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A novel fuzzy logic approach to contrast enhancement

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Abstract

Contrast enhancement is one of the most important issues of image processing, pattern recognition and computer vision. The commonly used techniques for contrast enhancement fall into two categories: (1) indirect methods of contrast enhancement and (2) direct methods of contrast enhancement. Indirect approaches mainly modify histogram by assigning new values to the original intensity levels. Histogram specification and histogram equalization are two popular indirect contrast enhancement methods. However, histogram modification technique only stretches the global distribution of the intensity. The basic idea of direct contrast enhancement methods is to establish a criterion of contrast measurement and to enhance the image by improving the contrast measure. The contrast can be measured globally and locally. It is more reasonable to define a local contrast when an image contains textual information. Fuzzy logic has been found many applications in image processing, pattern recognition, etc. Fuzzy set theory is a useful tool for handling the uncertainty in the images associated with vagueness and/or imprecision. In this paper, we propose a novel adaptive direct fuzzy contrast enhancement method based on the fuzzy entropy principle and fuzzy set theory. We have conducted experiments on many images. The experimental results demonstrate that the proposed algorithm is very effective in contrast enhancement as well as in preventing over-enhancement. © 2000 Pattern Recognition Society. Published by Elsevier Science Ltd. All rights reserved.

Keywords: Fuzzy logic; Fuzzy entropy; Contrast; Contrast enhancement; Adaptiveness; Over-enhancement; Under-enhancement

1. Introduction

Contrast enhancement is one of the most important issues of image processing and analysis. It is believed that contrast enhancement is a fundamental step in image segmentation. Image enhancement is employed to transform an image on the basis of the psychophysical characteristics of human visual system [1]. The commonly used techniques for contrast enhancement fall into two categories: (1) indirect methods of contrast enhancement and (2) direct methods of contrast enhancement [2].

The indirect approach is to modify the histogram. In a poor contrast image, the intensities only occupy a small portion of the available intensity range. Through histogram modification, the original gray level is assigned a new value. As a result, the intensity span of the pixels is expanded. Histogram specification and histogram equalization are two popular indirect contrast enhancement methods [3]. However, histogram modification technique only stretches the global distribution of the intensity. To fit an image to human eyes, the modification of intensity's distribution inside small regions of the image should be conducted. The basic idea of direct contrast enhancement method is to establish a criterion of contrast measurement and enhance the image by improving the contrast measure.

Contrast can be measured globally and locally. It is more appropriate to define a local contrast when an image contains textural information. Dhnawan et al. [4] defined a local contrast function in terms of the relative difference between a central region and a larger surrounding region of a given pixel. The contrast values are then enhanced by some of contrast enhancement

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functions, such as the square root function, the exponential, the logarithm and the trigonometric functions. This method is more efficient and powerful than the indirect method. However, this method may enhance noise and digitization effect for a small neighborhood, and may lose the details for a large neighborhood [5].

It is well known that the perception mechanisms are very sensitive to contours [6,7]. Beghdad and Negrate [5] improved the method in Ref. [4] by taking into account of edge detection operators, and defining the contrast with the consideration of edge information. Although this adaptive contrast enhancement method achieves a success in enhancing the major components of an image, the noise may be amplified too, especially in a relatively flat region. Laxmikant Dash and Chatterji [2] proposed an adaptive contrast enhancement scheme which enhanced contrast with a lower degree of noise amplification. The idea of this method is that the degree of contrast amplification may vary with the severity of brightness change. The brightness variation is estimated by local image statistics. As a result, when the brightness change in a region is severe, the degree of enhancement is high, and conversely, the enhancement is relatively low. Therefore, the noise in flat region is reduced. However, over-enhancement and under-enhancement occur sometimes.

Fuzzy set theory has been successfully applied to image processing and pattern recognition [8]. It is believed that fuzzy set theory is a useful tool for handling the uncertainty associated with vagueness and/or imprecision. Image processing bears some fuzziness in nature due to the following factors: (a) information loss while mapping 3-D objects into 2-D images; (b) ambiguity and vagueness in some definitions, such as edges, boundaries, regions, features, etc.; (c) ambiguity and vagueness in interpreting low-level image processing results [9,10]. Moreover, the definition of contrast of an image is fuzzy as well. Therefore, it is reasonable to apply fuzzy set theory to contrast enhancement. Pal and King [11] used smoothing method with fuzzy sets to enhance images. They applied contrast intensification operations on pixels to modify their membership values. Li and Yang [12] used fuzzy relaxation technique to enhance images. At each iteration, the histogram was modified. Both Refs. [11,12] are indirect contrast enhancement approaches.

In this paper, we will use maximum fuzzy entropy principle to map an image from space domain to fuzzy domain by a membership function, and then apply the novel, adaptive, direct, fuzzy contrast enhancement algorithm to conduct contrast enhancement.

2. Fuzzy entropy and membership function

In this section, the definition of an image using the fuzzy set notation will be explained and the fuzzy entropy, a measure of the fuzziness, will be defined.

