Histogram and Its Applications to Image Analysis

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Abstract

Histogram equalization (HE) is one of the most common and important algorithms in image enhancement. This article is the assignment of EE7403. It explains the definition and properties of histograms and analyzes the merits and limitations of HE, and finally describes the application of histograms.

Keywords: histogram; histogram equalization; Hough transform

1. Histogram

1.1. Definition

The histogram is one of the common methods used in image processing to analyze images. An image's histogram is the proportion of pixels with 256 gray values from 0 to 255 in the image. The histogram of a digital image $f(x,y)$ with gray level range $[0,L]$ is a discrete function:

$$p_f(f) = \frac{n_f}{n}$$

Where f is the gray level, n_f is the number of pixels with a certain gray level, and n is the total number of pixels in the processed image region.

1.2. Properties

Histograms are often used in image processing because they are less expensive in performing computation. The histogram of an image can reflect the characteristics to some extent, for example, when the histogram is concentrated in the low gray area, the image is dark and vice versa.

There are two common types of histograms, one is the RGB histogram, which draws the corresponding RGB histogram, the other is to grayscale the original image and then draw the grayscale histogram. The grayscale histogram reflects the frequency of each gray level pixel, and the larger the gray level, the larger the image brightness range (Zheng et al., 2021).

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The grayscale histogram reflects only the image grayscale, not the pixel position. One image corresponds to a unique grayscale histogram, but the same grayscale histogram may correspond to multiple images. When using contour lines to determine object boundaries, the histogram is used to better select boundary thresholds, which is especially useful for scene segmentation where the object has a strong contrast with the background.

Select a color image and draw its RGB histogram and grayscale histogram as shown in Figure 1 and Figure 2. It can be seen from the RGB histogram that the blue component is the most, that is, the sky and sea in the original image. The overall distribution of the grayscale histogram is relatively uniform, reflecting the obvious details in the original grayscale image.

2. Histogram Equalization

2.1. Definition of HE

Histogram equalization is the process of changing the grayscale histogram of the original image from a relatively concentrated grayscale interval to a uniform distribution over the entire grayscale range. The idea is to apply some kind of mapping transformation to the original image so that the histogram of the resulting image is uniformly distributed, which means that the dynamic range of the image is increased and the contrast is improved, and the image quality is enhanced. The enhancement of image quality is carried out by image histogram representation

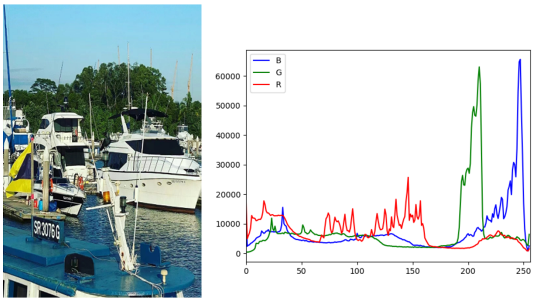

Figure 1: *Original image and corresponding RGB histogram.*

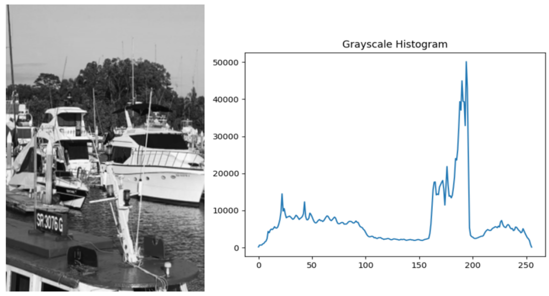

Figure 2: *Grayscale image and corresponding grayscale histogram.*

through HE (Senthilkumaran and Thimmiaraja, 2014). The method to achieve histogram equalization is to use the cumulative distribution function for grayscale mapping.

HE aims to obtain a uniform histogram by transforming the gray level f of the input image $f(x, y)$ to output image $g(x, y)$ through $g = T(f)$.

The HE algorithm is:

$$c(f) = \sum_{t=0}^{f} p_f(t) = \sum_{t=0}^{f} \frac{n_f}{n}, \quad f = 0, 1, \ldots, L$$

$$g = T(f) = round\left[\frac{c(f) - c_{min}}{1 - c_{min}} L\right], \quad c(f) \geq c_{min}$$

Where t is a dummy variable of the summation, C_{min} is the smallest positive value of all $c(f)$. g is approximately uniformly distributed in $[0, L]$.

