Based Edge Detection

Gradient based edge detection depends upon the first order derivatives in the image. Commonly used algorithms include the Sobel operator and Prewitt operator, which utilize kernels to detect edges in the x-axis and y-axis, that is, vertical and horizontal edges. Changes in intensity appear as spikes, on charting the derivative. Positive spikes represent a change from a darker to a lighter intensity and vice-versa.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Fig. 4: Sobel Kernel

-1	0	+1
-1	0	+1
-1	0	+1

G_x

+1	+1	+1
0	0	0
-1	-1	-1

G_y

Fig. 5: Prewitt Kernel

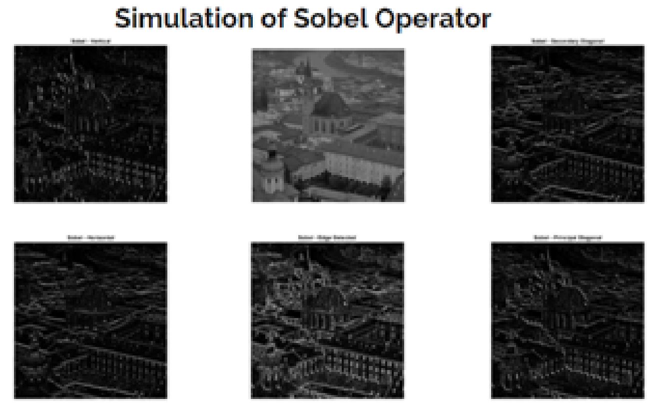

Fig. 6: Simulation for Sobel Operator

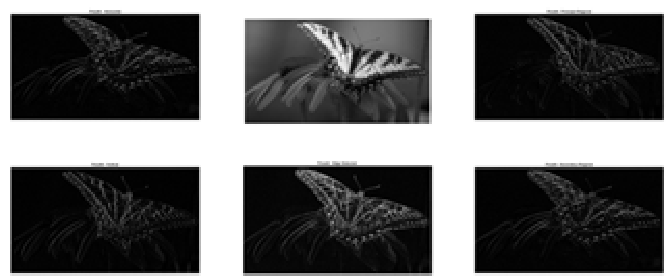

Fig. 7: Simulation for Prewitt Operator

A. Sobel Operator

It involves convolving a simple 3x3 kernel to calculate the derivative of the image. Two different kernels are needed to pan the two axes of the image. It uses a weighted function, where the pixels closer to the centre pixel have a higher contribution compared to those farther away. Sobel operator, being computationally simple and inexpensive, suffers from gross inaccuracy, and gives quite thick, smudged edges that introduce inaccuracies in the processed image.

B. Prewitt Operator

Similar to the Sobel operator, it too involves convolving two 3x3 matrices along both the axes of the image. But the Prewitt operator is not a weighted function, and gives equal weight to every pixel. As with Sobel operator, it is computationally inexpensive, but inaccurate and produces thick, smudged edges.

V. Gaussian Based Edge Detection

To overcome the relative inaccuracies resulting from the finite spread of the peak in gradient-based edge detection, we may use the second derivative of the image to locate the edges instead. As the edges are located on the zero-crossing of the graph, they are therefore able to be located more accurately. The graph changes from positive to negative when the intensity changes from darker to lighter and vice-versa. Gaussian-based edge detection includes Laplacian of Gaussian and Canny Edge Detection algorithms.

A. Laplacian of Gaussian

The Laplacian of Gaussian function, as evident in the name, uses the laplacian, or the two-dimensional partial derivative of the gaussian function of the image. The function is more computationally intensive and complicated mathematically, but provides better edge detection and sharper boundaries than gradient-based operators. There is only a single kernel we need to convolve with the image. The disadvantages of the LoG algorithm also exist. It is extremely sensitive to noise. Further, it does not preserve the curved edges very well. Finally, the LoG function introduces a lot of artificial noise in the final image when it is used for sharpening.

B. Canny Edge Detection

The Canny edge detection is a multi-step algorithm developed by John F. Canny in 1986. Canny Edge Detection is less sensitive to noise than any of the traditional methods, and also far more accurate than the methods discussed earlier, but simultaneously, it was also much more complex a task computationally. It consists of five steps:

- **Step 1 - Smoothing:** Smoothing, or blurring, is done to rid the image of noises. This is generally achieved by the means of an averaging mask.
- **Step 2 - Gradient Edge Detection:** A rough estimate of the edges is extracted using a gradient edge detection algorithm like Sobel or Prewitt operator.
- **Step 3 - Non-Maximum Suppression:** In this step, those pixels which do not correspond to a local maxima along an axis are removed, and only the highest local values, or maxima, are retained to produce single-pixel thick edges.

