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Block Overlapped Intensity-Pair Distribution Approach for Image Contrast Enhancement

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Abstract: In this study, we present an image contrast enhancement method based on block-wise intensity pair distribution. The proposed algorithm takes the local intensity-pair distribution, instead of using the intensity-pair distribution of the whole image. To deal with the issues of contrast stretch and over-enhancement, a linear magnitude mapping function is used as a substitute to a non-linear one. This linear mapping preserves the relative contrast enhancement ratio between the gray levels. The local information from blocks facilitates contrast enhancement, enhances subtle edge information and eliminates noises from the image. The proposed algorithm is suitable for detail analysis of image features.

Key words: Enhancement, image processing, anti-expansion force, expansion force, intensity pair

INTRODUCTION

Contrast enhancement is of vital importance in image processing. Its significance with respect to human and computer vision can't be disregarded. It is widely used for medical image processing and as a preprocessing step in speech recognition, texture synthesis and many other image/video processing applications (Pei *et al*., 2004). Different methods have already been developed for this purpose (Chen and Ramli, 2003a; Sun *et al*., 2005). Some of them employ simple linear/non-linear gray level transformation functions (Gonzalez and Woods, 1992), while some of the others rely on complex analysis of different image features such as edges (Boccignone, 1997), connected component information (Caselles *et al*., 1997) and so on.

A popular technique for contrast enhancement is Histogram Equalization (HE) (Gonzalez and Woods, 1992; Kim *et al*., 1998). As some image features are low in contrast, we usually transform it before display. The histogram equalization performs gray level transformation on the basis of the probability distribution of the input gray levels (Chen and Ramli, 2003b). The aim is to stretch the dynamic range of the histogram of an image which results in overall contrast improvement. The literature shows a considerable amount of research related to histogram equalization. It can be categorized into two principle classes-global and local histogram equalization (Kim *et al*., 2001). Global Histogram Equalization (GHE) utilizes the histogram information of the entire input image for its transformation function. Figure 1b shows the result of GHE on the original image as shown in Fig. 1a. Despite the fact that this global approach is appropriate for overall enhancement, it fails to adapt with the locally varying brightness of the input image (Kim *et al*., 2001) and translates the brightness to the average gray level of the image regardless of the input brightness (Kim, 1997). Local Histogram Equalization (LHE), also known as, Adaptive Histogram Equalization (AHE) (Kim *et al*., 1998), resolves this problem. It uses a small window that slides over the image sequentially and only the block of pixels that fall in the window are taken into account for histogram equalization and then gray level mapping is applied to the center pixel of that window. As a consequence, we gain benefit of histogram equalization as well as of local statistical information of the input image. Adaptive Contrast Enhancement (ACE) (Lee, 1980) which is a similar technique to LHE, which works with the local image characteristics. However, both LHE and ACE entail high computational cost and sometimes cause over-enhancement in some part of the image. In addition to this, they cannot discriminate among noise and useful features of the image. So they enhance noises along with the image features. To evade the high computational cost, an alternative approach is to apply non-overlapping block based HE. On the other hand, most of the time, these methods produce an undesirable checkerboard effects on enhanced images (Gonzalez and Woods, 1992).

As edges are considered to be a sensitive image feature for image understanding, a way to enhance the contrast of an image is to enhance its edges. Recently developed, Ridgelet and Curvelet transforms can be tailored to enhance edges in an image Stark *et al.* (2003). Curvelet-based Method is proposed by the scheme suggests application of three different thresholds for identifying the curvelet coefficients with noise, strong

