BLURRINESS-GUIDED UNSHARP MASKING

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ABSTRACT

It has been observed that enhancing a highly-blurred image region could often lead to unpleasant noise amplification. Motivated by this, an adaptive *unsharp masking* (UM) method is proposed in this paper, which incorporates the estimated local *blurriness* information into the enhancement process to adaptively determine the scaling factor for each pixel on the detail layer. To achieve this goal, a pixel-wise local blurriness estimation method is developed for generating a pixel-wise blurriness map, followed by individually converting each blurriness measurement on the map to a scaling factor via a mapping process. The proposed method not only avoids noise amplification in blurred regions but also addresses 'high-level' considerations, such as photographer's original intention on making background more blurred for creating special aesthetic effect. Extensive simulations conducted on various test images have demonstrated that our approach is able to deliver much superior perceptual quality of enhanced images compared to other state-of-the-art UM methods.

***Index Terms*—** Image enhancement, unsharp masking, blurriness estimation, layer decomposition.

1. INTRODUCTION

Unsharp masking (UM) [1] is one of the most widely-used image enhancement techniques for improving image's sharpness. The conventional UM algorithm consists of two stages. In the first stage, a linear shift-invariant (LSI) *low-pass* filter (e.g., Gaussian filter) is applied to the input image, and the resultant two output images, respectively referred to as the *base layer* and the *detail layer*, will be generated. The base layer contains the main structure of the input image's content, while the detail layer, which is obtained by taking the difference between the base layer and the input image, contains image's fine details only. In the second stage, the detail layer is boosted by multiplying a *fixed* scaling factor to each pixel and then added back to the base layer to generate the enhanced version of the input image.

Although the conventional UM algorithm is algorithmically simple and works reasonably well in general, however it could amplify unwanted noise and lead to the so-called *overshoot* artifacts presented in the enhanced image [2]. Extensive

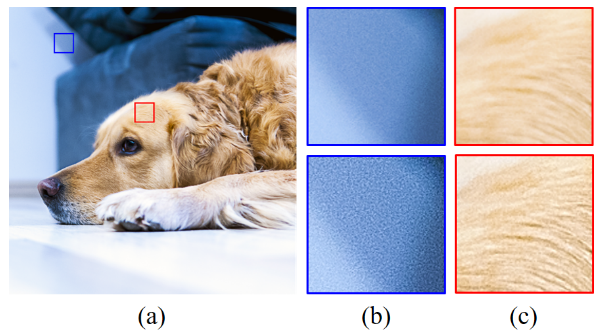


Fig. 1. Demonstrating enhancement problems: (a) an input image under enhancement; (b) undesirable enhancement for a patch from the blurred *background* where noise has been undesirably amplified; (c) a more welcomed enhancement result for a patch selected from the *foreground* object.

investigations (e.g., [2]–[14]) have been conducted in the past for improving the conventional UM algorithm on these concerns by: 1) employing a more sophisticated filter in the first stage for achieving a 'better' layer decomposition; and 2) applying *adaptive* (rather than *fixed*) scaling on the detail layer in the second stage. For the former, *edge-preserving* filters (e.g., [3]–[9]) have been widely used and found to be a fairly effective approach on preventing the overshoot artifacts in the enhanced image. For the latter, several state-of-the-art UM methods (e.g., [2], [13], [14]) incorporate local *contrast* information to determine the scaling factor for each pixel on the detail layer. Considerable perceptual-quality improvements have been delivered by these methods, compared with the conventional UM algorithm. However, noise amplification problem remains as an unsatisfactorily-solved issue. In this paper, a novel adaptive UM algorithm is proposed that utilizes image's *blurriness* information to determine the scaling factor for each pixel. This is motivated by the following key observations.

First, as mentioned earlier, background noise could be boosted and even appear more distinct than the image details of the main object as demonstrated in Fig. 1. Second, even if a given image region is noise-free, its image details could be too blurred to be enhanced by applying any image enhancement technique. In this case, a proper image *restora-*

tion method should be conducted rather than resorting to image *enhancement* approach. Lastly, blurred regions could be intentionally created by the photographer in the first place for creating aesthetic effect by highlighting the main object, as shown in Fig. 1. In this case, it becomes totally undesirable to enhance these blurred regions.

