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Contrast Enhancement using Histogram Equalization with a New Neighborhood Metrics

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ABSTRACT

In this paper, a novel neighborhood metric of histogram equalization (HE) algorithm for contrast enhancement is presented. We present a refinement of HE using neighborhood metrics with a general framework which orders pixels based on a sequence of sorting functions which uses both global and local information to remap the image greylevels. We tested a novel sorting key with the suggestion of using the original image greylevel as the primary key and a novel neighborhood distinction metric as the secondary key, and compared HE using proposed distinction metric and other HE methods such as global histogram equalization (GHE), HE using voting metric and HE using contrast difference metric. We found that our method can preserve advantages of other metrics, while reducing drawbacks of them and avoiding undesirable over-enhancement that can occur with local histogram equalization (LHE) and other methods.

Key words: contrast enhancement, histogram equalization, neighborhood metric

1. INTRODUCTION

A very popular technique for contrast enhancement of image is HE which is one of the well-known methods for enhancing the contrast of given images, making the result image have a uniform distribution of the gray levels. It flattens and stretches the dynamic range of the image's histogram and results in overall contrast improvement. Its basic idea lies on mapping the grey levels in the enhanced image through a transformation function based on the probability distribution of the input image greylevels (Fig. 1). This transformation function stretches the contrast of the high histogram region and compresses the contrast of the low histogram region. Generally, HE techniques are classified into two branches according to whether their transformation functions use global or local information [1-7].

GHE is simple and fast technique in which histogram of the whole input image is used to compute a histogram transformation function [8,9]. As a result, the dynamic range of the image histogram is flattened and stretched and the overall contrast is improved.

Computational complexity of this technique is relatively low and this makes GHE an interesting solution in many contrast enhancement applications. Nevertheless, one of the major drawbacks of this method is that it cannot adapt to local information of the input image. This feature results in the contrast deterioration of background and small objects.

On the other hand, LHE can enhance effectively, but the complexity of computation is very high due to its fully overlapped sub-blocks. LHE

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uses a sliding window method in which, for each pixel, local histograms are computed from the windowed neighborhood to produce a local grey-level remapping for each pixel. The greylevel of the pixel at the center of the neighborhood is changed according to the local greylevel remapping for that pixel.

LHE is capable of great contrast enhancement which can sometimes be considered over-enhancement. LHE-based methods are generally requiring more computation than other methods because a local histogram needs to be built and processed for every image pixel [10].

Some refined methods of HE is HE using Neighborhood Metrics which uses both global and local information to remap the image greylevels [11]. Local image properties, such as neighborhood metrics (NM), are used to subdivide histogram bins that would be otherwise indivisible using GHE (Fig. 2). Usage of neighborhood information in HE not only can affect in result image by improving local contrast but also make histogram of result

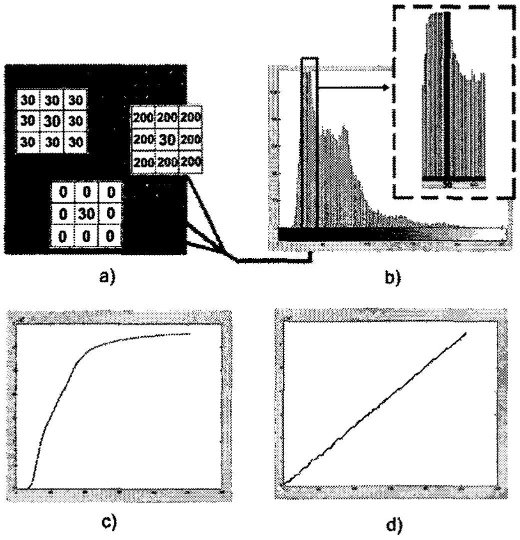

Fig. 1. GHEa) same intensity pixels of image, b) a current intensity bin of histogram of image, c) transformation /cumulative distribution/ function of image, d) cumulative distribution function of image enhanced by GHE.