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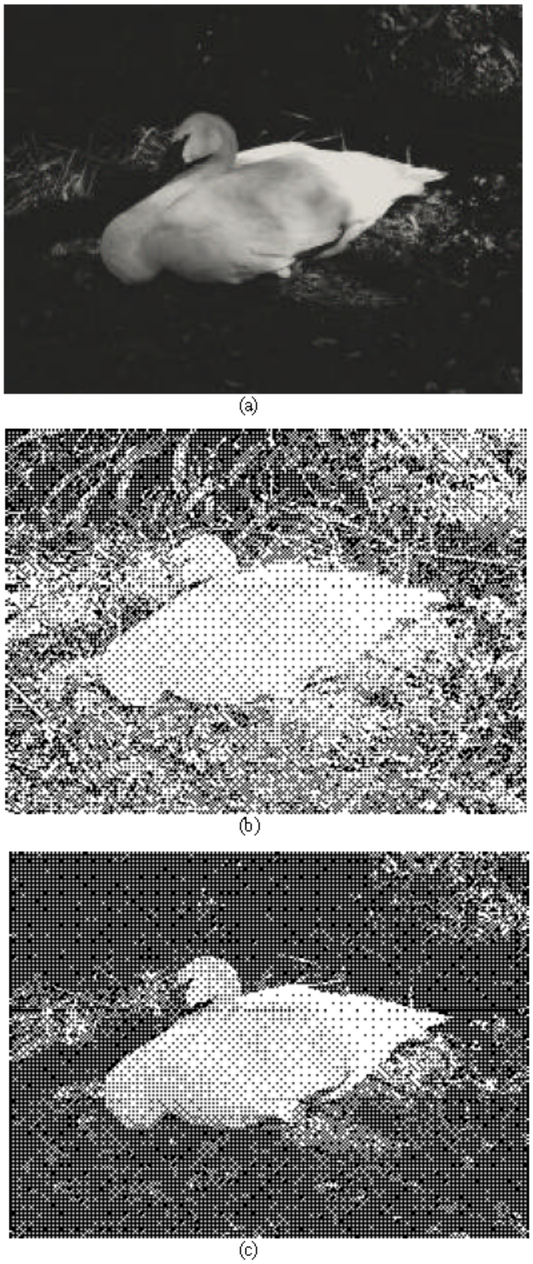

Fig. 1: (a) Original image, (b) Enhanced image resulting from GHE and (c) Enhanced image resulting from Intensity Pair Distribution based method

edges and weak edges. The coefficients with an absolute value in a small range are modified. Though in multi-scale edge enhancement t, curvelet based approach out performs wavelet approach (Velde, 1999), but for noiseless or near noiseless images its enhancement is not remarkly better than wavelet based enhancement (Starck *et al*., 2003). The main reason for this disparity is the principle of sub-band decomposition associated with a curvelet transform. Here, the sub-band decomposition imposes a relationship between width and length of the important elements. Some of the edges may not be able to fulfill this constraint and hence subsequently ignored by the curvelet transform.

On the other hand, Jen *et al*. (2005) proposed a straightforward approach for edge enhancement based on intensity-pair distribution that possesses both the local and global information of the image content. Based on the intensity difference in the intensity pair, either a set of expansion forces or a set of anti-expansion forces is generated to get an intensity mapping function, which curbs image noise and stretches contrast of edge regions in the output image. This mapping function is almost like GHE mapping function but incorporates some neighborhood information from intensity pairs. However this method cannot sharpen weak edges with low intensity-pair contribution. For this specific reason we see that, once all the intensity pairs are taken into account for force generation, intensity pairs of smooth region covering major portion of the gray level range will dominate present proposed algorithm takes advantage of the block-wise intensity pair distribution for edge enhancement.

Images contain two-dimensional arrays of intensity values with locally varying statistics, which results from different combinations of abrupt features, like edges and distinct homogeneous regions (Gonzalez and Woods, 1992). Since different parts of the image have different statistical characteristics we employ the block based approach, to deal with local information effectively. This leave fewer possibility for the smooth regions from other part of the image to have larger influence over the edge pairs and finally lead to better image contrast stretch. Figure 2 shows an example of how one portion of an image statistically differs from another. Unlike (Jen *et al*., 2005), where a nonlinear magnitude function was used to avoid over-enhancement and retain the natural look of the processed image. Present proposed technique uses a linear magnitude mapping function to keep the relative ratio between the forces at different gray levels since present search space is small. After obtaining the final intensity mapping function from the forces of intensity pairs, only the center pixel of that block is replaced and we move onto the next pixel to repeat the same procedure. The method introduced in this study encompasses the advantages of conventional intensity pair distribution method and block based approach for better edge extraction and enhanced image.

