A New Color Contrast Enhancement Algorithm for Robotic Applications

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Abstract—In this paper, we introduce a new spatial domain color contrast enhancement algorithm based on the alpha weighted quadratic filter. The goal of this work is to utilize the characteristics of the nonlinear filter to enhance contrast while recovering the color information. Automatic parameter selection is also important for autonomous robot systems. Therefore, we also present a modified image contrast measure Global logAMEE to incorporate the global image information in regular logAMEE. The new measure helps to choose the optimal parameters and to demonstrate the effectiveness of the proposed method. Experimental results show that the proposed algorithm can enhance the contrast and color efficiently and effectively, even in the presence of noise. Thus, the algorithm is suitable for use in real time robotic applications. Comparison with existing algorithms will be also presented.

Keywords - alpha weighted quadratic filter, color enhancement, Global logAMEE, robot vision

I. INTRODUCTION

Robots are used in varying fields of industry, military and security to assist and emulate human functions. Mobile cameras are the most widely used sensors in robot design and serve an important role in receiving signals and perceiving the outside world. It is straightforward for the human eye to perceive an image despite the presence of non-uniform illumination or colored light conditions. Unfortunately, the quality of images captured by the camera is not always satisfactory for robots and thus, it can be a very complex task to respond rationally based on the perceived low quality image. For example, surveillance cameras are expected to operate both day and night. The sensors have to adjust the white balance automatically based on the changing background light. Whereas cameras mounted on spacecrafts capture images with noise and with blurring effects. Most of these applications require real-time support. As such, it is important to develop a simple but effective color contrast enhancement algorithm to improve robot vision in the presence of noise and non-uniform illumination.

The goal of color contrast enhancement is to recover the color captured from image scenes and enhance the contrast similar to the human visual system. Several color contrast enhancement techniques have been proposed both in the spatial domain and the transform domain. Spatial domain enhancement algorithms are applied on the pixel value directly, such as the Retinex technique [1] and 3D histogram equalization [2]. The Retinex theory, which was first proposed by Land and McCann in 1971, achieves color consistency by computing the local ratio of a target pixel to its neighbors [1]. It explains how the visual system extracts information from a scene despite changes in illumination. Many variations of Retinex have been developed including Center-surround Retinex [3], multiscale Retinex [4], and multiscale Retinex with color restoration [5]. Wang and Luo proposed a new adaptive color contrast enhancement algorithm for digital images [6], which includes intensity adjustment, contrast correction, color enhancement and denoising steps. Their algorithm successfully solves underexposure and color casting problems, but has high computational complexity and fails when processing overexposed images.

For transform domain methods, the image is first transformed from a gray level image into the frequency domain by using the Cosine, Fourier, or Wavelet transforms and then the transform domain coefficients are modified to adjust the intensity range. The advantages of transform domain techniques are that they do not affect the ability to compress the original image, they require less memory space and possess a lower computational cost as compared to the spatial domain techniques [7]. Typically in color image enhancement, the color images are transformed into another color space where chromatic components are more uncorrelated from the achromatic component, such as HSV, YCbCr, PCA and then apply the gray image enhancement algorithm to only the luminance component to preserve the color information. However, the transform domain methods often introduce block artifacts and superfluous edges near block boundaries. There are other limitations such as they cannot simultaneously enhance all portions of the image very well and selection of the optimal parameters still poses a critical issue for automating the process [8].

Recently, several quadratic filters have been developed [9]. Traditionally, nonlinear filters have been used for grayscale image enhancement. The use of a positive alpha power in the quadratic filter has also been introduced to further enhance the overall contrast and also improve the local fine details and dark regions [10]. More recent works [11] have introduced the nonlinear filter for its ability to preserve contrast while simultaneously removing noise. From this point of view it is
possible to apply the alpha weighted quadratic filter in color image contrast enhancement by selecting parameters properly.

The goal of this work is to utilize the characteristics of the nonlinear filter to enhance image contrast while recovering color in the spatial domain. The rest of this paper is organized as follows: Section II introduces the alpha weighted quadratic filter (AWQF) and reviews the logAMEE measure for quantitatively evaluating the performance of enhancement algorithms. Section III introduces the new alpha weighted quadratic filter based color image contrast enhancement algorithm. Section IV presents the experimental results and comparisons to existing color enhancement methods. The conclusions are discussed in Section V.