Based on these observations, it is highly convincing to us that the *blurriness* information is an effective attribute that can be utilized to guide the image enhancement process such that those highly-blurred regions will receive less enhancement or even no enhancement at all. To accomplish this objective, a pixel-wise local blurriness estimation method is proposed in this paper to generate a pixel-wise blurriness map, followed by translating each pixel's blurriness measurement on the map into a scaling factor via a mapping process. Extensive simulation results obtained by using various test images have clearly demonstrated that our proposed *blurriness-guided* UM method is able to deliver superior perceptual quality of the enhanced image compared with that by using the conventional UM and other existing adaptive UM methods.

The rest of this paper is organized as follows. Section 2 describes the proposed blurriness-guided UM framework; especially, pixel-wise local blurriness estimation and adaptive scaling factor generation. Performance evaluations are provided in Section 3. Section 4 concludes this paper.

2. PROPOSED BLURRINESS-GUIDED UNSHARP MASKING

2.1. Proposed Pixel-wise Blurriness Estimation

For the development of our proposed blurriness-guided image enhancement algorithm, the pixel-wise blurriness map, denoted by M, is required to be generated, and it should possess two essential properties as follows. First, for each region presented at a certain focus level on the input image I, the blurriness estimated at each pixel within this region should have the same or nearly constant value. Second, two adjacent regions under different focus levels on I should yield a sharp and accurate boundary between their corresponding regions on M. Multiple blurriness estimation methods have been experimented (i.e., [15]–[18]). However, none of them is able to generate a blurriness map that could satisfy these two criteria. To address this problem, a novel pixel-wise blurriness estimation algorithm is proposed in this paper, which consists of two sequential stages as to be detailed in the following.

In the first stage, a recently-introduced state-of-the-art blurriness estimation algorithm, called the *just noticeable blur estimation* (JNBE) [18], is employed for generating the *initial* blurriness map $\widehat{M}$. The JNBE algorithm is essentially a sparse-representation-based approach. It estimates the degree of blurriness of an image patch based on a dictionary, which consists of a set of dictionary basis for the representation of each test image patch. The dictionary was established by learning from a large set of blurred patches. It has been found in [18] that a more blurred patch generally requires a smaller number of dictionary basis on its representation; in other words, a patch with a sparser representation tends to be more blurred. However, the $\widehat{M}$ generated by the JNBE algorithm is still very coarse as demonstrated in Fig. 2 (b), and it is far from satisfactory for being used to guide our image enhancement task. In particular, the JNBE algorithm fails to yield accurate boundaries among adjacent objects that are under different focus levels, and it could sometimes mistakenly judge a fairly flat region in the foreground as a blurred one. But, this region might contain some important weak details that cannot be completely ignored. For example, refer to those white areas appeared on the face of the test image "old man" in Fig. 2 (b).

To address these issues, a refinement process based on the *weighted least square* (WLS) estimation method [19] is developed and employed in the second stage to refine the coarse $\widehat{M}$ and generate a much improved blurriness map, denoted by M. In our approach, M is obtained by minimizing a cost functional $\mathcal{F}$ that is defined in [19] as follows:

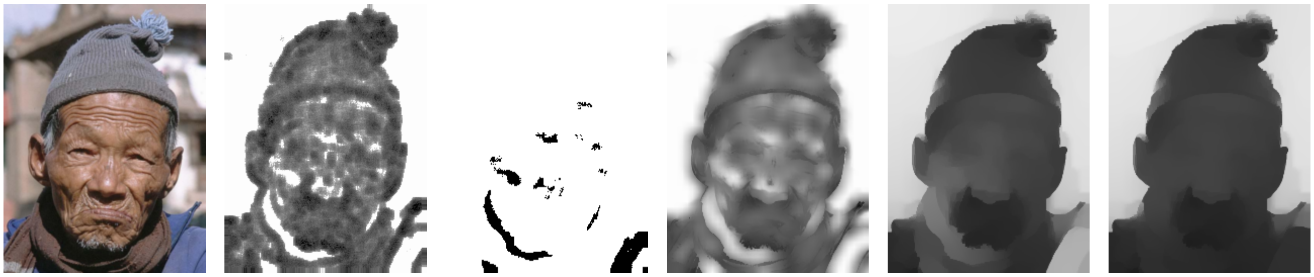
$$\mathcal{F} = \sum_p \left\{ w_p \left(M_p - \widehat{M}_p \right)^2 + \lambda \left[h_p (\partial_x M)_p^2 + v_p (\partial_y M)_p^2 \right] \right\}, \tag{1}$$

