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Multiscale Image Enhancement Based on Natural Visual System

[1]K. Vijila Rani, [2]A. Alvin Ancy
[1]Research Scholar
Information & Communication Engineering.
Anna University, Chennai, Tamil Nadu, India.
[2]Assistant Professor, Department of ECE.
Arunachala College of Engineering for Women.
Manavilai, Tamil Nadu, India.
Email: *[1]vijilaranijournal@gmail.com, [2]alvinancy11@gmail.com*

Abstract
Image enhancement is to modify images in such a way that the visual content contained in the image is improved for human perception. Producing digital images with good contrast and detail is a requirement for nearly all vision and image processing. Image enhancement has been practical for many applications in consumer, autonomous navigation, remote sensing, biomedical image analysis, and other image processing fields. Enhancement algorithm can be classified into direct and indirect enhancement procedures. Indirect enhancement algorithms enhance images without measuring the image contrast at different scales. Direct improvement measures the image distinction supported Human visual system. In this paper corn sweet effect and illumination correction method is used. By using illumination correction method intensity value increases, by using corn sweet effect the edges get sharpen and hence the overall contrast increases.

Keywords: *Image enhancement, Human visual system, luminance masking, contrast masking.*

INTRODUCTION

The main aim of image enhancement is to improve the clarity of the images for human viewers. It produces binary image with good contrast. Image enhancement has been practical for many applications in consumer, autonomous navigation, remote sensing, biomedical image analysis and other image processing field.

The histogram equalization improves the local contrast of the image. In transform based sequence ordered orthogonal transform which are mainly described and applied for detection and visualization of objects within an image [1]. Dynamic Histogram equalization partitioning, here the input histogram into sub histogram. It enhances the contrast well without introducing severe side effects [2]. In adaptive joint trilateral filter (AJTF) consists of domain, range and depth. It is used to sharpen the edges and remove the noise simultaneously. AJTF is a combination of Adaptive bilateral filter (ABF) and depth filter. ABF can be used for both sharpness enhancement and noise removal [3]. Just the noticeable noise simultaneously. AJTF is a combination of Adaptive bilateral filter (ABF) and depth filter. ABF can be used for both sharpness enhancement and noise removal [3]. Just noticeable depth difference (JNDD) consists of depth, depth order and the JNDD terms.

While enhancing the image may not be smooth, execution time is more. To overcome the problem, we introduce corn sweet effect [5] and illumination correction [6].

PROPOSED METHOD

The purpose of image enhancement is to improve the interpretability or perception of information in images for the human visual system. It consists of illumination correction and corn sweet effect. By using illumination method intensity value adjusted, by using corn sweet effect the edges get sharpen and hence the overall contrast increases.

Illumination Correction

Removal of uneven illumination of the image caused by sensor defaults (e.g. vignetting), non-uniform illumination of the scene, or orientation of the objects surface is the goal of illumination correction. Illumination correction is based on background