II. BACKGROUND

For this work, the Alpha Weighted Quadratic Filter (AWQF) is used as basis for color contrast enhancement. In this section, the necessary background of the AWQF is presented. The definition of the logAMEE measure is also reviewed in this section.

A. Alpha Weighted Quadratic Filter

The quadratic filter is widely used in grayscale image enhancement, feature detection and image denoising. It introduces nonlinear effects in traditional linear analysis in a relatively simple and manageable way. Mathematically, a complete linear quadratic filter can be defined as:

$$y(n) = \sum_i w_1(i)x(n-i) + \sum_i \sum_j w_2(i,j)x(n-i)\alpha(n-j)$$

(1)

The primary rules of designing a quadratic filter include: (1) symmetry, (2) isotropism, and (3) ensuring that the summation of the linear coefficients is one and that the coefficient of the quadratic term is zero [9]. In this paper, the proposed form of quadratic filter algorithm for edge detection is composed of two terms [12]: a quadratic linear filter \(y_0\) and a quadratic operator \(y_1\):

$$y(x) = y_0(x) + y_1(x)$$

(2)

After collecting and grouping the isotropic and symmetric terms together, \(y_0\), which is designed as the edge preserving nonlinear smoother, can be written as:

$$y_0 = h_0x_0 + h_1(x_0 + x_1 + x_5 + x_8) + h_2(x_0 + x_2 + x_4 + x_8) + w_{h_0}^2$$

$$+ w_1(x_0^2 + x_2^2 + x_4^2 + x_6^2) + w_2(x_0^2 + x_2^2 + x_4^2 + x_6^2)$$

(3)

While \(y_1\) which is the enhancement term can be written in the following form:

$$y_1 = s_1(x_0x_2 + x_0x_4 + x_0x_8 + x_2x_4 + x_2x_8 + x_4x_8)$$

$$+ r_1(x_2x_4 + x_0x_4 + x_0x_8 + x_2x_8 + x_4x_8 + x_4x_8)$$

$$+ r_2(x_0x_4 + x_2x_4 + x_0x_8 + x_2x_8)$$

(4)

Where, \(x\) is a 3 x 3 kernel with \(x_0\) in the center, and the coefficient \(s_i\) and \(r_i\) are weights that determine whether the couple is related or not related to the central pixel [9].

The Alpha weighted quadratic filter, as the name implies, is realized by raising each collected and grouped term to a power of alpha. In this case, \(y_0\) becomes:

$$y_0 = h_0x_0 + h_1(x_0 + x_1 + x_5 + x_8)^\alpha + h_2(x_0 + x_2 + x_4 + x_8)^\alpha$$

$$+ w_{h_0}^2 + w_1(x_0^2 + x_2^2 + x_4^2 + x_6^2)^\alpha + w_2(x_0^2 + x_2^2 + x_4^2 + x_6^2)^\alpha$$

(5)

And \(y_1\) becomes:

$$y_1 = s_1(x_0x_2 + x_0x_4 + x_0x_8 + x_2x_4 + x_2x_8 + x_4x_8)^\alpha$$

$$+ r_1(x_2x_4 + x_0x_4 + x_0x_8 + x_2x_8 + x_4x_8 + x_4x_8)^\alpha$$

$$+ r_2(x_0x_4 + x_2x_4 + x_0x_8 + x_2x_8)^\alpha$$

(6)

When a positive power of alpha is applied based on the positive power law, both the global and local contrast can be enhanced [11].

Rampini gives a recommended set of parameters in [9]. In this paper, we use these values for coefficients of the linear and quadratic terms:

$$h_0 = 0.2, h_1 = 0.1; h_2 = 0.1; w_0 = 0.8; w_1 = -0.1; w_2 = -0.1$$

$$s_1 = 0.25; s_2 = 0.25; \alpha = -0.125; r_2 = -0.25$$

(7)

In our approach, the parameters of alpha power are decided by experiment and the Global logAMEE measure. A study of the quadratic filter was addressed in [9], [11] and [12].

B. logAMEE

In the past, attempts at statistical measures of gray level distribution of local contrast enhancement such as those based on mean, variance, or entropy have not been particularly useful or meaningful. Morrow et al. [13] introduced a measure based on the contrast histogram, which has a much greater consistency than statistical measures. Thereafter, Agaian et al. developed the EME, EMEE [7] based on the Weber contrast, and the AME, AMEE [7] based on the Michelson contrast. Panetta et al. then incorporated the PLIP operation [14] into the measure and developed the logAME and logAMEE [15]. Each of the measures has different physical explanations within it, so it is necessary to choose a proper measure for specific applications.

