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Intensity and edge based adaptive unsharp masking filter for color image enhancement

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ABSTRACT

Enhancement of image quality is a fundamental process for a wide range of vision-based applications. Images captured under unfavorable environments are often degraded in information content, sharpness and colorfulness. In the attempts to improve an image, the unsharp masking filter is an attractive candidate for its computational efficiency. However, the filter is vulnerable to the over-range problem where pixel magnitudes are driven beyond permissible ranges. This drawback is particularly noticeable if a non-adaptive procedure is used in the enhancement. Hence, an adaptive gain adjustment method is proposed here aiming at minimizing the number of over-range pixels while maximizing the image sharpness and information content. In this method, colorfulness is improved via color channel stretching and contrast is enhanced by edge augmentation. Specifically, a hyperbolic-tangent function, whose scale is dependent on the original image intensity and detected edges, is constructed to adjust the gain in sharpness enhancement. A collection of natural images captured under poor illumination conditions are used in the test against conventional and mask-based image enhancement approaches. Results have demonstrated that the proposed method outperforms the others with regard to colorfulness, information content, and sharpness.

1. Introduction

Image processing is a widely used technology in a large number of vision-based applications. In particular, when interested phenomena can be captured in the form of digital images or equivalent data formats, image processing methods can be applied to accomplish desired goals. These include the visualization of blood vessels in medical diagnoses [1], remote sensing of resources for earth exploration [2], guidance of robots in manufacturing [3], inspection of machine wear debris for machine condition monitoring [4], object tracking [5], and pattern recognition [6].

In order to extract useful information from an image, a basic requirement is to improve the quality or to enhance the information contained in the image despite degradations caused by unfavorable capturing conditions. Fundamentally, contrast enhancement is often regarded as the front-end of the processing. For instance, a double plateaus histogram equalization approach was developed to restore noise corrupted infrared images [7]. Another possibility to enhance an image is to extend the intensity dynamic range for improved perceptual contrast [8]. Further research work had also been reported in [9], which addressed problems due to low illumination when the images were captured. In [10], authors tackled problems arisen for the effect of local illuminations. Moreover, methods for enhancements focused on enriching the image color using the Retinex theory was given in [11].

The statistics based schemes making use of the histogram to improve an image can be considered as a global approach. In these techniques, information about the image intensity is collected over all pixels globally. On the other hand, the image quality can be increased if processes are applied to pixels with information gathered from their selective local vicinities. In this class of local methods, enhancements are provided around object edges [12] either optically or digitally after the image is acquired. According to the human visual system, the contrast is increased hence more information is conveyed and extracted from the given image.

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The unsharp masking filter (UMF) is one of the representative algorithm frequently adopted for image processing applications and satisfactory results are obtained. The application of this filter for image enhancement is attractive for its simplicity of implementation. For example, the UMF had been used for fingerprint enhancement [13] in bioinformatics, and mammogram enhancement [14] in medical imaging. In the image processing context, the UMF functions with the addition of scaled edge back to the original image itself. The net effect is the sharpening of boundaries around objects, thus increases the visual impact for the human vision system and information content of the given image.

However, UMF design is challenging despite its simplicity. Difficulties often arise from the proper setting of the scale or gain factor, and extraction of the enhancing or edge component. In [15], edge extraction was carried out using a cubic kernel. Although results had been promising, the design parameters were arrived at after extensive trials. An optimal approach were reported in [16] where a training process were conducted with reference to a set of ideal images before determining the filter coefficients. The effect and the design of edge extraction were further studied in [17]. In the work reported, a Laplacian kernel was examined for its effectiveness in improving the UMF performance in the area of infrared imaging. A recent work had proposed to compress the edge magnitudes in order to mitigate artifacts in the resultant image [18]. Due to the filter structure, artifacts may arise when the filtered pixel magnitudes are driven beyond the permitted ranges for operations involving display, storage, and transmission. The research reported therein had also evaluated the results from using several edge extraction kernels. However, while a deterministic set of filter parameters were suggested, the generic applicability to a wide domain of images had not been revealed. On the other hand, a localized approach would be more desirable [19].

