International Conference on Computational Science and Information Management (ICoCSIM)
Vol. 1 (2012) 152-157

Image partitioning methods in spatial and frequency domain

M. Mahmood Ahmed[a], JasniMohamadZain[b], M. Masroor Ahmed[c]

[a,b,c]*Faculty of Computer System & Software Engineering,UMP, 26300, Kuantan, Malaysia*

Abstract

For partitioning the image, in spatial domain, contiguous neighbourhood pixels withsimilar properties are grouped together to make a region. These regions form processing blocks for the images during local enhancement. Additionally, many researchers, on the same pattern, divided the image histogram into many blocks. To split a candidate image or its histogram into regions, various methods are evolved by researchers. The paper reviews these existing partitioning methods and briefly illustrates the related contrast enhancement techniques. From this point onwards section one introduces the subject, section two, reviews existing partitioning techniques and section three presents conclusion by summarizing the paper.

Keywords**:** Regions, neighbourhood processing, point processing, contrast enhancement, histogram

1. Introduction

The paper reviews techniques which aim at dividing a given image or it's histogram into regions to be used by image enhancement methods. These enhancement methods use two approaches; area processing [1]-[5] and point processing [6]-[13]. Point processing is generally implemented by global techniques like histogram equalization. These global methods, take the whole image and implement enhancement techniques indiscriminately, which, generally results in imperfections in local details in multiple areas of the image. To preserve or improve local details, enhancement techniques were attempted within the bounds of local neighborhood, independent of each other. For this purpose, similar neighborhoods were grouped together into regions. Therefore to enhance contrast of a given image classifying image into different regions became a pre-processing step. This classification was based on mean, median, average and deviation of pixels characteristics in mutual comparison with the surrounding pixels.

Some of the researchers adopted the same pattern for global enhancement techniques using point processing. These point processing techniques deal with pixels directly hence they use image histogram for enhancement calculations. This histogram was divided into local blocks to process images on the pattern of spatial domain processing. The bases for division into blocks were once again mean, median, variance and average of pixel density /mean error. The paper review both set of techniques; first set of techniques partition image into distinct regions to employ area processing methods, second set divides image histogram into different blocks for employing point processing techniques effectively.

2. Existing partitioning techniques

Existing techniques are classified in two categories; spatial domain and frequency domain. First the article will cover spatial domain followed by frequency domain.

2.1. Spatial domain

This domain is related to coordinates of the target pixel. Normally a relation is established with its neighbourhood to mark regions of similar pixel properties.

2.2. *Division bybackground brightness levels*

This method considers that input images have global background in a continuous range. Let us represent gray level prior to background by p, gray levels of background by B and the overall gray level range by L.

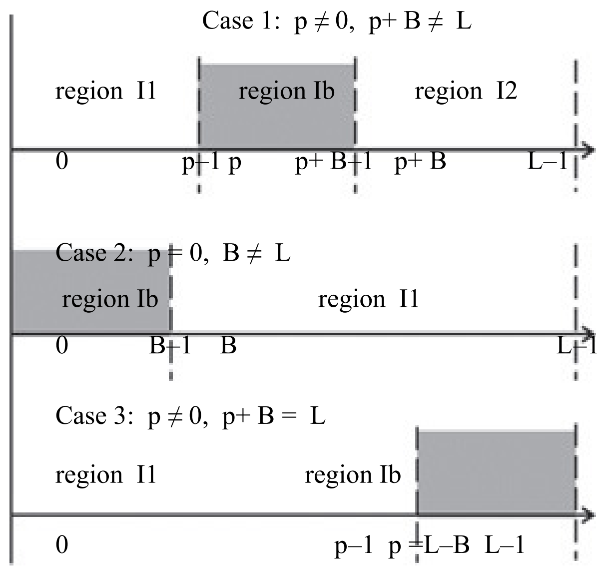

Fig 4: Background blocks -three cases[1]

As depicted in the figure, there could be only three cases, contiguous block of gray levels forming background could be in the beginning, middle or end of gray level range. Case one in fig 1 will have three sub images, rest two cases; case 2 and case 3 will have only two sub images. For the given image X the sub images from fig 1 are given by

$$X = I_1 \cup I_b \cup I_2 \quad (1)$$

$I_b$is the sub image of background gray levels whereas I_1 andI_2 are the sub images of left over image areas. $I_1 = \{X \le X_{p-1}\}$, $I_b = \{X_p \le X \le X_{p+B-1}\}$, $I_2 = \{X_{p+B} \le X \le X_{L-1}\}$, $p \neq 0$, $p + B \neq L$, and $X_b \in \{X_p, X_{p+1}, \ldots, X_{p+B-1}\}$. For each blockcumulative density c and probability density *pd* is given by the formula

