Optimized Content Adaptive Approach for Image Detailed Enhancement to Reduce Color Distortion

Mohammed Iqbal Dohan*
College of Computer Science and Information Technology, University of Al-Qadisiyah, Iraq.
E-mail: Mohammed.iqbal@qu.edu.iq

Nora Ahmed Mohammed
Mechanical Engineering Department, College of Engineering, University of Al-Qadisiyah, Iraq.

Mohammed Rajeh Mohammed
College of Biotechnology, University of Al-Qadisiyah, Iraq.

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Abstract

Digital imaging has significantly influenced the outcome of research in various disciplines. For example, artificial intelligence and robotics, biometric security, multimedia and image processing, etc. Technically, image processing and the Human Visual System (HVS) relies heavily on image enhancement to improve the content of the image. One of the biggest challenges in image processing is detail enhancement due to halo artefacts and gradient inversion artefacts at edges. It has been used to enhance the visual quality of an image. Most algorithms that used to enhance the detail of an image essentially depend on edge-preserving decomposition techniques. in general, the image consist of two major elements are a base layer and a detail layer, which extracted by edge-preserving decomposition algorithms. The detail layer is enhanced to improve the details of the generated image. we propose in this paper, a new model to preserve the sharp edges and achieve better visual quality than the existing norm-based algorithm to enhance the details of the image. Experiments show that the proposed method reduces the distortion at the edges. It improves the details of the generated image significantly.

Keywords


1056 http://www.webology.org
Introduction

Image processing is one of the most important tools to enhance a given image to make it more suitable for the objective function of a particular application (Allebach, 2005). The simple meaning is to improve the quality of an image. Image enhancement does not change the content of the original image, but it does change the dynamic range of the selected image so that it can be easily improved. Image enhancement techniques fall into two broad categories spatial and frequency domain methods (Chen et al., 2019). The spatial domain methods are directly operating on pixels, while the second broad operates on Fourier Transform (FT) of an image (De Hoop et al., 2010; Peng et al., 2014; Shindo et al., 2019).

In this paper, mostly we are considering edge-preserving smoothing techniques, gradient fields. The use of a spatial mask for image processing operations is known as spatial filtering operations. And the mask used is called spatial filters. Basic spatial filters are low pass filter, bandpass filter & high pass filter(L. Xu et al., 2011). If the location in image (x,y) is the centre of the mask, the grey level of the location (x,y) is replaced by using R, next we have to either convolute the mask over the next position or can say the location in the image, this operation is repeated for the same time (Chandrashekar & Sahin, 2014). This process is stopped when all pixel’s locations have been covered (Al-shammary et al., 2020; Alsaeedi et al., 2020; Aouadi et al., 2015; Bharathi & Sudhakar, 2019; Rudin et al., 1992).

Smoothing filters are used significantly to blur and reduce noise in the original image (Dai et al., 2015) (Kawala-Sterniuk et al., 2020). The image de blurring has to perform on the image before going for object recognition and all other techniques. Technically, the noise reduction by blurring is realized either by a linear filter and or by the use of nonlinear filtering. Low pass filtering (LPF) is an essential requirement is that all coefficients have to be positive (Kabaciński & Kowalski, 2010). The Neighborhood averaging is a special case of LPF, it occurs where all coefficients of LPF is equal. LPF blurs edges technique and other sharp details in processing image (Alsaeedi, 2016; Carcagnì et al., 2015; Portilla, 2009; Smith, 2006). Example of LPF:

\[
\frac{1}{9} \begin{pmatrix}
1 & 1 & 1 \\
1 & 1 & 1 \\
1 & 1 & 1
\end{pmatrix}
\]

The Median filtering uses for noise reduction instead of blurring (De Hoop et al., 2010). This filter works if two aspects are achieved (A et al., 2019; Bharathi & Sudhakar, 2019): first, the noise pattern must consist of strong, spike-like components; second, the feature to be preserved is edge sharpness. The median filtering is a nonlinear operation. Technically,
for each input pixel $f(x, y)$. The filter sorts the values of both pixel and its neighbors for
determining their median and assign its value to the output (C & Sivramakrishnan, 2019; Mohamed Ali et al., 2021). Guided Filter The general linear translational variable filtering method initially consists of three images (Peters, 2009): Input image (P), leading image (I) and output image (Q). The two images I and Q are predetermined depending on the application and may be identical (B & Holi, 2020). Equation 1 calculates the output of the filtering at pixel $i$, expressed as a weighted average.

$$Q_i = \sum_j W_{ij}(I)P_j$$ (1)

where: the $i, j \in$ pixel indexes, $W_{ij}$ (filter kernel) is a function of the guidance image $I$ and independent of image $P$. The guided filter is linear concerning the input image.