Since the proposed algorithm in this paper is intended to improve the contrast and restore the color, to quantitatively assess the contrast enhancement performance, we use the logAMEE [15] as the base measure and then incorporate the global contrast in the expression to better reflect the global intensity in this application. logAMEE is defined by Eq. 8:

$$\frac{1}{k_1k_2} \sum_{k=1}^{k_1} \sum_{\hat{j}=1}^{k_2} \left( \frac{I_{max,j} - I_{min,j}}{I_{max,j} + I_{min,j}} \right) \ln \left( \frac{I_{max,j} - I_{min,j}}{I_{max,j} + I_{min,j}} \right)$$

(8)
Where an image is divided to \( k \times k \) blocks, \( I_{\text{max},j} \) and \( I_{\text{min},j} \) are the maximum and minimum values of the pixels in each block separately and \( I_{\text{min},j} \cdot I_{\text{max},j} \) is the Michelson contrast with PLIP operation.

### III. Methodology

The color image quality depends on three fundamental factors: brightness, contrast, and color. The proposed algorithm consists of three steps: (1) Classification, (2) Intensity Adjustment and (3) AWQF color contrast enhancement. The flowchart and the corresponding intermediate results are shown in Fig. 1.

![Flowchart](image1)

**Figure 1. Flow of the proposed algorithm and intermediate results**

1) **Classification**

The intensity adjustment method we describe in the following step utilizes either the normalized Naka-Rushton function, which is comparable to the power law with a power less than 1 or we use the regular power law with a power greater than 1. To have a quantitative classification of these two types of images, we trained 30 images from Barnard’s dataset and the NASA dataset using a modified version of logAMEE and get an approximate interval of dataset and the NASA dataset using a modified version of two types of images, we trained 30 image factors: brightness, contrast and color. The proposed algorithm consists of three steps: (1) Classification, (2) Intensity Adjustment and (3) AWQF color contrast enhancement. The flowchart and the corresponding intermediate results are shown in Fig. 1.

![Flowchart](image2)

**Figure 2. Normalized Naka-Rushton function used for intensity adjustment.**

2) **Intensity Adjustment**

The power law is the most traditional method to modify the histogram and it is effective and straightforward. In real world applications which require real-time processing, it is still commonly used. For more complex problems like non uniform illuminated images captured from multiple light sources, Wang proposed an automatic intensity adjustment method based on the uses of the Naka Rushton equation (Fig. 2). Their algorithm can increase the intensity in the dark regions to eliminate underexposure and compensate the channel with a low mean value to get rid of color cast [6]. The Naka-Rushton function is described in Eq. 10.

\[
V_y = \frac{I}{I + H} \cdot \frac{I_{\text{max}}}{I_{\text{max}}}
\]

Where \( I \) represents the intensity value of each channel and \( I_{\text{max}} \) represents the maximum value of the input image. \( H \) is a function of global intensity and chrominance. Wang integrates the chrominance and contrast characteristics with the intensity as the adaption factor \( H \) and realize the automatic selection of adaption factor \( H \) [6]. In the proposed algorithm, we adjust the intensity with the Naka-Rushton function for the dark images to effectively eliminate the intensity loss and use the power law for other images for decreasing the average processing time.

3) **AWQF Color Contrast Enhancement**

To accomplish color and contrast enhancement and reduce the effects of noise, Wang provides 3 more steps to correct the intensity adjusted images [6]. Since AWQF inherently has the ability to enhance contrast while removing noise [11], it is used in this algorithm for enhancing the contrast in color images. As designed, the linear quadratic filter \( y_0 \) in Eq. 5 will serve as an edge preserving nonlinear smoother. It will remove noise while minimizing the blurring of edges. The quadratic term \( y_1 \) in Eq. 6 with a positive alpha power further enhances the contrast. By properly selecting the parameters with the Global logAMEE, it is also possible to enhance color as well in a
single step. The AWQF can enhance the image contrast and get vivid colors in a simple and fast way.

IV. EXPERIMENTAL RESULTS

Since Robots have been used in medical surgery, space applications, homeland security and other areas, it is practical to run the experiments on real camera captured images. The images we used for testing this algorithm include those from the Barnard dataset from which each image is captured under different lighting conditions and from the NASA Retinex research dataset. The proposed color image enhancement results are also compared with those generated by Wang’s algorithm and by the Retinex algorithm.