$$c_1(X_k) = \sum_{r=0}^{k} pd(X_k) = \sum_{r=0}^{k} \frac{n_k}{n} \quad (2)$$

for k=0, 1, ..., L-1, and n is the frequency of occurrence of pixels.whereas for each block transform function is given by $f(X) = X_{min} + (X_{max} - X_{min})c(X)$ and the output image $\boldsymbol{O}$ is formed by aggregating all the sub images, which then is given by $\boldsymbol{O} = f_1 \cup f_b \cup f_2$ .Each function$f$ relates to its own corresponding block. These calculations are for case 1; for case 2 and 3, one block will be dropped and calculations will be based on two sub images only.which will make the whole calculation simple. This method is implemented by authors of[1]in"Image enhancement using background brightness preserving histogram equalisation" (IEBPHE).

2.2.1. Partitioning on the weighted average value of the pixel

This weighted average value of the pixel with its surrounding, is established by convolving the input image with a Gaussian filter.Integers values obtained from this convolution of the Gaussian filter is made the base for partitioning the image. For a 2D Gaussian filter, the coefficients are calculated by applying the following equation.

$$G(i,j) = \frac{1}{\sqrt{2\pi\sigma}} exp\left(-\frac{i^2+j^2}{2\sigma^2}\right) \quad (3)$$

In this equation $\boldsymbol{\sigma}$ is standard deviation and i, jare the coordinates of the centre point of the filter, using this equation all coefficients are calculated and then these results are normalized. These normalised results, sum up to unity. For appropriate fit of Gaussian filter, value of $\boldsymbol{\sigma}$ needs to be selected accurately. Size of the Gaussian filter and value of $\boldsymbol{\sigma}$ is interrelated [2]. Consider a square filter of size S*S Size S is an odd integer valuewhich equals(2I+1) where I is a base line integer to ensure S is odd. The relation between **σ** and I is given by.

$$\sigma = \sqrt{-\frac{I^2}{2In(0.001)}} \tag{4}$$

Hence, size of the Gaussian filter is the only factor which needs to be carefully chosen. This will govern S or I for the above equation. Appropriate size Gaussian filter will accrue the correct set of values of coefficients during application. This set, in turn, will serve to be the desired base for image partitioning. After the image is successfully divided into sub images, histogram equalization is applied independently to each part. This method of image division is used by sub-regions histogram equalization (SRHE) which uses a robust HE variance [3]. This robust version,for an input image 'X' and probability density 'p' is given by the following equation.

$$T_{robust}(x) = .5\begin{pmatrix} X_0 + (X_{L-1} - X_0)\left(\sum_{k=X_0}^{x} p(k)\right) + \\ \left(X_0 + (X_{L-1} - X_0)\left(1 - \sum_{k=x}^{X_{L-1}} p(k)\right)\right) \end{pmatrix} \tag{5}$$

$$T_{robust}(x) = X_0 + (X_{L-1} - X_0)\left(.5p(x) + \sum_{k=X_0}^{x-1} p(k)\right) \tag{6}$$

In essence, this equation calculates HEfor inverse and normal image and then averages the results, which makes it robust. An additional advantage of Gaussian is due to low pass nature offilter which on application reduces the high frequency components of the image. This application leaves the low frequency features which normally compose of objects in the image. Hence, as an added benefit, pixels could be grouped into their respective objects, which may be used for contrast enhancement of objects.

2.2.2. Equal area dualistic sub-division

Image in this technique is partitioned into two equal area sub images. This division results in equal amount of pixels in both the sub images[4]. Normally this ends up into one dark and one bright sub image. For a given image *'X'*, when gray levels are presented by '*r*' this division is achieved by finding a separating point $x_D$which satisfies

$$\int_0^{X_D} p_r(r)dr = 0.5 \tag{7}$$

The purpose of this separating point is to have maximum entropy for the desired histogram. This technique is employed by Dualistic Sub-Image Histogram Equalization (DSIHE)[5]HE is applied to both the parts independently. Application of HE and aggregating the image back to one piece is almost identical to the process covered in earlier paragraph. The authors *of*[5]claims that DSIHE,by employing this method, improvedretention of image brightness.