From the comparison of Figure 3 and Figure 4, it can be seen that after the equalization process, the pixels will be relatively concentrated, the grayscale range will become larger, and the contrast will become larger, which effectively enhances the image.

In fact, in addition to the above pixel-based histogram, all attributes of the image such as gradient size, orientation, etc. can form a histogram, and Scale Invariant Feature Transform (SIFT) (Lowe, 2004) was developed based on this point. SIFT is an image descriptor for image-based matching developed by David Lowe in 1999 and completed in 2004.

2.2. Merits and limitations of HE

The advantages of histogram equalization are very obvious.

1. This method is usually used to increase the local contrast of an image, especially when the contrast of the useful data of the image is quite close, by which the luminance can be better distributed on the histogram. In this way, only the local contrast can be enhanced without affecting the overall contrast.
2. It is very useful for images where both the background and foreground are too bright or too dark, and can better show the details in overexposed or underexposed photos.
3. It is a fairly intuitive technique and is reversible so that if the equalization function is known, the original histogram can be recovered with little computational effort.
4. It can be easily implemented and has a rapid process time (Garg et al., 2011).

However, similarly, the method inevitably has some disadvantages:

1. The reduction of the gray level of the transformed image, which does not take into account the image edge information, and the disappearance of certain details.
2. For some images, such as histograms with peaks, the contrast is unnaturally over-enhanced after processing (Panse and Gupta, 2021).
3. No selection of the processed data, which may increase the contrast of background noise and decrease the contrast of useful details (Longkumer et al., 2014).
4. It has no method of regulating the measure of enhancement and may lead to it not getting to a balance between various aspects of the image sometimes (Wang and Ward, 2007).

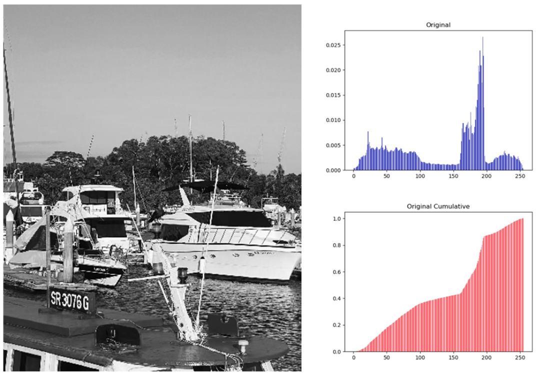

Figure 3: *The grayscale image, the corresponding histogram, and the cumulative histogram.*

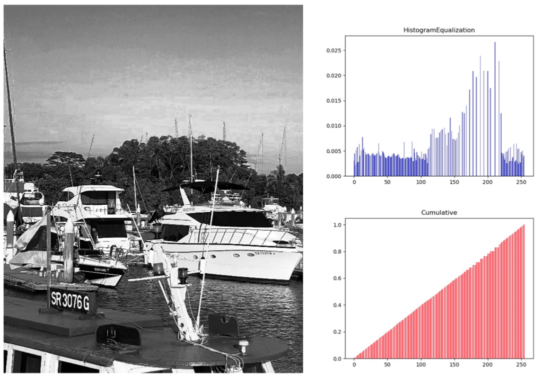

Figure 4: *The image after HE, the corresponding histogram, and the cumulative histogram.*

In response to the above drawbacks, scholars' improvements on classical HE can be divided in five categories. The first category is the sub-histogram equalization technique, which is mainly used for image contrast enhancement under brightness preservation, with representative algorithms such as BBHE (Brightness Preserving Bi-Histogram Equalization) algorithm (Kim, 1997), DSIHE (Dualistic Sub-Image Histogram Equalization) algorithm (Wang et al., 1999), RMSHE (Recursive Mean-Separate Histogram Equalization) algorithm (Chen and Ramli, 2003), etc.