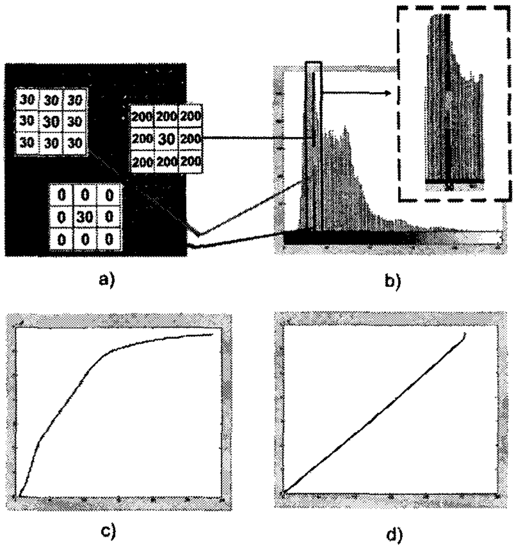

Fig. 2. HE using sorting function a) same intensity pixels with neighborhood pixels of image, b) current subbins of one bin of histogram of image, c) transformation /cumulative distribution/ function of image, d) cumulative distribution function of enhanced image.

image flatter. Choice of the metric influences how the bins are subdivided, affording the opportunity for additional contrast enhancement. This method can provide an improvement in contrast enhancement versus GHE, while avoiding undesirable over-enhancement that can occur with LHE and other methods. Nevertheless, NMs don't compute contrast difference between current pixel and its neighbors. Because they do not evaluate contrast difference between current pixel and its neighbors while using neighborhood pixels information. Therefore, in [12], we proposed contrast difference metric which computes contrast difference between current pixel and its neighbors. However, it can divide each bin into only 27 subbins. Subbin's quantities are directly effective to flatness property of result histogram of HE.

The goal of this paper is to find a new NM which preserves advantages of other NMs and reduces drawbacks of them. In what follows, the related works are discussed in Section2 and Section3 presents the novel NM. Section4 lists a few simulation results to demonstrate the effectiveness of the novel metric comparing to the GHE, HE using voting metric, and HE using contrast difference metric. Section5 serves as the conclusion of this paper.

2. RELATED WORK

Mark et al generalize the GHE by allowing any number of sorting functions on image pixels in place of greylevel of pixel $g(p)$ in algorithm1 [11]. The main role of sorting functions is to define a set of subbins for the algorithm. Sorting function allows us to choose functions that can order pixels using different criteria and to separate pixels that would be in the same bin in the original histogram into several of the subbins defined by the sorting functions. Allowing multiple sorting functions allows the more complete ordering of pixels by multiple sort keys (Λ_i). This generalized HE algorithm is given as algorithm2. For example, $\Lambda_1$as primary sort key which means a greylevel of image, $\Lambda_2$as secondary sort key which means some NMs, etc.

2.1. *Voting metric.*

Mark et al proposed voting metric written by β_m, which is defined as the number of pixels in the m by m square neighborhood centered on (x, y) whose greylevel value is strictly less than that of center pixel (x, y). For an image with dimensions N by M and depth D the greylevel of pixel (x,y) is denoted by function g: $[0,N-1]\mathrm{x}[0,M-1]\rightarrow[0,D-1]$ and $\gamma$is the function which extends an image function to be surrounded by a "background" of zero greylevel:

$$\gamma(x,y)=\begin{cases} g(x,y), & (x,y)\in[0,N-1]\mathrm{x}[0,M-1] \\ 0, & otherwise \end{cases} \tag{1}$$

Also the neighborhood voting metric,formally defined β_m: $[0,N-1]\mathrm{x}[0,M-1]\rightarrow$ $[0,m^2]$ is the function:

$$\beta_m(x,y)=\sum_{(x',y')\in R_m^{(x,y)}} v(x,y,x',y'). \tag{2}$$

which requires the following voting function:

$$v(x,y,x',y')=\begin{cases} 1, & \gamma(x,y)>\gamma(x',y'). \\ 0, & otherwise \end{cases} \tag{3}$$

Here $R_m^{(x,y)}$ is the set of pixels forming a square m by m neighborhood centered on (x, y) and m is a positive odd integer. The voting metric will tend to force pixels which have more neighbors with smaller greylevel to a higher intensity (and vice versa) if and when the bin is subdivided. Principle of this metric is illustrated in Fig. 3.

