

Content-Adaptive Automatic Image Sharpening

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Abstract— Optimal sharpness differs from image to image, depending on the content. In general, human observer prefers images of artifacts sharper and those of natural-objects less sharper. We have developed a content-adaptive automatic image sharpening algorithm that relies on the length of lines extracted from the image. It is applicable to images with various regions such as those contain natural and artificial objects. The proposed algorithm is expected to be used in image processing modules of image input/output devices, e.g. digital cameras, printers, etc.

Keywords—image sharpening; line feature; image quality

I. INTRODUCTION

Image sharpening is generally applied to scanned or photographed raw input images to improve their quality before output by, e.g., displaying or printing. It is a technique to restore blurred image by enhancing edges. Images with enhanced edges look as if they are of higher resolution. Because of this, almost all image signals (e.g. those for television, newspapers and photo-prints) are processed with sharpening filters.

The purpose of this study is to develop a method to automatically find the optimal magnitude of sharpening for each image. An automatic determination algorithm for the magnitude of image sharpening was developed by Inoue et al [1]. It can determine the magnitude of sharpening adaptively according to the sharpness of input images. That is, the blurred images are strongly sharpened, while the originally sharp images are sharpened little or even blurred. The algorithm evaluates the sharpness of an original image and processes the image so that the output image has the optimal sharpness; i.e., it premises the existence of the unique optimal sharpness for every image.

However, the optimal sharpness depends on the image content. It is said that the images of mechanical products or artifacts should be strongly sharpened, so that their stiffness be properly expressed. On the other hand, strongly sharpening the images of natural objects is not recommended. For example, human face images should not be sharpened, since we would not like to enhance wrinkles. Fig. 1 shows two images taken by the same camera and processed with the same sharpening filter. Though the artifact image (a) looks properly sharpened (c), the natural object image (b) does not look natural (d). The weaker sharpening process is desirable for image (b).

Thus, the automatic sharpness adjustment algorithm should be improved so that it considers the image content. Such knowledge is already used in image processing modules in digital cameras [2], in which the user specifies the kind of object being photographed and the processing parameters are selected accordingly. To make the process automatic, however, we cannot depend on object classification since, although certain kinds of objects (e.g. faces) have become automatically detectable, automatic object classification in general is still elusive. In this paper, we discuss the image properties that influence optimal sharpness and propose an algorithm for automatic adaptation of the magnitude of sharpening.



Figure 1. Images sharpened with the same magnitude. (a)(b) Originals (c)(d) Sharpened outputs.

II. APPLICATION OF THE FEATURE FOR NATURAL-OBJECT/ARTIFACT DISCRIMINATION

A. Natural-object/artifact discrimination

The observation above suggests that it may be useful to use the feature that can classify images into those with natural objects and those with artifacts. Tajima et al. developed a feature X for the purpose [3]. The feature X is defined as

$$X = \frac{\sum_{l=l_{\min}}^{l_h} l \cdot N_l}{\sum_{l=l_{\min}}^{\infty} l \cdot N_l}, \quad (1)$$

where l is the line length and N_l is the number of lines in the image whose length is l .

The steps to obtain the feature X is as follows. At first, pixel values of an RGB image are converted to L^* , a^* , and b^* (CIELAB color space) values. In the subsequent steps, only the L^* (lightness) component is processed.

- Edges are extracted using the Difference of Gaussian (DOG), zero-crossing extraction, and Sobel filtering. Edges that are stronger than a certain threshold in the Sobel output are chosen.
- Edge pixels forming segments are tracked, and line segments are found by fitting them to line equations.
- The numbers of long lines and short lines are counted, according to the threshold l_{th} . X is calculated using the counts. Here, l_{th} was set to be 20 pixels for images intended for print at 300 dpi resolution.

In [3], using the feature X , about 90% of images were classified to correct categories.

