A novel approach for edge detection using Lateral Inhibition & Otsu's Thresholding

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CERTIFICATE

This is to certify that report entitled AMIT B. BHAGAT (2K15/SWE/21) has carried out the major project titled **"** A novel approach for edge detection using Lateral Inhibition ***and Ostu's*** Thresholding **"** in partial fulfillment of the requirement for the award of degree of Master of Technology degree in Software Engineering by Delhi Technological University, New Delhi.

The major project is a bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2015-17. To the best of my knowledge the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any other degree or diploma.

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ABSTRACT

For over 30 years researchers in computer vision have been proposing new methods for performing low-level vision tasks such as detecting edges and corners. Edge detection is an important aspect for image processing, and primary step of spatial data extraction in geography information system. It has been applied to solve various image processing problems such as image segmentation, classification, image analysis and edge detection. One key element shared by most methods is that they represent local image neighborhoods as intensity with deviations modeled as noise. Due to computational considerations that encourage the use of small neighborhoods where this assumptions holds, these methods remain popular.

This thesis models the technique using the advantages of Lateral Inhibition and Otsu's thresholding for the edge detection. Lateral inhibition is a technique to enhance the sharpness of images, which is developed from Hartline's research on sensory inhibition. Conventional lateral inhibition operates on the entire image like high-pass filter, which also strengthens noise besides edges.

Otsu's Thresholding is a nonparametric and unsupervised method of automatic threshold selection for picture segmentation is presented. An optimal threshold is selected by the discriminant criterion, namely, so as to maximize the separability of the resultant classes in gray levels. The procedure is very simple, utilizing only the zeroth- and the first-order cumulative moments of the gray-level histogram. It is straightforward to extend the method to multi-threshold problems. Several experimental results are also presented to support the validity of the method.

The experimental results have shown that it gives the better result with less errors and the performance is superior to the popular edge detection methods like Sobel and Canny.

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Chapter 1

INTRODUCTION

1.1 Overview

The Edge detection process is the significant in image analysis, including texture feature extraction, image segmentation and shape feature extraction. Hence, edge detection gets to be most crucial. In most recent works, it turns into the best section of the digital image processing. Specialists developed many edge detection methods, for example, Prewitt detector, Kirsch detector, Roberts detector, Sobel detector et cetera, that are specifically on the pixel intensities.

The Canny edge detection algorithm [1] is one of the good edge recognition techniques. It deals with three morals: localization of edge, low error rate and single edge detection. There are numerous strategies of image segmentation which uses pixel properties categorize picture segment. The dearest strategies that are useful in numerous applications are color slicing, grey level thresholding[.2] Additionally it incorporate the essential of close-by segments, for instance, shape and edges of an image. The edge detection methods are usually applied for the extraction of edges of the image. The characteristics of the edges are some among the most essential as well as peculiar characteristic of an image, this could be utilized for the representation of an image. In in image processing field, there are lot of newly introduced techniques, which are executed, as neural networks, ant colony systems [3], clone choice calculation [4], wavelet change, cell neural system, genetic algorithm, particle swarm optimization and more work is centered around the exploration of digital image processing.

The gradient-based methods extract the pixel from images based on abrupt changes in pixel intensity. The gradient-based based strategies detect the pixels from an image based on sudden changes in intensities of pixels.

Such as the like Prewitt operators [5], Robert cross-gradient template [6], Sobel operators [7], the deformable templates [8], canny edge detector [9] and the Marr–Hildreth edge detector [10]. Generally, these edge detection methods are categorized into set of common techniques. The central pixel is utilized to recognize any contrast in the locality which could be ultimately demonstrates the pixel constitutes an edge. The restoration and enhancement of an image is making such a miracles in the area of digital image processing. Damaging of an image is due to diverse kind of noises [11]. Removal of a noise from an image is important step of image restoration. Removal of the undesirable pixels from an image is objective of decreasing noise. In this step, the undesirable pixel is changed and the new pixel is introduced according to its neighborhood. There are so many filtering algorithms starting with one then onto the next in view of the exactness. The image restoration includes valid signal processing techniques and for manipulation and enhancement of an image two dimensional signals are utilized. In the edge detection, we have to restrain ourselves from processing irrelevant data which are other than edge data. Edge are consists of pixels which shows drastic change in their gray value than their neighborhood pixels[12].

Generally, edges are the main part of an image which help us to identify an objects in an image according to their shapes. The detection of potential characteristics is done by identifying the changes in the gray values of the image. We can use filter to reduce the data, which is irrelevant in the process of edge detection, drastically and makes data easy for managing it[13]. This process ultimately provides the data which could use in the feature and shape extraction of the objects using edge detection. Edge extraction is the necessary step which is to be done to when there is an ambiguity in the recognition of shape and feature of the objects in an image.

In this thesis, we are devising a novel technique which gives a better solution to the edge detection problem . Our approach is efficient with respect to the correctness, low rate of false edge detection and accuracy.

Detection of edges joins a grouping of logical procedures that go for recognizing centers in a digitized image that has the changes in brightness of image emphatically or, more formally, has discontinuities[14]. The locations where sharp changes in brightness of image are specifically categorized into a group of curved line segments called edges. A similar issue of discovering discontinuities in one dimensional signs is called as step location and the issues of discovering discontinuations in sign after a while are considered as change identification. Extraction of edges is a principal apparatus in processing of image, vision of machine and PC, especially in the domain extraction of feature detection and of feature.

The edges obtained from a two dimensional picture of a scene three dimensional perspective could be delegated either perspective ward or perspective autonomous. A perspective autonomous edge ordinarily reflects natural properties of the three-dimensional articles, for example, surface shape and surface markings[15]. A perspective ward edge would change as the perspective changes, and normally represents the scene geometry, for example, things and subject impeding each other.

1.2 Motivation

The reason for recognizing sharp changes in brightness of image is for catching essential changes and events in characteristics of the real scenario. It can be demonstrated which under rather broad presumptions for image creation technique, brightness discontinuities of image are probably corresponding to depth discontinuities, varieties in scene illumination, material property changes and surface orientation discontinuities.

In the perfect case, the aftereffect of application a detector of edges to a picture can prompt a group of joined curve which demonstrate the limits of items, the marking limits of surface and also edges that relate to surface orientation discontinuities. Along these lines, the application a detection of edges technique for an image could essentially decrease the bulk information to be handled which could be considered as less relevant and protect the vital auxiliary properties of an image. On the off chance that the detection of edges procedure is effective, the resulting work like extraction of an information from the first picture could thusly be disentangled. Be that as it may, it isn’t generally easy in acquiring these actual edge from genuine image with high complications.

Extraction of Edges from non-insignificant pictures are generally distorted by fragmentation, implying that the edge-curves aren’t attached, missed edge portions and additionally false edges not relating to fascinating marvels in the picture – in this way confusing the consequent task of information extraction from the picture.