The Laplacian filter (LLF) is one of the most methods used to the analysis of image processing. This filter build based on invariant Gaussian kernel functions (L. Xu et al., 2011). The limitation of LLF does not work well for representing edges, as such as edge-preserving smoothing and tone mapping. Several techniques and representation schemes have been proposed to implement the local Laplacian filters. For example, neighborhood filtering, anisotropic diffusion, and specialized wavelet bases (Chen et al., 2019; Kaubruegger et al., 2018). Although these techniques are very successful but they suffer from computational complexity. In our work, explain the state of the art in edge-aware processing using standard Laplacian filters (Paris et al., 2011). To detect the edge of an image that distinguishes large-scale from small-scale details basically use the threshold of pixel values. Therefore, we proposed a set of filters that satisfy four requirements: edge-preserving smoothing, detail enhancement, tone mapping, and inverse tone mapping. The proposed method has several advantages: its simplicity and flexibility, depending on Gaussian convolutions and pointwise nonlinearities, finally, the proposed method does not require any optimization or post-processing (Gonzalez et al., 2008; Kalukin et al., 2000). The proposed technique has consistently produced high-quality results without degrading edges or introducing halos.

An image gradient might directly modify an image with intensity or alter the image. It could also be that it normally extracts data from the image. A gradient is another term used to describe color gradients. Mathematically, the gradient of a two-variable (object function of image intensity) is applied to each proposed image as a second vector whose elements are given by derivatives with the two directions horizontal and vertical. The points of the gradient vector of each purpose image will increase in the direction of the highest possible intensity, therefore its length corresponds to the speed of the change process in its direction.
Since the intensity of the image is hardly a known pattern for detected points in the image. It has been used perfectly in deepening the continuous intensity of the points of an image. Using some additional assumptions about the spinoff, the spinoff of the continuous intensity power is calculated as the power on the sampled intensity power, i.e., the digital image. Approximations of the spinoff functions are summarized in different degrees of accuracy of the power. The significantly most common approximation to the image gradient is the convolution operation using a kernel such as the Sobel operator or the Prewitt operator. To build blocks in image processing the gradient. The image gradient is used by the cagy edge detector to detect the edge. They are also typically used in maps, geographic information, and image displays to convey additional information. Image gradients are typically used in maps and visual representations to convey additional information. A geographic information system (GIS) uses color gradients for, among other things, rise and population density (L. Xu et al., 2011).

Literature reviews that addressed to optimization enhance details of image A new image enhancement algorithm that handles the dark regions and edges was proposed in 2012 by Rivera et al. (Mittal & Rajam, 2020). Generally, when an image is acquired in a non-normal lighting environment that produces a dark image and has low brightness. The method aims to preserve the information of the flat regions by smoothing, sharpening the gradient (edge) and improving the visibility of the dark regions. This work generates maximum improvements by creating a mapping function that generates an ad hoc transform for each image. This algorithm can detect and group the most common features from the pieces of information that getting from the boundary and textured regions of an image. Certainly, the essential parameter human visual system is used to enhance the image in term of detail so that it can be perceived in good quality.

The nonlinear transform based approach for color image enhancement is proposed by Deepak et al. (Perona & Malik, 1990) in 2011. The RGB color system is a basic color model in a digital color image. The changes in brightness and angle are not accepted in RGB model. In this work, the useful extension of RGB image to hue saturation value (HSV) color space is implemented for processing the image. In this work, the illumination component V of HSV color space is the key component for image enhancement, and the other two components H and S are kept without modification. In the beginning, the step was to divide the V component into small overlapping blocks. These blocks will helps in performing the luminance enhancement. The second step was to adjust the contrast of each pixel based on the value of the center pixel and its corresponding neighbor pixels. After successfully performing the two enhancement steps, the V component is again combined with the H and S components to obtain the raw RGB image.
In Multiscale retinex image enhancement scheme based on fusion approach for color restoration is presented by Parthasarathy et al (Durand & Dorsey, 2002) in 2012. In general, the low-cost imaging systems that capture images are of low quality and the display does not show the image with low reliability. The multiscale retinex algorithm consists of two main phases which are used to enhance the image based on the contrast parameter. The first phase work to consider the gain values of each pixel. In the second phase, minimizing the background power consumption show image better. However, in digital image processing, the image enhancement process is a very important step, it produces images with high effectiveness. The authors proposed to take the essential enhancement source as illuminance for color restoration in a degraded mode of input images. The multiscale retinex algorithm mainly focuses on the degraded regions in the image obtained by the nonlinear condition. Lastly, the multiscale retinex method shows a good enhancement rate compare with the single-scale retinex method.