2.1. Image representation in fuzzy set notation

An image X of size $M \times N$ having gray levels ranging from L_{min} to L_{max} can be modeled as an array of fuzzy singletons [8,11]. Each element in the array is the membership value representing the degree of brightness of the gray level l ($l = L_{min}, L_{min}+1, \ldots, L_{max}$). In the fuzzy set notation, we can write

$$X = \{\mu_X(x_{ks})/x_{ks},\ k = 1,2,\ldots,M,\ s = 1,2,\ldots,N\}, \tag{1}$$

where $\mu_X(x_{ks})$ denotes the degree of brightness possessed by the gray level intensity x_{ks} of the (k,s)th pixel.

2.2. Entropy of fuzzy set

The degree of ambiguity of an image X can be measured by the entropy of the fuzzy set, which is defined as [8,11]:

$$H(X) = \frac{1}{MN}\sum_{k=1}^{M}\sum_{l=1}^{N} S_n(\mu_X(x_{kl})), \tag{2}$$

where $S_n(\cdot)$ is a Shannon function

$$\begin{aligned} S_n(\mu_X(x_{kl})) = &-\mu_X(x_{kl})\log_2\mu_X(x_{kl}) \\ &-(1-\mu_X(x_{kl}))\log_2(1-\mu_X(x_{kl})) \end{aligned}$$

$$k = 1,2,\ldots,M,\ l = 1,2,\ldots,N. \tag{3}$$

$H(X)(0 < H(X) < 1)$ measures the fuzzy uncertainty, caused by the inherent variability and/or fuzziness rather than the randomness. Shannon's function $Sn(\cdot)$ increases monotonously in $[0, 0.5]$ and decreases monotonously in $[0.5, 1]$ with a maximum at $\mu_X(x) = 0.5$.

2.3. Membership function

Membership function characterizes the fuzziness in a fuzzy set. It essentially embodies all fuzziness for a particular fuzzy set, and its description is essence of fuzzy property or operation. The membership function of a fuzzy set maps all the elements of the set into real numbers in $[0, 1]$. The larger values of the membership represent the higher degrees of the belongings. That is, the membership value represents how closely an element resembles an ideal element.

The most commonly used membership function for a gray level image is the S-function defined as [13]

$$\mu_X(x_{mn}) = S(x_{mn}, a, b, c) = \begin{cases} 0, & 0 \leqslant x_{mn} \leqslant a, \\ \frac{(x_{mn}-a)^2}{(b-a)(c-a)}, & a \leqslant x_{mn} \leqslant b, \\ 1 - \frac{(x_{mn}-c)^2}{(c-b)(c-a)}, & b \leqslant x_{mn} \leqslant c, \\ 1, & x_{mn} \geqslant c. \end{cases} \tag{4}$$

where a, b, and c are the parameters which determine the shape of the S-function. Notice that in this definition, b is not necessarily the midpoint of the interval $[a, c]$, and can be any point between a and c.

3. Proposed method

The main purpose of this paper is to enhance the contrast in fuzzy domain effectively and adaptively. The first step is to map an image from space domain to fuzzy domain using the S-function as the membership function. Then we propose a more powerful and adaptive fuzzy contrast enhancement method than adaptive contrast enhancement (ACE) method with adaptive power variation and interpolation techniques [2]. The proposed approach employs fuzzy entropy principle and fuzzy set theory. It can automatically determine the related parameters according to the nature of the image.

3.1. Mapping an image to fuzzy domain

As mentioned before, the performance of fuzzy enhancement depends on the membership function. The selection of parameters a, b and c for S-function becomes an important issue since these parameters decide the shape of the membership function, S-function. The criterion to determine the membership function in this paper is to reduce noise and minimize the information loss. Furthermore, the determination of the membership function should be based on the characteristics of the image.

Algorithm 1. Assume the image has gray levels from L_{min} to L_{max}. The detailed procedure to determine parameters a and c is described as follows.

1. Obtain the histogram $His(g)$.
2. Find the local maxima of the histogram, $His_{max}(g_1), His_{max}(g_2), \ldots, His_{max}(g_k)$.
3. Calculate the average height of the local maxima.

$$\overline{His_{max}(g)} = \frac{1}{k}\sum_{i=1}^{k} His_{max}(g_i).$$

4. Select a local maximum as a peak if its height is greater than the average height $\overline{His_{max}(g)}$, otherwise, ignore it.
5. Select the first peak $P(g_1)$ and the last peak $P(g_k)$.
6. Determine the gray levels B_1 and B_2, such that the information loss in the range $[L_{min}, B_1]$ and $[B_2, L_{max}]$ equals to f_1, $(0 < f_1 < 1)$, that is,

$$\sum_{i=L_{min}}^{B_1} His(i) = f_1,$$

$$\sum_{i=B_2}^{L_{max}} His(i) = f_1.$$

7. Determine parameters a and c as below:

Let $f_2 =$ constant, $(f_2 < 1)$

(a) $a = (1 - f_2)(g_1 - L_{min}) + L_{min}$
 if $(a > B_1)$
 $a = B_1$
(b) $c = f_2(L_{max} - g_k) + g_k$
 if $(c < B_2)$
 $c = B_2$

In our experiments, f_1 and f_2 are set to 0.01 and 0.5, respectively. The gray levels less than the first peak of the histogram may correspond to the background while the gray levels greater than the last peak may relate to noise. The idea behind the above algorithm is to reduce noise and maintain enough information of the image. Since the peaks of the histogram contain essential information, we cover the range between the two limits to avoid important information loss.