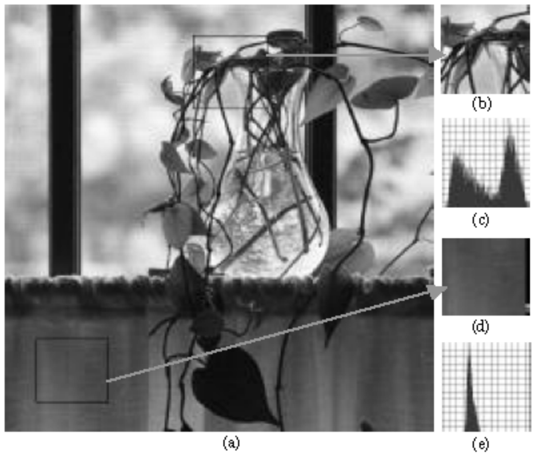

Fig. 2: (a) Original image, (b) Upper region. (c) Histogram of (b), (d) Lower region and (e) Histogram of (d)

INTENSITY-PAIR DISTRIBUTION METHOD

This section will in brief illustrate the Intensity-Pair distribution method for image enhancement. The algorithm presented in (Jen *et al*., 2005) extracts both the global and local information. It starts with computing the intensity-pair distribution. For a given image, each pixel is checked with its 8-connected neighbors. Due to the commutative property of intensity pair, only 4-neighboring pixels in raster order are scanned. Now to find intensity pairs belonging either to the smooth region or the edge region, we take the intensity difference within the pair. If the intensity difference is above a predefined threshold we treat that pair as an edge pair otherwise that belongs to a flat region. To increase the contrast of the image and make the edges sharp, we stretch the intensity of the edges pairs.

In order to have contrast stretch of edge pairs, we give expansion force to all gray levels of the gray level range of those pairs. In a real 2D image many edge exists. So, we accumulate all the expansion forces between the edge pairs. Now the smooth intensity pairs might lie within the gray level range of the edge pair. Due to the contrast stretch of the edge pair, those smooth regions will also be stretched. To avoid these circumstances, anti-expansion forces are generated within the gray level range of the smooth intensity pairs. Similarly all the anti-expansion forces are accumulated for those intensity pairs of the smooth region and then subtracted from the expansion forces to obtain the net expansion force. Here, our algorithm makes sure that the anti-expansion forces preserve the smoothness for flat regions in the net-expansion force. Still the magnitude of the net-expansion force might be high enough to cause some unnatural and overly enhanced image. To reduce the dynamic range of the net expansion force, a magnitude mapping function M(.) is applied which constrains the expansion force to an extent such that the image looks natural. A proposed mapping function is

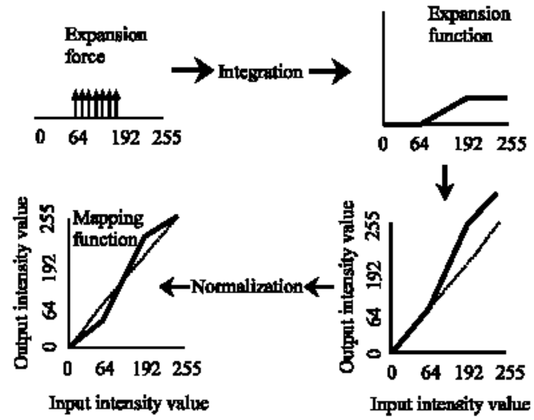

Fig. 3: Intensity mapping function generation procedure

$$Y = M(X) = X^{1/m} \tag{1}$$

where X is the net-expansion force, Y denoting adjusted net-expansion force and m is the behavior controlling parameter. Finally the expansion forces are integrated and normalized to get the expansion function for intensity mapping. Figure 3 shows the procedure for generation of intensity mapping function and Fig. 1c shows the enhanced image resulting from using the conventional approach. Notice that the contrasts of some of the edges have not improved significantly. This happened because the contrast stretch exploited the global information with total disregard for contrast stretch needed only for a particular region.

BLOCK BASED INTENSITY-PAIR DISTRIBUTION METHOD

In the proposed method, our objective is to bring out the subtle details of the image by letting the less frequent intensity-pairs to contribute almost equally to the expansion function, which stretches the gray levels. Unlike Jen *et al*. (2005) where a single expansion function is used to map all the gray level values of the input image, the proposed approach divides the image into overlapping blocks and a different expansion function is generated for each block based on the intensity-pairs of that block. The local statistics obtained from the block, intensity of the center pixel is computed. In case of global intensity pair distribution method, since the smooth intensity pairs will generate trains of anti-expansion force, due to the high occurrences of those pairs the anti-expansion force might nullify the expansion force. As a result, in the net-expansion force there will be no effect from those edge pairs and no contrast stretch. In case of block-based intensity pair distribution, since we focus only to the intensity pairs falling inside the block, there is no scope for the smooth regions to dominate the edge pair forces.