In 2009 (Paris et al., 2011), Bronte et. al presented methods for fog detection. The authors proposed a reason why the images captured by the cameras may have abnormal conditions due to heavy fog and the camera sensors cannot detect the content using an appropriate method. They assume that the road from a certain distance is a problem area, which is mainly caused by two reasons are: The skylight is zero in total, so the whole environment is covered by fog, which creates the water waves in the air cans vision zero. Second, the images of the dark area taken by the (b/w) camera cannot reliably show the content, so the prediction of the road implemented by camera projection angle signals or quaternions, and Angle-Axes. In general, using black and white cameras instead of color cameras has a higher probability of obtaining good information. The proposed method can detect the content in the fog-infested region, which is implemented by computing the estimation distance based on the camera projections, also improves the dark images taken in the darkest region when the sky light is also zero. The proposed method optimizes the design of an automatic image processing scheme that depends on the system to solve the dark region problem.

In 2012 (Dai et al., 2015), Chaofu et. al. proposed a hybrid spatio frequency based on an image optimization algorithm. The image information is analyzed depending on the frequency domain, the potation does not produce good enhancement of the image, so to handle this problem the authors proposed a spatio-frequency-based hybrid system for degradation of images in less time, which will increase the performance of the digital image system. when the analyses of image information depend on spatial information, localization of the perturbation content is given. It helps in improvement in the small processing time required. While reducing the run time complexity, the performance of the system is also
increased. The use of spatial domain alone cannot accomplish the entire task of frequency domain improvement. The previous works that deal with the frequency domain improvement of the system do not have a suitable transformation method to meet the practical requirements. Technically, by using both transformation methods (top-hat, bot-hat) will give the ability to smooth the regions in the spatial domain. the hybrid model improves both inner and outline details of the image.

An improvised watermark detector-based image enhancement approach is proposed by A. Poljicak, L. Mandic, M. Strgar Kureci in the year 2012 (Hidaka & Kurita, 2007). In the digital image processing field, the watermarking process is a popular security method used for authentication and copyright protection. Moreover, incidental/accidental hacking results in a situation where the authenticated person faces the problem of detecting his watermark and this situation frequently happens due to attacks. To improve the detection convolution filter is used to improve the quality of the image based on the image enhancement process. When a watermark is inserted in the image for authentication and copyright protection should have robust behavior against all attacks namely JPEG compression, Scan copy etc. When the third party wants to get the watermark then it results in the situation where authenticated user finds difficulty in detecting his watermark which results in a malicious situation. The detection rate of the watermark considerably reduces after passing through various malicious attacks and in our proposed work convolution filtering technique along with robustness is implemented for better image perception. Finally providing privacy protection to personal information needs more equipped algorithms and high end transform as well as filtering techniques. Image enhancement is playing important role in watermark detection from the watermarked image in a reliable way.

Image enhancement using JND parameter for stereo images proposed by Jung et al in 2012 (Farbman et al., 2008) it has two mechanisms: the reference and no-reference are used for enhancing the image process. The image output from the reference technique compared with the input image for better statistics and in non-reference. In reference, the output image is compared with the input image for good statistics while in the non-reference approach they are not compared with the input image. The pixels potentially are accepted the data-encrypted or not, the overflow/underflow value of pixel occurs when the status of pixels are not allowed to accept these data. The overflow and underflow lead to abnormal behaviour in the image, and image enhancement by the method of just perceptible difference is successful in accurately obtaining the status of pixels. Although various enhancement techniques have been proposed in the literature for different images, improving the quality of stereo images is still a problem. Here, a parameter called "just noticeable" (JND) is used for sharpness enhancement to achieve a better perception of
stereo images, but the sharpness enhancement leads to an over enhancement problem. To solve this problem, an optimized Binocular Just-Noticeable Difference (BJND) is proposed to provide the best performance accuracy over the classical methods. In (C. Xu, 2016), Cheng et al. presented an HVS-based approach to image enhancement for the visual system (HVS) is an essential parameter for image quality analysis. HVS can distinguish between the noisy content and the singular content of the image. Although there are many parameters to analyze the quality of digital images, HVS is still an essential tool to analyze image quality. The authors have used the logarithmic image processing model together with the HVS to develop a high-functional approach to improve the image. The just perceptual difference is another parameter used depending on the reference system to analyze HVS effective good images for better perception. LIP-HVS model depends on JND is accordingly a new parameter for image enhancement in multiscale approach. The performance and qualifications have been good enhancement over the classical systems without reference, the approximate which does not meet the practical needs in various research areas based on image processing domain has been introduced. In (Farbman et al., 2008) 2012, the authors of proposed contrast enhancement for dark images based on non-dynamic Stochastic Resonance.