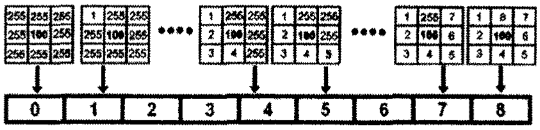

Fig. 3. The principle of dividing one subbin into subbins of histogram by voting metric.

2.2 *Contrast difference metric*

We suggested contrast difference metric in our previous work [12]. Contrast difference metric was used as third sort key because other NMs don't evaluate contrast difference between current pixel and its neighbors. This drawback is illustrated in Fig. 4. Those four cases are included in one subbin of one bin of histogram by voting metric. Central pixels of case b and c may not require additional contrast from neighborhood pixels in those cases. However, central pixels of case a) and d) require additional contrast from neighborhood pixels with small difference intensities from central pixels.

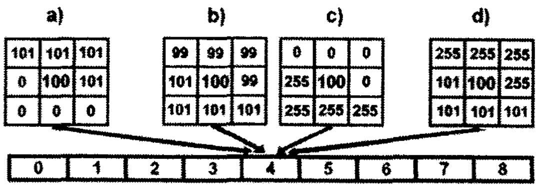

Fig. 4. Same intensity pixels with different neighborhood pixelsin one subbin of one bin of histogram.

Therefore, we proposed contrast difference metric. Let's denote an auxiliary function

$$[f(x,y)]^{+}=\begin{cases} f(x,y), & f(x,y)>0 \\ 0, & otherwise \end{cases} \tag{4}$$

and left average difference (L.a.d) function, as well as right average difference (R.a.d) function, respectively by the following formulas which uses neighborhood voting function βm :

$$L.a.d=\frac{1}{\beta_m(x,y)}\sum_{(x',y')\in R_m^{(x,y)}}[\gamma(x,y)-\gamma(x',y')]^{+}. \tag{5}$$

$$R.a.d=\frac{1}{m^2-1-\beta_m(x,y)}\sum_{(x',y')\in R_m^{(x,y)}}[\gamma(x',y')-\gamma(x,y)]^{+}. \tag{6}$$

The idea behind L.a.d and R.a.d functions are that average greylevel differences are computed between the pixel and its neighborhood pixels respectively with the less and the more greylevels than the pixel itself.

Now let us to define our metric, which we call the *contrast difference metric* with threshold value by the formula:

$$\varepsilon_m(x,y)=\begin{cases} 1, & L.a.d < Threshold < R.a.d. \\ 3, & L.a.d > Threshold > R.a.d. \\ 2, & otherwise \end{cases} \tag{7}$$

In Fig. 5, we can see how contrast difference metric can divide one subbin into three subbins of histogram.

Algorithm 1. Global Histogram Equalization

for each pixel p in the image **do**
    deposit p in temporary bin $b_{g(p)}$
end for
$j \leftarrow 0$
for each temporary bin b_i **do**
    Copy pixels b_i into histogram bin $h_{(j/D)}$.
    $j \leftarrow j + |b_i|$ $\{|b_i|$ = number of pixels in b_i $\}$
end for
for i=0 to D-1 **do**
    Set greylevel of each pixel in bin h_i to i.
end for

Algorithm 2. Histogram Equalization with Generalized Sorting Functions

Let the sorting functions be λ_1 through λ_k.

for each pixel p in the image **do**
    deposit p in temporary bin $b_{(\lambda_1(p), \lambda_2(p), \cdots, \lambda_k(p))}$.
end for
Sort function bins using λ_1 as the primary sort key, λ_2 as the secondary sort key, etc.
$j \leftarrow 0$
for each temporary bin b_i in sorted order **do**
    Copy pixels b_i into histogram bin $h_{(j/D)}$.
    $j \leftarrow j + |b_i|$ $\{|b_i|$ = number of pixels in b_i $\}$
end for
for i=0 to D-1 **do**
    Set greylevel of each pixel in bin h_i to i.
end for