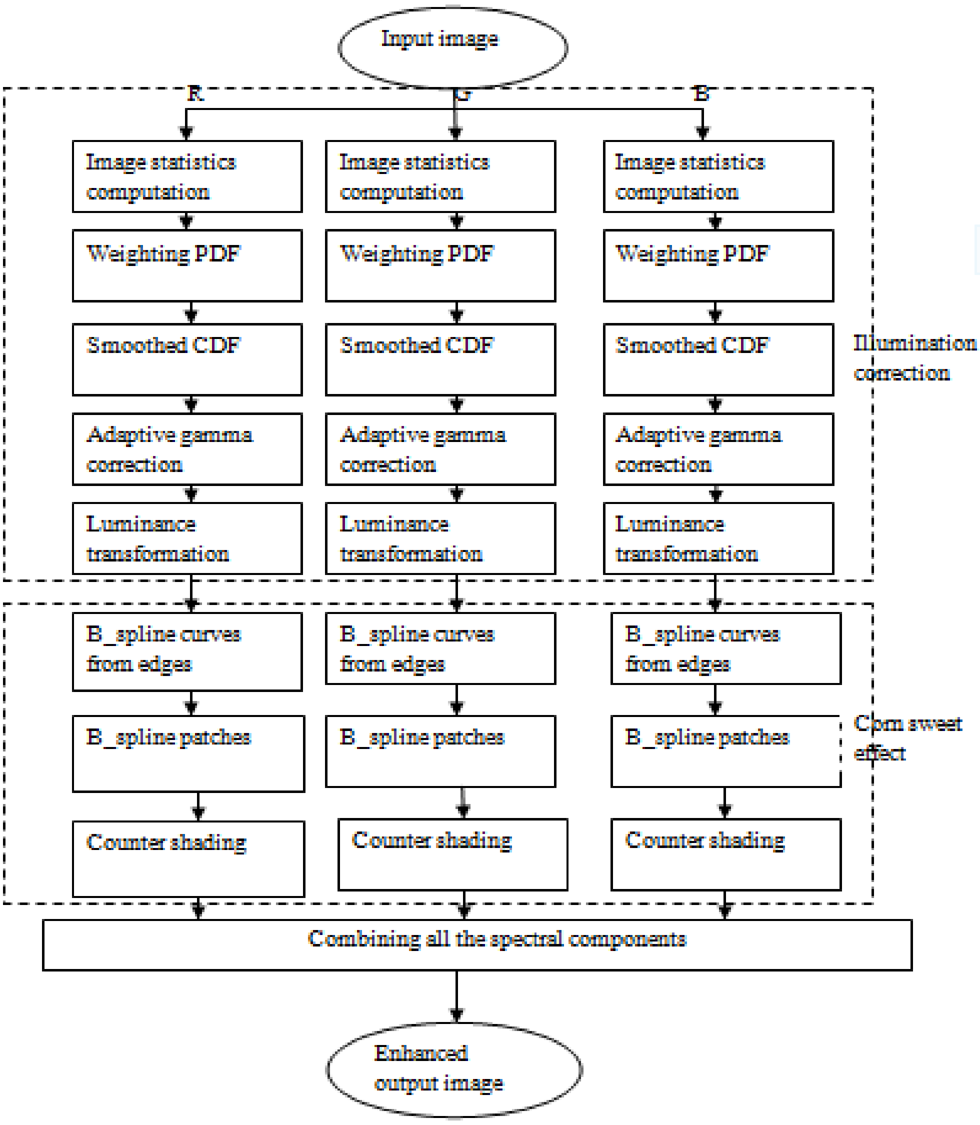

Fig.1. Block diagram of proposed method

subtraction. This type of correction assumes the scene is composed of the background as homogeneous and small objects brighter than the background.

Step 1) Image Statistics Computation

Suppose that *X* ={x (i,j)}denotes an incoming 2D image composed of l discrete gray levels in the range [$l_{\min}, l_{\max}$]where $l_{\max}$ is the maximum luminance of the incoming image, and $l_{\min}$ is the minimum luminance of the incoming image. *X(i, j)* represents the intensity of the incoming image at the location (i, j)and *X(i, j)*$\in$ { $l_{\min}$ $l_{\min}$ +1, $l_{\min}$ +2,…, $l_{\max}$ }.The probability density function (PDF) is defined as follows:

$$PDF(l) = \frac{n_l}{MN} \quad (1)$$

Where $l = l_{\min}, l_{\min}+1, l_{\min}+2, ...l_{\max}$, n_l denotes the number of pixel for luminance l, and MN denotes the total number of pixels in the incoming image.

Step 2) Weighting probability density function

The weighting probability density function can be expressed as follows:

$$PDF_\omega = \max(PDF) \times \left(\frac{PDF(l) - \min(PDF)}{\max(PDF) - \min(PDF)}\right)^\alpha \quad (2)$$

Where

$l = l_{\min}, l_{\min}+1, l_{\min}+2, ..., l_{\max}$, PDFω ($l$) represents the weighting probability density function, max (PDF) denotes the maximum probability density of PDF (l), min (PDF) denotes the minimum probability density of PDF(l), and α represents the adaptive parameter that can be set to 0.5.

Step 3) Smoothed cumulative Distribution function

The original cumulative distribution function (CDF) is smoothed and can be expressed by using the PDFω(l) as follows:

$$CDF_s(l) = \sum_{l=l_{\min}}^{l_{\max}} \frac{PDF_\omega(l)}{\sum PDF_\omega} \quad (3)$$

$l = l_{\min}, l_{\min}+1, l_{\min}+2, ..., l_{\max}$, ∑PDFω represents the sum of the weighting probabilities, and CDFs represents the smoothed *CDF*.

Step 4): Adaptive Gamma correction

By using the gamma correction, the transform function can be calculated as follows

$$T(l) = (l_{\max} - l_{\min}) \times \left(\frac{l}{l_{\max} - l_{\min}}\right)^\gamma \quad (4)$$

Where

$l = l_{\min}, l_{\min}+1, l_{\min}+2, ..., l_{\max}$ with T(l) represents the transform function and $\gamma = 1 - CDFs(l) \times p$ with p represents the adaptive parameter that can set to 1.

Step 5): Final Luminance transformation

The output image can be expressed as

$$Y = \{T(X(i,j)) \mid \forall X(i,j) \in X\} \quad (5)$$

Where X (i, j) represents the intensity of the incoming image at the location (i, j) and Y (i, j) represents the intensity of the output image (i, j).

Corn Sweet Effect

Frequently used by artist to enhance contrast is counter shading adjacent to edges. Counter shading usually takes the form of a non-linearly increasing or decreasing luminance ramp known as corn sweet profile. The counter shading depends both on the amount of desired enhancement and on the presenceand shape of nearby features. The algorithm consists of three stage process

1. Based on the input edges, segment the image into a collection of non-

overlapping regions bounded by B-spline curves.