where the subscript p denotes the pixel location. The partial differentiation operators ∂_x and ∂_y compute the derivatives along the horizontal (i.e., x-axis) and the vertical (i.e., y-axis) directions on M, respectively. The first term of (1) is the *data* term, which is used to prevent M from being deviated away from the initial map $\widehat{M}$ drastically. Meanwhile, the second term of (1) is the *smoothness* term, which forces M to be as smooth as possible. The constant λ provides a trade-off between these two terms, and $\lambda = 0.2$ is empirically set in this approach.

The *confidence weight* w_p in (1) indicates how confident of the initial blurriness estimation $\widehat{M}_p$ obtained at the pixel p. The main objective of introducing this weighting factor is to discard those unconfident (i.e., unreliable) initial blurriness estimations by setting $w_p = 0$. As previously mentioned, the JNBE algorithm often mistakenly yields such 'white' pixels on the $\widehat{M}$ within objects that are in focus. Fortunately, the number of such 'white' pixels are usually quite small according to our observations. To identify these locations, the mean shift [20] segmentation algorithm has been adopted for this task and conducted on $\widehat{M}$. Based on the segmentation results, w_p is determined as follows:

$$w_p = \begin{cases} 0, & \widehat{M}_p > \phi \text{ and } size(R_p) < N_t; \\ 1, & \text{otherwise,} \end{cases} \tag{2}$$

where R_p denotes the mean-shift segmented region containing the pixel p. Thresholds ϕ and N_t are empirically deter-



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

Fig. 2. Results of various blurriness map refinement schemes: (a) original image; (b) the initial blurriness map $\widehat{M}$ generated by using the JNBE algorithm [18]; and (c) the confidence weightage map computed according to (2). The follow-up three refined blurriness maps M are obtained by using: (d) the bilateral filter [4], (e) the WLS estimation method [19], and (f) the same WLS approach but with further incorporation of our proposed adaptive weighting scheme using the developed *confidence weightage map* as shown in (c).

mined as follows: $\phi = 0.9$[1] and $N_t = 0.025 \cdot N$, where N is the total number of pixels of the input image I. An example of the confidence weightage map computed via (2) is demonstrated in Fig. 2 (c), from which one can see that the small 'white' regions in Fig. 2 (b) have been successfully detected and assigned with zero weights in Fig. 2 (c).

Furthermore, the *smoothness weights* h_p and v_p in (1) are used to adapt the amount of smoothing imposed at each pixel location. These weights are determined from the input image I according to the gradients $\partial_x I$ and $\partial_y I$, measured along the horizontal direction (i.e., x-axis) and vertical direction (i.e., y-axis), respectively:

$$h_p = \left(|(\partial_x I)_p|^\gamma + \kappa\right)^{-1} \text{ and } v_p = \left(|(\partial_y I)_p|^\gamma + \kappa\right)^{-1}, \quad (3)$$

where κ is a small constant number imposed for avoiding the divided-by-zero incidence, and the exponent γ controls the sensitivity of h_p and v_p, respectively. In our approach, $\kappa = 10^{-5}$ and $\gamma = 2$ are used. According to (3), the smoothness weights will be small for those pixel locations that incur large gradients on I. This helps to preserve those strong edges on $\widehat{M}$ that correspond to sharp object boundaries on I. Finally, the optimal M that minimizes the objective functional $\mathcal{F}$ in (1) can be obtained by solving a derived linear system as practiced in [19].

