MEASURING ISOTROPIC LOCAL CONTRAST: A CIRCULAR MASK BASED APPROACH

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ABSTRACT

Many image processing tasks depend on contrast measures, which can be used to compare and improve contrast enhancement algorithms. Contrast definitions are not always suitable for all situations. In particular an isotropic local contrast measure, that produces a flat response to sinusoidal gratings, can be difficult to obtain. In this paper we review the main existing contrast measures, and propose a new approach, denoted as Circular Mask Metric (CMM). It is based on band-pass filters and circular mask based local contrast computations. This approach has been applied on different test images and with three contrast enhancement methods, in order to show its potentialities for contrast enhancement algorithm testing and improving.

Keywords: isotropic local contrast, contrast enhancement comparing, circular mask based approach

1 INTRODUCTION

Contrast is an important factor in image processing. In fact, contrast deeply influences human perception [Ware00], and has to be considered both in natural images enhancing [Gonza92] and in visualization tasks. Contrast is a measure of a relative variation of luminance, and its importance is due to the fact that human vision system depends more on local variations of luminance than on absolute luminance.

Many contrast enhancement algorithms have been developed [Zimme88, Kim01] in order to improve natural images. Comparison among them is often performed only by visual appearance, while a correct test should also be done measuring contrast; contrast itself can be used to optimize enhancement [Ji94]. Since contrast is also very important in visualization tasks, for example for information display purposes [Ware95], measuring contrast could be also useful for data visualization algorithms.

There are several contrast definitions, and only in a few cases, contrast is computed by using an isotropic method (i.e. with a method that produces a flat response to sinusoidal gratings). In this paper we will briefly review the most common contrast measures, and propose a new local isotropic contrast measuring method. It is based on a band-pass filter and circle-based local contrast computations. The proposed algorithm will then be tested by comparing results of three well known contrast enhancement algorithms on natural test images. Results are coherent with visual commonly used comparison.

This paper is organized as follows: section 2 introduces some background, while Section 3 explains in detail our algorithm. Section 4 tests proposed algorithms on three well known contrast enhancement algorithms, and finally conclusions and highlights for possible future work are given in Section 5.

2 BACKGROUND

Contrast is a measure of relative variation of luminance. Given luminance L, Weber contrast is defined as:

$$C^W = \Delta L / L \qquad (1)$$

Having sinusoids or other periodic patterns with luminance periodically ranging from L_{min} to L_{max}, contrast can be defined as (Michelson contrast):

$$C^M = (L_{max} - L_{min})/(L_{max} + L_{min}) \qquad (2)$$

Neither C^W nor C^M can however be used for measuring contrast in natural images, since bright and dark spots can easily modify the whole image contrast. A local band-limited contrast measure has been introduced by Peli [Peli90]:

$$C^P_j(x,y) = BP_j(x,y)/LP_{j+1}(x,y) \qquad (3)$$

where $BP_j(x,y)$ and $LP_{j+1}(x,y)$ are band-pass and low-pass filtered images in (x,y) (this is a local contrast measure); j is the band of the filter. Lubin [Lubin95] modified Equation (3) in:

$$C^L_j(x,y) = \frac{LP_j(x,y) - LP_{j+1}(x,y)}{LP_{j+2}(x,y)} \qquad (4)$$

C^P and C^L, as defined before, measure contrast only as changes from the local background, and this is analogous to in-phase responses of vision mechanism [Winkl99]. Quadrature responses are not considered. In fact, by measuring C^L for a bidimensional sinusoidal grating produces again a sinusoid, varying between $\pm C^M$ with the same frequency as the original sinusoid, while local contrast should be everywhere the same and equal to C^M (the sinusoid is the same in all the test image).

This is a problem that must be considered when computed local contrast has to be put in correspondence with psychophysical results; actually, in this case the contrast is perceived as a constant value on the bidimensional sinusoidal grating.

In order to take into account both in-phase and quadrature, Lubin [Lubin95] applies oriented filtering to C^L_j and sums the squares of in-phase and quadrature responses for each channel to get a phase-independent oriented contrast measure.

