Global and local contrast enhancement algorithm for image using wavelet neural network and stationary wavelet transform

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A new contrast enhancement algorithm for image is proposed employing wavelet neural network (WNN) and stationary wavelet transform (SWT). Incomplete Beta transform (IBT) is used to enhance the global contrast for image. In order to avoid the expensive time for traditional contrast enhancement algorithms, which search optimal gray transform parameters in the whole gray transform parameter space, a new criterion is proposed with gray level histogram. Contrast type for original image is determined employing the new criterion. Gray transform parameter space is given respectively according to different contrast types, which shrinks the parameter space greatly. Nonlinear transform parameters are searched by simulated annealing algorithm (SA) so as to obtain optimal gray transform parameters. Thus the searching direction and selection of initial values of simulated annealing is guided by the new parameter space. In order to calculate IBT in the whole image, a kind of WNN is proposed to approximate the IBT. Having enhanced the global contrast to input image, discrete SWT is done to the image which has been processed by previous global enhancement method, local contrast enhancement is implemented by a kind of nonlinear operator in the high frequency sub-band images of each decomposition level respectively. Experimental results show that the new algorithm is able to adaptively enhance the global contrast for the original image while it also extrudes the detail of the targets in the original image well. The computation complexity for the new algorithm is $O(MN)\log(MN)$, where M and N are width and height of the original image, respectively.

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Traditional image enhancement algorithms are as follows: point operators, space operators, transform operators, and pseu-color contrast enhancement. Recently, some new algorithms for image enhancement have been proposed. Zhou gave a kind of algorithm for contrast enhancement based on fuzzy operators[1]. However, the algorithm cannot be sure to be convergent. Tang gave a kind of adaptive enhancement algorithm for far infrared image sequences[2]. Performance of the algorithm is affected greatly by mathematic model. Lots of improved histogram equalization algorithms were proposed to enhance contrast for kinds of images[3]. The visual quality cannot be improved greatly with above algorithms. Tubbs gave a simple gray transform algorithm to enhance contrast for images[4]. However, the computation burden of the algorithm was large. Based on Tubbs algorithm, Zhou gave a new kind of genetic algorithm to optimize nonlinear transform parameters[5]. Although the algorithm can enhance contrast for image well, the computation burden is larger. Intelligence and adaptability of many existing enhancement algorithms are worse and much artificial interference is required, which restricts their wide applications. Most of them only enhance either the global or the local contrast for image.

To solve above problems, a new algorithm employing incomplete Beta transform (IBT), simulated annealing algorithm (SA), and wavelet neural network (WNN) is proposed. To improve optimization speed and intelligence of algorithm, a new criterion is proposed based on gray level histogram. Contrast type for original image is determined employing the new criterion. Contrast for original images is classified into seven types: particular dark (PD), medium dark (MD), medium dark slightly (MDS), medium bright slightly (MBS), medium bright (MB), particular bright (PB), and good gray level distribution (GGLD). The new algorithm is still a kind of gray transform method. IBT operator transforms original image to a new space. A certain criterion or objective function is used to optimize nonlinear transform parameters. SA is used to determine the optimal nonlinear transform parameters. In order to reduce the computation burden for calculating IBT, a new kind of WNN is proposed to approximate the IBT in the whole image. The global contrast is enhanced well employing above gray level transform method. The local contrast is enhanced employing a kind of nonlinear operator proposed by Laine[6]. We expand the nonlinear operator to stationary wavelet transform (SWT) domain so as to extrude the detail of the targets in the original image.

Tubbs employed unitary incomplete Beta function to approximate above three nonlinear functions[4]. The incomplete Beta function can be written as

$$F(u) = B^{-1}(\alpha,\beta) \times \int_0^u t^{\alpha-1}(1-t)^{\beta-1}\mathrm{d}t, \quad 0 < \alpha, \beta < 10. \tag{1}$$

In general, when the image is particular dark, $\alpha < \beta$, as shown in Fig. 1(a), where $\alpha = 2$, $\beta = 9$. When the image is particular bright, $\alpha > \beta$, as shown in Fig. 1(b), where $\alpha = 6$, $\beta = 3$. When the image is all gray levels centralized on the middle certain region type, $\alpha = \beta$, as shown in Fig. 1(c), where $\alpha = 3$, $\beta = 3$.