It is worthwhile to mention that the bilateral filter [4] was originally suggested in the JNBE [18] for refining the initially-estimated blurriness map $\widehat{M}$. However, one can see from Fig. 2 (d) that the bilateral filter delivered a fairly poor refinement result M; it fails to filter out the noisy structures, nor to yield sharp region boundaries. Other local smoothing filters, such as the guided filter [6] and the domain transform filter [8], have also been investigated, and they all produce similar poor results (not presented here) as that of the bilateral filter according to our simulations. On the other hand, the WLS-based approach is able to deliver a much better refined map M, even without the use of the confidence weighting (see Fig. 2 (e)). With further incorporating confidence weights, the final refined blurriness map is fairly smooth and meets our initially imposed goals about what the final blurriness estimation map should look like in order to facilitate the follow-up blurriness-guided UM process.

[1] The blurriness values on $\widehat{M}$ have been normalized to the range of [0, 1].

2.2. Proposed Pixel-wise Adaptive Scaling

The obtained M as described previously will be utilized as a guidance information to determine the scaling factor (i.e., enhancement strength) for each pixel. The entire adaptive enhancement process can be mathematically described as

$$\tilde{L} = B + \Lambda \otimes T, \quad (4)$$

where $\tilde{L}$ is the enhanced luminance component; B and T are the *base layer* and the *detail layer* decomposed from the input luminance component L, respectively, as described previously; that is, $L = B + T$. The *scaling factor matrix* Λ is used to scale the detail layer T through a pixel-wise multiplication (denoted by the symbol $\otimes$). The generation of the matrix Λ is described in the following.

As explained in Section 1, enhancing a highly-blurred image region is undesirable, because it is quite unlikely to yield an appreciable enhancement, while often causing unwanted artifacts in return. Therefore, intuitively it is more appropriate to assign smaller scaling factors to the pixels in those highly-blurred regions for imposing less amount of enhancement, or even no enhancement at all. To realize this goal, the *generalized Gaussian function* is chosen as the mapping process to translate the blurriness map M_p into a scaling factor matrix Λ_p for each pixel location p. To be specific, our proposed mapping function is defined as

$$\Lambda_p = \rho \cdot \mathcal{G}(M_p) + \eta, \text{ where } \mathcal{G}(M_p) = e^{-\left(\frac{M_p}{\alpha}\right)^\beta}. \quad (5)$$

The parameters α and β determine the *scale* and the *shape* of the function $\mathcal{G}(M_p)$, respectively. Note that the scale parameter α determines how wide the range of blurriness will be assigned with large scaling factors. On the other hand, the shape parameter β controls how fast of the transition changing from large values of scaling factors to small ones. In our simulations, the typical setting for these two parameters are suggested as follows: $\alpha = 1$ and $\beta = 6$.

Since $\mathcal{G}(M_p) \in (0, 1]$, the obtained Λ_p will fall into the range of $(\eta, \rho + \eta]$. This means that ρ and η decide the maximum and minimum scaling factors that could be imposed by (5). Note that setting large values to these two parameters will clearly yield more perceivable enhancement; however, this might also cause undesirable over-shooting artifacts in return. In our simulations, $\eta = 1$ and $\rho = 2.5$ are empirically determined and constantly used for all test images.

3. EXPERIMENTAL RESULTS

Extensive simulations have been conducted on a variety of test images to evaluate the enhancement performance of the proposed blurriness-guided unsharp masking (BUM) approach. Our proposed BUM is a general UM framework that can be deployed with various layer-decomposition filters. In this paper, the enhancement results obtained by using our BUM with the widely-used Gaussian filter are demonstrated. Our approach has been compared to the conventional UM [1] and three other adaptive UM methods—i.e., the *generalized unsharp masking* (GUM)[2] [14], the *adaptive unsharp masking* (AUM) [2], and the *cubic unsharp masking* (CUM) [12] algorithm. To compare their resulted image quality, we choose to use visual (i.e., subjective) comparisons to justify the superiority of our proposed approach, since currently there is no widely-accepted quantitative performance evaluation metric for evaluating image enhancement result, to the best of our knowledge.

