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A Histogram based Image Quality Index

Abstract. *Image quality evaluation plays a very important role in any image processing application. A number of efforts have been made in the last decade to develop generalized image quality metrics. However, a common and easily applicable image quality measure is yet to be developed. In this paper, a new Histogram-based Image Quality Index (HQI) is proposed for use in place of traditional error summation methods. It can be calculated easil and erforms si nificantl better than the widel used ima e distortion ualit metric Mean S uared Error MSE .*

Streszczenie. *W artykule zaproponowano nową metodę poprawy jakości obrazu nazwaną HQI – Histogram based Image Quality Index. Metoda może zastąpić dotychczas stosowana metodę sumowania błędów. (**Indeks jakości obrazu bazujący na histogramie**)*

Keywords: Digital Image, Histogram, Quality Measure.
Słowa kluczowe: jakość obrazu, histogram

Introduction

In this paper, a Histogram based Image Quality Index (HQI) is proposed to be used in place of traditional error summation methods. It is relevant to various image processing applications and provides significant comparisons across different types of image distortions. The proposed new index is not only calculated easily, but it also performs significantly better than the commonly used distortion metric MSE.

Digital images are subject to a lot of distortions during various processes (acquisition, compression, storage, transmission, reproduction, etc.) in the digital world. For this reason, image quality metrics are needed to determine the amount of deterioration of images. In the last decades, a great deal of effort has been made to develop general image quality metrics. But still it has not been possible to find a generally accepted image quality measure.

Today image quality metrics can be classified according to the availability of an original (distortion-free) image with which the distorted image is to be compared. Most existing approaches are known as “full-reference”, meaning that a complete reference image is assumed to be known [1−6]. In some practical applications, the reference image is not available and a “no-reference” or “blind” quality evaluation approach is preferred [7]. This paper focuses on full-reference image quality evaluation.

The simplest and most widely used full-reference quality metric in the literature is the Mean Square Error (MSE), which is calculated by averaging the squared intensity differences of deteriorated and reference digital image pixels, along with the related quantity of Peak Signal to Noise Ratio (PSNR). These statistical metrics are useful because they are simple to calculate, have clear physical meanings and are mathematically suitable in the context of optimization. At the present time, the PSNR and MSE are employed universally, regardless of their questionable performance, and they are not very well matched to perceived visual quality as mentioned in the references [8−12].

Digital Image Histogram and Image Quality Index

A digital image is a digital representation (normally binary) of a two-dimensional set of data (M×N). Depending on whether or not the image resolution is fixed, it may be of a vector or a raster type. Without some qualifications, the term “digital image” usually refers to raster images, also called raw or bitmap images [13].

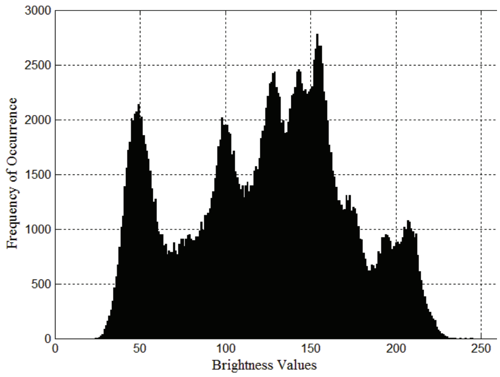
In statistics, a histogram is a graphical representation showing a visual impression of the distribution of data and it is used to show the frequency distribution of a set of measurements. In digital imaging, a histogram consists of tabular frequencies, shown as neighbouring rectangles, raised over discrete intervals, with an area equal to the frequency of the observations in the interval. The height of a rectangle is also equal to the frequency density of the interval, i.e., the frequency divided by the width of the interval [14]. The total area of the histogram is equal to the number of data (M×N). A histogram may also be normalized displaying relative frequencies. It then shows the proportion of cases that fall into each of several intervals [15]. The categories are generally specified as uninterrupted, non-overlapping intervals of a brightness value. The intervals must be adjacent and are chosen to be of the same size.

An image histogram is a type of media that acts as a graphical representation of the brightness values' distribution in a digital image. It plots the number of pixels for each brightness value (Fig. 1). By looking at the histogram for a specific image, a viewer will be able to review all tonal distribution at a glance. Today, image histograms are presented on many modern digital cameras. Users can easily use them as an aid to show the distribution of tones captured and whether image detail has been lost to blown-out highlights or blacked-out shadows.

