J. Indian Inst. Sci., Mar.–Apr. 1999, **79**, 89–97.

A contrast enhancement technique based on visual significance

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Abstract

Histogram equalization technique is a well-known method of enhancing the contrast of digital images. However, a drawback of this classical technique is that it enhances the whole image indiscreetly, resulting in unnecessary details. We propose a method that identifies visually significant regions and then enhances the image using the classical histogram equalization technique. Results illustrating the operation and superior performance of the proposed algorithm along with classical histogram equalization are presented.

Keywords: Histogram equalization, visual significance, focus, contrast, texture.

1. Introduction

The principal objective of any enhancement algorithm is to process a given image so that the result is more suitable than the original image for a specific application. The main aim of enhancement process is to increase the dynamic range of a given image. Histogram equalization (HE) is considered to be a powerful classical enhancement technique[1, 2] and many variants of it are found in the literature. Histogram-based brightness-preserving enhancement techniques are found in Kim[3] and Roomi *et al.*[4] Bukhanwala and Ramabadran[5] considered visually significant regions for enhancing the image. The proposed method first partitions the given image into segments which are further divided into small regions called windows. Using statistical measures, visually significant segments are selected. The whole image is histogram-equalized using statistics collected from select segments.

2. HE

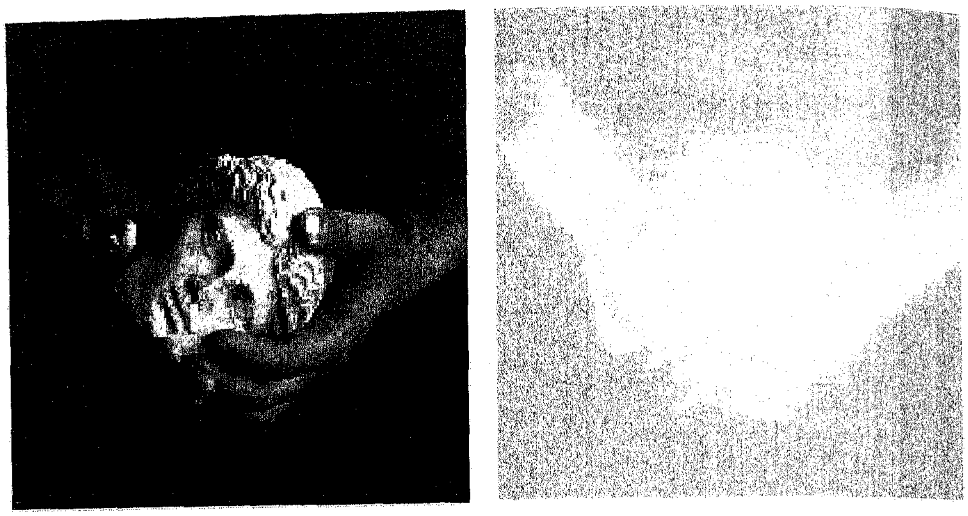
HE maps the input grey levels to a grey level which is proportional to its cumulative density. Hence the probability of each grey level in resulting image is uniformly distributed.[2] Let $X = \{X(i, j)\}$ be the given image which is composed of L discrete grey levels.

$$X \in \{X_0, X_1, \ldots, X_{L-1}\} \qquad (1)$$

where $X(i, j)$ denotes the intensity value at spatial location (i, j). Now for every grey level in the image, the probability density function P_k is defined as,

$$p_k = \frac{n_k}{N} \text{ for } k = 0, 1, 2, \ldots\, L-1, \qquad (2)$$

where n_k is the number of times that level k appears in the image, and N the total number of pixels in the image. The plot between n_k and k known as histogram can be plotted. HE



(a) Original image-*Hand*. (b) Result of histogram equalization.

FIG. 1.