The most recent approach is performed in [Winkl99]. Winkler and Vandergheynst construct an isotropic contrast measure C^I_j as the square root of the energy sum of oriented filter responses, normalized by a low-pass band. In particular oriented filter responses are obtained by using directional analytic filters. Filter design is also reported; proposed approach is based on a class of non-separable filters that generalize the properties of analytic functions in 2-D.

3 PROPOSED ALGORITHM

The basic idea of the proposed circular mask metric (CMM) algorithm consists in the definition of a metric to measure isotropic local contrast, which is easy to implement and which produces the expected results when applied on sinusoidal gratings.

The pseudo-code of the CMM algorithm is reported in Fig. 1. In particular, a band-pass filter is first applied on the original image (one of the three test images is reported in Fig. 2 as an example) to select only those frequencies corresponding to a particular spatial size. This size is computed in pixels so that it can be converted into spatial frequencies depending on actual pixel dimension and observer-image distance [Ware00]. The filter used is an ideal band-pass filter [1] in Fourier domain truncated with a circular symmetric window function in the image domain. For each pixel of the filtered image, minimum and maximum values in a circle-based region (around chosen pixel) are computed; radius (r) of the circle is corresponding to the selected spatial frequency used for the filter (see Fig. 3). The difference between the maximum and the minimum value for each pixel is used to create a new image (reported in Fig. 4) that represents a numeric measure of the local contrast of the original image for the selected spatial frequency. Brighter regions are characterized by a high level of local contrast. The average on the pixel values of the new image is then computed, thus obtaining the mean local contrast for the selected spatial frequency.

4 EXPERIMENTAL RESULTS AND REMARKS

In this Section, the results of the proposed algorithm are shown by means of three examples.

We have chosen to deal with original images whose contrast needs to be enhanced, in order to demonstrate how, by means of the proposed metric, an effective measure of local contrast can be achieved.

[1] Xite[Lønne94] has been used as image processing library.

```
for each r from rmin to rmax (with
step s)
{
 //calculate low and high cut-off
 //frequencies for band-pass filter
 //frequencies are relative to
 //the Nyquist frequency
 lof = 2/(2*r+s);
 hif = 2/(2*d-s);

 //apply the band-pass filter
 //dim is the image dimension
 fimg = b_p(image,dim,lof,hif);

 //produce the image representing
 //the local contrast for a r
 //radius filter
 for each pixel p(x,y) of fimg
 {
  //find min and max in a circular
  //region of radius r centered
  //in p(x,y)
  min = min_value(p(x,y),r);
  max = max_value(p(x,y),r);

  lcontrast = max - min;
  lcrepres [x][y] = lcontrast;
 }

 // save local contrast repres.
 save_image(lcrepres);

 // calculate the mean value of
 // local contrast for a selected
 // radius r
 mean_lc = sum of pixel values in
           lcrepres / area;
}
```

Figure 1: Pseudo-code for the CMM algorithm. Local contrast representation (lcrepres) and mean local contrast (mean_lc) are computed for each radius value between rmin and rmax (with step s)

Figure 2: *Tree* original image

Figure 3: *Tree* image after band-pass filtering (r=4)

In each example, the CMM algorithm is first applied on the original image. Three different contrast enhancement techniques are then applied to the original image: the global Histogram Equalization (HE) [Gonza92], the Adaptive Histogram Equalization (AHE) [Zimme88] and the Partially Overlapping Sub-block Histogram Equalization (POSHE) [Kim01]. Finally, the CMM algorithm is applied to each resulting image. On each image, the CMM algorithm is used with a circular-mask radius ranging from 2 to 32 and the results obtained, representing the local contrast for the selected radius, are used to generate a diagram representing the mean local contrast for each band frequency. Frequency response is very useful to correlate the frequency domain behavior of contrast

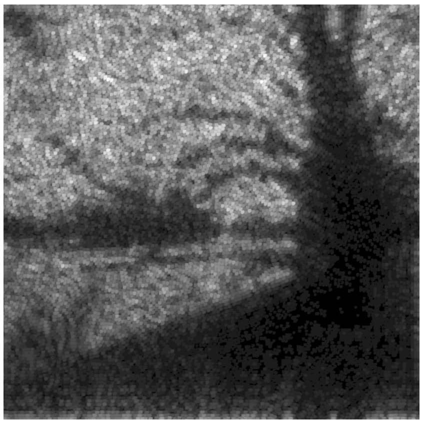

Figure 4: Graphical representation of local contrast (r=4)

enhancement algorithms with human eye frequency sensitivity [Ware00]. In order to obtain a direct graphical representation, a scale ranging from 0 to $2^n - 1$ (where n is the number of bit per pixel[2]) has been chosen to measure the local contrast.