1.3 Problem Statement

From the analysis of edge detectors which are widely used, that are Sobel and Canny, their drawbacks are as follows

- The outputs of both the algorithms are binary in nature .The can not tell us about how much pixel value qualifies as an edge which is the pixel intensity of an image from Sobel and Canny edge detectors
- We have to process and adjust a lot of parameters to get a little good output.
- Edge detectors like Sobel which are unable to find edges for low light an corrupted images.
- The gaussian filter smooth outs the edges of the image , which makes them blur at some extent . That makes detectors hard to find edges from the image.

1.4 Scope

In the proposed approach, lateral inhibition is used to enhance the edges of the image. The Algorithm will project the edge of image as well as enhance the contrast. With the Lateral Inhibition algorithm, the picture's unique characteristics and the determined edge location are unalterable. In the event, that the picture's gray value is altered due to illumination intensity, image could likewise be upgraded as well as the edge could be obtained efficiently using Lateral Inhibition algorithm.

The aim of the image thresholding is to get pixels from the image that forms the shape of the objects in the image. The thresholding generates an image in which foreground pixels depicts the shape of the objects and keep the background pixels in contrast with the foreground pixels . This makes the image into binary form .

The scope of the approach is summarized as follows

- Processing the image using Lateral Inhibition
- Extracting the edges by applying the thresholding on the Laterally Inhibited image

1.5 Report Organization

The rest of the report is organized as follows

Chapter 2 provides the literature review which gives brief idea about basic Edge Detectors.

Chapter 3 describes the Lateral Inhibition.

Chapter 4 describes the Ostu's Thresholding Method

Chapter 4 explains the proposed methodology. It explains the method of the Edge detection method using Lateral Inhibition and Thresholding .

Chapter 5 shows the experimental results which includes qualitative as well as quantitative comparison with some Edge Detectors.

Chapter 6 concludes the thesis.

Chapter 2

LITERATURE SURVEY

2.1 Types of Edge Detectors

Detection of edges joins a grouping of logical procedures that go for recognizing centers in a digitized image that has the changes in brightness of image emphatically or, more formally, has discontinuities. The locations where sharp changes in brightness of image are specifically categorized into a group of curved line segments called edges. A similar issue of discovering discontinuities in one dimensional signs is called as step location and the issues of discovering discontinuations in sign after a while are considered as change identification[16]. Extraction of edges is a principal apparatus in processing of image, vision of machine and PC, especially in the domain extraction of feature detection and of feature.

The edges obtained from a two dimensional picture of a scene three dimensional perspective could be delegated either perspective ward or perspective autonomous. A perspective autonomous edge ordinarily reflects natural properties of the three-dimensional articles, for example, surface shape and surface markings. A perspective ward edge would change as the perspective changes, and normally represents the scene geometry, for example, things and subject impeding each other.

An edge of an image could be described as line that separates the two region with respect to the difference in their gray values of the pixels[1]. In the field of digital image processing, edge detection and extraction is mostly studied subject. In general sense, an edge of an image describes the drastic change in the pixel intensities. This is the basic phenomena behind many edge detection algorithms.

John Canny[17] stated that, the edge detectors are exploit to locate and extract the line which encloses the region, which specifies the particular shape of an object in an image. This is the boundary of an object which separates it from the background. According to the Alberto Martin and Sabri Tosunoglu [22], an edge is a peculiar transition in a pixel intensities in a certain directions through the pixels which concludes it. Nick Efford [23]defined an edge as a separating line between object on the foreground and the background . The most popular edge detection operators are Castan operator, Laplacian of Gaussian filtering, Sobel filtering, moment-based operators, , , Canny, and Shen & Prewitt filtering [17][21].

The classification of Edge detectors, generally, is done according to the order of the gradient use to detect the variations in the gray level. i.e. first order gradient and second order gradient[23]. As the edges correspond to the sudden transition of gray value, step edges should have greater first order gradient as well as zero crossing of the second order gradient . For first order operator, local maxima of an image convolved with the operator is the edge of an image. This is the basic idea behind the Canny[17], Sobel[19] Robert[20] and Prewitt[21] operators.

The basic idea behind the edge detectors are as follows ,

The edges in the image are the discontinuities in the image . These discontinuities could be calculated by applying first order derivative and second derivation on the image . There could be following possibilities

a. First order derivative is zero . It means that, there is no any variation in intensity, which concludes that there is no any edge in the region.
b. First order derivative is non zero constant value. It means that, there is a constant variation in intensity, which concludes that there is an edge in the region .
c. First order derivative is varying in nature . It means that there is a variable change in the intensities of the pixels.
d. Second order derivative is zero. It means that, there is a constant variation in the intensities.
e. Second order derivative is constant. It means there is a constant rate of variations in the intensities .

The common idea behind the detection of edges can be summarized as

1. Find the region in the image where the first derivative has the greater value than the threshold of the image.

2. Find the regions in the image where there is an zero intersection for second derivative.

Yang et al. [18] Proposed log Sobel operator for the detection of an edge. This operator uses the technique i.e. log of brightness, which makes it suitable for the online edge detection with greater speed and accuracy. The edge detection using log Sobel operator gives perfect quality and tactile effects. Prewitt operator, Robert algorithm and Sobel algorithm are the opponents of the log Sobel operators . It is always compared with the prior operators. The processing time of the log Sobel operator is faster than the Sobel, Robert and Priwitt operators and it gives results with improvement in quality. There are many applications in which this operator outperforms with high accuracy and suitable for the real time edge detection.

Prakash et al. [24] proposed Bacterial Foraging Algorithm for edge extraction which is derived from the concept of binarizations . The of the objects in an image is recognize by the Bacterial Edge detection method and this is the widely studied field of image processing and computerized vision. Bacterial Foraging technique transforms an image into binary image. This process is done in two phases, in first phase an input image is firstly transformed into binary image by applying the global threshold. In the second phase, there is an exploitation of bacteria , which accumulates randomly according to the edges of an image.

An electromagnetic edge detection of an image is introduced by Wang et al.[25] This method is a combination of two methods that is cellular neural networks (CNN) and distributed genetic algorithm (DGA). The prior are applied for the training of the genetic algorithm. This proposed DGA CNN edge detector is a good tool of obtaining edges in the images like low light or infrared images where illumination is too low to detect edge easily for other edge detectors.

Edge detection in the images with low illumination, like infrared images, is a vast researched area. Yu et al.[26] developed a new technique called galaxy templet method which collects the superstring markings presented in an image, called mark mining. This technique deals with the blurring problems by mining the superstrings mask structures. It gives good result through the accuracy of complete mining with low errors.