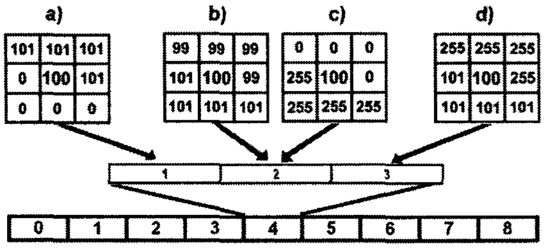

Fig. 5. The principle of dividing one subbin into subbins of one subbin of histogram by contrast difference metric, (threshold=10).

3. NEIGHBORHOOD DISTINCTION METRIC

We are now introducing a new neighborhood metric. This metric not only can preserve main ideas of voting and contrast difference metrics but also can divide one bin of histogram into more subbins than voting and contrast difference metric. When using voting metric, one bin of histogram is divided into nine subbins (Fig. 3). Contrast difference metric can divide one bin of histogram into twenty seven subbins (Fig. 5).Proposed distinction metric can divide two thousand forty subbins in one bin of histogram. By separating many subbins, histogram of result image will be very flat which is closely ideal form of HE. Distinction metric is expressed by following formula:

$$d_m(x,y) = \sum_{(x',y')\in R_m^{(x,y)}} t(x,y,x',y'). \tag{8}$$

which requires the following *distinction function*:

$$t(x,y,x',x') = \begin{cases} \gamma(x,y)-\gamma(x',y'), & \gamma(x,y)>\gamma(x',y'). \\ 0, & otherwise \end{cases} \tag{9}$$

This metric is defined by distinction between greylevel of current pixel and its neighborhood pixels of which greylevel are less than that of current pixels.

From formula9, we can see that distinction metric can preserve the idea of voting metric which uses only neighborhood pixels with smaller greylevel than current pixel greylevel. Moreover it uses the main idea of contrast difference metric that evaluates contrast difference between current pixel and its neighborhood pixels greylevels.

One bin of histogram can be divided by distinction metric into 2040 subbins. Hence we can see that distinction metric greatly separates many subbins in one bin of histogram. We can easily compute minimum and maximum value of formula8 which means that if intensities of current and all neighborhood pixels equal to zero, minimum value of formula8 equal zero, and if intensities of current and all neighborhood pixels are equal to 255 and 0 respectively, maximum value of formula8 equal 2040.

To evaluate the effectiveness of proposed metric comparing to the GHE, HE using voting metric, and HE using contrast difference metric, our experiment focused on the case of m=3. The comparison was made using three quality measurements: contrast-per-pixel (C), histogram flatness (σ) and image distortion (δ) by following formulas respectively:

$$C = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(\sum_{(m,n)\in R_3^{(i,j)}} |\gamma(i,j)-\gamma(m,n)|)}{M*N*8}, \tag{10}$$

$$\sigma = \frac{\sum_{0}^{D-1}(|h_i|-\mu_h)^2}{D}, \tag{11}$$

$$\delta = \frac{1}{MN}\left([\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(|f_1(i,j)-f_2(i,j)|)^{\beta}]^{1/\beta}\right) \tag{12}$$

where $|h_i|$ is the size of the i-th bin of the image's histogram, and μ_h is the mean histogram bin size. A smaller value of σ indicates a flatter histogram. The flatness measure indicates the degree of success towards both reducing the number of empty bins and ensuring that each bin has an equal number of pixels [11]. Minkowsky metric δ measures distortion between two images on basis of their pixelwise differences [13].