2.3. Frequency domain

In frequency domain,instead of image its histogram is divided into different parts. This is normally apre-processing step to employ some relevant technique to enhance contrast of a given image. This review, in the subsequent text, will cover various methods of decomposing histogram of a given images. Each method has two parts; dividing criterion and mathematical formulation which handles splitting and aggregating process. A criterion for each technique is independent but splitting and aggregating formulas are mostly common. These formulas will be covered here before moving to individual techniques. Formula for an input image ***I*** is given by

$$f(\bar{\boldsymbol{I}}) = \{f(I(i,j))|\ \forall I(i,j) \in I\} \tag{8}$$

Whereas *i, j* are pixel coordinates. Image section (two in this case$_{U\&\ L)}$ with *m*as partitioning point is given by

$$I_U = \{I(i,j)|\ I(i,j) > I_m,\ \ \forall\ I(i,j) \in \bar{\boldsymbol{I}}\} \tag{9}$$

$$I_L = \{I(i,j)|\ I(i,j) \le X_m,\ \ \forall I(i,j) \in \bar{\boldsymbol{I}}\} \qquad 10)$$

For output image *Y* transform function (with *C (i)* as cumulative density) for each image region is defined by

$$\bar{Y}(i,j) = \begin{cases} I_0 + (I_m + I_0)C_l(i), & if\ i \le i_m \\ I_0 + (I_{L-1} + I_{m+1})C_u(i), & if\ i > i_m \end{cases} \tag{11}$$

Process of aggregation for output image is given by formula

$$\bar{\boldsymbol{Y}} = I_U \cup I_L \tag{12}$$

With the understanding of these common formulas let us move on to the criteria of partitioning for each technique.

2.3.1. Dividing histogram by mean or median

Mean or median frequency is used to divide histogram of a given image into two parts.Partitioning point is preserved, while both parts are processed independently. After processing both parts are re-joined with mean still preserved. This tends to retain image brightness to a large extent which was a critical issue at hand to be resolved. However the method is successful only where the histogram is quasi-symmetrical around the partitioning point. The authors of [6], show implementation of this technique in Brightness preserving bi-histogram equalization method (BBHE).

This criterion of mean or median may be used recursively which will take the advantage of partitioning to a deeper level. Recursion count will determine the number of resulting sub-images. It is given by $2^{\mathbf{n}}$ whereas **n** is the recursion count. With the increase in number of sub-images, mean value of final output image keeps getting closer to mean value of input image. This is the desired goal which retains image brightness. The authors of [7] show that this division technique is used by Recursive Mean Separate HE Method (RMSHE). Further the authors in [8]illustrate, mathematically, that the brightness of the output image is better preserved as recursions increases.

2.3.2. Using threshold for dividing image

To ensure retention of input image brightness, a threshold is established where the difference between brightness of input and output image is minimum. This threshold is used as partitioning point to split the image into two sections. For a given image *I*, if the threshold is set at *t* then the two image parts are given by $I_1 = [0, t]$ and $I_2 = [t+1, L-1]$. Chen and Ramli in [9] show that this division is used by Minimum Mean Brightness Error Bi-HE Method (MMBEBHE). Such divisions may also be done by using multiple thresholds. These are placed at predetermined points. Connected components above and below these thresholds are marked for analysis. Jafar and Ying in [10] implement this technique in Multi component bi histogram equalization (MCBHE).

2.3.3. Shape based division

Division is based on the criteria of "Shape". Local minima and maxima are detected in the image histogram. Based on these contours histogram is divided into different sub sections. This process is done recursively till the time no dominating portion exists in any of the resulting sub-histograms.ManpreetKaur et al, in[11]explainthe way this technique is used in Mean Brightness Preserving HE (MBPHE). Additionally authors of [12] illustrate the use of this division in Dynamic Histogram Equalisation (DHA).

2.3.4. Division of histogram intoblocks

In this method instead of complete histogram only the range which practically exists is considered. This range is divided into blocks. Next eachblock is stretched proportionately to increase the effective range of histogram. This ensures a locally uniform stretching. It is shown in fig. 2