In general, images are based on three contents that degrade the image: noise, blur, and artifacts, all of which can degrade the image content to the extreme in various applications. In particular, these three contents can cause more degradation under abnormal lighting conditions, resulting in dark and low-contrast images. Generally, the thresholds for low-contrast images are low, i.e., they are below the thresholds and are also noisy, which makes the processing of such images a difficult task. Random Noise Estimation is a challenge in several research works. To overcome this challenge, noise estimation is the major limitation that often occurs in dark images.

In this paper we proposed a novel approach to handle the level that effect of internal noise estimation of noisy content in dark images by adding some more noise to create the neutralization condition. the performance was implemented with different types of noise distributions methods, these methods are:

1. Gaussian distribution method
2. Uniform distribution method
3. Poisson distribution method
4. Gamma distribution method
At the last step, the method was evaluated by three important factors are: the improvement factor related to contrast, the improvement factor related to color, and the perceptual quality measure.

**Research Method**

The best way to Sharpen the image is to enlarge the coordinate elements of a source image, but the limitation is that *halo artifacts* and *gradient reversal artifacts* are introduced (Allebach, 2005). To reduce these effects, the pixels of the coordinate elements at the sharp edges are enlarged, and the rest remain the same. The core idea of our proposed model to handle global optimization problems. However, our system based on two phases are: data fidelity term and a regularization term with adjusting control the level of improvement these term by A Lagrange factor($\lambda$). The equation below shows optimization problem:

$$
\min_E \left\{ \sum_P \left( E_{P} - I_{P} \right)^2 + \lambda \cdot C(E - KoI) \right\}
$$

(1)

where E is a Detail-enhanced image, I is an Input image, P is an index of the pixel of the image I, and o is an element-wise product operator. 

$$
K_p = 1 + \frac{K}{1 + e^{\eta(V_p - \bar{V}_p)}}
$$

(3)

Where $V_p$= variance of the pixels in the 3x3 the neighborhood of the $p^{th}$ pixel, $\bar{V}_p$ is a mean value of all the local variances. Equation 4 guarantees that the factors of the pixels with small variance are close to $1+k$ and the factors of the pixels with large variance are close to 1.

$$
\eta = \frac{\ln(0.01)}{(\min(V_p) - V_p)}
$$

(4)

In Equation (1) the second term contains a discrete counting metric; the solving of that metric is difficult. Same as Equation (10), so we are introducing auxiliary matrices to approximate the solution. Consider the following problem:

$$
\min_{E, h, v} \left\{ \sum_P \left\{ \left( E_{p} - I_{p} \right)^2 + \beta \left( (\partial_x (E_{p} - I_{p}) - h_p) \right)^2 + \left( (\partial_y (E_{p} - I_{p}) - v_p) \right)^2 \right\} + \lambda \cdot C(h, v) \right\}
$$

(5)
Where $\beta$ means controlling parameter responsible for control the similarity between auxiliary matrices $h, v$ and $\partial_p (E_p - I_p)$, $\partial_x (E_p - I_p)$

If $\beta$ parameter has a good large value, the solution of the optimization problem (4) is equivalent to (1). Problem (4) is handled by minimizing $h, v$ and $E$ in turn. A set of the variables are set in each iteration as values that come from the previous iteration. The $\beta$ parameter is set to be a small value $\beta_0$ at the beginning and multiplied by a constant $k$ after each time. The process ends when $\beta$ is greater than $\beta_{\text{max}}$. In our experiment, we set $k=2$, $\beta_0 = 2$ times $\lambda$, and $\beta_{\text{max}} = 10^5$. The details of the solution procedure are given below.