These measures reflect the three goals of improving contrast, flattening the histogram and minimizing distortion effects on image structure. For our experiments with the neighborhood metrics, we used an algorithm3 which is presented in [11]. Letting $|b|$ denote the number of pixels in each subbins, then the current histogram bin hj in algorithm3 is considered "optimally full" if $|h_j|$ is at least $|b|/2$ less than B which is optimal bin size that is

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Algorithm 3. Histogram Equalization with Neigborhood metric λ

for each pixel p in the image **do**
  deposit p in temporary bin $b_{g(p),\ \lambda(p)}$.
end for
Sort function bins using g as the primary sort key, and λ as the secondary sort key, etc.
$j \leftarrow 0$
for each temporary bin b_i in sorted order **do**
  {The current bin h_j is considered "full" if it contains B pixels. Thus, if less than half of b_j fits h_j then start filling h_{j+1}.}
  if $B-|h_i| < |b_i|/2$ **then**
  $j \leftarrow j+1$
  end if
  Copy pixels b_i into histogram bin h_j.
end for
if $j < D-1$ **then**
  Respace bins h_0 through h_i evenly through h_{D-1}.
end if
for i=0 to $D-1$ **do**
  Set greylevel of each pixel in bin h_i to i.
end for

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the total number of pixels in the image divided by the number of greylevel intensities D.

4. RESULT

The proposed metric is applied to the all of Brodatz texture images and Mars moon image. Total result is shown in Table1. From Table1, proposed distinction metric can preserve contrast value and can reduce flatness sufficiently with little distortion.

Total flatness value of proposed metric is reduced by about 4 times less than that of voting metric. Also we specially concentrated 17 Brodatz images which weren't improved in contrast by voting metric β_3 comparing to GHE. We can see detail result on Table2.

In addition, contrast difference, voting and distinction metrics are compared with GHE in scatter plots of Fig. 6. In Fig. 6, horizontal and vertical axes are demonstrated by contrast value of GHE and HE using above NMs respectively. If there are points that fall above the diagonal line, these points indicate that image contrasts enhanced by HE using current NMs are more than contrasts of GHE and other hand below points indicate that these contrast are less than that of GHE. All points are fallen below the diagonal line in Fig. 6a which means that all contrast value of those 17 images enhanced by voting metric are less than contrast of GHE. In Fig. 6b and Fib6c, five and four points are fallen below the diagonal line, which means that contrast value of those five and four images enhanced by contrast difference metric are less than that of GHE. In Fig. 6d, only two points are fallen below the diagonal line, which means that proposed metric can enhance image contrast more than other metrics for all Brodatz images while only two image contrasts enhanced less than GHE. Furthermore, we can compare how those methods

Table 1. Results for mean values of quality measurements on 112 Brodatz images.

	HE	β3	ε3	D3
Contrast	35.21	36.31	36.69	36.64
Flatness	24530	8311	5721	1971
Distortion	0.1749	0.1865	0.1901	0.1923

Table 2. Resultsof values of quality measurements of HE and HE using Contrast Difference Metric and novel Distinction Metric on the 17 brodatz images.

Images	GHE			ε_3 T=5			D_3		
	c	σ	δ	c	σ	δ	c	σ	δ
D6	51.64	271800	0.34	52.66	2514	0.35	51.75	2252	0.34
D10	43.19	347240	0.34	44.97	4956	0.33	44.71	746	0.34
D25	39.42	784540	0.40	35.77	64917	0.37	37.87	33927	0.38
D32	55.15	389690	0.40	56.47	3291	0.41	56.04	3560	0.41
D33	42.38	416900	0.40	43.32	3803	0.40	42.95	4694	0.40
D34	53.15	741700	0.38	51.09	43981	0.37	53.75	16305	0.37
D40	35.77	330310	0.30	35.95	11812	0.29	36.43	2562	0.30
D43	53.09	877240	0.49	49.88	55941	0.44	54.63	16290	0.48
D44	38.60	861670	0.39	37.41	68080	0.34	38.55	29487	0.37
D45	29.05	396370	0.30	30.06	18225	0.28	30.32	3920	0.29
D47	29.38	392580	0.38	30.78	11038	0.38	30.66	1641	0.25
D67	39.25	241650	0.26	39.96	1979	0.26	39.68	1298	0.26
D75	25.95	547880	0.23	26.15	40385	0.18	26.74	10895	0.20
D101	36.78	319350	0.22	38.05	3737	0.21	37.95	1400	0.22
D102	39.56	409700	0.23	39.76	11279	0.23	40.96	4749	0.24
D108	37.07	330670	0.29	38.57	3833	0.28	38.42	1640	0.29
D109	51.15	402420	0.35	51.56	5813	0.36	51.95	7120	0.35
Mean	41.21	474220	0.06	41.32	20917	0.32	41.96	8382	0.32