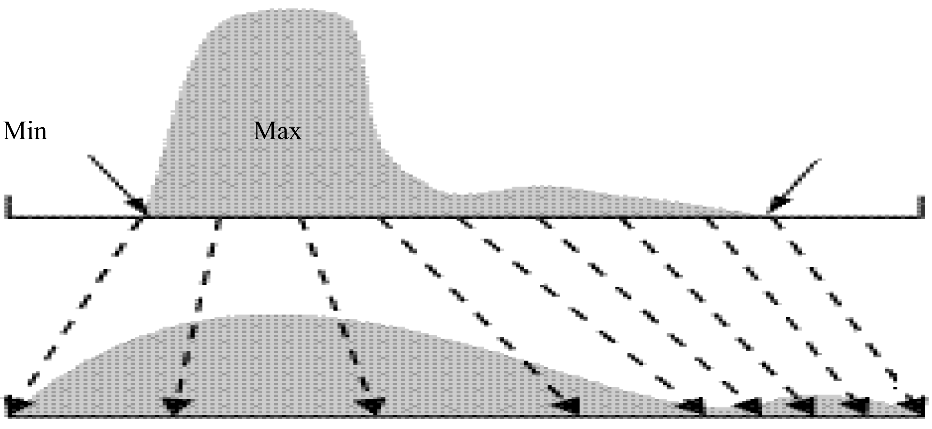

Fig 5: Partitioning of Histogram into blocks

Let us say histogram is divided into *K* blocks. The ratio for this resizing is calculatedby (Max_{New} –Min_{New}) / (Max - Min). Each block is stretched by the same ratio. If it is desired to use complete spectrum of histogram from 0 – 255 for resized range then Max_{New}=255and Min_{New}=0. However, in some cases, to ovoid over correction, the stretch required might be a little less. Insuch a case Max_{New}=Max+*l*andMin_{New}=Min-*l* whereas *l* is the spread required on each side of the existing histogram. Therefore the formula for the gray levels in each block is given by

$$GrayLvl_{new} = \frac{(Max_{new} - Min_{new})}{(Max - Min)}(GrayLevel - Min) + Min_{new} \qquad (13)$$

Some researchers also added pixel ratio in different blocks, which means, blocks with more pixels will spread more and with less pixels will spread less. Once these new blocks are established, they are likely to enhance contrast due to stretching. However some techniques use this as pre-processing to apply their algorithm. Authors of [13] provide a detailed mathematical elaboration of this technique and application of Dynamic Regional HE on each block.

3. Conclusion

The partitioning techniques, presented in the paper differ in two ways; criteria of division and number of sub parts. In spatial domain, these techniques attempt to mark regions of homogenous neighbourhoods. On the other hand, in frequency domain, these techniques divide histogram in sub blocks. These blockshelp retain desirable image properties. Each image partitioning method has its own - best fitting - contrast enhancement technique.These techniques contribute to improve local contrast. They are, therefore, adopted by local processing techniques. Although we did not discuss the performance & computational cost ofpartitioning and aggregating the images or the histograms but these aspect, may play an important role in choosing a method of image partitioning and related contrast enhancement technique. In real lifeapplications, the variety of images involved are often too wide tobe covered with only one choice. Therefore, any specific type of pre-processing or contrast enhancement technique may not be kept in the forefront. Instead of that, practical scalability on a variety of choices is most desirable for resolving practical image processing issues.

References

1. Tan, T. L., Sim, K. S. and Tso, C. P. Image Enhancement using Background brightness preserving histogram equisition. *Electronic letters.* Feburary 2, 2012.
2. Chen Hee Ooi, Nicholas Sia Pik Kong, Haidi Ibrahim, Derek Chan Juinn Chieh. Enhancement of color microscipic images using toboggan method. 2009.
3. Ibrahim, Haidi and Kong, Nicholas Sia Pik. Image Sharpening Using Sub-Regionss Histogram Equalization. *Consumre Electronics.* 0098, May 2, 2009, Vol. 55, 2, pp. 891-895.

4. Wang, Chao and Ye, Zhongfu. Brightness Preserving Histogram Equalization with Maximum Entropy: A Variational Perspective. *IEEE Transactions on Consumer Electronics.* 2005, Vol. 51, 4, pp. 1326-1334.
5. Wang, Y, Chen, Q and Zhang, B. Image Enhancement based on equal area dualistic sub-image histogram equalization method. *IEEE Transactions Consumer Electronics.* 1999, Vol. 45, 1, pp. 68-75.
6. Kim, Y -T. Contrast enhancement using brightness preserving bi-histogram equalization. *IEEE Trasactions Consumer Electronics.* 43, 1997, Vol. 1, pp. 1-8.
7. Chen, S -D and Ramli, A R. Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation. 2003a, Vol. 49, pp. 1301-1309.
8. Sim, K S, Tso, C P and Tan, Y. Recursive Sub-Image Histogram Equalization Applied to Gray Scale Images. *Pattern Recognition Letters.* 2007.
9. Chen, S D and Ramli, A R. Minimum mean brightness error bi-histogram equalization in contrast enhancement. *IEEE Transaction on Consumer Electronic.* 2003b, Vol. 49, 4, pp. 1310-1319.
10. Jafar, I and Ying, H. Multilevel component-based histogram equalization for enhancing the quality of grayscale image. 2007, pp. 563-568.
11. Kaur, Manpreet, Kaur, Jasdeep and Kaur, Jappreet. Survey of Contrast Enhancement Techniques based on histogram equalization. 2011, Vol. 2, 7.
12. bdullah-Al-Wadud, M, et al. A dynamic histogram equalisation for image contrast enhancement. 2007, Vol. 53, 2, pp. 593-600.
13. Iwanami, T., et al. An Adaptive Contrast Enhancement Using Regional Dynamic Histogram Equalization. Vol. None, pp. 719-722.