0	1	1	2	2	2	1	1	0
1	2	4	5	5	5	4	2	1
1	4	5	3	0	3	5	4	1
2	5	3	-12	-24	-12	3	5	2
2	5	0	-24	-40	-24	0	5	2
2	5	3	-12	-24	-12	3	5	2
1	4	5	3	0	3	5	4	1
1	2	4	5	5	5	4	2	1
0	1	1	2	2	2	1	1	0

Fig. 8: Laplacian of Gaussian Kernel

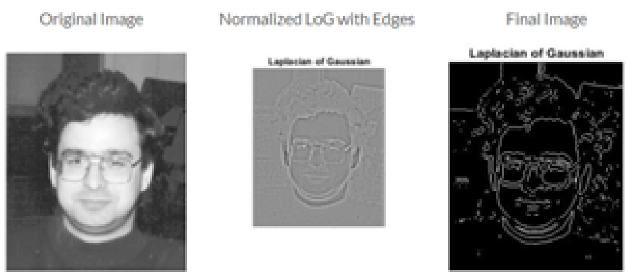

Fig. 9: Simulation for Laplacian of Gaussian

- **Step 4 - Double Thresholding:** The technique of thresholding is applied next, wherein two thresholds are set up. Pixels over the higher threshold are classified as strong edges, and those that fall in between the two thresholds are classified as weak edges. Everything below the lower threshold is suppressed to give a crisper boundary outline.
- **Step 5 - Edge tracking by Hysteresis:** In the final step, the weak edges which are connected to one strong edge are converted into strong edges, while those which are not connected to any strong edge are again suppressed, giving extremely clear boundaries in the image.

VI. Image Thresholding

Image thresholding is used to convert the image pixels into binary levels. The input to such a thresholding algorithm is usually a grayscale image and a threshold. The output is a binary image.

A. Global thresholding

Global thresholding consists of setting an intensity value (threshold) such that all pixels having intensity value below the threshold belong to one phase, the remainder belong to the other. Global thresholding is as good as the degree of intensity separation between the two peaks in the image. It is an unsophisticated segmentation choice. An example for global thresholding as given in the Fig. 11 in which we can observe that for a threshold value of 127 the individual components of the image can be segregated. The global thresholding option in 3DMA allows the user to pick a single global threshold for a 3D image or separate thresholds for each 2D slice in the image. Some experimental options has also been provided to provide automatic choice of threshold by performing a binormal fit to the two-peak histogram and setting a threshold at the interpeak minimum as determined by the normal fits.

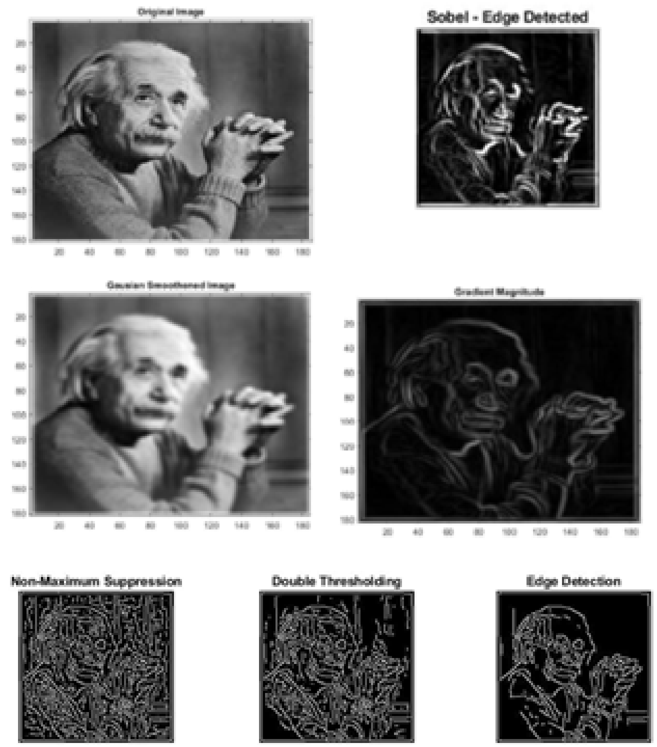

Fig. 10: Canny Edge Detector

B. Otsu's Method for Global thresholding

It is a method which involves iterating through the all possible threshold values and calculate a measure of spread for pixel level in each side of threshold, that is, the pixels either fall on the background or the foreground,

- First it creates a histogram of the input image.
- Within class variance - Then it divides the histogram levels based on the given threshold into 2 levels (segregate background and foreground).
- Between class variance - it takes into account variance difference of 2 classes.

