A Multiscale Region-Based Motion Detection And Image Histograms

[A]sanjeev Kumar Singh And [B]madhvi Gupta

[ab]*School of Engineering& Technology, IFTM University Moradabad,U.P India*

Abstract

In an Image Processing context, the Image Histograms of an image normally refers to a histogram of the "pixel intensity values".It contains Cumulative histogram, Effect of gray-level mapping on histogram, Histogram equalization, Histogram specification, Local enhancement, Color processing. Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image.[1] Color or intensity can be used as the measure.

Keywords: *Histogram equalization, intensity histogram , contrast stretching, pixel intensity values ,pixel values, gray level image.*

1. Introduction

Image Histograms is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8-bit grayscale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those grayscale values.

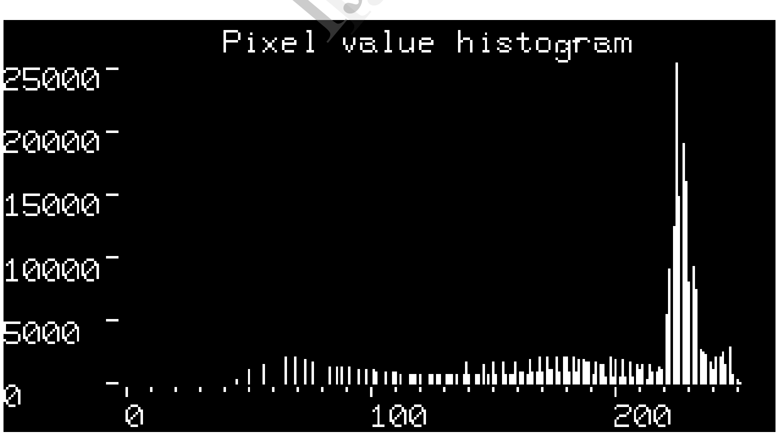
Histogram-based approaches can also be quickly adapted to occur over multiple frames, while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per pixel basis where the information result are used to determine the most frequent color for the pixel location. This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in Video tracking.
A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed.

2. Cumulative histogram

Each array element gives the number of pixels with a gray-level less than or equal to the gray level corresponding to the array element.
Easily constructed from the histogram.
Cumulative frequencies , cj, are computed from histogram counts, hi using,

$$c_j = \sum_{i=0}^{j} h_i$$

cumulative histogram has a steep slope in densely populated parts of the histogram
cumulative histogram has a gradual slope in sparsely populated parts of the histogram



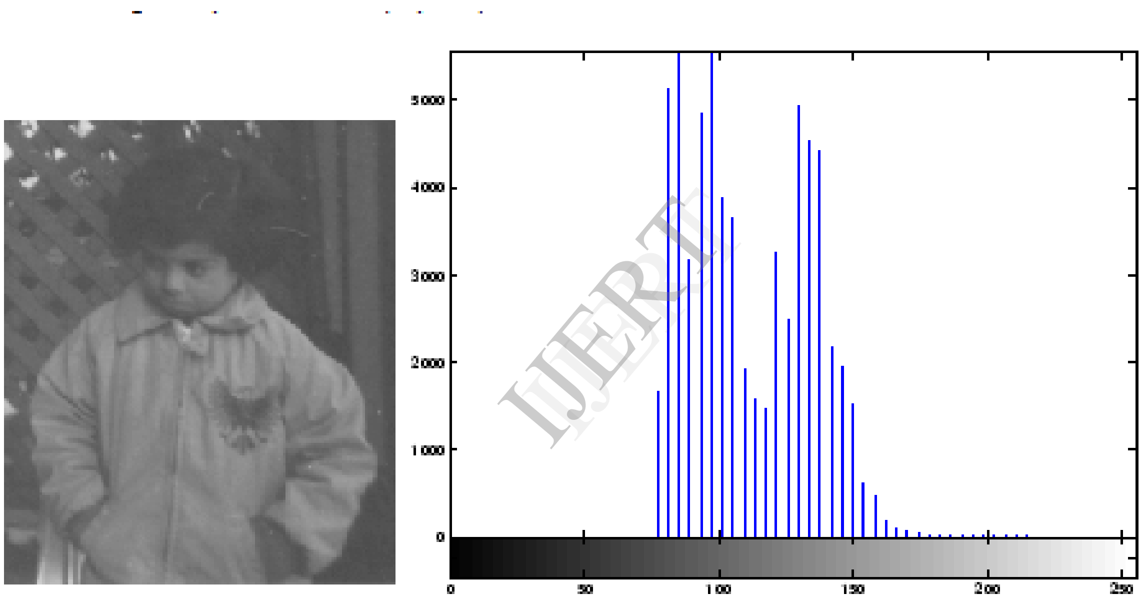
3. Adjusting Pixel Intensity Values

Understanding Intensity Adjustment

Image enhancement techniques are used to improve an image, where "improve" is sometimes defined objectively (e.g., increase the signal-to-noise ratio), and sometimes subjectively (e.g., make certain features easier to see by modifying the colors or intensities).