Jie et al. [27] introduced a new technique of edge detection based on cellular neural networks and Prewitt operator . For segmenting an image , this technique gathers the cellular neural networks and Prewitt operator . The neural network is beneficial for mixing of features information as well as develops optimally. For the quality assessment, this cellular neural network is introduced recently into this technique to combine features knowledge into optimization process.

Sobel–Zernike moments technique is introduced by Dong et al. This technique reformats the image into subpixel image and detect edge points. In this technique there is a grouping of two operators Sobel operator and Zernike operator which gives fast results. The analysis of its results shows reduction of execution time with more accuracy that the original Zernike operator[28].

Vector operator technique is proposed by Lira et al.[29] that enhances the edges for multispectral satellite images. The primary objective of this technique is to edge detection by removing the edge content spread over the distant groups of the multispectral image. This method calculates fast result which involved moving window with vector difference. This techniques is designed and discussed about multispectral images and their edge detection in details.

The enhanced white Gaussian technique is proposed by Qinghang et al. [30] which analyses and detects edges in the corrupted images. This technique deals with the problem of white gaussian noise . This edge detector is highly sensitive to the white gaussian noise to which other edge detectors are not. An edge is prone of being located in the locality of this white gaussian noise. This edge detection technique gives the good results while reducing the calculation overhead.

The fuzzy relation edge detection technique is introduced by Kumar et al. which can be used on gray scaled as well as colored images. It uses the Laplacian operator for analyzing the attached edges presented in an image . It gives results with accuracy with low error rate. The detection of connected edges is done by Laplacian constructor method with improved divergence that gives enhanced results[31].

The implementation of Canny algorithm is introduced by Anjum et al. for the edge detection . This edge detector is applied on the whole image and it is related to the image size[17]. There is a removal of an inherent dependencies among the different blocks, which process simultaneously and parallelly using canny image detector . This edge detection technique gives a fast results on images and videos also.

The widely using edge detectors and their working are as follows ,

Sobel Edge Detector

The first order derivative depicts the change in the intensities[18]. Sobel edge detector calculates a derivative applying the variations among the row and column of 3×3 mask in which centrally located pixel is assigned to weight of 2 for the ease of smoothing.

The Sobel operator uses the basic idea that the edge is nothing but the drastic transition in gray levels . This Sobel operator works on finding the gradients which show the transition in gray levels of an image. It deals with the problems like minute discrete and numbered value changes along every direction. It gives ordinary gradient, while dealing with high frequencies. Gx and Gy are the two masks that are used in this method, for horizontal and vertical gradient estimation.

The process of calculation of gradient is done by making frequencies smooth, i.e advancement of Gx in correct direction while Gy in depressing direction and at every pixel the estimation of gradient is calculated using $|G| = (Gx2 + Gy2)1/2$. For the computation of gradient vectors and discrete filter just eight points are enough. And the important condition is divisibility of a gradient vector. The efficiency of execution and correctness of final result solely depends on both the axis directions , where detection of edge is done by analysis of directions and size. The estimation of gradient along x axis is done convolution of mask for x axis with original image , the same is true for y axis also.

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

Gx

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

Gy

Prewitt Edge Detector

The Prewitt operator uses the basic idea that the edge is nothing but the drastic transition in gray levels . This operator works on finding the gradients which show the transition in gray levels of an image. It deals with the problems like minute discrete and numbered value changes along every direction. It gives ordinary gradient, while dealing with high frequencies. Gx and Gy are the two masks that are used in this method, for horizontal and vertical gradient estimation.[19]

The Prewitt operator detects the edges in an image by analyzing the intensity regions where we could get maximum high for the transition in intensities from dark to light. From prevention of blurring as well as avoidance of difficulty, we take small kernels. The measurement of y axis slope is done by turning the kernel Gx through 90° degree and it gives the orientations.

-1	0	1
-1	0	1
-1	0	1

Gx

-1	-1	-1
0	0	0
1	1	1

Gy

Robert operator

The Robert Operator is applied for edge detection in the field of image processing as well as computerized vision. Using discrete method, Robert operator calculates the gradient of an pixel intensities in image. The Robert operator uses the basic idea that the edge is nothing but the drastic transition in gray levels . This operator works on finding the gradients which show the transition in gray levels of an image[20]. It deals with the problems like minute discrete and numbered value changes along every direction. It gives ordinary gradient, while dealing with high frequencies. Gx and Gy are the two masks that are used in this method, for horizontal and vertical gradient estimation.

For the transversely neighborhood pixels, it estimates the total of the differences among them. This is the basic idea behind the discrete method. The both the kernels are 90° degree shifted to each other. The maximum limit to which both the kernel Gx and Gy responds is 45° degree. The magnitude and gradient orientation is calculated which is ultimately used to detect edges in an image.

-1	0
0	1

Gx

0	1
-1	0

Gy

Canny Edge Detector

The much popular edge detection technique applied in the field of computer vision as well as digital image processing is Canny operator. Actually it is a collection of many methods that calculates as well as improves edges in an image. The implementation of Canny algorithm is introduced for the edge detection . This edge detector is applied on the whole image and it is related to the image size[17]. There is a removal of an inherent dependencies among the different blocks, which process simultaneously and parallelly using canny image detector . This edge detection technique gives a fast results on images and videos also. The raw images are often consists of noise. The noise presented in an image is the one of the biggest hurdles in the image processing. Many algorithms are prone to yield wrong result due to noise. In Canny edge detector, gaussian filter is used to remove gaussian noise. Along with this, due to change prone results, there is a need to have algorithm dynamic and flexible nature which could give results with low error rate in all conditions. The following two factors are introduced to provide our requirements,

The factors are:

1. The size of the operator for the gaussian filter should be small so that we could not missed small details . Because , if we take large gaussian filter, it will ultimately blur the image and make difficult for the next processes to find details in an image.
2. Using both the borderlines with hysteresis allow additional accuracy during the thresholding.

The 2-D unique image initially conceded over Gaussian method to decrease noise then x and y axis gradient is calculated same as in Sobel and Prewitt operator. The edge identification image is then exposed to traced and thresholds.