According to information theory [8,11–13], entropy measures the uncertainty of an information system. A larger value of the entropy of a system indicates more information in the system. The selection of parameter b is based on the maximum fuzzy entropy principle. That is, we should compute the fuzzy entropy for each b, $b \in [a+1, c-1]$, and find an optimum value b_{opt} such that

$$H_{max}(X, a, b_{opt}, c) = max\{H(X; a, b, c) \mid L_{min} \leqslant a < b < c \leqslant L_{max}\}.$$

After b_{opt} is determined, the S-function is decided and will be used to map the image to fuzzy domain.

3.2. Adaptive fuzzy contrast enhancement with adaptive power variation

ACE combines local contrast measurement with contour detection operator, therefore, it is very efficient for contrast enhancement. Also the improved version, adaptive power variation method, uses local statistics and successfully reduces noise amplification. However, some parameters, such as minimum and maximum amplification constants, were not determined automatically. Furthermore, they were not determined according to the characteristics of the image. Thus, the method may over-enhance some images while it may under-enhance others. Moreover, in the regions that are flat, it may need de-enhancement of the contrast instead of enhancement since these regions usually are associated with background or noise. The goal of our proposed method is to take care of the fuzzy nature of an image and the fuzziness in the definition of the contrast to make the contrast enhancement more adaptive and more effective, and to avoid over-enhancement/under-enhancement.

Algorithm 2. Given an $M \times N$ image X with L different gray levels, and parameters a, b_{opt} and c selected by the above method, the adaptive fuzzy contrast enhancement can be described as follows.

Step 1. Construct the membership μ_X which measures the fuzziness of an image X:

$$\mu_X(x_{mn}) = S(x_{mn}, a, b_{opt}, c), \quad m = 0, 1, \ldots, M^{-1},$$
$$n = 0, 1, \ldots, N^{-1}.$$

Step 2. For each pixel (m, n) with $\mu_X(x_{mn})$, apply edge gradient operator, such as Laplacian or Sobel operator, and find edge value of the image in fuzzy domain $\delta_{\mu(x_{mn})}$. Here, we use Sobel operator.

Step 3. Compute the mean edge value $E_{\mu(x_{mn})}$, within a window W_{mn} centered on pixel (m, n), using the formula:

$$E_{\mu(x_{mn})} = \sum_{(m,\,n) \in W_{mn}} (\mu(x_{mn})\delta_{\mu(x_{mn})}) \Bigg/ \sum_{(m,\,n) \in W_{mn}} \delta_{\mu(x_{mn})}.$$

Step 4. Evaluate the contrast related to the membership value $\mu(x_{mn})$,

$$C_{\mu(x_{mn})} = |\mu(x_{mn}) - E_{\mu(x_{mn})}| / |\mu(x_{mn}) + E_{\mu(x_{mn})}|.$$

Step 5. Transform the contrast $C_{\mu(x_{mn})}$ to $C'_{\mu(x_{mn})}$

$$C'_{\mu(x_{mn})} = (C_{\mu(x_{mn})})^{\sigma_{mn}},$$

where σ_{mn} is the amplification constant, $0 < \sigma_{mn} < 1$ for enhancement, and $\sigma_{mn} > 1$ for de-enhancement.

Step 6. Obtain the modified membership value $\mu'(x_{mn})$ using the transformed contrast $C'_{\mu(x_{mn})}$:

$$\mu'(x_{mn}) = \begin{cases} E_{\mu(x_{mn})}(1 - C'_{\mu(x_{mn})})/(1 + C'_{\mu(x_{mn})}) & \text{if } \mu(x_{mn}) \leqslant E_{\mu(x_{mn})}, \\ E_{\mu(x_{mn})}(1 + C'_{\mu(x_{mn})})/(1 - C'_{\mu(x_{mn})}) & \text{if } \mu(x_{mn}) > E_{\mu(x_{mn})}. \end{cases} \tag{5}$$

Step 7. Defuzzification: transform the modified membership value $\mu'(x_{mn})$ to the gray level by the formula:

$$x'_{mn} = \begin{cases} L_{min}, & \mu'(x_{mn}) = 0, \\ L_{min} + \frac{L_{max} - L_{min}}{c - a}\sqrt{\mu'(x_{mn})(b - a)(c - a)}, & 0 < \mu'(x_{mn}) \leqslant \frac{(b-a)}{(c-a)}, \\ L_{min} + \frac{L_{max} - L_{min}}{c - a}\left(c - a - \sqrt{(1 - \mu'(x_{mn}))(c - b)(c - a)}\right), & \frac{(b-a)}{(c-a)} < \mu'(x_{mn}) < 1, \\ L_{max}, & \mu'(x_{mn}) = 1. \end{cases} \tag{6}$$

For the proposed algorithm, the determination of amplification constant σ_{mn} in step 5 is quite critical. We improve the performance by the following considerations: (1) make the determination of constant σ_{mn} more adaptive and automatic; (2) decrease the degree of enhancement in the regions which are either too dark or too bright; (3) enhance/de-enhance the images based on the nature of the local regions of the images.