Intensity adjustment is an image enhancement technique that maps an image's intensity values to a new range. To illustrate, this figure shows a low-contrast image with its histogram. Notice in the histogram of the image how all the values gather in the center of the range.

```
I = imread ('pout.tif');
Figure; imshow (I);
Figure; imhist (I, 64);
```



If you remap the data values to fill the entire intensity range [0, 255], you can increase the contrast of the image.

The functions described in this section apply primarily to grayscale images. However, some of these functions can be applied to color images as well.

Adjusting Intensity Values to a Specified Range

You can adjust the intensity values in an image using the imadjust function, where you specify the range of intensity values in the output image.

For example, this code increases the contrast in a low-contrast grayscale image by remapping the data values to fill the entire intensity range [0, 255].

```
I = imread ('pout.tif');
J = imadjust (I);
Imshow (J);
Figure, imhist (J, 64)
```

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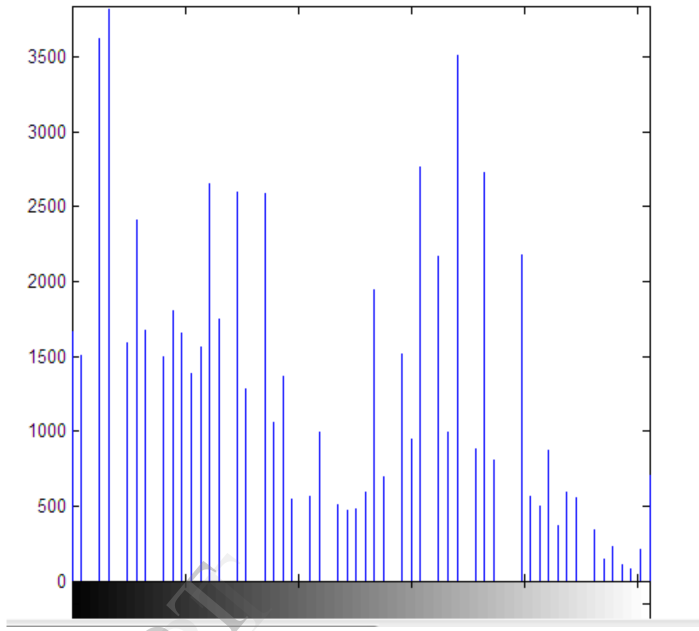
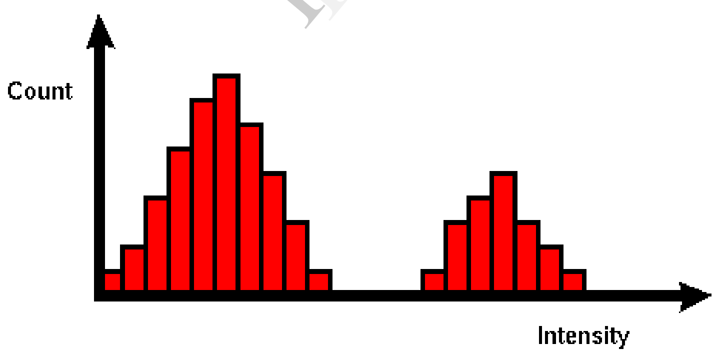
This figure displays the adjusted image and its histogram. Notice the increased contrast in the image, and that the histogram now fills the entire range.



Intensity Histogram



Histogram

The histogram of a digital image with gray levels in the range [0,L-1] is a discrete function h(rk) = nk, where rk is the kth gray level and nk is the number of pixels in the image having gray level rk.

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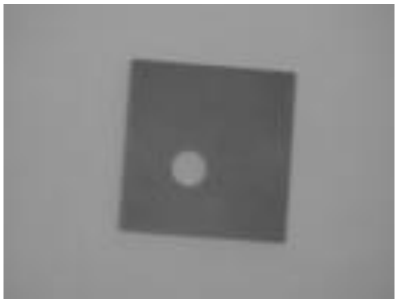
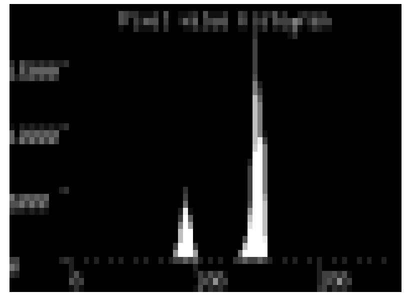
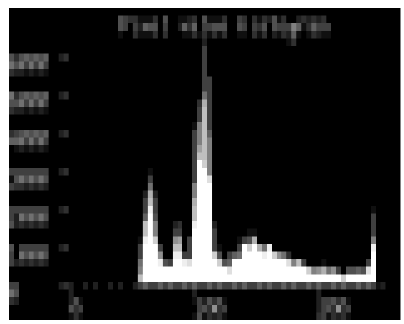
The intensity histogram for the input image is