The horizontal axis of the graph represents the brightness value variations, while the vertical axis represents the number of pixels (frequency of occurrence) in that particular gray tone. The left side of the horizontal axis represents the black and dark areas, the middle represents medium gray and the right hand side represents light and pure white areas. The vertical axis represents the size of the area that is captured in each one of these zones. Thus, the histogram for a very bright image with few dark areas and/or shadows will have most of its data points on the right side and center of the graph. Conversely, the histogram for a very dark image will have the majority of its data points on the left side and center of the graph.

Image histograms can be useful tools for thresholding. Because the information contained in the graph is a representation of pixel distribution as a function of tonal variation, image histograms can be easily analyzed for peaks and/or valleys which can be used to determine a threshold value. This threshold value can be used for some image processing applications (edge detection, image segmentation, co-occurrence matrices, etc.).

(a)



(b)

Fig. 1. Original test image Lena (a) and its histogram (b)

The number of bits representing each pixel determines how many colors can be displayed. For example, in an grayscale mode, the monitor uses 8 bits each pixel, allowing the display of 2^8 (256) different colors. This number determines the boundaries of the histogram's horizontal axis. The number of pixels in the image (M×N) determines the boundaries of the histogram's vertical axis.

An image for which quality should be determined is primarily not the result of a photographic process in a camera, but the result of storing or transmitting the image. A typical example is a digital image that has been compressed, stored or transmitted, and then decompressed again. Unless a lossless compression method has been used, the resulting image is normally not identical to the original image and the deviation from the original image is then a measure of quality. By considering a large set of images and determining a quality measure for each of them, some statistical methods or quality indexes are used to determine an overall quality measure of the compression/distortion method. Most of all existing methods use pixel by pixel operations. But in this study, the process of measuring is realized by using images' histogram values as explained and detailed below.

Definitions of the Proposed Histogram based Image Quality Index Method

Let us assume the image is represented by *M* rows and *N* columns. Then, $x = \{x_i | i = 1, 2, 3, \ldots \ldots, M \times N\}$ and $y = \{y_i | i = 1, 2, 3, \ldots \ldots, M \times N\}$ are the original and the test image pixel values, respectively. $\forall\, x_i, y_i \in Z^+$ is a brightness value from the i^{th} position of the image and $0 \leq x_i, y_i \leq 255$.

In addition, $h_x = \{(h_x)_j | j = 0, 1, 2, \ldots \ldots, 255\}$ and $h_y = \{(h_y)_j | j = 0, 1, 2, \ldots \ldots, 255\}$ are the frequencies of occurrence of the original (x) and the test (y) images' brightness values, respectively. $\forall\, (h_x)_j, (h_y)_j \in Z^+$ is a frequency of the occurrence of brightness values from j^{th} position of the histogram and $0 \leq (h_x)_j, (h_y)_j \leq M \times N$.

Using the valuable information above, the proposed quality index is composed of two components, defined as follows:

(1) $$\text{HQI} = \Delta_{TC}\text{Factor} \times \text{HD}$$

The first component of the HQI is Δ_{TC}Factor (inter-histogram difference factor). Histograms obtained from the original image and the test image are applied to the extraction process as seen below.

(2) $$\Delta = |h_x - h_y|$$

The Δ is a difference vector [256×1] between the original and the test image histograms. Total change (Δ_{TC}) between the original and the test image histograms can be calculated by summation of all indices of the Δ (eq. 3) and $0 \leq \Delta_{TC} \leq 2 \times \mathrm{M} \times \mathrm{N}$.

(3) $$\Delta_{TC} = \sum_{n=1}^{256} \Delta_n$$

Then, Δ_{TC}Factor varying between 0 (worst) and 1 (best) is calculated using Δ_{TC} as seen below:

(4) $$\Delta_{\mathrm{TC}}\mathrm{Factor} = 1 - \left(\frac{\Delta_{\mathrm{TC}}}{\Delta_{\mathrm{TC}_{\max}}}\right)$$

$\Delta_{\mathrm{TC}_{\max}}$ expression means that the upper limit on the amount of histogram change is $(2 \times \mathrm{M} \times \mathrm{N})$. The range of $\Delta_{\mathrm{TC}}\mathrm{Factor}$ is [0, 1]. The best value 1 is achieved if and only if $h_x = h_y$.