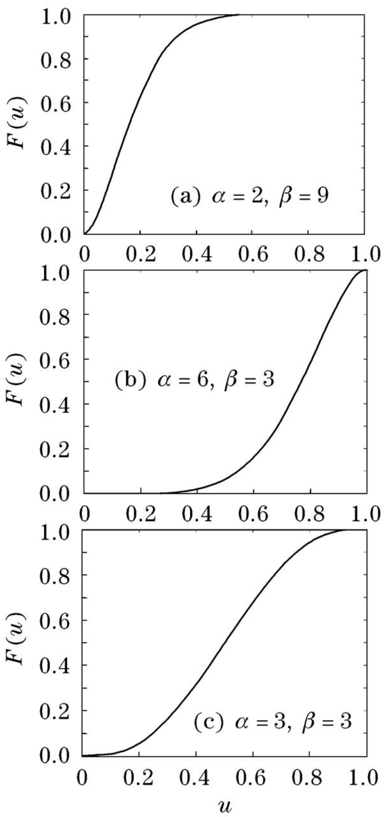

Fig. 1. Three kinds of classical gray level transform functions.

IBT is a kind of integral operator. It can be implemented by numerical algorithm. All the gray levels of original image have to be unitary before implementing IBT. All the gray levels of enhanced image have to be inverse-unitary after implementing IBT[4].

Objective function in Ref. [4] is employed to evaluate the quality of enhanced image. The function can be written as

$$f = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} g'^{2}(i,j) - \left[\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} g'(i,j)\right]^{2}, \quad (2)$$

where M, N show width and height of original image, $g'(i,j)$ shows gray level value at (i,j) in enhanced image. The bigger f is, the more well proportioned the distribution of image gray level is. The better contrast of enhanced image is, the better the visual quality of enhanced image is.

Based on gray level histogram, contrast for original images is classified into seven types: PD, MD, MDS, MBS, MB, PB, and GGLD. Classification criterion is shown in Fig. 2.

Given that original image has 255 gray levels, the whole gray level space is divided into six sub-spaces: $S1$, $S2$, $S3$, $S4$, $S5$, $S6$, where S_i $(i = 1, 2, \cdots, 6)$ is the number of all pixels which distribute in the ith sub-space. Let

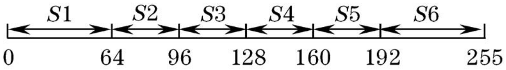

Fig. 2. Image classification sketch map based on gray level histogram.

$$S = \max_{i=1}^{6} S_i,\ S_1 = \sum_{k=2}^{6} Sk,\ S_2 = \sum_{k=2}^{5} Sk,\ S_3 = \sum_{k=1}^{5} Sk,$$

$$S_4 = S1 + S6, \quad S_5 = S2 + S3, \quad S_6 = S4 + S5,$$

the following classification criterion can be obtained.

if $S = S1$ & $S1 > S_1$,
  image is PB;
else if $S_2 > S_4$ & $S_5 > S_6$ & $S_5 > S1$ & $S_5 > S6$ & $S2 > S3$,
  image is MD;
else if $S_2 > S_4$ & $S_5 > S_6$ & $S_5 > S1$ & $S_5 > S6$ & $S2 < S3$,
  image is MDS;
else if $S_2 > S_4$ & $S_5 < S_6$ & $S1 < S_6$ & $S6 < S_6$ & $S4 > S5$,
  image is MBS;
else if $S_2 > S_4$ & $S_5 < S_6$ & $S1 < S_6$ & $S6 < S_6$ & $S4 < S5$,
  image is MB;
else if $S = S6$ & $S6 > S_3$,
  image is PB;
else
  image is GGLD;
end

where symbol & represents logic "and" operator.

In order to enhance contrast of image well, we base on the SA, to optimize continuous variables[7]. Having made lots of experiments to every type of images, the range of α and β can be determined by Table 1.

Next we discuss how to obtain optimal α and β by SA. Let $\mathbf{x} = (\alpha, \beta)$, $F(\mathbf{x})$ is function to be minimized, corresponding to Eq. (2), where $a_i < \alpha$, $\beta < b_i$ $(i = 1, 2)$.