The amplification constant can be determined by the brightness variation which is estimated by local image statistics [2]. We use fuzzy logic to perform contrast enhancement. Given a window W_{mn} with size $S_m \times S_n$, the fuzzy entropy of the brightness in the region W_{mn} is calculated by

$$\rho_{mn} = -\sum_{(i,j) \in W_{mn}} (P_{ij} \log_2 P_{ij}) / \log_2(S_m S_n), \tag{7}$$

where $P_{ij} = \beta_{ij} / \sum_{(u,v) \in W_{mn}} \beta_{uv}$ and $\beta_{uv} = \mu(x_{uv})\delta_{\mu(x_{uv})}$, $\mu(x_{uv})$ is the membership, and $\delta_{\mu(x_{uv})}$ is the edge value.

To obtain the amplification constant σ_{mn} for contrast enhancement, the following algorithm is proposed.

Algorithm 3. Let $His(g)$, $g = L_{min}, \ldots, L_{max}$, be the histogram of a given image.

1. Determine the ranges of the low degree of contrast enhancement $[\mu(a), \mu(g_l)]$ and $[\mu(g_h), \mu(c)]$, g_l and g_h are the gray levels that meet the following conditions: $\sum_{g_i = a}^{g_l} His(g_i) \leqslant f$, and $\sum_{g_i = g_h}^{c} His(g_i) \leqslant f$, where $f < 1$, which indicates the percentage of pixels in the range of the low degree of contrast enhancement. We use 0.005 for f here.
2. Compute the fuzzy entropy ρ_{mn} for each window centered on pixel (m, n) under consideration. Then find the maximum and minimum fuzzy entropy ρ_{max} and ρ_{min}, respectively, through the entire image.
3. The power value σ_{mn} is computed by

$$\sigma_{mn} = \begin{cases} \frac{\mu(g_l)}{\mu(x_{mn})}\left[\sigma_{min} + \frac{(\rho_{mn} - \rho_{min})(\sigma_{max} - \sigma_{min})}{\rho_{max} - \rho_{min}}\right], & \mu(x_{mn}) < \mu(g_l), \\ \sigma_{min} + \frac{(\rho_{mn} - \rho_{min})(\sigma_{max} - \sigma_{min})}{\rho_{max} - \rho_{min}}, & \mu(g_l) \leqslant \mu(x_{mn}) \leqslant \mu(g_h), \\ \frac{\mu(x_{mn})}{\mu(g_h)}\left[\sigma_{min} + \frac{(\rho_{mn} - \rho_{min})(\sigma_{max} - \sigma_{min})}{\rho_{max} - \rho_{min}}\right], & \mu(x_{mn}) > \mu(g_h). \end{cases} \tag{8}$$

where $\sigma_{min} = (c - a)/2(L_{max} - L_{min})$, $\sigma_{max} = 1$, and ρ_{max} and ρ_{min} are the maximum and minimum values of entropy through all sub-regions of the entire image, respectively.

Since the value of σ_{min} significantly affects the degree of the enhancement of an image, the determination of σ_{min} should relate to the contrast of the given image. If the contrast of the original image is relatively low, σ_{min} should be small. Conversely, σ_{min} should be large to avoid over-enhancement. We exploit the width of the histogram to estimate the relative global contrast of an image. If the contrast is low, the width of the histogram is narrow, therefore, σ_{min} will be small and the degree of the contrast enhancement will be high. In the homogeneous region, the amplification constant σ_{mn} should be large and close to σ_{max}. That is, there should be no enhancement, or even de-enhancement should be performed on the homogeneous regions, according to the requirement of the applications.

The basic idea behind the amplification constant is that if ρ_{mn} is low, which implies that the brightness variation is severe, and the degree of enhancement is high, hence, amplification constant σ_{mn} should be small. Conversely, if ρ_{mn} is high, the respective region is relatively flat, or $\mu(x_{mn})$ is inside the range of low degree enhancement, then σ_{mn} should be large.

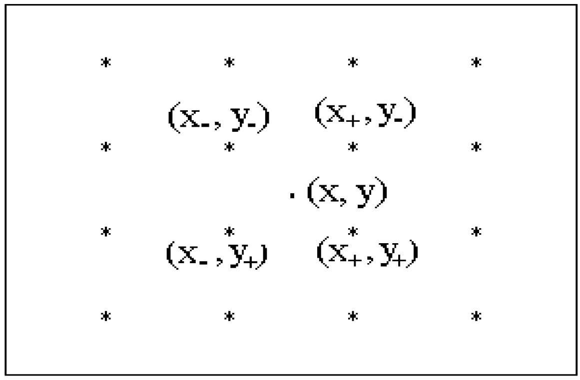

Fig. 1. Sample points (∗) and resultant point (·).