This means that the images of artifacts have high proportion of long lines, while the images of natural objects contain many short lines. This may be a good criterion for the image sharpening. The hypothesis is that the human vision likes the images with many long lines strongly sharpened and those with many short lines not so strongly.

B. Preliminary experiment

To confirm this hypothesis, a preliminary experiment was carried out. Twenty-five images were taken by a high quality single-lens reflex digital camera (Nikon D70s). The size of the raw data is 3008×2000. The size was reduced to 1504×1000 and printed at 300 dpi resolution. This format is the standard format throughout this study. From the original image, three sharpened images with differing magnitude of sharpening were created. The sharpening process is expressed by

$$g(i, j) = f(i, j) + m \cdot (f_{G1}(i, j) - f_{G2}(i, j)), \quad (2)$$

where $f_{G1}(i, j) = k_g \otimes f(i, j)$ and $f_{G2}(i, j) = k_g \otimes f_{G1}(i, j)$. k_g is a 5×5 Gaussian kernel whose σ is 0.5 pixel. The DOG-filtered image is multiplied by m and added to the original

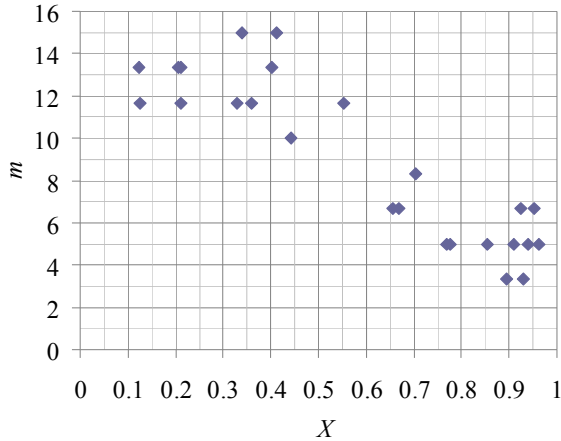


Figure 2. Relation between the feature X and the optimal sharpening magnitude m .

image. This is the typical sharpening process with ‘unsharp masking’. m is the magnitude of sharpening.

We generated three sharpened images with varying m : 5, 10, 15. Including the original image, we used four images. They were printed with a high resolution ink-jet printer (CANON MP960) on gloss photo papers. Each of three subjects selected one image that he/she judged as of the highest quality.

Fig. 2 shows the experimental result. Each judgment is plotted as a point representing X and the optimal m . We can see the apparent negative correlation between them. The lower X is, the higher the optimal m is. The correlation coefficient is -0.895 . From this result, it is expected that the optimal m can be determined from X , which can be calculated from an image. The relation may be described in the form of Eq.(3). The parameters α and β can be obtained by experiments such as above.

$$m = -\alpha X + \beta \quad (3)$$

III. LOCAL ADAPTABILITY TO THE IMAGE PROPERTY

Though the sharpening magnitude determination based on the feature X is a good solution, we are confronted by another problem. If the property is homogeneous over an image, e.g. all image regions are filled with a building or the image contains only trees, the optimal value for m will be adequately determined. However, in general, an image consists of regions with various properties: for example, an image may contain a house in front and trees in background. In such a case, X for the whole image corresponds to the average property of the image. In the latter example, too much sharpening will be applied to the trees, but too little to the house. To solve this problem, the local adaptation of m to each image region is required.

A. Proposed method for local adaptation

Throughout this study, an RGB image is, at first, converted to the CIELAB image. The sharpening process described below is applied only to the lightness (L^*) image. After the process, the sharpened L^* image is re-combined with original a^* and b^* images to generate the color output.

We reconsider the feature X . X is the ratio of the number of pixels in short lines to that in all lines. As artifacts have more long lines, it may mean that we should strongly sharpen the image near long lines, but we should not otherwise.