The BBHE is carried out by decomposing the input image based on its mean to obtain two independent equalized sub images and preserve the mean brightness of the image. However, it is unable to maintain the natural look of the image. RMSHE is used as an image enhancement of the BBHE to reliably maintain the brightness of the image.

The second type of technique is modified HE techniques, which is mainly for some specific gray levels for contrast enhancement, representative algorithms such as AHE (Adaptive Histogram Equalization) algorithm (Stark, 2000). The third one is histogram variation (Wang and Ye, 2005), which is mainly used for image contrast enhancement under luminance protection. The fourth category is local histogram equalization techniques, mainly used for image detail enhancement, such as POSHE (Partially Overlapped Sub-block Histogram Equalization) algorithm (Kim et al., 2001). The fifth category is the image enhancement technique based on transform domain equalization (Kaur and Singh, 2017), which is mainly used for image detail enhancement.

In the last two years, scholars have also made several innovative improvements and comprehensive applications of HE. Li(Li et al., 2021) proposes a brightness-preserving dynamic histogram equalization method, which makes the average intensity of the output image almost equal to the input, thus satisfying the requirement of maintaining the average brightness of the image.

3. Application of histogram

Histogram is used in many areas, and its applications include Hough transform, Histogram of oriented gradient, SIFT, etc. Hough transform is one kind of feature extraction, which is widely used in image analysis to identify features in objects, such as lines, circles, and ellipses. Hough transformations are related to histograms in that they both use a similar accumulator concept and both convert image data to digital data for further processing.

In 1962, Paul Hough proposed a method for detecting straight lines in images based on the principle of mathematical duality, which was mainly applied to detect straight lines in binary images in the field of pattern recognition.

In the rectangular coordinate system (x, y), a straight line can be expressed by the equation $y = ax + b$, but when the line is perpendicular to the x-axis, the slope is infinite, which would be inconvenient if the computer is used for numerical calculations, so Duda and Hart (Duda and Hart, 1972) proposed the Hesse normal form to represent the parameters of the line: $x \cos\theta + y \sin\theta = \rho$. The problem of divergence of the original parameter space

Figure 5: *Lines detection with Hough transform.*

(a, b) is solved by using the parameter space (ρ, θ), and then the parameters of each line segment can be compared.

The advantages of the Hough transform include insensitivity to local defects, robustness to random noise, and suitability for parallel processing.

The generalized Hough transform was proposed by Ballard (Ballard, 1981) in 1981, which adapts the Hough transform to the principles of template matching. The generalized Hough transform does not require the ability to give an analytic formula for the shape to be detected and it can detect any given shape. Illingworth (Illingworth and Kittler, 1988) proposed the relationship between Hough method and other transformations, promoting the application of Hough transform in image processing.

To address the drawbacks of high computational cost and poor real-time performance of the Hough transform, and to lift the limitation of most improved algorithms in terms of image size, Fernandes and Oliveira (Fernandes and Oliveira, 2008) proposed an improved HF, namely Kernel-based Hough transform (KHT). The approach operates on clusters of approximately collinear pixels and for each cluster votes are cast using an oriented elliptical-Gaussian kernel. This method significantly improves the performance of the voting scheme and makes the transformation more robust to the detection of spurious lines. In addition, other scholars (Guo et al., 2009) improved HT by reducing the number of votes using the gradient direction, which also achieved better results.

Zhao (Zhao et al., 2021) combined classical Hough transform with deep learning and proposed the method of Deep hough transform, which is a one-shot end-to-end learning framework for line detection and obtaining good results. Fröhlingsdorf (Fröhlingsdorf et al., 2022) found that the high-frequency acoustic noise share often harms the perceived sound quality of vehicles, and proposed a new method to automatically separate the inverter noise share based on the Hough transform for the complex and time-consuming acoustic optimization process.

Through the promotion, Hough transform has become a key method and an effective tool in the field of image processing, especially in the field of linear detection, and has been continuously innovated and developed based on its predecessors.

4. Conclusion

This article shows some of the contents learned in EE7403. In addition to the above-mentioned Hough transform, Histogram of Oriented Gradients (HOG) and Histogram matching are also common applications of histograms, which also have a profound impact on computer vision. The histogram is a simple and widely used image enhancement method, which is of great significance to image processing and analysis.