The second component of the HQI (in eq. 1) is HD (Histogram Distortion) and it refers to the correlation quality between h_x and h_y. It is calculated by the classical correlation formula as seen below:

(5) $$HD = \frac{\sum_{j=0}^{255}\left((h_x)_j \times (h_y)_j\right)}{\sum_{j=0}^{255}\left((h_x)_j\right)^2}$$

Like the Δ_{TC}Factor, the best HD value is also 1, which is obtained when $h_x = h_y$. The explanations above show that the best HQI value is 1, which results when Δ_{TC}Factor and HD values are equal to 1. The worst value of the HQI is 0, which occurs when $\Delta_{TC} = \Delta_{\mathrm{TC}_{\max}}$.

Experimental Results

Some sample images downloaded from [16] are shown in Fig. 2. They are tuned with all well-known distortions to yield the same MSE values relative to the original image, except for the JPEG compressed image with a slightly smaller MSE value. The MSE, Δ_{TC}, Δ_{TC}Factor and HQI results are given in Table 1. The MSE results for Fig. 2−b,−c,−d,−f,−g,−h are similar, meaning that the imposed different distortions have the same effect on them. This implies the fact that the MSE parameter solely does not enable distinguishing for all probable cases between the original image and test image. Therefore, it exhibits a very poor performance in terms of a numeric quality measure. However, using the proposed histogram based HQI metric as a new quality measure, it can be statistically shown that Fig. 2−g is much worse affected compared to Fig. 2−b,−c,−d,−e,−f.