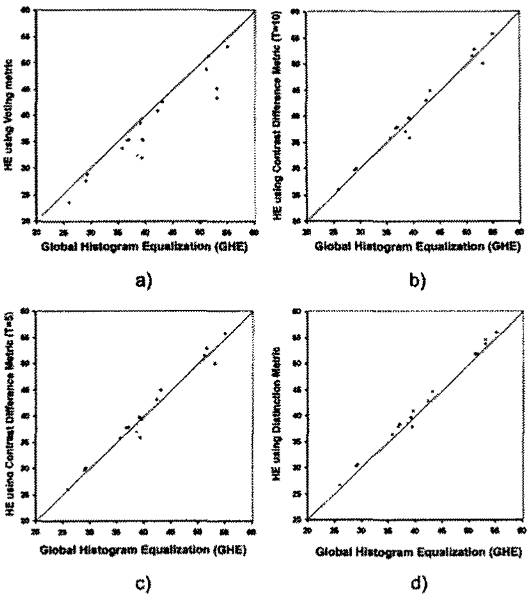

Fig. 6. Scatter plots of contrast per pixel the 17 Brodatz images a) GHE vs HEusing voting metric, b) GHE vs HE using contrast difference metric (T=10), c) GHE vs HE using contrast difference metric (T=5), d) GHE vs HE using distinction metric.

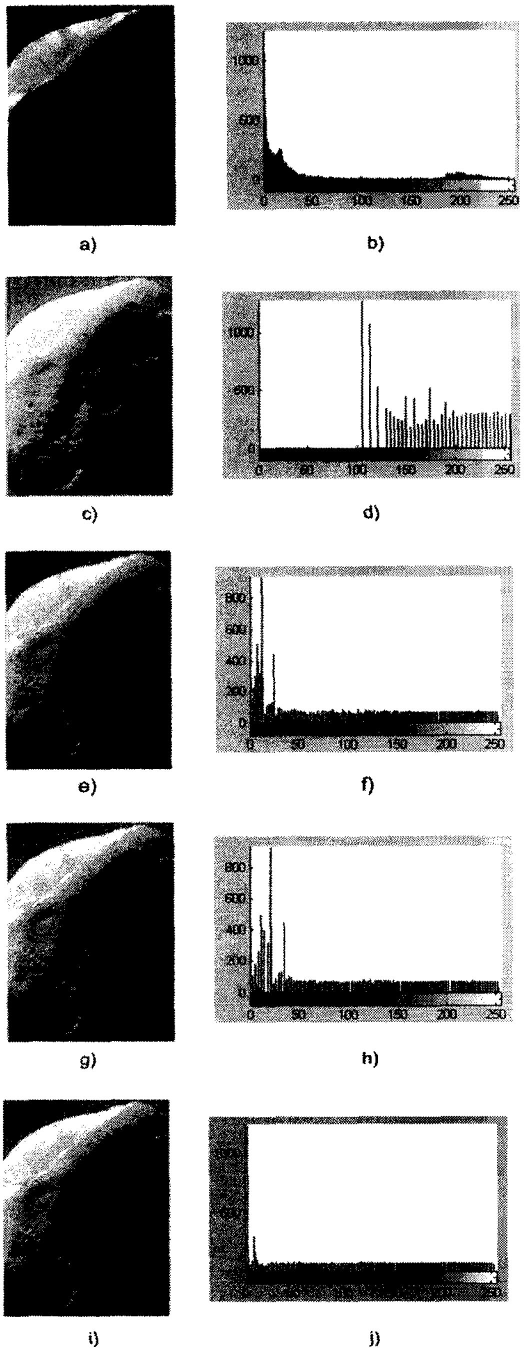

Fig. 7. Result of the Mars moon: a) and b) original image and its histogram, c) and d) enhanced by GHE and its histogram, e) and f) enhanced by HE using voting metric and its histogram, g) and h) enhanced by contrast difference metric and its histogram, i) and j) enhanced by distinction metric and its histogram.