3.3. Speed up by interpolation

The adaptive fuzzy contrast enhancement method discussed in subsection B requires extensive computation when the window becomes large, since the modified gray level is obtained by convoluting the window pixel by pixel. A significant speed up can be obtained by interpolating the desired intensity values from the surrounding sample mapping [2,14]. The idea of the interpolation technique is that the original image is divided into sub-images and the adaptive fuzzy contrast enhancement method is applied to each sub-image to obtain the enhanced sample mapping, and the resultant mapping of any pixel is interpolated from the four surrounding sample mappings. In this way, we only need to calculate the sample mapping using the proposed algorithm, which requires more computation time and the values of other pixels can be obtained by interpolation, which requires much less time. Given a pixel at location (m, n) with membership value $\mu_X(x_{mn})$, the interpolated result is (Fig. 1)

$$\begin{aligned} f(\mu_X(x_{mn})) = {} & ab f_{--}(\mu_X(x_{mn})) + a(1-b) f_{-+}(\mu_X(x_{mn})) \\ & + (1-a) b f_{+-}(\mu_X(x_{mn})) \\ & + (1-a)(1-b) f_{++}(\mu_X(x_{mn})), \end{aligned} \tag{9}$$

where $a = (m_+ - m)/(m_+ - m_-)$ and $b = (n_+ - n)/(n_+ - n_-)$, f_{+-} is the sample mapping at location (m_+, n_-), which is the upper right of (m, n). Similarly, the subscripts $++$, $-+$, and $--$ are for the locations of the pixels of the lower right, low left and upper left of (m, n), respectively.

In the interpolative technique, the original image is divided into non-overlapping regions, CR_{ij} $(i = 0, 1, \ldots, N_x, j = 0, 1, \ldots, N_y)$, called contextual regions (CR). Every resultant pixel is derived by interpolating four surrounding mappings, each associated with a contextual region. Thus, the result of each pixel is affected by a region which is the union of the four surrounding contextual regions, called equivalent contextual region (ECR) (Fig. 2). The mean edge membership value $E_{\mu(x_{mn})}$ and fuzzy entropy ρ_{mn} are calculated for each contextual region. The region, which is made up of the mapping points, is a rectangle concentric with contextual region CR_{ij}, but twice its size in each dimension. This region is termed as mapping region, MR_{ij} (Fig. 2). The resultant mean edge value and fuzzy entropy are used to calculate the contrast, $C_{\mu(x_{mn})}$, amplification constant σ_{mn} and modified membership value $\mu'(x_{mn})$ with respect to one of the four mapping regions. After all of four mappings have been obtained, the final result is calculated by taking bilinearly weighted average of these four results.

Consider an image with contextual regions CR_{ij} $(i = 0, 1, \ldots, N_x, j = 0, 1, \ldots, N_y)$ of size $S_x \times S_y$. Every mapping for the pixels through the whole image will form a subset of the original image. Four mappings will form four sub-images that consist of alternate contextual regions (Fig. 3). These four sub-images are named intermediate images $IM_{kl}(x, y)$ where $k = 0, 1$ and $l = 0, 1$, which correspond to CR_{ij} with odd or even i and j, respectively. Notice that only in the central area, every pixel is involved in all four intermediate images, while the pixel located on the border or in the corner, it may be in one or two intermediate images.

The bilinear weights, which are used to obtain the resultant membership value, form a cyclic function of x and y with a period in each dimension equal to $2S_x$ and $2S_y$, respectively. The two-dimensional period function is defined by

$$W(x, y) = W_x(x) W_y(y), \tag{10}$$

$$W_x(x) = \begin{cases} \frac{x}{S_x}, & 0 \leqslant x \leqslant S_x, \\ \frac{2S_x - x}{S_x}, & S_x < x < 2S_x, \end{cases} \tag{11}$$

$$W_y(y) = \begin{cases} \frac{y}{S_y}, & 0 \leqslant y \leqslant S_y, \\ \frac{2S_y - y}{S_y}, & S_y < y < 2S_y. \end{cases} \tag{12}$$

The detailed algorithm for adaptive fuzzy contrast enhancement with power variation and interpolation techniques is described as follows.

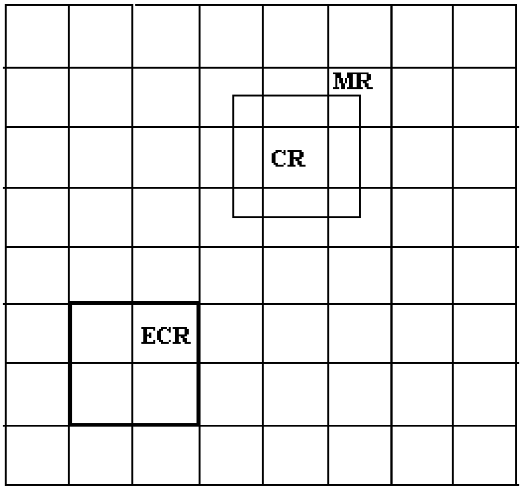

Fig. 2. Contextual regions (CR), mapping regions (MR), and equivalent contextual regions (ECR).