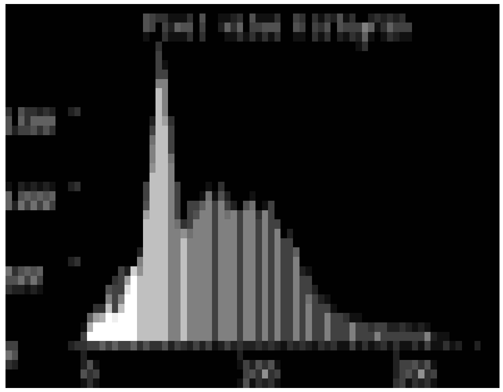


The histogram of image is



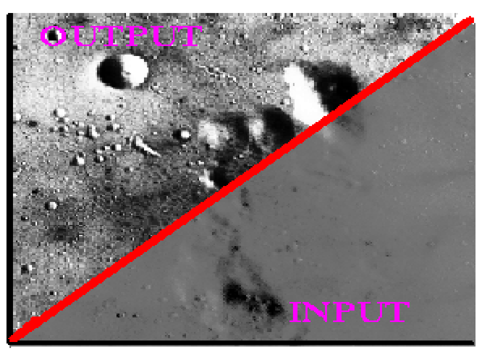
This time there is a significant incident illumination gradient across the image, and this blurs out the histogram.
The image :

Also has low contrast. However, if we look at its histogram,



We see that the entire intensity range is used and we therefore cannot apply contrast stretching. On the other hand, the histogram also shows that most of the pixels values are clustered in a rather small area, whereas the top half of the intensity values is used by only a few pixels. The idea of histogram equalization is that the pixels should be distributed evenly over the whole intensity range, i.e. the aim is to transform the image so that the output image has a flat histogram.

4. Histogram Equalization



Histogram modeling techniques (e.g. histogram equalization) provide a sophisticated method for modifying the dynamic range and contrast of an image by altering that image such that its intensity histogram has a desired shape. Unlike contrast stretching, histogram modeling operators may employ non-linear and non-monotonic transfer functions to map between pixel intensity values in the input and output images. Histogram equalization employs a monotonic, non-linear mapping which re-assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities (i.e. a flat histogram). This technique is used in image comparison processes (because it is effective in detail enhancement) and in the correction of non-linear effects introduced by, say, a digitizer or display system.

Histogram equalization involves finding a grey scale transformation function that creates an output image with a uniform histogram (or nearly so).

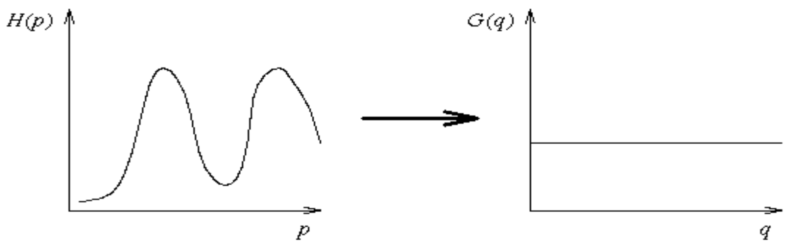
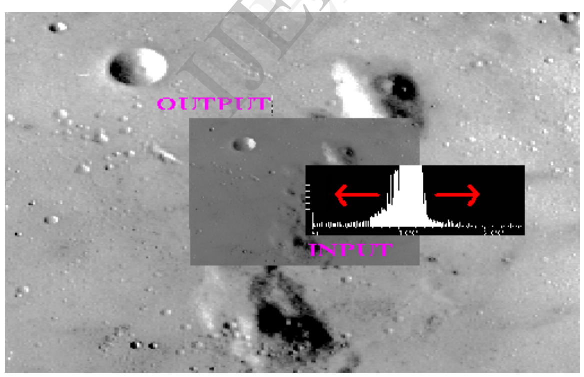


Figure 4.2 Histogram equalization.