The Canny edge detector is much efficient than Sobel edge detector. The working is as follows,

1. The Gaussian filter is used to smooth out the image and reduce the noise, with standard deviation sigma .
2. The intensity derivative and the direction of edge are calculated for every pixel in the image. Here, the edge is considered as the portion where there is an intensity with locally maxima towards the derivative direction . This point shows the ridge in the image.
3. There is an spurious response to the derivative. So non-maximal suppression is calculated. In this step, there is an omission of ridge pixels which not its maximum intensity. This makes the edges crisp and thin .
4. In this step, there is an application of threshold two times, which determines the important edge.
5. This is the final step . In this step, there is s suppression of weak and nonconnected edges

Chapter 3

LATERAL INHIBITION

3.1 Description

In biology, Lateral Inhibition is the ability of an enacted neural unit to diminish the movement of its neighborhood units. Sidelong hindrance limits from spreading of movement possibilities from actuated neurons to neighborhoods horizontally. This makes an increased contrast which permits upgraded tangible capacity. This is additionally named as parallel hostility and establishes fundamentally in visual procedures, additionally in preparing like material, sound-related, and even olfactory. Cells that utilization horizontal hindrance display essentially in the thalamus and cerebral cortex and shape up Lateral Inhibitory Networks (LINs). Artificial Lateral Inhibition has been went with Artificial sensory system, similar to vision chips, hearing frameworks, and optical mice. Parallel restraint between neurons that are far off spatially, however as far as methodology of stimulus. This marvel is thought to help in shading separation.The lateral Inhibition phenomena is found and confirmed by Hartline and his exploration group while doing an electrophysiological research the stallion shoe crab's vision [32].

Visual inhibition

Lateral Inhibition improves the contrast in vision. This capacity shows in the mammalian retina. While in dim, a boost of little light will enact the distinctive photoreceptors.[33] That is cell pole. The cell poles, central to the stimulus, will restore the signals of the light to the cerebrum, while different poles on the boost which are outside the stimulus will restore a dark flag to the cerebrum. This transition from light to dull makes a more sharpness in image. This phenomena additionally creates the Mach band visual impact.

During the time spent visual Lateral Inhibition photo-receptor cells help the cerebrum in seeing a image with better contrast. The light wave hits on the eye by experiencing the pupils, corneas and the lens(optics).[34] That, at that point, sidesteps the amacrine cells, ganglion cells, flat cells and bipolar cells for achieve the photo-receptors pole cells that retain light. The poles end up noticeably activated by the the light energy and discharge a signal of excited neuron to the other cells horizontally.

The bar cells transmit that excited signal, integral to the Ganglion cell, open field to ganglion cells since flat cells react by sending an inhibited signals to the adjcent poles for making an adjust which enables well evolved creatures to see more distinctive image. The retinal ganglion cells will get an enacted neural reaction however just from the central bar.[35] The focal bar would transmit its initiated reaction specifically to bipolar cells that thusly would hand-off the signals to the ganglion cells. This inhibitory signal delivered by horizontally cells makes high focused as well as adjusted signals to the ganglions cell in retina to send to the cerebral cortex from the optical nerve.

Each microphthalmia of stallion shoe crab's ommateum is considered as a responsive sensor. They found a hindrance of responsive sensor by its nearby open sensors and the restraint impact is totaled spatially. A particular responsive sensor will probably hinder by the closer open sensors instead of the removed ones. The restraint among cells is common. Each open sensor is a neighboring receptor to its nearby responsive sensors. It's restrained by its neighboring responsive sensors and it represses its contiguous open sensors in the meantime. This is the last period of nerve fiber's exercises

In retinal picture, the very energized responsive sensors in illuminatingly light range inhibit more emphatically than the receptive sensors in illuminatingly dark territory. The exercises responsive are commonly inhibiting more emphatically instead of the more distant receptive sensors. Along these lines, the gradient of intensity in image captured by retina, that is an edge of image, has fortified contrast. The hinderence of tactile data is typically useful.[36] The essential characteristics of visual scene are reinforced. Along these lines, the spatial determination is pushed. The lateral inhibition system in retina sensors’ activities are conflicting. So, the contrast is upgraded. The contiguous receptive sensors are a simple nerve system. It takes a shot at information gotten from photoreceptors and the spatial characteristics are impacted. The whole information and its handling happens in the starting stage of vision.

The Hering framework illusion, synchronous contrast, and Mach groups, depicted underneath, are three cases of the noticeable impacts of sidelong restraint (for the most part we are very unaware of it).[36]

Fig.3.1. Optical illusion

- The object in both the images are of same gray level but the left object seems brighter than right one due to comparatively dark background
- The center picture on the left gets little lateral inhibition from its dark surround.
- In the left image the central pixel is getting low lateral inhibition due to dark pixels in the background. So there is less suppression of brightness.
- In the right image the central pixel is getting more lateral inhibition due to bright pixels in the background. So there is more suppression of brightness.
- So. Our visual neurons get stimulations due the contrast in the images. This lateral inhibition is low in left image as compare to right one. Hence, we see left image is more brighter than the right one.[37]

A. Herman Grid

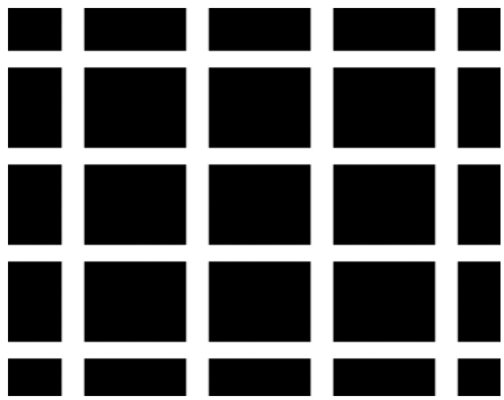


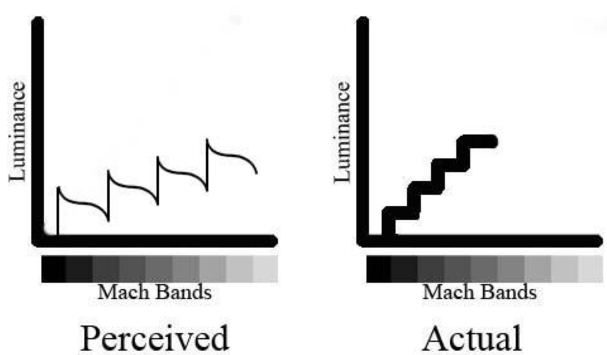
Fig.3.2. Herman Grid

- When we look at this image, called Herman Grid, many of could find dark clouds around the corners of the cubes, where the grid lines are intersecting (note that, this is not true when we look straight)
- At the corners of the cubes, there is an intersection of bright lines , so on the central pixel of the intersection, there is a lateral inhibition from four sides.
- At the sides of the cubes, there is an collapsing of bright lines , so on the central pixel has a lateral inhibition from two sides,
- So. Our visual neurons get stimulations due the contrast in the images. This lateral inhibition is more at the corners of the cubes as compared to the sides of the cubes. Hence, we see darks clouds at the intersections.[38]

B. Mach Band

Fig.3.3. Mach Bands

The above image is called Mach band. This is the collection of strips of different gray levels, sequencing gradually from darker to the brighter. When we at the center of the strips we can find the right side looks brighter as compared to the left side.[39] This is due to right side is having near the edge of brighter strip while the left side is near to darker strip. Therefore, at the right side, there is a more suppression of brightness due to lateral inhibition as compared to the left side.