For the first example, the *Tree* image (Fig. 2), already presented in Section 3, has been used. In Fig. 5,6 and 7 are shown the images resulting from the application of the global equalization, AHE and POSHE algorithms, respectively. As shown in

Figure 5: *Tree* image after HE

the diagram reported in Fig. 8, the effect of global equalization performed on the *Tree* image is an improvement of the overall contrast but a worsening of the lo-

[2]In particular, all reported images are on 256 gray levels.

Figure 6: *Tree* image after AHE

Figure 7: *Tree* image after POSHE

cal contrast. This is a typical behavior of a global contrast equalization technique on images characterized by regions with very different brightness; as expected, this phenomenon is clearly highlighted by the proposed metric. Furthermore, the diagram shows how the best results can be obtained by applying the AHE algorithm. POSHE, even if faster than AHE, results in a lower improvement of the local contrast. However, both AHE and POSHE enhance noise possibly introduced by image acquisition.

For the second example, the *Room* image reported in Fig. 9 has been used. In Fig. 10 and 11 the equalized images are shown. The results of CMM on the *Room* image (reported in Fig. 12) are comparable to those obtained with the *Tree* image.

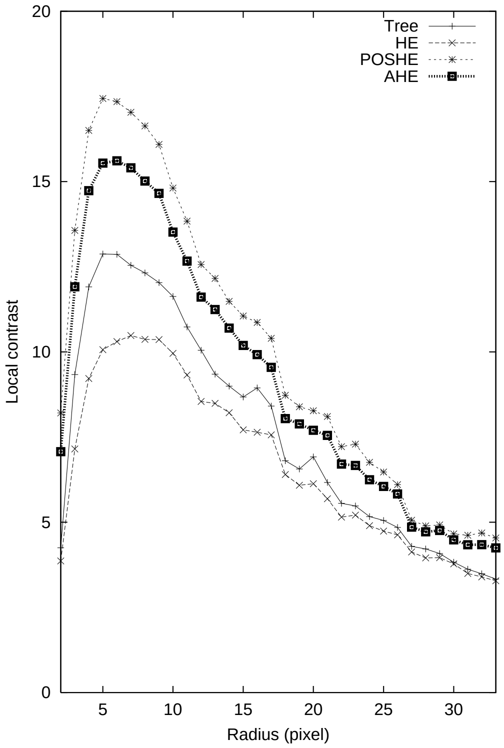

Figure 8: *Tree* local contrast vs. circular mask radius

The third example is based on the *Mountain* image reported in Fig. 13. In Fig. 14 and 15 the HE and AHE equalized images are shown. The diagram in Fig. 16 shows that the mean local contrast is higher for the globally equalized image than for the original one. The same conclusion can be reached through a subjective comparison between Fig. 13 and Fig. 14. In addition, the proposed metric is able to give a region-based numeric measure of

Figure 9: *Room* original image

Figure 10: *Room* image after HE

Figure 11: *Room* image after AHE

the local contrast through a graphical representation. In fact, in the original image (Fig. 13) the sun and the clouds are better outlined and the corresponding regions in the local contrast representation obtained from CMM (Fig. 17) have a higher level of brightness, as discussed in Section 3. On the contrary, in the globally equalized image (Fig. 14), the local contrast is higher on the mountains and on the village, where the local contrast representation presents a higher level of brightness (Fig. 18). Thanks to the availability of a numeric graphical representation of local contrast, the proposed metric is able to highlight how the results that can be obtained by a contrast enhancement technique are strictly dependent on the characteristics of the original image and on the frequencies considered, as well as on the particular region of the image taken into