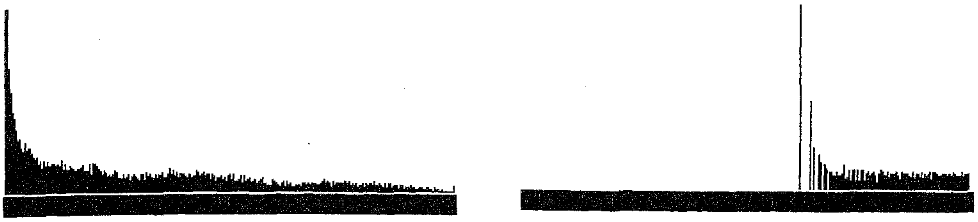
technique equalizes the image by using cumulative density function as a transform function, which is given by,

$$f(x) = X_0 + X_{L-1} - X_0 \sum_{j=0}^{x} p_j . \qquad (3)$$

Then the resulting image can be found as $Y = \{f(X(i, j)) | \forall\ X(i, j) \in X\}$. Note that the HE method is *global* and *blind* such that it does not take input visual detail into account while enhancing any image.

One example of HE is illustrated in Fig. 1 where the first one is an original image *hand* of 256 grey levels and the second is the result of HE. This result shows the convincing performance of HE in enhancing the contrast of an image as a consequence of dynamic range expansion, which can be easily understood by comparing the respective histograms of those images shown in Fig. 2. As stated earlier, histogram technique can introduce a significant change in brightness of an image and reveal the details of unwanted regions of the image creating annoying effect. It can be observed from Fig. 1 that the overall contrast of the input image is degraded after HE. This is the direct consequence of excessive change in brightness by HE when the image has a high density over low grey levels, whereas the image shown in Fig. 3, enhanced by the proposed method, has no degradation.

Another example which shows the limitation of HE is illustrated in Fig. 4 where the first image *spine* is a given original image and the second is the result of HE. It is obvious that the resultant image has unnatural enhancement around the spine. More fundamental reason behind such limitations is that HE is not image content-dependent so as to maintain mean brightness and visual quality. The subsequent section proposes a new contrast-enhancement algorithm that would alleviate the drawback of HE.



(a) Histogram of original image–*Hand*. (b) Histogram of histogram-equalized image.

FIG. 2.

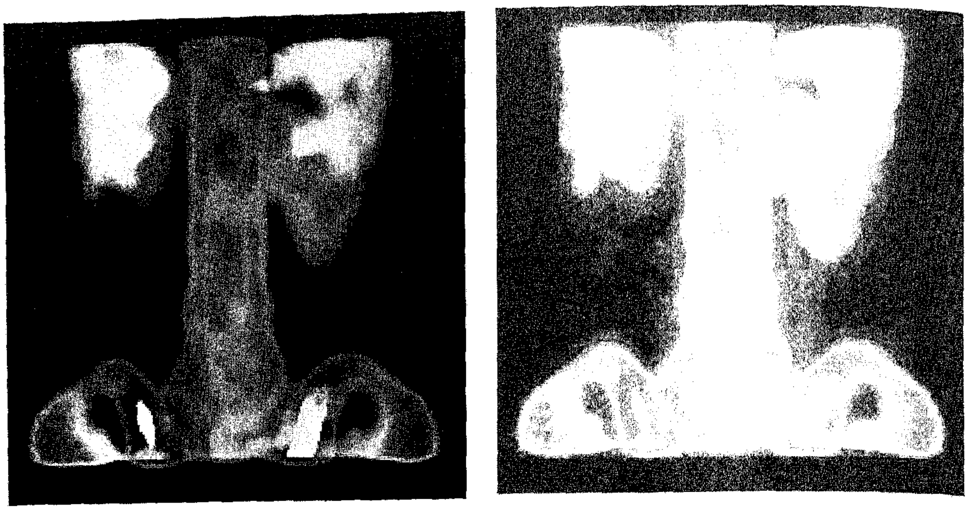
3. Proposed technique

Since the conventional HE technique is global and blind, the proposed algorithm enhances the given image based on visually important regions of an image, thus bringing effectiveness. In an image, the visually important or significant region is characterized by the quantity of focus, contrast and texture present in that region. The proposed algorithm exploits the usefulness of HE but calculates the histogram based on the image data available in visually important regions of an image. This would require first the identification of visually important regions of an image by calculating certain statistical parameters and secondly calculating and applying HE on them.