Fig. 3 shows some enhancement results on the test image "Parrot" produced by the proposed BUM and four other comparable UM methods. It can be clearly observed from Fig. 3 (b) that the conventional UM algorithm has yielded amplified noise on the highly-blurred region. The GUM, AUM, and CUM algorithms have delivered slightly improved results compared with that of the conventional UM. However, the GUM algorithm also fails to avoid the amplified noise (see Fig. 3 (c)). Although both the AUM and the CUM methods have effectively avoided noise amplification, they failed to yield sufficient amount of enhancement on those weak details from those less-blurred regions (see Fig. 3 (d) and (e), respectively). Clearly, our proposed approach has constantly delivered the best subjective enhancement results as shown in Fig. 3 (f). For more enhancement results of our proposed BUM, please refer to the supplementary material.

[2]The original GUM algorithm has an extra histogram equalization step conducted on the base layer for contrast enhancement. However, for a fair comparison, this step has been removed in our simulations.

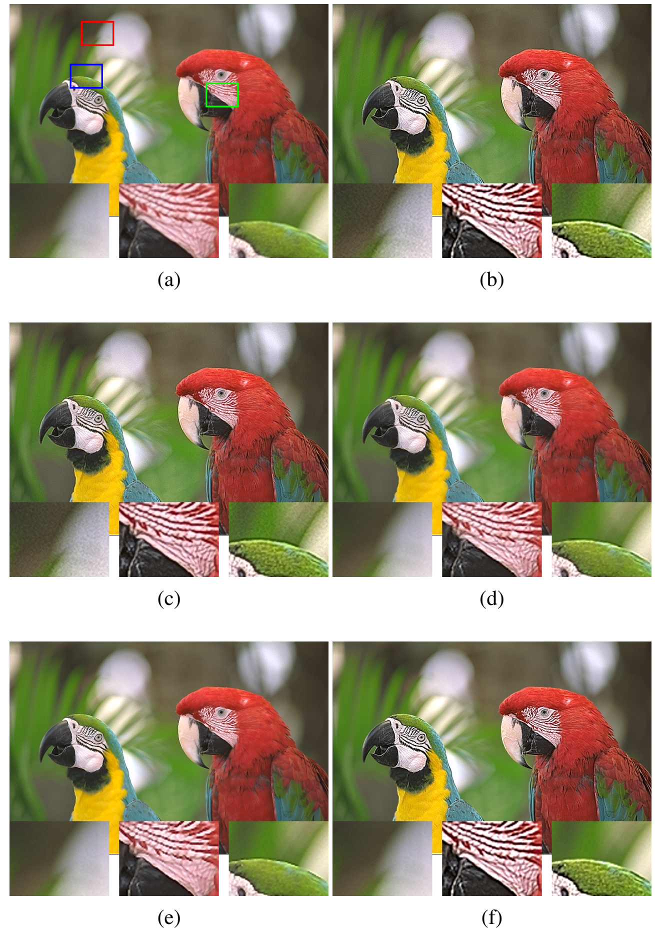


Fig. 3. Visual comparison of the enhancement results on the image "Parrot"; (a) original image; (b) conventional UM; (c) GUM with the Gaussian filter [14]; (d) AUM [2]; (e) CUM [12]; (f) our proposed BUM with the Gaussian filter.

4. CONCLUSION

In this paper, a novel *blurriness-guided* adaptive unsharp masking method is proposed that incorporates the blurriness information into the enhancement process. The proposed method is motivated by several key observations which suggest that enhancing those highly-blurred image regions is undesirable. The key contributions of the proposed method lie in the development of a two-stage pixel-wise blurriness estimation method for generating an accurate blurriness map, followed by mapping this map to a scaling factor matrix so that adaptive enhancement can be applied to all pixels of the input image. Extensive simulations conducted on various test images have clearly and consistently demonstrated that the proposed blurriness-guided adaptive UM method is able to deliver superior perceptual quality on the enhanced image compared with that by using the conventional UM and other existing adaptive UM methods.

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