3.2 Preprocessing algorithm

Extraction of Edge

The Lateral Inhibition model is system of 5×5 in size and the relating picture is gotten as

$$r_p = \sum_{j=1}^{n} k_{p,j} I_j \qquad (1)$$

$I(m,n)$- gray value of the pixel (m,n) of processed image

$$I(m,n) = f[\sum_{i=-2}^{2} \sum_{j=-2}^{2} a_{ij} I_0(m+i\,,\, n+j)] = f[R_0(m,n)] \qquad (2)$$

$I_0(m,n)$- gray value of the pixel (m,n) of original image

a_{ij}- coefficient of inhibition for a pixels (i,j) corresponding to a centrally situated pixel.

f - inhibitory compelling relational function between the output and input.

$R_0(m,n)$- lateral inhibitory compelling coefficient of the pixels (m,n).

In visual neural framework, the functions of one nerve cell to its encompassing nerve cells are generally steady as well as reliable. The edges don't have limitation directionally. Hence the inhibition value ought to be commonly similar as indicated by the inside. Suppose the value for the middle is a_{00}. Their encompassing value are α_2 and the fringe value are α_2.

Then the competing coefficient of the lateral inhibition network is

$$\begin{aligned} R_0(m,n) = {} & a_{00} \times I_0\,(m,n) + \\ & \alpha_1\left[\sum_{i=-1}^{1} \sum_{j=-1}^{1} (m+i\,,\, n+j) - I_0\,(m,n)\right] + \\ & \alpha_2\left[\sum_{i=-1}^{1} \sum_{j=-1}^{1} (m+i\,,\, n+j) - \sum_{i=-1}^{1} \sum_{j=-1}^{1} (m+i\,,\, n+j)\right]. \end{aligned} \qquad (3)$$

Since the visual nerve cells are arranged in a similar input dimension and the contending coefficients are near zero. The templet of inhibition coefficient fulfills

$$a_{00} + 8\alpha_1 + 16\alpha_2 = 0 \qquad (4)$$

The format is resolved as follows .

-0.025	-0.025	-0.025	-0.025	-0.025
-0.025	- 0.075	-0.075	-0.075	-0.025
-0.025	-0.075	1	-0.075	-0.025
-0.025	-0.079	-0.075	-0.075	-0.025
-0.025	-0.025	-0.025	-0.025	-0.025

Fig.3.4. Lateral Inhibition Template

The template is joined with (4) and the contending coefficients are gotten. The picture's edge can be acquired with the accompanying condition.

$$I(m,n) = \begin{cases} 1, & R_0(m,n) \geq T \\ 0, & R_0(m,n) < T \end{cases} \qquad (5)$$

3.3 Enhancement of Image

The lateral inhibition model is:

$$r_p = e_p + \sum_{\substack{j=1 \\ j \neq p}}^{n} k_{p,j} e_j \qquad (6)$$

e_P - the result without inhibition.

$k_{p \cdot j}$- the inhibition coefficients of encompassing pixel.

e_j - the output of encompassing pixels.

r_p - the result after inhibition.

The condition j ≠ p implies that the pixels don't show inhibition with themselves.

Suppose $F(x, y)$is a matrix of original image. $G(x, y)$ is the image matrix masked by the lateral inhibition template. $M(x, y)$ is an enhanced result . That is:

$$M(x,y) = k_1 G(x,y) + k_2 F(x,y) \qquad (k_1 + k_2 = 1) \qquad (7)$$

The edge of image is improved while there is an image processing using the lateral inhibition framework. Be that as it may, few details of image is missed at a specific degree. Hence, the inhibited image is summed with an actual image. The edge is improved, as well as the avoidance of detail lost. For the convenience, the average of weights will be, i.e. $k_1 = k_2 = 0.5$

If the enhanced image's edge is retrieved, suppose $N(x, y)$ is the output of edge retrieval, there is:

$$N(m,n) = \begin{cases} 1, & M(x,y) > T \\ 0, & M(x,y) < T \end{cases} \qquad (8)$$

Under the situation in which a system is steady, the coefficient of inhibition is chosen. Since an entire gray values of inhibited picture is changed, the outcome is hard to appear as a picture. So the equalization of energy must be finished. Suppose the prepared picture's energy is same with the actual image. Assuming the distribution of gray of the actual image $f(x, y)$ is, its energy is characterized as $E = |f(x,y)|^2$. suppose ɳ is the energy proportion of the original image to the inhibited image. The inhibited image is multiplied to ɳ. At that point, the enhancement in image is acquired.[40]

3.4 Theoretical analyses of lateral inhibition under illumination changes

The execution of lateral inhibition model for dealing with the change in illumination is dissected hypothetically here. Taking accommodation of analysis into consideration, we assume that the inhibited weight parameters in the network $[\alpha_{ij}]_{M\times N}$ creates rings. Assuming a framework I_0 has gray levels of pixels of the original image, lattice I_r is the one fused with changes in illumination, matrix F_{illus} is the changes in illumination and R is the improved picture.

Using these assumptions,

$$I_0(x\ ,y\ ) + F_{illus}(x\ ,y\ ) = I_r(x,y) \tag{9}$$

$$R(x,y) = I_r(x,y) + [\ \textstyle\sum_{i=-M}^{M}\sum_{j=-N}^{N}\alpha_{ij}.I_r(x\ +\ i, y\ +\ j)] \tag{10}$$

where (x, y) means the position of pixel, resides in those matrixes. Eqs. (3) and (4) indicate that

$$R(x,y) = I_r(x,y) + [\ \textstyle\sum_{i=-M}^{M}\sum_{j=-N}^{N}\alpha_{ij}.I_0(x\ +\ i, y\ +\ j)] +$$

$$[\ \textstyle\sum_{i=-M}^{M}\sum_{j=-N}^{N}\alpha_{ij}.F_{illus}(x\ +\ i, y\ +\ j)] \tag{11}$$

In ideal case, we anticipate that $R(x,y) = I_r(x,y) + [\ \sum_{i=-M}^{M}\sum_{j=-N}^{N} I_0(x\ +\ i, y\ +\ j)]$, that is, changes in illumination don't hinder the lateral inhibition task at all:

$$\textstyle\sum_{i=-M}^{M}\sum_{j=-N}^{N}\alpha_{ij}\ .F_{illus}(x\ +\ i, y\ +\ j) = 0 \tag{12}$$

In the remaining of this area, regardless of whether a few sorts of alternations in illumination fulfill Eq. (6) or not, are investigated.

A. Constant change in illumination

A constant change in illumination demonstrates that $F_{illus}\ (x\ ,y\ )\ \equiv c, \forall\ (x,y)$, while c is a discretionary constant.