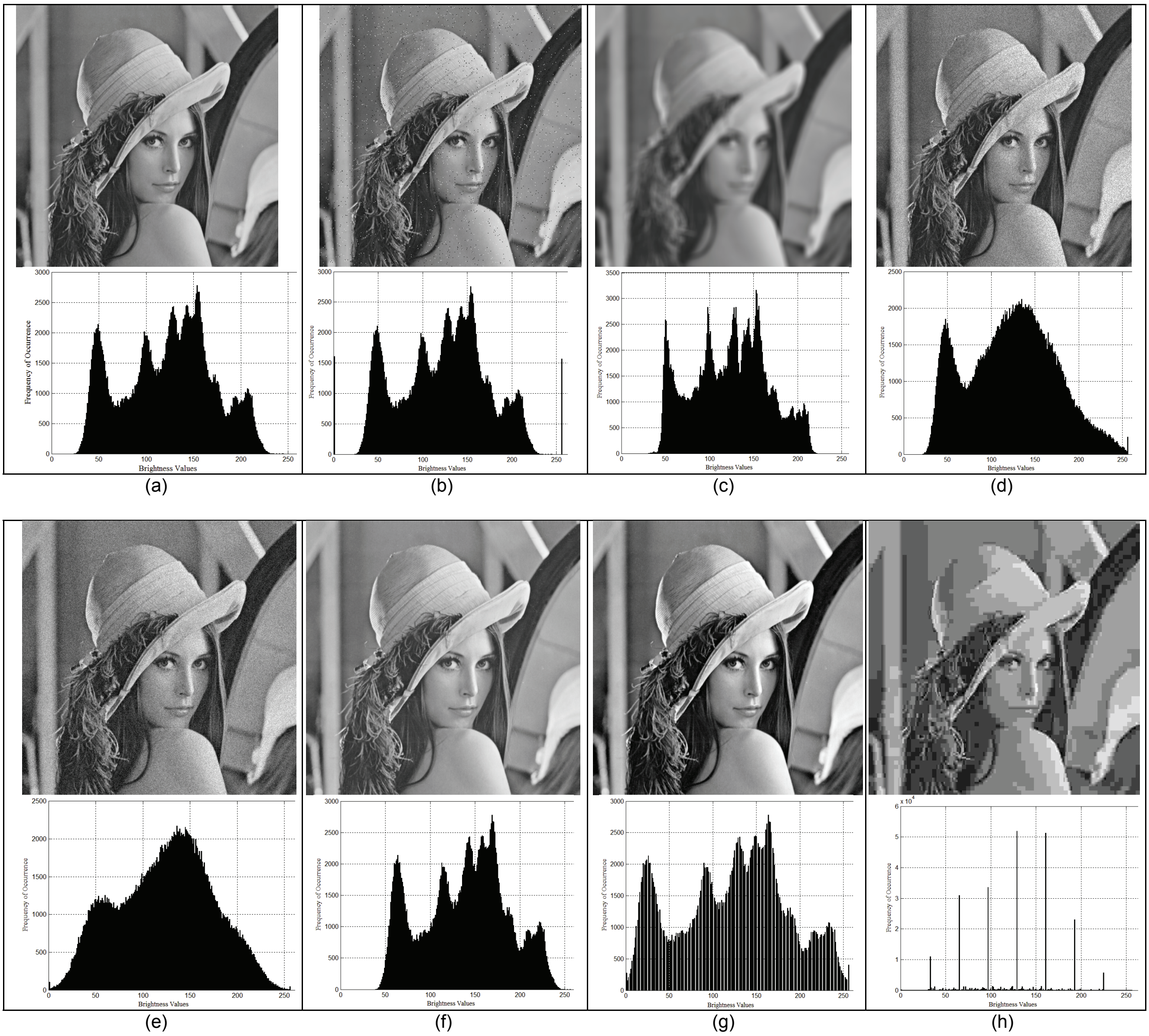


Fig. 2. Evaluation of the "Lena" images and their histograms contaminated by some noises. (a) Original "Lena" image, 512×512, 8 bits/pixel; (b) Impulsive Salt & Pepper noise MSE=225, HQI=0.975; (c) Blurring noise, MSE=225, HQI=0.906; (d) Multiplicative Speckle noise, MSE=225, HQI= 0.829; (e) Additive Gaussian noise, MSE=225, HQI= 0.800; (f) Mean Shift noise, MSE=225, HQI=0.677; (g) Contrast Stretching noise, MSE=225, HQI=0.510; (h) JPEG Compression, MSE=225, HQI=0.211.

As seen from Table 1, only Δ_{TC}Factor value or only HD value are not used to express the level of statistical image histogram quality. So, obtaining the HQI values by multiplying these two components provides the means for a highly refined quality measure result that can be safely utilized for image distortion analysis studies.

Only an example (Lena image) under different well-known distortions is resented in this a er Fi . 2 .

The HQI can be applied to local regions using a sliding window approach. This can be very useful in examining any portion of a test image in order to clarify whether only a specific part of the image has been distorted or worked out for any reason. For example, starting from the top-left corner of an image, a sliding window of size S×S moves horizontally and vertically all around the images until the bottom-right corner is reached. At f^{th} step, the local quality index HQI_f can be computed within the sliding window seen as follows:

$$HQI_f = \Delta_{TC}Factor_f \times HD_f \quad (6)$$

Afterwards, it is straightforward that the lowest HQI_f result implies the worst distorted test image portion.

Conclusions

A new histogram based image quality index (HQI) is proposed in this paper. Our experimental results indicate that it outperforms the MSE significantly under different types of image distortions (mean shift, jpeg, blurring etc.). So, a simple implementation of the new philosophy exhibits very promising results.

The proposed HQI is composed of two variables. The first, Δ_{TC}Factor denotes the changing in frequency of occurrence of image brightness values between the original and test images. The second component HD denotes the correlation quality between the original image and test image histograms (i.e., h_x and h_y). The HQI is obtained by multiplying the values of these two variables.

Table 1. Statistical quality measures (MSE and HQI) of Lena image with different types of distortions.

Test Image	Distortion Type	MSE	Δ_{TC}	Δ_{TC} Factor	HD	**HQI** (Δ_{TC} Factor× HD)
Fig. 2 (b)	Impulsive Salt & Pepper	225	6350	0.987	0.988	**0.975**
Fig. 2 (c)	Blurring	225	48828	0.906	1.000	**0.906**
Fig. 2 (d)	Multiplicative Speckle	225	55912	0.893	0.929	**0.829**
Fig. 2 (e)	Additive Gaussian	225	62620	0.880	0.910	**0.800**
Fig. 2 (f)	Mean Shift	225	118116	0.774	0.875	**0.677**
Fig. 2 (g)	Contrast Stretching	225	169732	0.676	0.755	**0.510**
Fig. 2 (h)	JPEG Compression	215	406538	0.224	0.941	**0.211**

Experimental results show that the MSE exhibits a very poor performance in terms of a numeric quality measure. On the other hand, the proposed HQI can be used to statistically distinguish any test images with different kinds of distortions resulting in exactly same MSE values.

In addition to these valuable results, the HQI can be utilized to evaluate the performance of data hiding algorithms mainly based upon digital image processing in addition to the classical steganalysis methods.

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