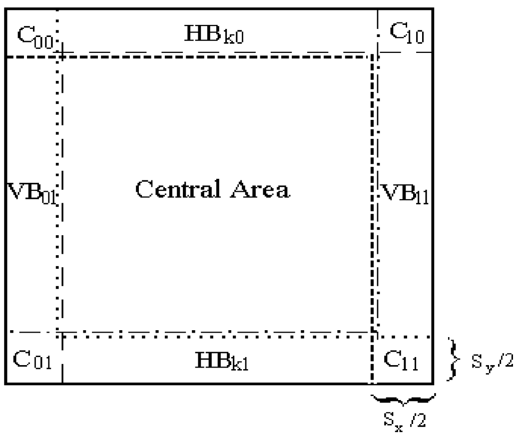

Fig. 3. The image is divided into four subimages, IM_{00} (–·–·–), IM_{01} (- - - - - -), IM_{10} (··· ···), IM_{11} (– – –), their common central area, the border regions, HB_{kl}, VB_{kl}, and the corner regions C_{kl}.

Algorithm 4. Input an $M \times N$ image with gray level L_{min} to L_{max}, parameters for S-function, a, b_{opt}, and c, the low degree of enhancement ranges $[L_{min}, g_l]$, and $[g_h, L_{max}]$, and amplification constants σ_{max} and σ_{min}.

/*Initialize $\mu'(x, y)$, which stores the enhanced
  membership value */
for $i = 0$ to $M - 1$
  for $j = 0$ to $N - 1$
    $\mu'[i][j] = 0$;
/* Mapping an image into fuzzy domain */
for $i = 0$ to $M - 1$
  for $j = 0$ to $N - 1$
    $\mu_X(x_{ij}) = S(x, a, b_{opt}, c)$
/* Compute the mean edge value and fuzzy entropy */
for $i = 0$ to $M - 1$
  for $j = 0$ to $N - 1$
  {

$$E_{\mu(x_{ij})} = \sum_{(i,\, j) \in CR_{ij}} (\mu(x_{ij})\delta_{\mu(x_{ij})}) / \sum_{(i,\, j) \in CR_{ij}} \delta_{\mu(x_{ij})}$$

$$L_{ij} = -\sum_{(i,\, j) \in CR_{ij}} (P_{ij} \log_2 P_{ij}) / \log_2 (S_x S_y)$$

  }
/* Compute the values of contextual regions */
for $k = 0$ to 1
  for $l = 0$ to 1
  {
    for $i = k$ to $N_x - 1$ with step size of 2
      for $j = l$ to $N_y - 1$ with step size of 2
      {
        compute $C_{\mu(x_{ij})} = |\mu(x_{ij}) - E_{\mu(x_{ij})}| / |(\mu(x_{ij}) + E_{\mu(x_{ij})}|$
        compute $C'_{\mu(x_{ij})} = (C_{\mu(x_{ij})})^{\sigma_{ij}}$, where σ_{mn} is
          computed by Eq. (8)
        compute the modified membership
          value $M(i,j)$
      } /* end of i and j loop */
/* Weight the intermediate images and sum results */
for all (x, y) in the central area
      $\mu'(x, y) = \mu'(x, y) + M(x, y)W_x(x + kS_x + S_x/2)W_y(y + lS_y + S_y/2)$;
for all (x, y) in the horizontal borders
      $\mu'(x, y) = \mu'(x, y) + M(x, y)W_x(x + kS_x + S_x/2)$;
for all (x, y) in the vertical borders
      $\mu'(x, y) = \mu'(x, y) + M(x, y)W_y(y + lS_y + S_y/2)$;
for all (x, y) in the corners
      $\mu'(x, y) = M(x, y)$;
    }/* end of k, l loop */
/* Defuzzification */
for $i = 0$ to $M - 1$
    for $j = 0$ to $N - 1$
      compute modified gray level x'_{ij} using Eq. (6).

4. Experimental results and discussions

We have applied the proposed algorithm to a variety of images. As mentioned before, the commonly used techniques for contrast enhancement can be categorized as (1) indirect methods of contrast enhancement and (2) direct methods. Histogram specification and histogram equalization are two most popular indirect contrast enhancement methods [3]. Laxmikant Dash and Chatterji [2], Dhnawan et al. [4], and Beghdad and Negrate [5] have discussed and shown that the direct contrast enhancement approaches are better than indirect contrast enhancement approaches. The newly developed approach, the ACE with adaptive power variation approach,

Table 1
The parameters for the images

Image	Size	a	b	c	Low enhancement range	σ_{min}	σ_{max}	CR size
Fig. 4 (ed100)	352×240	13	14	146	[1, 18], [118, 255]	0.26	1	8×8
Fig. 5 (airplane)	512×512	107	237	238	[0, 142], [223, 255]	0.26	1	16×16
Fig. 6 (couple)	256×256	0	1	158	[0, 2], [148, 255]	0.31	1	16×16
Fig. 7 (light-tower)	480×320	48	141	201	[0, 82], [194, 255]	0.30	1	8×8
Fig. 8 (window)	384×256	27	138	204	[0, 30], [188, 255]	0.35	1	16×16
Fig. 9 (lena)	512×512	24	214	215	[0, 36], [212, 255]	0.37	1	16×16