Eq. (2) gives

$$\sum_{i=-M}^{M}\sum_{j=-N}^{N}\alpha_{ij}\,.\,F_{illus}(x\ +\ i, y\ +\ j) = \sum_{i=-M}^{M}\sum_{j=-N}^{N}(\alpha_{ij}.c) = c.\sum_{i=-M}^{M}\sum_{j=-N}^{N}\alpha_{ij} = 0 \quad (13)$$

which shows that constant brightening changes don't influence the picture improvement outputs.

B. Linearly varying change in illumination

A linearly varying change in illumination shows that $F_{illus}\ (x\ ,y\ )\ \equiv c, \forall\ (x, y)$, where a, b and c are subjectively chosen constants. Then

$$\sum_{i=-M}^{M}\sum_{j=-N}^{N}\alpha_{ij}\,.\,F_{illus}(x\ +\ i, y\ +\ j) = \sum_{i=-M}^{M}\sum_{j=-N}^{N}[\alpha_{ij}(ax + ai + by + bj + c)$$

$$= [\ [(ax + by + c)\sum_{i=-M}^{M}\sum_{j=-N}^{N}\ \alpha_{ij} +\ a.[\ \sum_{i=-M}^{M}\sum_{j=-N}^{N}(\alpha_{ij}.\,i)]$$

$$+\, b.[\ \sum_{i=-M}^{M}\sum_{j=-N}^{N}(\alpha_{ij}.\,j)] \quad (14)$$

Wherein $(ax + by + c)\ \sum_{i=-M}^{M}\sum_{j=-N}^{N}\ \alpha_{ij}\ = 0$. Regarding $a.[\ \sum_{i=-M}^{M}\sum_{j=-N}^{N}(\alpha_{ij}.\,i)]$

we have

$$\sum_{i=-M}^{M}\sum_{j=-N}^{N}(\alpha_{ij}.\,i) =\ \sum_{r=1}^{X}\sum_{i_x i_y \in S_r}(\alpha_r.\,i_x) \quad (15)$$

(9)

where X is the number of circular ring in the inhibition framework (e.g., $X\ =\ 3$ in Fig. 2), S_r gathers all the corresponding indices in the rth rings (e.g., S2=_(−1, −1), (−1, 0), (−1, 1), (0, 1), (1, 1), (1, 0), (1, −1), (−1, 0)_in Fig. 2) and α_r represents the inhibition weight in the rth ring. Recalling the matrix of inhibition weights is symmetric horizontally, thus $\sum_{i_x i_y \in S_r} i_x \equiv 0$ resulting in

$$\sum_{i=-M}^{M}\sum_{j=-N}^{N}(\alpha_{ij}.\,i) =\ \sum_{r=1}^{X}\sum_{i_x i_y \in S_r}(\alpha_r.\,i_x) = a.\sum_{r=1}^{X} 0 = 0 \quad (16)$$

$b.[\ \sum_{i=-M}^{M}\sum_{j=-N}^{N}(\alpha_{ij}.\,j)] =\ 0$ can be acquired comparatively. To close, directly variation in changes in illumination don't influence the picture improvement outcome.

C. Stochastic change in illumination

A stochastic change in illumination shoes that $F_{illus}\ (x\ , y\ ) \equiv random + c\ , \forall\ (x, y)$, where c is a arbitrarily chosen constant and random is a zero-mean random number complying with few predetermined distribution.

Then the condition will be

$$\sum_{i=-M}^{M} \sum_{j=-N}^{N} \alpha_{ij} \,.\, F_{illus}(x\ +\ i, y\ +\ j)$$

$$= \sum_{i=-M}^{M} \sum_{j=-N}^{N} \alpha_{ij} \,.\, random + c$$

$$= \sum_{i=-M}^{M} \sum_{j=-N}^{N} \alpha_{ij} + c \qquad (17)$$

Since $E(random) = 0$, then $E[\sum_{i=-M}^{M} \sum_{j=-N}^{N} (\alpha_{ij}. random)]$. In this manner stochastic changes in illumination are relied upon not to influence the picture improvement comes about.[41]

Chapter 4

THRESHOLDING

4.1 Description

The selection of the efficient threshold of the gray value to extract foreground object from the background in an image is very crucial. There are a lot of thresholding methods have been proposed till date. For the best case scenario, the background and foreground has a lot of difference with respect to the gray level values.[42] The histogram of such an image must have s deeper as well as sharper valley among two peaks showing object and backgrounds in an image. This should be falls the threshold at the valley's bottom. But in the real life scenario, there is difficulties to get such a bottom of valley, where valley itself has broader in structure or thicker, or sometimes there is an uneven levels of two peak, or in more general, it is not look like a valley.

Image segmentation makes partitions of picture according to the area or object, which is the important process in the feature extraction of an image. Considering the gravity of image segmentation, the image thresholding process should be simple and effective because thresholding has vital importance in the image segmentation. There are so many techniques are available now a days, but there are very few of them which is as much popular as Class variance method which is introduced by Otsu[43]. Ostu's method is mostly utilized in image segmentation, as it gives results with low error rate. The basic idea behind this method is that it considers highest inter-class variance between the background and objects. One dimensional Ostu thresholding gives good result for image segmentation, if an image is rich in quality and has background invariable to the changes.

Otsu's thresholding [43]is a famous global automatic thresholding method. There are many applications where this technique performed a crucial role. Hardware implementations are needed for rising the processing speed of Ostu's method. These are requirements the requirements for the real time applications. There are several techniques have been introduce up till now and the research is going on in the field of thresholding. Xiaolu Yang has given an improved median-based Algorithm [3], WANG Hongzhi and DONG Ying has proposed new method for selection of optimal threshold value for defect detection[44], Ningbo Zhu1 and Gang Wang have proposed fast algorithm based on improved histogram[45].

4.2 Working

The basic idea behind the Ostue method is that, it considers pixels which could be further classified into two classes, i.e. background and forground. The forground pixels are those which create a shape of an object which is the main items of an image and the remaining pixels are background pixels. The Ostu method process on the image pixels and finds out optimal threshold value in such a way that intra class variance should be minimum or equivalent, which ultimately makes the inter class variance maximum.[46] This method tries all the values for the threshold and calculates the variance of the gray level from both sides of the thresholds. That is, pixel which could be either in background or foreground. This process is carried out in iterations. The ultimate motive of the Ostu method is the selection of a threshold which has the minimum tatal of the background and foreground spreads.