5. Contrast stretching



Contrast stretching, Normalization

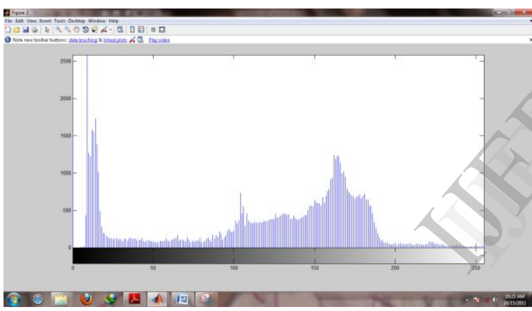
Contrast stretching (often called normalization) is a simple image enhancement technique that attempts to improve the contrast in an image by `stretching' the range of intensity values it contains to span a desired range of values, e.g. the full range of pixel values that the image type concerned allows. It differs from the more sophisticated histogram equalization in that it can only apply a linear scaling function to the image pixel values. As a result the `enhancement' is less harsh. (Most implementations accept a gray level image as input and produce another gray level image as output.)

Illustration:

Normalization is commonly used to improve the contrast in an image without distorting relative gray level intensities too significantly.

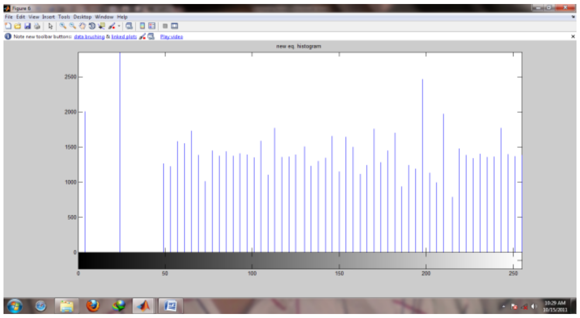
We begin by considering an image :-

Which can easily be enhanced by the most simple of contrast stretching implementations because the intensity histogram forms a tight, narrow cluster between the gray level intensity values of 79 - 136,



After contrast stretching, using a simple linear interpolation between c = 79 and
d = 136, we obtain

Compare the histogram of the original image with that of the contrast-stretched version



6. Local enhancement

Histogram equalization and histogram specification techniques are based on gray-level distribution over the entire image

Gray-levels containing important information in a small neighborhood (region of interest) may not be present in sufficient quantities to affect the computation of a mapping based on global information

At each pixel do the following :

- Compute the cumulative histogram based on a small neighborhood around the pixel to be mapped
- Apply histogram equalization using this cumulative histogram

7. Color processing

Can apply histogram equalization to color images

Don't want to apply it using the RGB color model - equalizing R, G, and B bands independently causes color shifts.

It must convert to a color model that separates intensity information from color information (e.g. HSI)

Color processing can then apply histogram equalization on the intensity band.

8. Future Scope:

This paper presents an approach for motion detection using 3D image histogram sequence analysis. The idea of this approach is to remove the process of motion estimation into the field of 3D image histogram sequences by analysis of their statistical characteristics. A functional and statistical model of a system for motion detection has been created. This model includes procedures for image processing like: mode filtering for homogenizing the area of objects and its background, defining 3D image histogram sequences as well as procedures for defining statistical characteristics of the 3D image histograms sequences, choice and analysis of criterions for motion estimation. The experimental results prove that the relationship between statistical characteristics of the 3D image histograms sequences and process of motion estimation is a guarantee for creating a reliable and high precision motion detection system as well as for image compression using 3D entropy functions analysis. Such a system can be used for security control of banks, airports, military objects, embassies, shops etc.

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CONCLUSION

It provides foundation for implementing image processing algorithm using modern software tools. Solutions to problems in the field of Digital Image Processing generally requires an extensive experimental work involving software simulation and testing with large set of sampling images. The actual implementation of these algorithms requires parameter estimation, algorithm revision and comparison of solutions.

The drawback of the method is that it requires 3% to 6% more processing than Gaussian Mixture method, but, like the Gaussian Mixture method, ours is appropriate for online application with an image resolution of 320*240 or less with our implementation. However, MDPA distance calculations could be performed in parallel to speed up processing..

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. In this technique of image classification distance metric and integrated region matching are familiar.

Histograms can also be taken of color images either individual histogram of red, green and blue channels can be taken, or a 3-D histogram can be produced, with the three axes representing the red, blue and green channels, and brightness at each point representing the pixel count. It relies on color histograms, texture information, and successive division of candidate rectangular image regions to model the background and detect motion

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Sanjeev Kumar Singh

MTech (II Year)
IFTM University, Moradabad
(UP) INDIA – 244102

Madhvi Gupta

MTech (II Year) .
IFTM University, Moradabad
(UP) INDIA - 244102

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