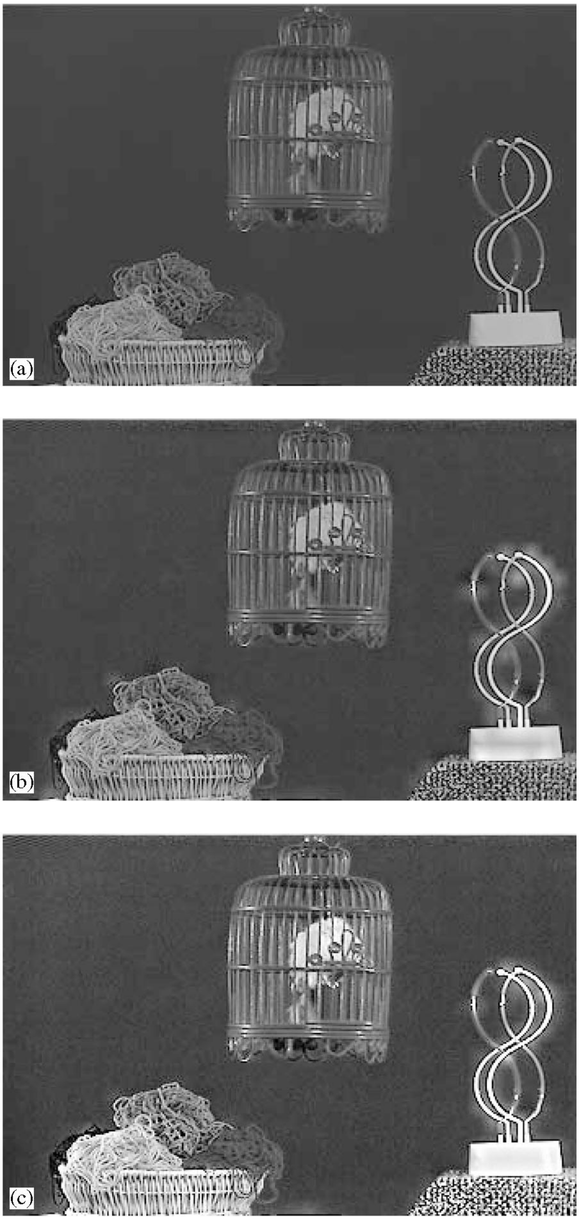

Fig. 4. (a) The original image ed100 with size 352×240. (b) The image enhanced by ACE method. (c) The image enhanced by the proposed method.

produces better results [2]. In order to demonstrate the performance of the proposed method, we compared the experimental results of the proposed approach with those of ACE with adaptive power variation approach. Here, we present a few of the experimental results. The sizes of the images, parameters a, b and c, ranges of low degree enhancement, low and high limits of amplification constant σ_{min} and σ_{max}, and the sizes of contextual regions (CR) are listed in Table 1.

Figs. 4(a)–9(a) are the original images, Figs. 4(b)–9(b) and 4(c)–9(c) are the results obtained by the method in Ref. [2] and the proposed method, respectively. Unless mentioned, the amplification constants σ_{min} and σ_{max} used for the method in Ref. [2] are the same as that used for the proposed method, as shown in Table 1, for the comparison purpose.

Fig. 4(a) is a low-contrast, dark image. After employing the proposed method, the three major components of the image are well enhanced as shown in Fig. 4(c). The contours of the cage, and the yarn on the right of the basket are distinct in (c), but the counterparts in (a) and (b) are quite vague. Moreover, the pet in the cage, the basket and the statue are more apparent than that in (a) and (b). While 4(b) under-enhanced most of the parts of the image, it over-enhanced the rings of the right-hand side of the image.

The original image in Fig. 5(a) is relatively bright and blur. Comparing (c) with (b), the contrast enhancement is evident, especially the letters and the emblem on the airplane, the shadow on the surface of the mountain and the ridges of the mountains are better enhanced. On the other hand, several areas of image (b) were over-enhanced.

Comparing the images in Figs. 6(a)–(c), we can see that the contrast was enhanced significantly through the entire image in (c). The contour of the girl becomes clear, the face of the man, the sofa and the carpet are well outlined, and the background is much more distinct in (c).

Based on the results shown in Figs. 4–6, we can see that the proposed method is more effective than the method in Ref. [2]. Now, we will show that our proposed method not only effectively enhances the contrast, but also significantly reduces or even eliminates the over-enhancement.

In the light tower image series, the result of Fig. 7(c) is better than 7(b) due to the following facts: (1) the details

Fig. 5. (a) The original image airplane with size 512×512. (b) The image enhanced by ACE method. (c) The image enhanced by the proposed method.

Fig. 6. (a) The original image couple with size 256×256. (b) The image enhanced by ACE method. (c) The image enhanced by the proposed method.