For convenience, some symbols are defined as starting temperature T_0, a test for step variation N_{S}, a test for temperature reduction N_{T}, a reduction coefficient r_{T}, a varying criterion c. Detailed steps on SA can be found in Ref. [7].

When IBT is used to enhance image contrast, IBT is calculated pixel-to-pixel. Operation burden is very large when number of pixels in original image is large. Different IBT is calculated to different α and β. Different IBT needs to be calculated one time in every iterative step during optimization. To improve operation speed during the whole optimization, a new kind of WNN is proposed to calculate the IBT.

Let $f(x) \in L^2(R^n)$, WNN can be described approximately as[8]

$$Wf(x) = \sum_{i=1}^{N} w_i \Psi[(a_i x - \tau_i)], \quad (3)$$

where τ_i is translation factor, a_i is scale factor, $Wf(x)$ shows the output of WNN. The translation factor, scale

Table 1. Range of α and β

Parameter	PD	MD	MDS	MBS	MB	PB
α	[0, 2]	[0, 2]	[0, 2]	[1, 3]	[1, 4]	[7, 9]
β	[7, 9]	[1, 4]	[1, 3]	[0, 2]	[0, 2]	[0, 2]

factor and wavelet basis function, which are on the same line, are called wavelet unit. Thus the whole WNN implements a map: $F : R^n \rightarrow R$.

Parameters to be estimated are w_i, a_i, τ_i, $i = 1, 2, \cdots, N$ (where N is the number of wavelet unit). The output of WNN is linear combination of all the output of wavelet units. "Forgetting factor" algorithm is used to train weight of WNN. Iterative prediction error algorithm is employed to train translation factors and scale factors.

Let

$$\boldsymbol{\theta} = [a_1, a_2, \cdots, a_N, \tau_1, \tau_2, \cdots, \tau_N],$$

$$z_i(x) = \boldsymbol{\Psi}(a_i x - \tau_i),$$

Eq. (3) is rewritten as

$$Wf(x) = \sum_{i=1}^{N} w_i z_i(x) = \boldsymbol{\varphi}_t^{\tau} \mathbf{W}_t. \tag{4}$$

Definition:

$$\boldsymbol{\varphi}_t = [z_1(t), z_2(t), \cdots, z_N(t)]^{\mathrm{T}},$$

$$\mathbf{W}_t = [w_1(t), w_2(t), \cdots, w_N(t)]^{\mathrm{T}},$$

where $z_i(t)$ and $w_i(t)$ show the output of ith wavelet unit at time t and corresponding to weight respectively, T shows transpose of matrix.

"Forgetting factor" algorithm can be written as

$$\mathbf{W}_t = \mathbf{W}_{t-1} + \mathbf{K}_t[y_t - \boldsymbol{\varphi}_t^{\tau} \mathbf{W}_{t-1}], \tag{5}$$

$$\mathbf{K}_t = (\alpha + \boldsymbol{\varphi}_t^{\tau} \mathbf{P}_{t-1} \boldsymbol{\varphi}_t)^{-1} \mathbf{P}_{t-1} \boldsymbol{\varphi}_t, \tag{6}$$

$$\mathbf{P}_t = [\mathbf{P}_{t-1} - \mathbf{K}_t \boldsymbol{\varphi}_t^{\tau} \mathbf{P}_{t-1}]/\alpha, \tag{7}$$

where α is forgetting factor, $0 < \alpha \leq 1$.

Parameter matrix $\boldsymbol{\theta}$ can be estimated by following iterative prediction error algorithm:

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \mathbf{R}_t[y_t - \boldsymbol{\varphi}_t^{\tau} \mathbf{W}_{t-1}], \tag{8}$$

$$\mathbf{R}_t = \frac{\mathbf{S}_{t-1} \mathbf{T}_t}{1 + \mathbf{T}_t^{\tau} \mathbf{S}_{t-1} \mathbf{T}_t}, \tag{9}$$

$$\mathbf{S}_t = [\mathbf{S}_{t-1} - \mathbf{R}_t \mathbf{T}_t^{\tau} \mathbf{S}_{t-1}], \tag{10}$$

where $\mathbf{T}_t = \partial Wf(x)/\partial \boldsymbol{\theta}$ shows gradient vector of output for WNN. Weight, translation factors and scale factors are trained iteratively and mutually with above two algorithms.