2. To encode the intensity adjustment the appropriate counter-shading profile within each region was determined using B-spline patches.
3. Apply the counter shading to the image.

Step 1): B-spline curves

Input edges can be defined manually by the user in an image editing application of their choice. Boundary detection algorithms as they locate important image edges (e.g. object boundaries) but ignore less salient edges. Output is a set of edges connected through junctions. Artistic control is through rough scribbles that are refine edges data later stage.

Step 2): B-spline patches

A spline function that has minimal support with respect to a given degree, smoothness and domain partition is known as B-spline or basis spline. Any A spline function can be expressed as a linear combination of B-splines of the given degree. B-splines that has knots that are equidistant from each other-splines is called cardinal B-splines and can be used for numerical differentiation and curve fitting of experimental data. It contains two steps

- Find the maximum possible extent
- Handles intersection between rays

Step 3): Counter shading

The control meshes for the B-spline surfaces are defined; the full contrast profile can be constructed. This is achieved by rendering the surfaces and projecting their depth values. This could be efficiently done by using the depth image produced by an off-screen rendering process with open GL or any other renderer.

EXPERIMENTAL RESULTS

In this the input image is low contrast color image. In the proposed method consists of two steps i.e. illumination correction and corn sweet effect. In the illumination correction method, it is mainly to adjust the intensity level from low level or vice versa. By using corn sweet effect, it selects the area from the edges and increase the contrast. The metric used is Blind reference less image spatial quality evaluator (BRISQUE).

(a) (b) (c) (d) (e) (f) (g) (h)

Fig.2. *(a) input image (b) (c) (d) red, green and blue image (e) (f) (g) luminance masking for red, green and blue image (h) enhanced output image*

BRISQUE is statistically better than the full-reference peak signal-to noise ratio and the structural similarity index and is highly competitive with respect to all present-day distortion-generic NR IQA algorithms. BRISQUE has very low computational complexity, making it well suited for real time applications. BRISQUE features may be used for distortion-identification as well. To illustrate a new practical application of BRISQUE, we describe how a non-blind image denoising algorithm can be augmented with BRISQUE in order to perform blind image denoising. Results show that BRISQUE augmentation leads to performance improvements over state-of-the-art methods. It does not compute distortion specific features such as ringing blur or blocking but instead uses scene statistics of locally normalized luminance to quantify possible losses of naturalness in the image due to the presence of distortion.

BRISQUE is an attractive option for practical applications. One such application could be using a quality measure to augment the performance of image repair algorithms. BRISQUE features are used to transform a non-blind image denoising algorithm into a blind image denoising algorithm. Blind image denoising algorithms seek to reduce the amount of noise present in corrupted images, without any additional information such as the noise variance. The intensity of the image can be expressed as

$$\hat{I}(i,j)=\frac{I(i,j)-\mu(i,j)}{\sigma(i,j)+c} \quad (6)$$

Where i ϵ 1, 2…… M, j ϵ 1, 2…… N are the spatial indices and

M- Image height

N- Image width

c- Constant(c=1)

μ(i, j)- Local mean

σ (i, j)- Local variance

(a) (b) (c) (d) (e)

Fig. 3. *Test images*

$$\mu(i,j)=\sum_{k=-K}^{k}\sum_{l=-L}^{L}\omega_{k,l}I_{k,l}(i,j) \quad (7)$$

where ω= $\{\omega_{k,l}|k=-K,\ldots,K,\ l=-L,\ldots L\}$ is a 2Dcircularly-symmetric Gaussian weighting function sampled outto 3 standard deviations and rescaled to unit volume.

Table 1. *Performance Analysis*

Images	Histogram Equalization	Adaptive Histogram Equalization	Contrast Stretching	Direct Enhancement Algorithm	Proposed Method
Street	49.210	37.321	27.040	17.453	16.010
Small girl	50.453	39.356	28.026	18.120	13.051
Nature	52.286	41.110	30.201	20.302	14.720
School	59.380	49.234	39.301	19.018	15.832
Hydrant	52.379	42.001	31.091	20.306	14.601

In histogram equalization the value can be higher for small girl image. But adaptive histogram equalization can have greater value than the histogram equalization. Compare to all the method performance metric can be greater for proposed method. Here the images can be tested for various low contrast color image. Compare to the entire color image the small girl image can have greater metric.

CONCLUSION

This paper deals with enhancing the image considering the human visual system. Our experimental result shows that the existing enhancement algorithm performed by luminance masking and contrast making at different scales does not provide the corn sweet effect which is perceived by human visual system. To overcome the problem the proposed method introduces corn sweet effect following illumination correction. By using illumination correction method intensity value increases, by using corn sweet effect the edges get sharpen and hence the overall contrast increases.

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