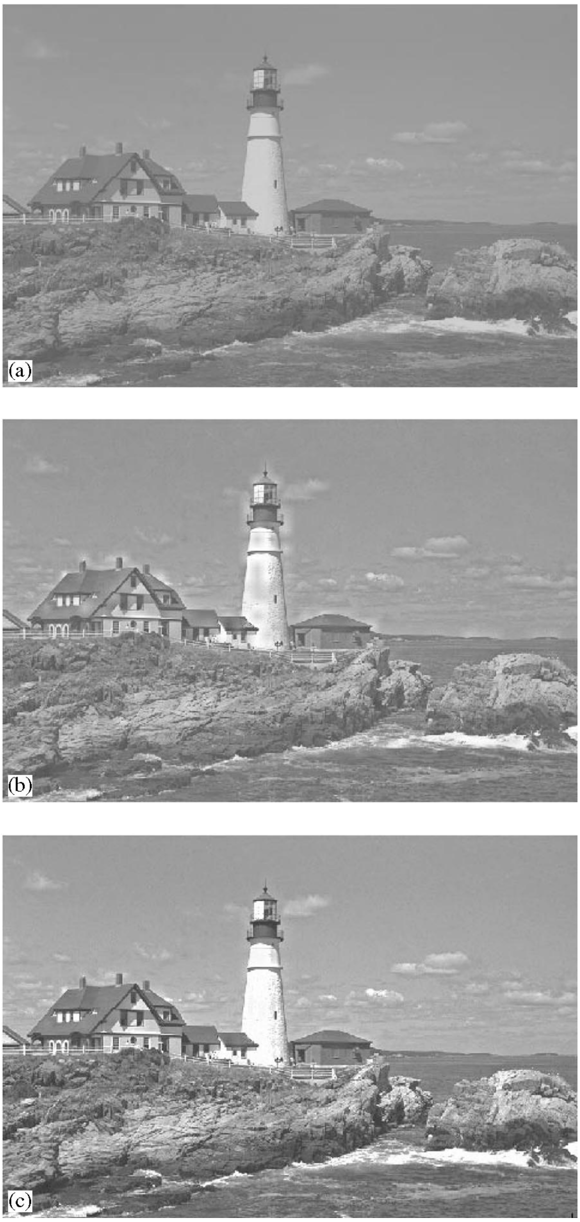

Fig. 7. (a) The original image with size 480 × 320. (b) The image enhanced by ACE method. (c) The image enhanced by the proposed method.

Fig. 8. (a) The original image with size 384 × 256. (b) The image enhanced by ACE method. (c) The image enhanced by the proposed method.

of (c), such as the houses, rocks, water, clouds, etc. are more distinct than that of (a) and (b); (2) the apparent distortions on the upper part of the tower and on the roofs of the houses are shown in (b). These are caused by over-enhancement.

For Fig. 8(c), the background is uniform after enhancement, and major components of the image are much clearer than that in (a) and (b). However, in Fig. 8(b), the background becomes very noisy and the contour of the leaves of the trees are non-uniform and unnatural. It is again caused by over-enhancement.

The over-enhancement problem of ACE method can also be found in Fig. 9. In (b), the amplification constants σ_{min} and σ_{max} are 0.4 and 0.85, respectively, which are relatively higher than the values used in Ref. [2]. Even though these values are relatively higher, still the over-enhancement is very strong. The whole image in (b) is noisy. Some homogeneous areas (face and shoulder)

Fig. 9. (a) The original image with size 512×512. (b) The image enhanced by ACE method. (c) The image enhanced by the proposed method.

become non-homogeneous and not natural, and the background has some unnatural, noisy spots as well. However, in (c), the main features of the image are enhanced without amplifying noise.

From the above experiments, we can conclude that the proposed approach outperforms ACE method with the following advantages: (1) The contrast enhancement is more effective with a better adaptability. (2) The over-enhancement is significantly decreased or eliminated. The superior performance of the proposed approach is due to the following reasons: (a) The proposed approach takes care of the fuzziness in the images by using fuzzy set theory and fuzzy entropy principle. (b) The necessary parameters are determined automatically based on the nature of the images. (c) The proposed approach uses global and local information to decide enhancement/de-enhancement, therefore, it can prevent over-enhancement effectively. (d) The proposed approach has better adaptive capability by employing σ_{mn} (refer Eq. (8)).

5. Conclusions

Contrast enhancement is a fundamental step in image segmentation, and plays an important role in image processing, pattern recognition, and computer vision. The commonly used techniques for contrast enhancement fall into two categories: (1) indirect methods and (2) direct methods. Direct approach to contrast enhancement is more useful because it has considered both global and local information of the image. Fuzzy logic has been found many applications in image processing and pattern recognition, etc. In this paper, we propose a novel, adaptive, direct, fuzzy contrast enhancement method based on the fuzzy entropy and fuzzy set theory. The experimental results have demonstrated that the proposed algorithm is more adaptive and effective for contrast enhancement compared to ACE method. Moreover, it significantly reduces the over-enhancement/under-enhancement due to its better adaptive capability. The proposed approach may find wide applications in image processing, pattern recognition and computer vision.

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