3.1. *Computation of statistical parameters*

To analyze an image statistically, it is first divided into segments which are further divided into windows. Simple statistical measures are then calculated for each window, and based on these measures, the parameters ‘Contrast’, ‘Focus’ and ‘Texture’ are computed for every segment.

FIG. 3. Result of the proposed method.



(a) Original image-*Spine*. (b) Histogram-equalized image.

FIG. 4

3.1.1. *Segmentation and windowing*

Segmenting[5] the given image is essential for parameter computations, hence the first step, which refers to dividing the given image into a number of rectangular blocks (called segments); further, each segment is divided into small square-size blocks called windows. The number of horizontal and vertical partitions has been maintained equal, and hence the resulting segments have the same aspect ratio as the original image.

3.1.2. *Algorithm for computing statistical parameters*

a) For each window *W*, the following statistical measures are found.

   (i) Mean pixel intensity *M*(*W*)

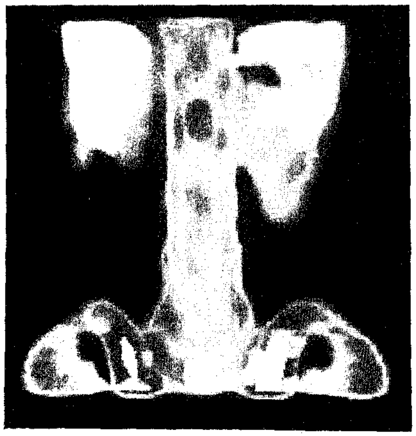


FIG. 5. Result of the proposed image.

(ii) Mean absolute deviation $D(W)$
(iii) Horizontal edge count $HEC(W)$
(iv) Vertical edge count $VEC(W)$
(v) Normalized mean edge magnitude $EM(W)$
where the normalization is with respect to $D(W)$.

Let $W(l, m)$ denote the value of pixel at the lth row and mth column.

$$\text{Let } THLD_{(x,y)} = \begin{array}{ll} 1 & x > y \\ 0 & \text{otherwise} \end{array}$$

$$\text{Let } CLIP_{(x)} \quad \begin{array}{ll} x & x > 0 \\ 0 & \text{otherwise} \end{array}$$

The different statistical measures are calculated as follows:

$$M(W) = \frac{1}{(L * M)} \sum_{1}^{L} \sum^{M} W(l, m) \tag{4}$$

$$D(W) = \frac{1}{(L * M)} \sum_{1} \sum_{1}^{M} | W(l, m) - (W) | \tag{5}$$

$$HEC(W) = \frac{1}{(L * M)} \sum_{1}^{L} \sum_{1}^{M} THLD(| W(l, m) - W(l, m+1) |, \xi(W)) \tag{6}$$

$$VEC(W) = \frac{1}{(L * M)} \sum_{1} \sum_{1}^{M} THLD(| W(l, m) - W(l+1, m) |, \xi(W)) \tag{7}$$

$$EM(W) = \frac{1}{(D(W))} \left(\frac{EMH(W) + EMV(W)}{HEC(W) + VEC(W)} \right) \tag{8}$$

$$\text{where } EMH(W) = \sum_{1}^{L} \sum_{1}^{M} CLIP(| W(l, m) - W(l, m+1) | - \xi(W)) \tag{9}$$

$$EMV(W) = \sum_{1}^{L} \sum_{1}^{M} CLIP(| W(l, m) - W(l+1, m) | - \xi(W)) \tag{10}$$

$$\xi(W) = \lambda * D(W).$$

Typical values of λ are between 0.8 and 1.2. Thus, to qualify as an edge the change in pixel intensities must exceed $\xi(W)$. Note that every measure defined above requires only $O(n)$ computations, where n is the number of pixels processed and hence the quick computations.