Above IBT can be calculated by the above WNN. That is to say, input parameters α, β, g are input to trained WNN and output g' for IBT is obtained directly. Considering generalization ability, training speed and accuracy, 100000 points are selected as sample sets. That is to say, parameters α and β, which are between 1 and 10, are divided into 10 parts at the same interval. Parameter x, which is between 0 and 1, is divided into 1000 parts at the same interval. The dimension number of input layer and output layer is determined according to the dimension number of input samples and output samples. Mexican hat wavelet is selected as mother wavelet

$$\Psi(x) = (1 - x^2)\mathrm{e}^{-x^2/2}. \tag{11}$$

The "forgetting factor" α equals to 0.97 in the WNN. Mean square error is selected as error index and set as 0.00001.

SWT has been independently discovered several times, for different purpose and under different names, e.g. shift/translation invariant wavelet transform, redundant wavelet transform, and un-decimated wavelet transform[9]. Based on discrete SWT, a kind of nonlinear enhancement operator, which was proposed by Laine in 1994, is employed to enhance the local contrast for image[6].

Let $f_s^r[i,j]$ be the gray values of pixels in the rth sub-band in the sth decomposition level, where $s = 1, 2, \cdots, L$; $r = 1, 2, 3$. $\max f_s^r$ is the maximum of gray value of all pixels in $f_s^r[i,j]$. The contrast enhancement approach can be described by

$$g_s^r[i,j] = \begin{cases} f_s^r[i,j], & |f_s^r[i,j]| < T_s^r \\ a \cdot \max f_s^r\{\mathrm{sigm}[c(y_s^r[i,j] - b)] - \\ \mathrm{sigm}[-c(y_s^r[i,j] + b)]\}, & \\ & |f_s^r[i,j]| \geq T_s^r \end{cases}, \tag{12}$$

$$y_s^r[i,j] = f_s^r[i,j]/\max f_s^r. \tag{13}$$

Steps of contrast enhancement algorithm for image based on WNN and SWT are determining the type of input infrared image, implementing global enhancement, doing discrete SWT to the global enhanced image, while the nonlinear operator in SWT domain is implementing local contrast enhancement, and doing inverse SWT to reconstruct the image.

Symmlet wavelet with two vanishing moments is used to make discrete SWT in the experiment. Global enhanced image is decomposed into three levels. The new algorithm enhances two images whose contrast is worse. Figure 3 shows nonlinear gray transform curve, where $\alpha = 2.8700$, $\beta = 1.3172$. Figure 4 indicates nonlinear gray transform curve, where $\alpha = 1.5148$, $\beta = 3.5267$. The nonlinear transform curves in Figs. 3 and 4 are used to enhance the global and the local contrast of

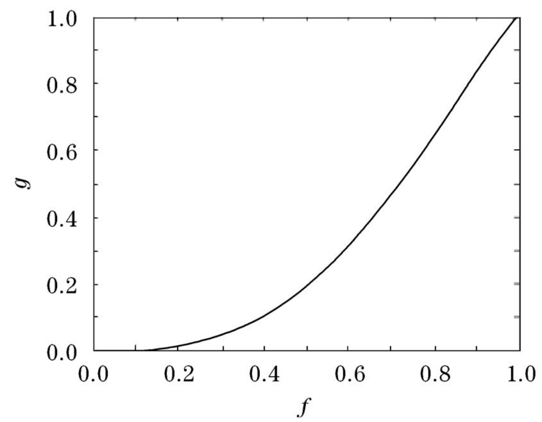

Fig. 3. Gray levels transform curve ($\alpha = 2.8700$, $\beta = 1.3172$).