When the block slides over the pixels at the edges, we have more edge pairs, which then give rise to more expansion forces at edge regions. Moreover, to avoid unnatural or overly enhanced features due to the large magnitude expansion force, the contrast enhancement approach based on global intensity-pair distribution (Jen *et al*., 2005) uses a magnitude mapping function on the net expansion force, which is nonlinear in nature. Due to the nonlinearity, the ratio between the forces at different gray levels does not remain the same. So the resultant net expansion forces do not reflect properly the forces of the intensity pairs anymore. Our proposed method confines attention to the block only and we have less number of intensity pairs, there is less option of having net-expansion force with extremely large magnitude. Here the proposed contrast enhancement algorithm makes use of a linear magnitude mapping function to compress the dynamic range of the net expansion forces and to keep the relative contrast enhancement ratio between the gray levels which otherwise will be lost incase of non-linear mapping function.

In present algorithm, the first step is to identify a block and retrieve its intensity pair distribution. This distribution gives us the local information. If an edge falls inside the block then we will have many edge pairs. The expansion force and anti-expansion forces are computed in the same manner as discussed in the previous section. To compress the dynamic range of the net expansion forces, we use a linear magnitude mapping function. An example of such a mapping function M(.) is

$$Y = M(X) = X / \max(f_0, f_1, \ldots f_i, \ldots, f_{255}) \quad (2)$$

where fi is the number of times expansion force is added for the I-th gray level. The next step is to integrate the net-expansion force to generate the expansion function and normalize it to fit in the range 0 to 255. This function is used as the final intensity mapping function for the center pixel of the block. Since only the pixels inside the block are taken into account for the generation of the intensity mapping function and computation of center pixel's intensity, we are dealing more with the local information.

FOR (Each pixel position (x,y) in the input image) {

1. Scan through every pixel within the block centered at pixel position (x,y) to calculate the intensity-pair information.
2. **FOR** (Each intensity-pair) {
   IF (Intensity difference > preselected Threshold)
   Train of expansion forces is generated between the gray level range of intensity pair.
   ELSE
   Train of anti-expansion forces is generated between the gray level range of intensity pair.}
3. Accumulate the expansion and anti-expansion force.
4. For each gray level k, calculate the net expansion force based on the following equation:
   NetExpansionForce[k]
   = **ExpansionForce[k]**-
   g x AntiExpansionForce[k]
   here, g is chosen to be 0.1 empirically. If the net expansion force at k is negative, reset that value to zero.
5. Apply the magnitude mapping function M (.) over the net expansion force.
6. Integrate the net expansion force to obtain the expansion function T and normalize it to fit within the range 0 to 255.
7. The intensity value for the output image at pixel position (x,y) is calculated using the following equation:

   $\mathbf{w \times T[1(x,y)] + (1-w) \times 1(x,y)}$
   here, **w** is a combination factor with $0 \le \mathbf{w} \le 1$
   }

Fig. 4: Summary of the proposed algorithm

Next, the block is moved to the next pixel and the same procedure is repeated until the end of the image is reached. Here contrast enhancement based on intensity-pair distribution is performed on each block of information so that it can adapt to the subtle edge enhancement and partial light condition in the same way the block overlapped histogram equalization works. The proposed algorithm is basically a block overlapped intensity-pair distribution based image enhancement approach with a linear magnitude mapping function. This idea is summarized more clearly in Fig. 4.

RESULTS

The results from preceding algorithms and the proposed algorithms are simulated on various images and weighed against the enhancement ability of the proposed approach. Figure 5 shows the original image along with simulation results from LHE, Intensity Pair Distribution method and the proposed method. The Block Intensity-Pair distribution method has given improved enhancement of the image, especially with the lower part of the Saturn and its rings. While, LHE method has done over enhancement also bringing out noises, Intensity-Pair distribution method couldn't enhance much. Comparatively in Fig. 5d one notices that our approach has quite effectively enhanced the image contrast on the whole.