The main aim is to find the value where the sum of background and foreground spread is minimum.

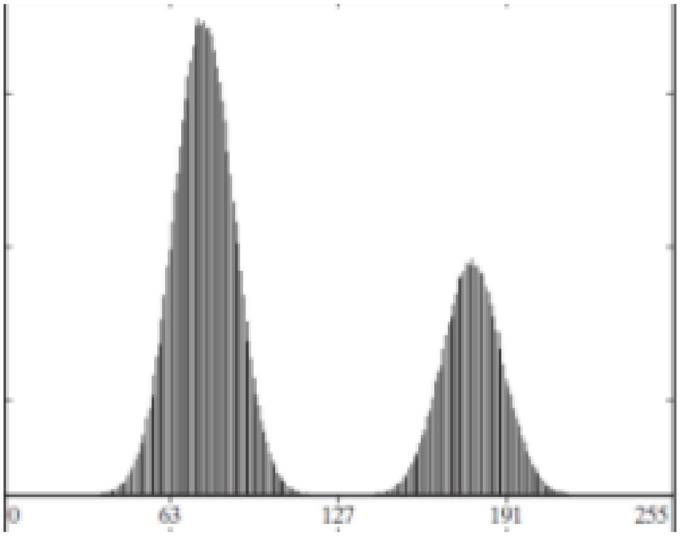

Fig. 11: Example for Global Thresholding

Fig. 12: Simulation for Otsu's Method on Global Thresholding

VII. Morphological process

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image

- The language of Mathematical Morphology is set theory.
- Sets in Mathematical Morphology represents objects in an image.
- A mathematical tool for investigating geometric structure in image.
- Motive is to extract useful features from shape.
- Shape analysis became easy in case of binary images.
- Pixel Locations describe the shape.
- Digital Morphology is a way to describe or analyze the shape of a digital image.

The components extracted are useful in the representation and description of region shape like,

- **Image pre-processing:**Noise filtering, shape simplification.
- **Enhancing object structure:** Skeletonizing, thinning, thickening, convex hull,object marking.
- **Segmentation:** Segmenting objects from background.
- **Quantitative description of objects:** Area, perimeter,etc.

Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to grayscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest. Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels.

Fig. 13: Boundary Extraction - Morphological Process

A. Primary operations:

- **Dilation:** It is an enlargement operation, which combines two sets using vector addition of set elements.
- **Erosion:** it is the reverse of dilation. It combines two sets using vector subtraction of set elements.
- **Opening:** Erosion followed by dilation.
- **Closing:** Dilation followed by erosion.

VIII. Watershed Algorithm

It is an algorithm for segmentation of different objects of an image. The watershed algorithm treats all the pixels values as a local topography . The algorithm floods basins from the markers until basins attributed to different markers meet on watershed lines. In many cases, markers are chosen as local minima of the image, from which basins are flooded.

References

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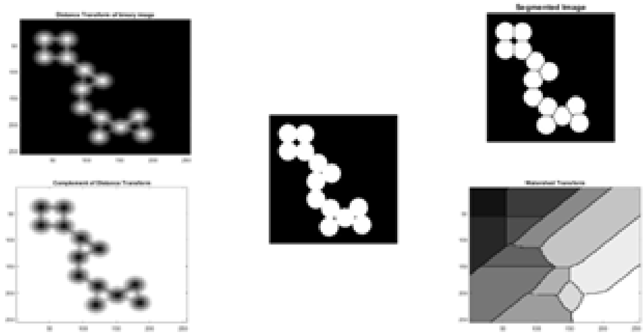

Fig. 14: Simulation for Image Segmentation through Watershed Algorithm

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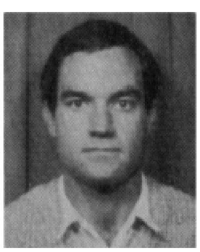

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