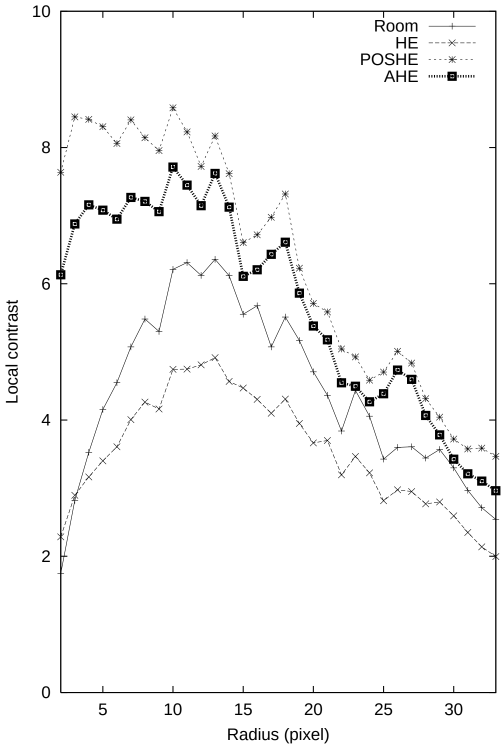

Figure 12: *Room* local contrast vs. circular mask radius

account.

As expected, POSHE and AHE produces the best results. For comparison, the local contrast representation for the image treated with AHE is reported in Fig. 19. It is worth to note that, even if the behavior of different contrast enhancement techniques is similar, actual contrast values can be very dissimilar from an image to another (e.g. compare Fig. 8 and Fig.

Figure 13: *Mountain* original image

Figure 14: *Mountain* image after HE

Figure 15: *Mountain* image after AHE

12).

5 CONCLUSION AND FUTURE WORK

In this paper a new circular-mask based algorithm for computing isotropic local contrast has been proposed.
This algorithm, referred as Circular-Mask Metric (CMM), is able to generate local contrast values for test images, also producing expected results when applied on sinusoidal gratings.

The approach is based on band-pass filters and circular-mask based local computations.

Proposed algorithm has been tested on three different natural images, each one

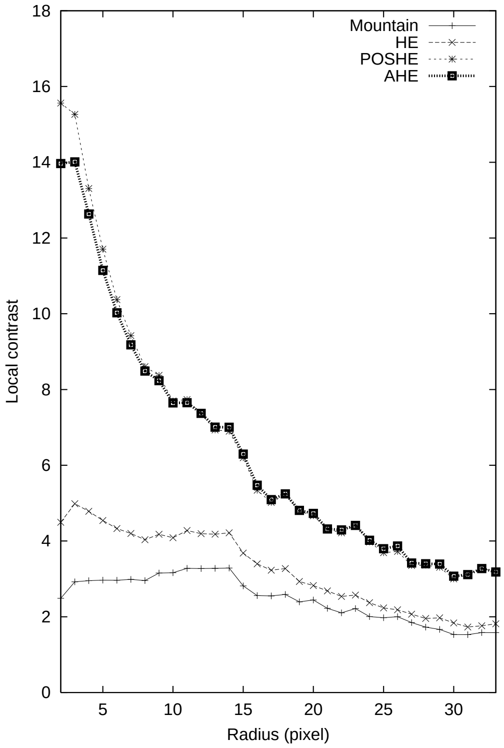

Figure 16: *Mountain* local contrast vs. circular mask radius

improved with three contrast enhancement techniques; results show that CMM method can give a quantitative representation of subjective local contrast.

Future work will be aimed to further improve CMM metric, and to use such metric in order to improve contrast enhancement techniques with a particular attention to human eye frequency sensitivity.

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Figure 17: Graphical representation of local contrast for the original *Mountain* image (r=4)

Figure 18: Graphical representation of local contrast for the *Mountain* image treated with HE (r=4)

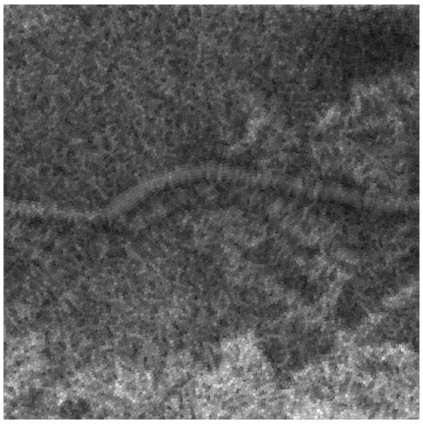

Figure 19: Graphical representation of local contrast for the *Mountain* image treated with AHE (r=4)

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