b) After calculating measures for all windows within a segment, mean and mean absolute deviation of this measure over the entire segment are also calculated. Suppose a segment S has

K windows. Let W_k denote Kth window. The segmental mean of the measure $F(W)$ denoted by $M(S)\_F(W)$ and segmental deviation denoted by $D(S)\_F(W)$ are given, respectively, by

$$M(S)\_F(W)=\frac{1}{k}\sum_{1}^{K}F(W_k)$$

$$D(S)\_F(W)=\frac{1}{k}\sum_{1}^{K}|F(W_k)-M(S)\_F(W)|$$

A simple measure of contrast is provided by the deviation of pixel intensities in a region. Therefore, the contrast $C(S)$ of a segment S is given by

$$C(S)=M(S)\_D(W)+D(S)\_M(W). \tag{11}$$

The first term is a measure of the local contrast within each window in an average sense. The second is a measure of global contrast within the segment.

Focus (sharpness) is an important visual feature since it represents the intent of the user. The focus $F(S)$ of a segment S is computed by the average normalized mean edge magnitude over the entire segment, i.e.

$$F(S)=M(S)\_EM(W). \tag{12}$$

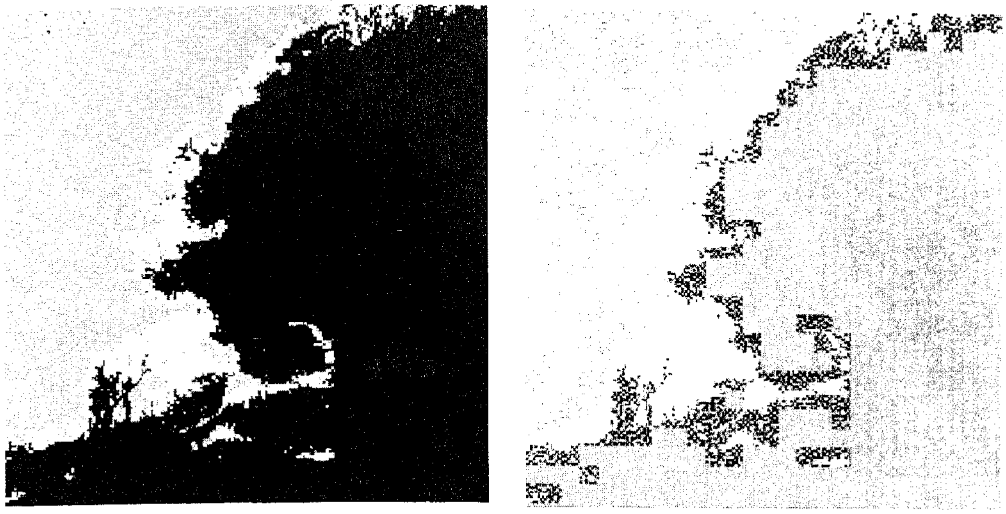
Texture[1] refers to the surface nature of objects. Although it can be measured in many ways (autocorrelation, frequency domain methods), to keep the complexity low, we will calculate the texture of a segment as:

$$T(S)=\frac{1}{(D(S)\_D(W))}+\frac{1}{(\min(D(S)\_HEC(W),D(S)\_VEC(W)))} \tag{13}$$