References

Xuming Zheng, Xin Yang, Zhongyu Lu, and Qiang Xu. The method for the determination of creep cavitation model based on cavity histogram. *Materials at High Temperatures*, 38(5):383–390, 2021.

N Senthilkumaran and J Thimmiaraja. Histogram equalization for image enhancement using mri brain images. In *2014 World congress on computing and communication technologies*, pages 80–83. IEEE, 2014.

David G Lowe. Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 60(2):91–110, 2004.

R Garg, B Mittal, and S Garg. Histogram equalization techniques for image enhancement. *International Journal of Electronic Communication Technology*, 2(1): 107–111, 2011.

Vijay Panse and Rajendra Gupta. Medical image enhancement with brightness preserving based on local contrast stretching and global dynamic histogram equalization. In *2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT)*, pages 164–170. IEEE, 2021.

Nungsanginla Longkumer, Mukesh Kumar, and Rohini Saxena. Contrast enhancement techniques using histogram equalization: a survey. *International Journal of Current Engineering and Technology*, 4(3):1561–1565, 2014.

Qing Wang and Rabab K Ward. Fast image/video contrast enhancement based on weighted thresholded histogram equalization. *IEEE transactions on Consumer Electronics*, 53(2):757–764, 2007.

Yeong-Taeg Kim. Contrast enhancement using brightness preserving bi-histogram equalization. *IEEE transactions on Consumer Electronics*, 43(1):1–8, 1997.

Yu Wang, Qian Chen, and Baeomin Zhang. Image enhancement based on equal area dualistic subimage histogram equalization method. *IEEE transactions on Consumer Electronics*, 45(1):68–75, 1999.

Soong-Der Chen and Abd Rahman Ramli. Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation. *IEEE Transactions on consumer Electronics*, 49 (4):1301–1309, 2003.

J Alex Stark. Adaptive image contrast enhancement using generalizations of histogram equalization. *IEEE Transactions on image processing*, 9(5):889–896, 2000.

Chao Wang and Zhongfu Ye. Brightness preserving histogram equalization with maximum entropy: a variational perspective. *IEEE Transactions on Consumer Electronics*, 51(4):1326–1334, 2005.

Joung-Youn Kim, Lee-Sup Kim, and Seung-Ho Hwang. An advanced contrast enhancement using partially overlapped sub-block histogram equalization. *IEEE transactions on circuits and systems for video technology*, 11(4):475–484, 2001.

Amandeep Kaur and Chandan Singh. Contrast enhancement for cephalometric images using wavelet-based modified adaptive histogram equalization. *Applied Soft Computing*, 51:180–191, 2017.

Ying Li, Weipan Xu, Haohui Chen, Junhao Jiang, and Xun Li. A novel framework based on mask r-cnn and histogram thresholding for scalable segmentation of new and old rural buildings. *Remote Sensing*, 13(6):1070, 2021.

Richard O Duda and Peter E Hart. Use of the hough transformation to detect lines and curves in pictures. *Communications of the ACM*, 15(1):11–15, 1972.

Dana H Ballard. Generalizing the hough transform to detect arbitrary shapes. *Pattern recognition*, 13(2): 111–122, 1981.

John Illingworth and Josef Kittler. A survey of the hough transform. *Computer vision, graphics, and image processing*, 44(1):87–116, 1988.

Leandro AF Fernandes and Manuel M Oliveira. Real-time line detection through an improved hough transform voting scheme. *Pattern recognition*, 41(1): 299–314, 2008.

Siyu Guo, Tony Pridmore, Yaguang Kong, and Xufang Zhang. An improved hough transform voting scheme utilizing surround suppression. *Pattern Recognition Letters*, 30(13):1241–1252, 2009.

Kai Zhao, Qi Han, Chang-Bin Zhang, Jun Xu, and Ming-Ming Cheng. Deep hough transform for semantic line detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2021.

Katja Fröhlingsdorf, Stefan Pischinger, Marco Günther, Christoph Steffens, and Stefan Heuer. Automated inverter noise separation in the interior of electric vehicles using adapted kirsch-compass kernel and hough-transformation. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, page 09544070221076591, 2022.