The two images in Fig. 3 show different lighting conditions, namely, under exposure and under strong sun light. The “paper” image in Fig. 3 is captured under exposed. The original image is from the Barnard dataset and categorized as a “too dim” image by human evaluators. In robotic night vision surveillance applications, it is important to recover colors and details under this kind of undesirable luminance. In this case the Retinex algorithm (from photoFlair) does not restore the intensity well and Wang’s algorithm does not recover the saturation well. In comparison, the result from the proposed algorithm has more vivid color.

The “white house” image is from the NASA database where the original image is taken in strong sunlight showing
much loss of color and details in the shadows. The NASA’s Retinex algorithm retains the details under the house shadows; however, it also brings halo artifacts to the bottom left trees. Compared with Wang’s algorithm, the proposed algorithm has better contrast especially in the railings portion of the white house.

Fig. 4 reflects some real world problems encountered by robotic assistant applications. In robotic surgery, the surgeon uses either a direct telemanipulator or computer control to operate the instrument movement. Thus the image captured by the robot camera is required to truly and precisely reflect the real position of organs and vessels. Unfortunately, medical images are always of low contrast and poor resolution, due to the limitations of the hardware system or limitations on allowable exposure time, such as in the case of X-rays. Performing color contrast enhancement on medical images is shown as the first example in Fig. 4. In this low contrast situation, neither Wang’s algorithm nor the Retinex algorithm enhances the mass portion. The block artifacts and halo effects from these two algorithms may mislead the surgeon’s diagnosis. In comparison, the proposed algorithm enhances the breast cancer in the mammogram image, which is useful information for surgeons. Another example is the aerial image captured by the aerial cameras. The second row of Fig. 4 is a typical image taken from the Earth’s orbit. This type of image contains many low contrast and dark areas. In addition, the presence of the atmospheric layer may cause blurring effects on the image. All three methods reveal the extent of the sediment outwash in the aerial image after processing. Notice that more details are recovered and more vivid color is shown with the results of the proposed algorithm.

The benefits of using the alpha power in the quadratic filter design are shown in Fig. 5. The theoretical analysis shows that when a positive alpha is applied, based on the power law, both the global and local contrast is enhanced. The experimental results prove this and further demonstrate that by properly choosing the alpha power, the color can be better recovered.

The Global logAMEE measure is not only a tool for objectively judging the enhancement performance but also provides a mathematical tool to automatically select the optimal parameters. This is an important requirement for quality autonomous robot systems. By plotting the Global logAMEE value of the enhanced image versus the parameters for a specific image, we can get a descriptive graph to help select the parameters. We determine the optimal parameters by looking at the graph for the local extreme. Fig. 6 shows the Global logAMEE measure for the underexposed image of the striped shirt from the Barnard dataset and its Global logAMEE measure with a different parameter c in Eq. 5. From Fig. 6 (b), it is seen the local extreme is achieved at c = 1.5 which corresponds to the image with the best visual quality. The comparison of the optimal results and results with other parameters are also shown in Fig. 6.

Sometimes there will be more than one local extreme in the Global logAMEE measure, as an example shown in Fig. 7. For the same shirt image, the parameter c and d are to be determined and there are multiple local extremes in the global logAMEE plot. Fig. 7 (c)-(e) shows three enhanced images with same global logAMEE value 0.1493 but with different parameter values. It is worth noticing that global logAMEE is an average measure for k1 x k2 blocks among the whole image. So although the global logAMEE gives the same value for these three images, the three enhanced images differ in each image’s local details. By simply averaging the three images, the resulting image can leverage on the best qualities of the three images. The global logAMEE value of the average image is 0.1001 which further pulls the measure to the extreme which means the quality of the average image is further improved. This result also agrees with the subjective judgment.
We have introduced a new Alpha Weighted Quadratic Filter based color image contrast enhancement for robot vision applications. The analysis and experimental results show that the proposed algorithm has less computational complexity while achieving either improved or comparable color enhancement with Wang’s algorithm. The algorithm has been shown to provide better visual contrast than the Retinex algorithm. We also presented a new Global logAMEE to make it possible to select parameters automatically. The measure helps to classify when an image is underexposed. Due to the simplicity and efficiency, this algorithm is suitable for Robotic applications, where real-time performance is required.

REFERENCES