Algorithm steps:

1. Compute histogram and probabilities of each intensity level.
2. Set up initial class probability and initial class means.
3. Step through all possible thresholds maximum intensity.
4. Update qi and μi.
5. Compute between class variance.
6. Desired threshold corresponds to the maximum value of between class variance.

a. Original Image

b. Image after thresholding

Fig.4.1. Thresholding

Let the component of an image histogram be denoted by

Where n is the total number of pixels in the image, nq, is the number of pixels that having intensity level q, and L is the total number of possible intensity levels in the image (remember, intensity levels are integer values). Now, suppose that threshold k is chosen such that $C1$ is the set of pixels with levels $[0,1,2, \dots, k]$ and $C2$ is the set of pixels with levels $[K+1, \dots, L-1]$. Ostu's method is optimum, in the sense that it chooses the threshold value k that maximizes the between class variance , defined by

Here, $P_1(k)$ is the probability of set $C1$ occurring :

$$P_1(k) = \sum_{i=0}^{k} P_i \tag{17}$$

For example, if we set K=0, the probability of set $C1$ having any pixels assigned to it is zero. Similarly, the probability of set C2 occurring is

$$m_1(k) = \frac{1}{P_1(k)} \sum_{i=0}^{k} ip_i \tag{18}$$

The terms m1(k) and m2(k) are the mean intensities of the pixels in sets $C1$ and $C2$, respectively. The term $m_G(k)$ is the global mean (the mean intensity of the entire image):

$$m_G(k) = \sum_{i=0}^{L-1} ip_i \tag{19}$$

Also, the mean intensity up to level k is given by

By expanding the expression for σ_B^2, and using the fact that$P_2(k) = 1 - P_1(k)$,
We can write the between-class variance as

$$\sigma_B^2 = P_1(k)(m_1(k) - m_G)^2 + \ P_2(k)(m_2(k) - m_G)^2 \tag{20}$$

The ratio of the between class variance to the total intensity variance

$$\eta(k\ ) = \ \frac{\sigma_B^2(k)}{\sigma_G^2} \tag{22}$$

Is a measure of the separability of image intensities into two classes (e.g., objects), which can be shown to be in the range

$$0 \leq \eta(k^*) \leq 1 \tag{23}$$

Where k is the optimum threshold. The measure achieves its minimum value for constant images(whose pixels are completely inseparable into two classes) and its maximum value for binary images(whose pixels are totally separable).[48]

Ostu's Thresholding automatically selects thresholds value in histograms of the gray level by detailed analysis through many iterations.[43] It tries to find the threshold value heuristically by applying condition like whether intra level variance is lowest or not and select, ultimately, the minimum value. The lowest intra variance shows that there is a perfect separation of foreground and background pixels with low ambiguity. This is the degree to which both the class is separable to each other.

The Ostu method has its own unsupervised and nonparametric characteristics.[43] The benefits of this method is as follows

1. Process is so simplistic in nature.
2. This method can be used for the problems which demand multi thresholding due to its adaptability which is the main requirement in variety of problems.
3. The automatic selection of stable threshold which is globally optimal that is lowest of among all, without trapped into locally optimal values.
4. The ultimate result is the thorough analysis of histogram and belongingness of the pixels into the classes according its background or foreground character.
5. There is no need of supervision which makes it general and simple for many decision based problems such as thresholding

Chapter 5

PROPOSED APROACH

5.1 An application of Lateral Inhibition and Ostu's Thresholding for Edge Detection

The introduced approach of Edge Detection which is based on Lateral Inhibition and Ostu's thresholding Optimization is organized in two phases .

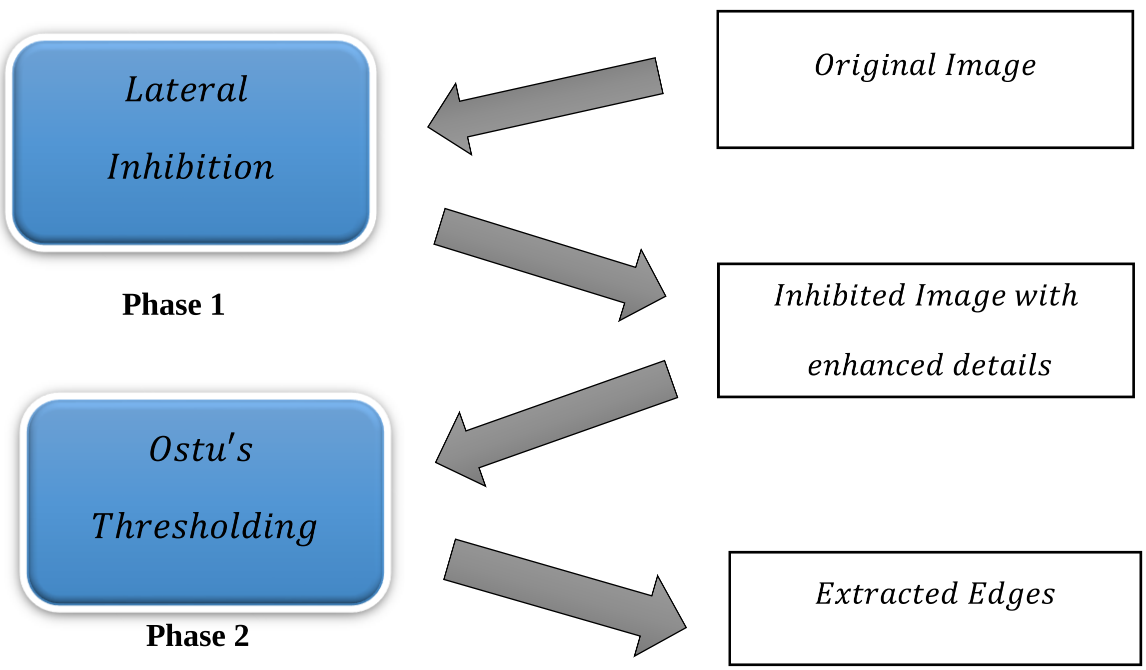


Fig.5.1. The pipeline of Proposed Method

Phase 1 : Extraction of edges of an Image using Lateral Inhibition

In this phase , we use the Lateral Inhibition technique to enhance the edges and contrast of the image . This is done by diminishing the brightness of the neighborhood pixels using the lateral inhibition template . This will ultimately create an Inhibited image which will be enhanced in edges and contrast.