$$\min_E \left\{ (E_p - I_p)^2 + \beta \left( (\partial_x (E_p - I_p) - h_p)^2 + (\partial_y (E_p - I_p) - v_p)^2 \right) \right\}$$  \hspace{1cm} (6)

The value of the global minimum in (5) is obtained by taking the derivative of the problem, to fasten the computational speed; we diagonalize the derivative operator after Fast Fourier Transform (FFT).

$$E = F^{-1} \left( \frac{F(1) + \beta (F(\partial_x) F(h+1) + F(\partial_y) F(v+1))}{F(1) + \beta (F(\partial_x) F(h) + F(\partial_y) F(v))} \right)$$  \hspace{1cm} (7)

Where $F = \text{FFT}$ operator; $F^{-1} = \text{IFFT}$ operator; *= complex conjugate Computing $(h, v)$ when $E$ is known: The $(h, v)$ estimation subproblem corresponds to minimizing

$$\min_{h,v} \left\{ \lambda \cdot C(h, v) + \sum_p \left\{ \beta \left( (\partial_x (E_p - I_p) - h_p)^2 + (\partial_p (E_p - r_p) - v_p)^2 \right) \right\} \right\}$$  \hspace{1cm} (8)

To obtain a detailed image, estimate $E$ with Equation (6) and $h, v$ with Eq (7) when $\beta$ is larger than $\beta_{\text{max}}$. In Eqn (9) the analytical solution of two subproblems are shown.

$$\begin{cases} 
(h_p, v_p) \\
(0,0), \text{if } \partial_x (E_p - r_p)^2 + \partial_y (E_p - I_p)^2 \leq \frac{2}{\beta} \\
(\partial_x (E_p - r_p), \partial_y (E_p - r_p)), \text{otherwise} 
\end{cases}$$  \hspace{1cm} (9)

The traditional $L_0$ smoothing method is shown in Eq (10) as:

$$\min_{S} \left\{ \sum_p (S_p - I_p)^2 + \lambda \cdot C(S) \right\}$$  \hspace{1cm} (10)
Where \( s = \text{edge-preserving smoothing} \) \( I, \lambda, C(S), P \) are defined in Eq. (1). After handling the minimization issue, we obtain \( s \). The detail layer (D) of the input image will be \( I - S \). To obtain a detail enhanced image \( E \), an enhanced detail layer is added to the source image. For example, if the detail layer is enhanced \( K \) times to the input image, then \( E = I + K \cdot D \).

After the algebraic transformation, it can be shown that:

\[
\begin{align*}
(S_p - I_p)^2 = \frac{(E_p - I_p)^2}{K} \quad & \quad S = \frac{(K + 1) \cdot I - E}{K} \\
\end{align*}
\]  

Equation (112) and = the optimization problem Eq (10) are equal.

\[
\min_E \left\{ \sum_p (E_p - I_p)^2 + \lambda \cdot k^2 \cdot C \left( \frac{(k+1) \cdot I - E}{k} \right) \right\} 
\]  

Here \( C \left( \frac{(k+1) \cdot I - E}{k} \right) = L_0 \text{ norm} \). The value of \( k \) that in the denominator does not affect the norm value, however, the optimization problem compute as (Eq 13):

\[
\min_E \left\{ \sum_p (E_p - I_p)^2 + \lambda \cdot k^2 \cdot C(E - (k + 1) \cdot I) \right\} 
\]  

**Result**

![Figure 1 original image](http://www.webology.org)

![Figure 2 Enhanced k=4 and lamda =0,016](http://www.webology.org)

![Figure 3 Enhanced k=4 and lamda =0,032](http://www.webology.org)

![Figure 4 Enhanced k=4 and lamda =0,08](http://www.webology.org)
Conclusion

The main goal of the detail enhancement algorithm is to increase the visual quality of an image. The detail enhancement technically depends on edge-preserving decomposition algorithms. Generally, the image consist of two main layers are: the base layer and the details layer. There are mainly algorithms that used for details layer work to improving detail image while preserving the edges for the image can be done by using Edge-preserving decomposition algorithms. We propose in this paper a new criteria-based detail optimization technique that produces the image and its detail has been optimized. It preserves the sharp edges of the image and produces an image that has good visual quality compared to the existing norm-based algorithm. Empirical results of our proposed method show a better reduction of color distortion around edges in the detail enhanced image.

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