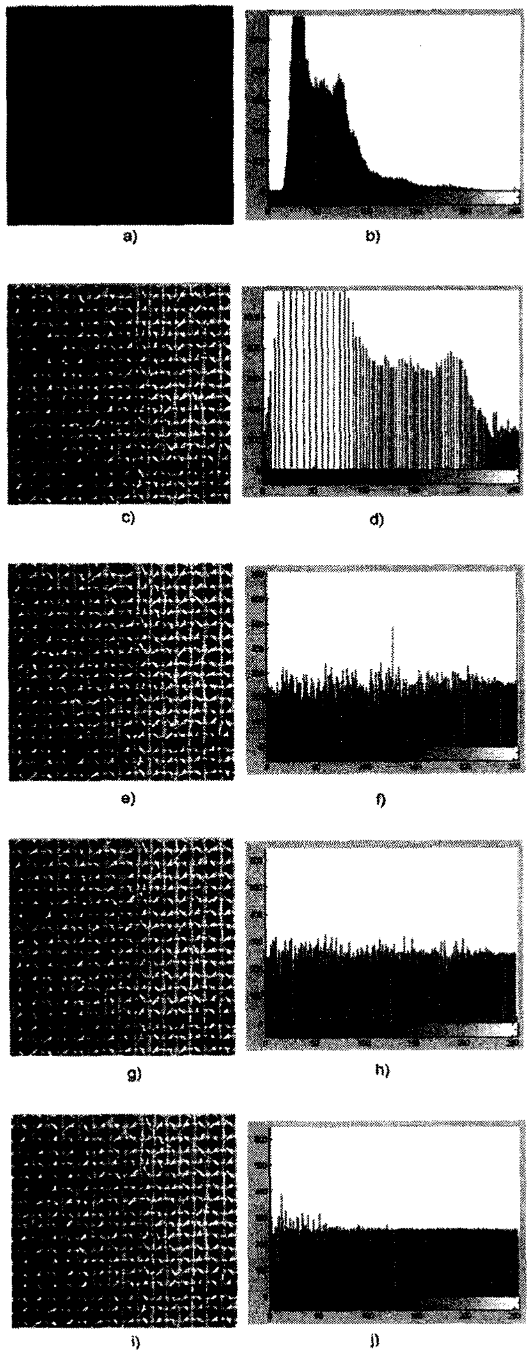

Fig. 8. Example for Brodatz texture (D52) a) and b) original image and its histogram, c) and d) enhanced by GHE and its histogram, e) and f) enhanced by HE using voting metric and its histogram, g) and h) enhanced by contrast difference metric and its histogram, i) and j) enhanced by distinction metric and its histogram.

works to increase contrast of the image and reduce flatness of the histogram from Fig. 7 and Fig. 8. Total time complexity of proposed method is equal to that of voting and contrast difference metrics.

5. CONCLUSION

In this work, we proposed new neighborhood metric which can preserve advantages of other NMs, while reducing drawbacks of them and avoiding undesirable over-enhancement that can occur with LHE and other methods. We investigated its efficiency applying to the Brodatz textures and comparing to other metric such as GHE, HE using voting metric and HE using contrast difference metric, using three quality metrics. The distinction metric achieves better histogram flatness than GHE, HE using voting metric, and HE using contrast difference metric while avoiding the large distortions and computational overhead of LHE.

Future work might involve the design of additional metrics, either for use in specific domains or with desirable properties for image processing in general.

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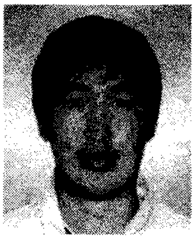

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