The Lateral Inhibition model[41] is system of 5×5 in size and the relating picture is gotten as

$$r_p = \sum_{j=1}^{n} k_{p,j} I_j \qquad (24)$$

$I(m,n)$- gray value of the pixel (m,n) of processed image

$$I(m,n) = f[\sum_{i=-2}^{2}\sum_{j=-2}^{2} a_{ij} I_0(m+i\ ,\ n+j)] = f[R_0(m,n)] \qquad (25)$$

$I_0(m,n)$- gray value of the pixel (m,n) of original image
a_{ij}- coefficient of inhibition for a pixels (i,j) corresponding to a centrally situated pixel.
f - inhibitory compelling relational function between the output and input.
$R_0(m,n)$- lateral inhibitory compelling coefficient of the pixels (m,n).
In visual neural framework, the functions of one nerve cell to its encompassing nerve cells are generally steady as well as reliable. The edges don't have limitation directionally. Hence the inhibition value ought to be commonly similar as indicated by the inside. Suppose the value for the middle is a_{00}. Their encompassing value are α_2 and the fringe value are α_2.
Then the competing coefficient of the lateral inhibition network is

$$\begin{aligned} R_0(m,n) = {} & a_{00} \times I_0\ (m,n) + \\ & \alpha_1\left[\sum_{i=-1}^{1}\sum_{j=-1}^{1}\left(m+i\ ,\ n+j\right) - I_0\ (m,n)\right] + \\ & \alpha_2\left[\sum_{i=-1}^{1}\sum_{j=-1}^{1}\left(m+i\ ,\ n+j\right) - \sum_{i=-1}^{1}\sum_{j=-1}^{1}\left(m+i\ ,\ n+j\right)\right]. \end{aligned} \qquad (26)$$

Since the visual nerve cells are arranged in a similar input dimension and the contending coefficients are near zero. The templet of inhibition coefficient fulfills.

$$\begin{bmatrix} -0.025 & -0.025 & -0.025 & -0.025 & -0.025 \\ -0.025 & -0.075 & -0.075 & -0.075 & -0.025 \\ -0.025 & -0.075 & 1 & -0.075 & -0.025 \\ -0.025 & -0.075 & -0.075 & -0.075 & -0.025 \\ -0.025 & -0.025 & -0.025 & -0.025 & -0.025 \end{bmatrix}$$

The template is joined with (4) and the contending coefficients are gotten. The picture's edge can be acquired with the accompanying condition.

$$I(m,n) = \begin{cases} 1, & R_0(m,n) \geq T \\ 0, & R_0(m,n) < T \end{cases} \qquad (27)$$

Phase 2 : Thresholding of an inhibited image using Ostu's method

In this phase , we use Ostu thresholding technique in which we will step through L possible values of k and compute the variance at each step.[38] We the select the K that gave the largest value of variance. That value of k is the optimum threshold . The idea of maximizing the between class variance is that the larger this variance is, the more likely it is that the threshold will segment the image properly. Note that this optimality measure is based entirely on parameters that can be obtained directly from the image histogram.

Let the component of an image histogram be denoted by

Where n is the total number of pixels in the image, nq, is the number of pixels that having intensity level q, and L is the total number of possible intensity levels in the image (remember, intensity levels are integer values). Now, suppose that threshold k is chosen such that $C1$ is the set of pixels with levels $[0,1,2,\dots,k]$ and $C2$ is the set of pixels with levels $[K+1,\dots,L-1]$. Ostu's method is optimum, in the sense that it chooses the threshold value k that maximizes the between class variance , defined by

Here, $P_1(k)$ is the probability of set $C1$ occurring :

$$P_1(k) = \sum_{i=0}^{k} P_i \tag{28}$$

For example, if we set K=0, the probability of set $C1$ having any pixels assigned to it is zero. Similarly, the probability of set C2 occurring is

$$m_1(k) = \frac{1}{P_1(k)} \sum_{i=0}^{k} ip_i \tag{29}$$

The terms m1(k) and m2(k) are the mean intensities of the pixels in sets $C1$ and $C2$, respectively. The term $m_G(k)$ is the global mean (the mean intensity of the entire image):

$$m_G(k) = \sum_{i=0}^{L-1} ip_i \tag{30}$$

Also, the mean intensity up to level k is given by

By expanding the expression for σ_B^2, and using the fact that$P_2(k) = 1 - P_1(k)$,
We can write the between-class variance as

$$\sigma_B^2 = P_1(k)(m_1(k) - m_G)^2 + P_2(k)(m_2(k) - m_G)^2 \tag{31}$$

The ratio of the between class variance to the total intensity variance

$$\eta(k\ ) = \frac{\sigma_B^2(k)}{\sigma_G^2} \tag{32}$$

Is a measure of the separability of image intensities into two classes (e.g., objects), which can be shown to be in the range

$$0 \leq \eta(k^*) \leq 1 \tag{33}$$

Where k is the optimum threshold. The measure achieves its minimum value for constant images(whose pixels are completely inseparable into two classes) and its maximum value for binary images(whose pixels are totally separable).

Chapter 6

RESULTS AND DISCUSSION

6.1 Implementation

The proposed Edge detection method based on Lateral Inhibition and Ostu's thresholding is implemented on a machine having specifications as follows :

Processor : Core $i3$ @2.27 GHz CPU

RAM : 3 GB

Operating System : Windows 10

MATLAB Version : 2016

The test images used for the proposed edge detection method are $Lena$ and $Cameraman$ of resolution 128×128 of gray format with pixel density 8.

Fig.6.1 Lena

Fig.6.2 Cameraman

6.2 Results

The proposed method is applied on the test images, that are $Lena$ and $cameraman$. The original images are firstly subjected to the Lateral inhibition algorithm in which lateral inhibition templet is applied to get enhanced details. The outputs are the Inhibited images. Then we applied Ostu's thresholding to extract edges from the Inhibited images.

The Output images, we get in each phase, are as follows :

Original **Inhibited Image** **Output Image**

Fig 6.3 Lena

For test image $Lena$, the Ostu's threshold is 0.0627 and the execution time is 1.018 sec.

Original **Inhibited Image** **Output Image**

Fig 6.4 Cameraman

For test image $Cameraman$, the Ostu's threshold is 0.1216 and the execution time is 1.09sec.

6.2 Comparison

The proposed method is compared with the popular edge detection methods, which are Sobel and Canny. From the analysis of results, it is found that the proposed method is outperforming. The output images from the proposed method, the Sobel method and Canny method are as follows :

Proposed Method **Sobel** **Canny**

Fig.6.5 Comparison for Lena

Proposed Method **Sobel** **Canny**

Fig.6.6 Comparison for Cameraman

Note that, here we took default thresholds for Sobel and Canny methods which are 0.074 and [0.019 , 0.047] so as to make comparisons fairly with any manual interference.[26]

Here, we can easily see that the proposed method extracts small details, which are the Sobel method is failed to capture. In comparison with the Canny method, canny method suffered from detecting false edges and missed the small details due to the use of Gaussian filter which blurred the image during processing time while the proposed method gives the actual edges.

Chapter 7

CONCLUSION

7.1 Conclusion

In this thesis, a novel technique of edge detection is introduced. From the execution and analysis of the proposed method, we can conclude that the proposed method is successfully developed. It gives the better result with less errors and the performance is superior to the popular edge detection methods, as we have seen from the comparisons. There are many problems in the field of digital image processing where this combination, Lateral Inhibition and Ostu's thresholding, can be useful. The proposed method has the number of applications due to its simplicity.

7.2 **Future work**

There is a lot of scope where this proposed method can be implemented with the image processing methods like image restoration, image enhancement. Our future work is to optimize the proposed method using optimizing algorithms to troubleshoot the problems related to the edge detection process.

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