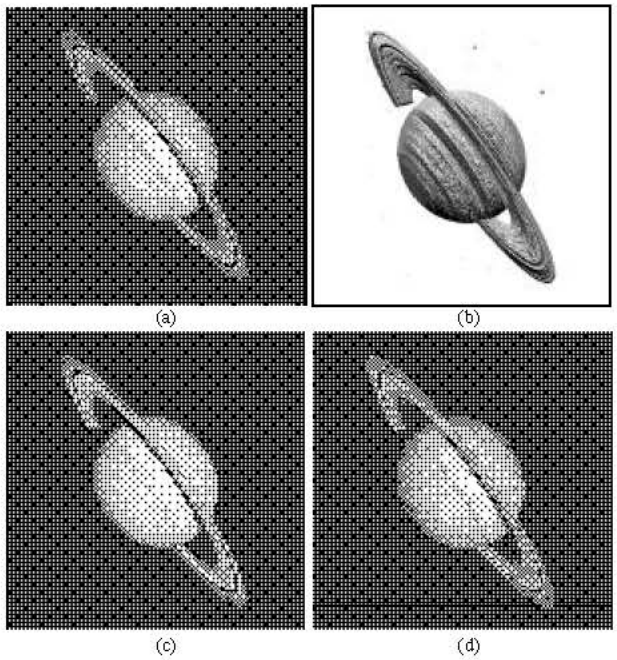

Fig. 5: (a) Original image, (b) Enhanced image by LHE with block size 3×3, (c) Enhanced image by intensity-pair distribution based method with behavior controlling parameter m = 2 and combination factor k = 0.8 and (d) Enhanced image by block based intensity pair distribution with combination factor w = 0.6 and block size 3×3

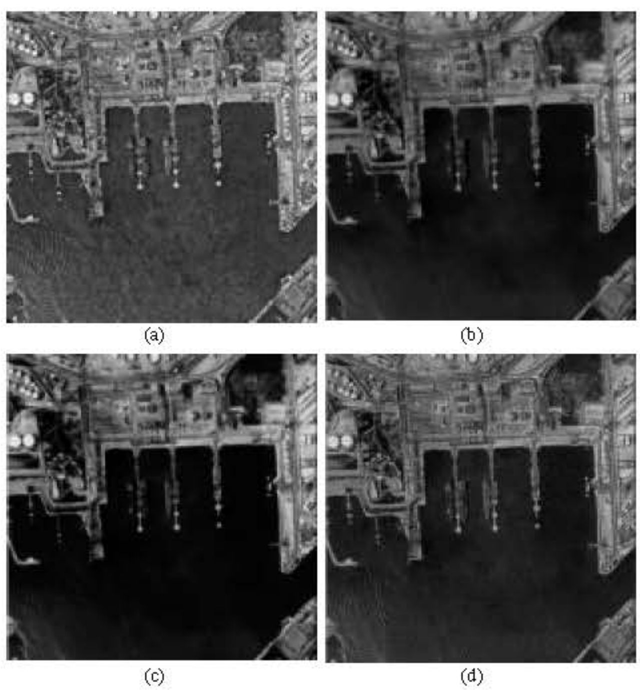

Fig. 6: (a) Original image, (b) Curvelet enhanced image, (c) Intensity pair distribution method enhanced image and (d) block based intensity pair distribution method enhanced image

Simulation result from applying the proposed method (g = 0.1, w = 0.6 and block size 3×3) on satellite image is shown in Fig. 6d, compared with Fig. 6b resulting from curvelet transform (c = 3, l = p = 0.5 and s = 0) and Fig. 6c resulting from conventional Intensity-pair distribution method (m = 2, g = 0.1 and k = 0.6). Here the edges and contrast at the upper portion are much more distinct in case of the enhanced image resulting from the proposed algorithm. Moreover, curvelet transform has also increased the overall brightness of the images, which might not be desirable in other images. In all respects be it edge representation, image brightness and contrast, our proposed approach has performed significantly better.

CONCLUSION

In this study, we propose a block based intensity pair distribution method with a linear magnitude mapping function for image contrast enhancement. Since only the block intensity pairs contribute to the intensity mapping function and smooth regions cannot nullify the expansion force of edge pairs, delicate edges are extracted and image enhanced. Simulation results have shown that the proposed method has done a considerable improvement compared with the existing methods. In view of the fact that the expansion forces do contribute to the contrast stretch, as a future research, we look forward to analyze these expansion forces deeply for image enhancement.

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