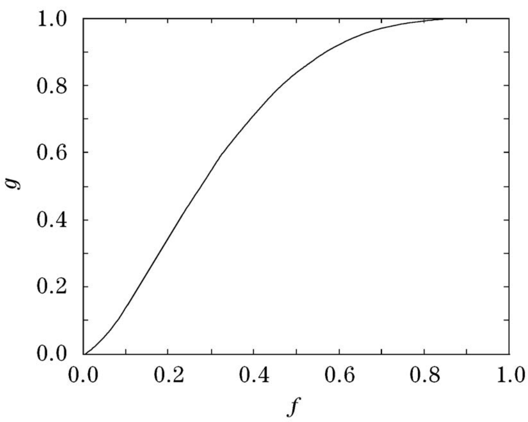

Fig. 4. Gray levels transform curve ($\alpha = 1.5148$, $\beta = 3.5267$).

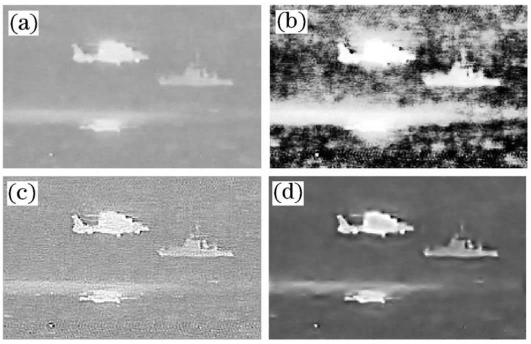

Fig. 5. Infrared multi-target image (a) and enhanced images by HE (b), USM (c), and the new algorithm (d).

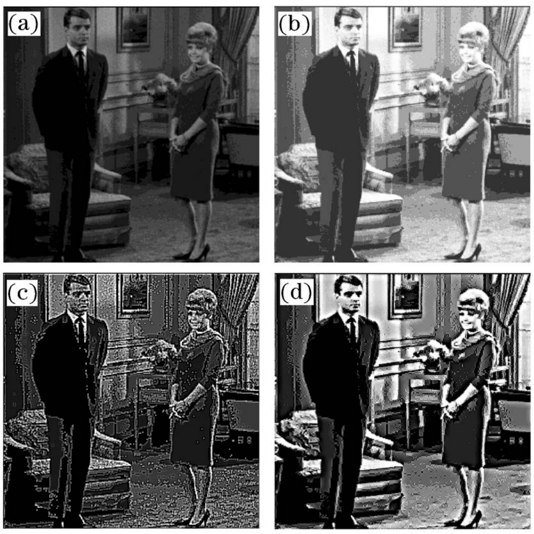

Fig. 6. Couple image (a) and enhanced images by HE (b), USM (c), and the new algorithm (d).

Figs. 5(a) and 6(a), respectively. In order to extrude excellent performance of the new algorithm, two traditional contrast enhancement algorithms are compared with the new algorithm. They are histogram equalization (HE) and unsharpened mask algorithm (USM) respectively.

According to Figs. 5(b) — (d), it is very obvious that the enhanced image using the new algorithm is better than HE and USM in visual quality. Above infrared image belongs to MBS type. This is a MBS image. Another couple image is enhanced employing the new algorithm in order to show excellent performance of the new algorithm. Figure 6(b) — (d) show enhanced images employing HE, USM and the new algorithm, respectively. We can draw the same conclusion from Fig. 6 as from Fig. 5.

From Fig. 5 to Fig. 6, it is very obvious that the new algorithm is more excellent in visual quality than HE and USM. HE enhances all the pixels in the image so that some useful detail loses and clutter in the background is enhanced, too. Although USM algorithm can enhance detail of targets in the image, the global contrast is worse and the clutter in the background is magnified. Compared with HE and USM, using the new algorithm, the global contrast is enhanced greatly while the detail of targets in the image is extruded well.

IBT is used to enhance adaptively the global contrast for image. Optimization for nonlinear transform parameters employs fast simulated annealing algorithm (FSA). WNN is used to approximate IBT so as to reduce operation burden. Experimental results show that the new algorithm can enhance adaptively the global contrast for image effectively while extrude detail information in the original image well. The new algorithm is more excellent than HE and USM in visual quality. The computation complexity of the global contrast enhancement is $O(MN)$. The computation complexity of the local contrast enhancement is $O(MN)\log(MN)$. The total computation complexity of the new algorithm is $O(MN)\log(MN)$, where M and N are the width and height of the original image respectively.

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