To actualize this idea, we define $M_l(i, j)$ instead of m . Though m was a constant, $M_l(i, j)$ is an image. We call it a ‘magnitude mask’. We replace the sharpening process in (2) by (4), which uses the magnitude mask.

$$g_1(i, j) = f(i, j) + M_l(i, j) \cdot (f_{G1}(i, j) - f_{G2}(i, j)) \quad (4)$$

$$M_l(i, j) = \begin{cases} m_{\max} & \text{if } D_l(i, j) \leq L \\ m_{\min} & \text{otherwise} \end{cases} \quad (5)$$

where m_{\max} is the maximum sharpening magnitude, m_{\min} is the minimum sharpening magnitude, $D_l(i, j)$ is the distance to the nearest long line, and L is the influence range of the long line.

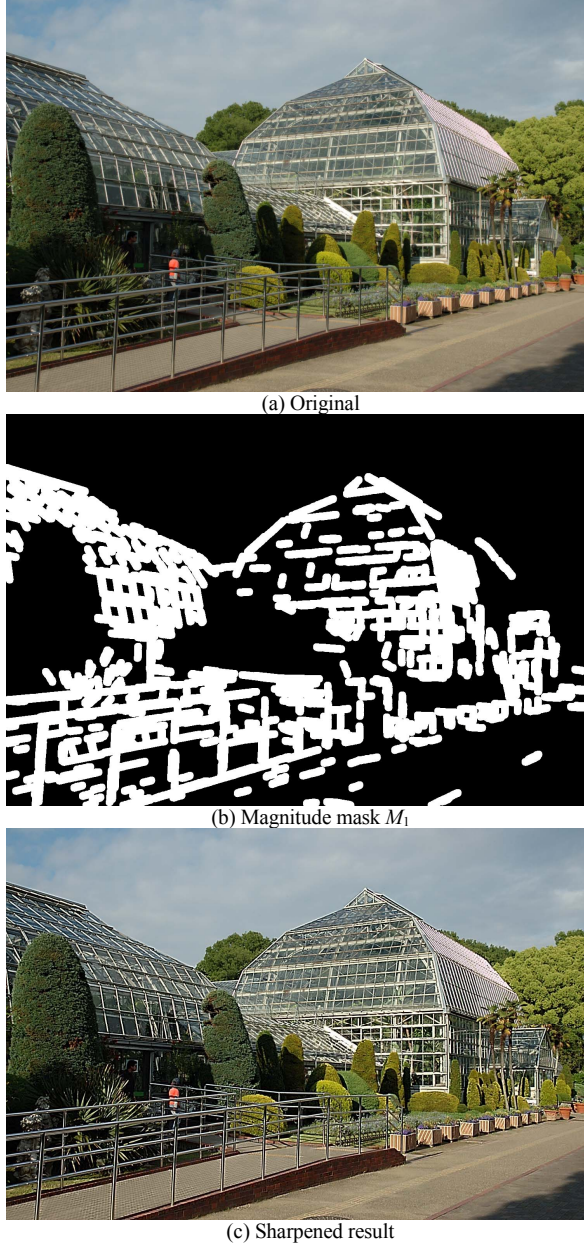


Figure 3. Image sharpening using M_1 .

The parameters were determined by trial and error as $m_{\max} = 15$, $m_{\min} = 5$ and $L = 10$ (pixels) for the standard format image. This algorithm was applied to an image (Fig. 3). Fig. 3(a) is the original image, which contains both buildings with metal frames and trees. Lines are detected in this image. Based on the long lines the magnitude mask is created. Fig. 3(b) shows the magnitude mask M_1 as a binary image, where white pixels have m_{\max} and black pixels have m_{\min} . The result image is shown in Fig. 3(c). Though the image size is reduced to about 1/2 because of the limit of this paper, we can see that the buildings in front are strongly sharpened and the trees in back are weakly sharpened. Overall image quality was significantly improved. The merit of the proposed idea was confirmed.