The first term is the reciprocal of the segmental deviation of the deviations of windows. The second term is the reciprocal of the minimum of the segmental deviation of the horizontal and vertical edge counts in the windows. In a textured region with repetitive details, the segmental deviations can be expected to be small resulting in a high value for $T(S)$. After $C(S)$, $F(S)$ and $T(S)$ are computed for an image as above, they are normalized so that their range is from 0.0 to 1.0. This is because the interest is only in the relative values of these features for the different segments within an image. Thus, for example, segments with a high absolute contrast value in a high-contrast image and low absolute contrast value in a low-contrast image may have the same relative contrast value. These normalized feature values are then combined to evaluate the visual significance $V(S)$ of a segment as follows :

$$V(S)=F(S)\,[\alpha C(S)+(1-\alpha)T(S)] \tag{14}$$

where α is a real number between 0 and 1 with typical values ranging from 0.5 to 0.8. In the above equation, the focus of a segment is given more importance than the other two features which is quite appropriate since focus represents the user's intention. The range of $V(S)$ is also between 0.0 and 1.0. To identify the visually important segments within an image, a visual threshold VT needs to be chosen. Segments with $V(S) > VT$ are considered to form the subject, and segments with $V(S) < VT$ the background.



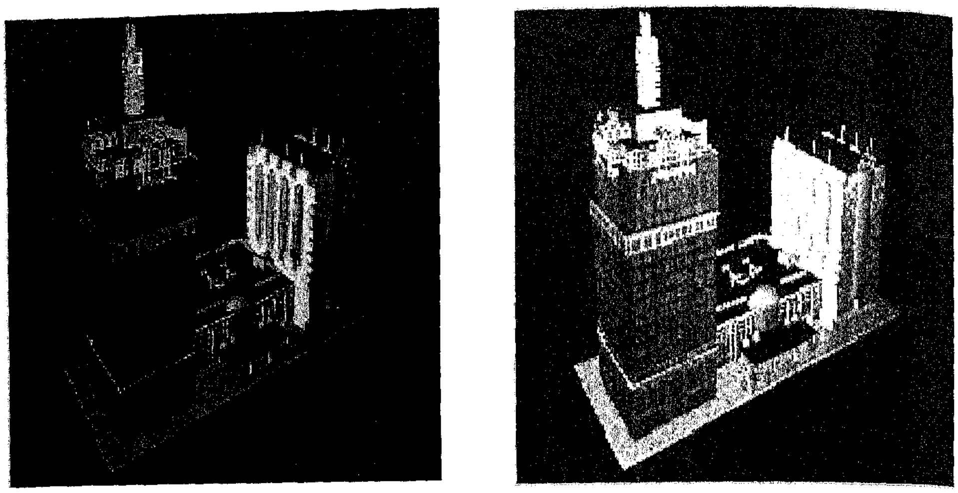
(a) Original image–*Cape*. (b) Histogram-equalized image.

FIG. 6.

3.2. *Enhancement*

Once the visually significant regions have been identified by the above procedure, the conventional HE is applied but by taking image data from visually significant segments. While applying HE, the cumulative density (eqn 2) is calculated for pixels present in the segments qualifying as visually important and user intended. Then, the whole picture is equalized using cumulative density resulting in natural enhancement and suppression of details of unwanted regions.

FIG. 7. Result of the proposed method.



(a) Original image–*ntsc.* (b) Result of the proposed method.

FIG. 8.

4. Results and discussion

To demonstrate the performance of the proposed algorithm, 256 grey-level images have been taken and the results are compared with those of the histogram-equalized images. Observations from Fig. 1 reveal that conventional HE unnecessarily enhances the background, whereas the proposed method (Fig. 3) preserves the background, while enhancing the user-intended regions. Also in Fig. 4, the background is unnecessarily enhanced and the edges of *spine* are degraded. The proposed method (Fig. 5) enhances the regions of interest alone. Figure 6 reveals that HE enhances the image overall and blurs the coastal regions. On the other hand, the proposed method (Fig. 7) provides natural enhancement with more picture details. Also, Fig. 8 emphasizes the utility of the proposed algorithm. Every statistical measure defined in this method requires only O(n) computations, where n is the number of pixels processed and hence the quick computations.

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