In this work, an adaptive approach in determining the filter parameters is developed. The aim is to enhance the image quality in terms of the information content and the sharpness of objects appearing in the image. In addition, the design is also focused on minimizing the number of over-ranged pixels in order to reduce artifacts. Specifically, a localized gain adjustment is carried out depending on the intensity of the original pixel and the magnitude of the extracted edge where a hyperbolic function profiled gain schedule is employed. This is realized by reducing the gain for pixels of extreme intensities so as to avoid driving pixels over the permissible range. Furthermore, since high edge magnitudes are obtained from local neighborhoods where sufficient contrasts are available, therefore large magnitude edge augmentation is not necessary to improve the contrast. The net effect is that the scaling of the edge component is localized and adapted to the content of the image instead of a fixed and pre-assigned value.

The rest of the paper is organized as follows. In Section 2, the basics of the UMF are described as a motivation of the current work. The development of the proposed filter structure and the parameter settings are presented in Section 3. Section 4 details the experiments conducted to verify the performance of the proposed approach. Evaluations of the results are also discussed. In Section 5, a conclusion is drawn.

2. Unsharp masking filter

The basic principle of the unsharp masking filter is to augment a scaled and highlighted version of the image to its original version [15–19]. Since the human visual system is able to perceive an imaged object based on its relative intensity with respect to its surrounding even the given image is monochrome. Therefore, with a given color image, it is first converted into a gray or monochrome image, processed using the UMF and then re-converted back to the color original. Fig. 1 illustrates the filtering process.

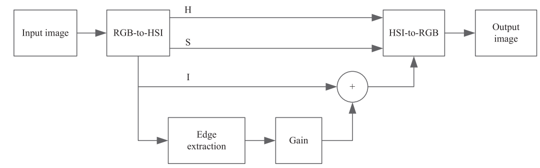

Fig. 1. Unsharp masking filtering process.

2.1. Filtering process

Let the input color image be given by

$$\mathcal{I} = \{I_{uv}\}, \quad I_{uv} = \{R_{uv}, G_{uv}, B_{uv}\}, \tag{1}$$

where $u = 1, \ldots, U$; $v = 1, \ldots, V$, are the width and height of the image, respectively. The total number of pixels in the image is therefore $N = U \times V$. The variables R_{uv}, G_{uv}, B_{uv} denote the pixels in the corresponding color channels. In practice, digital image pixel magnitudes are represented as an 8-bit digital format representing 256 quantization levels. It is also implementation convenient to normalize the pixel magnitudes to unity, that is,

$$I_{uv} \in [0, \quad 1] \leftarrow I_{uv} \in [0, \quad 255]. \tag{2}$$

The color image is then converted from RGB to HSI color space [20],

$$\{H, S, I\}_{uv} = \mathcal{T}_{RGB}^{HSI}\{R, G, B\}_{uv}, \tag{3}$$

and the I-channel representing the monochromatic gray content is used for the UMF. In the filtering process, edges or high-passed pixels are extracted from

$$d_{uv} = \mathcal{K}_{mn} g_{uv}, \quad \text{for } mn \in \Omega, \tag{4}$$

where $g_{uv} = \frac{1}{3}(R + G + B)_{uv}$ corresponds to the I-channel as defined in the HSI color space. The edge extraction kernel is given by $\mathcal{K}_{mn}$, and $\Omega \in (m = u \pm w/2, \quad n = v \pm w/2)$ is a neighborhood window of size $w \times w$ around the pixel at coordinate (u, v). It should be noted that with the hardware design in the camera circuitry, the gray image is maintained within-range, that is $0 < g_{uv} < 1$.

Based on the UMF principle, the enhanced image h_{uv} is obtained from

$$h_{uv} = g_{uv} + \lambda_{uv} d_{uv}, \tag{5}$$

where λ_{uv} is the gain factor determining the strength of the augmented edge d_{uv} to the original image. It is worth to point out that in conventional UMF implementations, the gain $\lambda_{uv} = \lambda$ is maintained as a constant for all pixels in the image.

2.2. Behavior of conventional filtering

As aforementioned, the gain factor is kept constant in most UMF implementations. However, there is no guarantee that all input images have the same characteristic as different objects may be captured under different environments. Hence, it is not trivial to determine a proper scaling to augment the edges, otherwise undesirable artifact and over-range pixels would appear.

From an inspection of the UMF governing process, Eq. (5), the resultant pixel magnitude $\tilde{h}_{uv}$ could be driven out of the allowed magnitude range if the original pixel is in its extreme value. This is noticeable when $g_{uv} \to 0$, and $g_{uv} \to 1$ with a finite magnitude edge d_{uv} added. Moreover, the output pixel is over-ranged if the edge itself is large, that is $d_{uv} \to \pm 1$. Although the principle of UMF also predicts that the image quality would be improved with a