B. Improved method

When we closely observe the result image (Fig. 3(c)), we find small regions that look unnatural. In Fig. 4, a part of the image is magnified. Fig. 4(a) is the original image, and (b) is the sharpened result. The building region and the tree region are touching each other in this part. We can see that the tree region, where the edge of the building is very near, is sharpened more strongly than other tree regions. This unnatural effect occurs because the distance from the contour of the building is within the influence range L . In addition, it is not desirable that the border between the regions sharpened with different magnitude is clearly observed.

To avoid these drawbacks, we propose to improve the method in two steps.

- (1) If the pixel is near a short line, the magnitude of sharpening is set to be small, even if it is near a long line.

The magnitude mask $M_2(i, j)$ is designed as

$$M_2(i, j) = \begin{cases} m_{\max} & \text{if } D_l(i, j) \leq L \text{ and } D_l(i, j) < D_s(i, j) \\ m_{\min} & \text{otherwise,} \end{cases} \quad (6)$$

where $D_s(i, j)$ is the distance to the nearest short line.

- (2) The magnitude of sharpening is made to gradually change from m_{\max} to m_{\min} according to the distance from long lines.

Considering this step, the magnitude mask is further revised to

$$M_3(i, j) = \begin{cases} \frac{D_{\min}(i, j)}{D_l(i, j) + D_{\min}(i, j)} \cdot m_{\max} & \text{if } M_2(i, j) = m_{\max}, \\ m_{\min} & \text{otherwise,} \end{cases} \quad (7)$$

where $D_{\min}(i, j)$ is the distance to the nearest pixel whose $M_2(i, j)$ is m_{\min} .

After these two steps, the magnitude mask $M_3(i, j)$ is no more a binary image but a gray image. Applying this revised method, the result image becomes Fig. 4(d). Fig. 4(c) shows the all lines detected in this region. We can observe that the building region and the tree region are sharpened properly with different magnitudes, and we cannot see any unnatural effect on the border between the two regions.

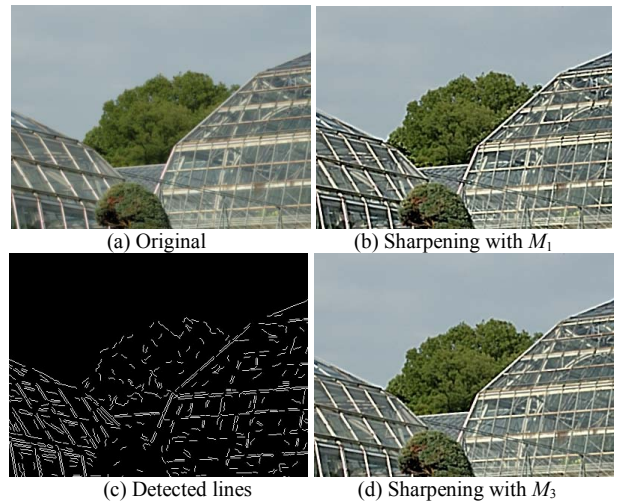


Figure 4. Result of the algorithm improvement.

IV. SUBJECTIVE EVALUATION EXPERIMENT

A. Experimental setup

We prepared 30 images in the standard format. The raw image was sharpened by the unsharp masking method (2), varying the magnitude m ($m=5, 10, 15$), and by the proposed method (4). As the magnitude mask, $M_3(i, j)$ in (7) is used instead of $M_1(i, j)$. The five images (raw, $m=5, 10, 15$ and $M_3(i, j)$) were printed by a CANON MP960 ink-jet printer on the gloss photo paper with the resolution of 300 dpi. They were evaluated under the fluorescent lamp illumination.

Subjects were requested to compare the five images and select two most preferable quality images. The reason for selecting two instead of one is that there were very similar-looking images and it was sometimes hard to select only one image. Sixteen subjects (22~65 years old) participated in this evaluation.

Fig. 5 shows the ratio that each image was chosen as one of the two best quality images. As two images were selected, the total sum of the ratios is 2.0. The error bars show the standard deviations. Though the ratio of proposed method and that of $m=5$ are similar, the proposed method shows the best result (61.9 %) with statistical significance. Among the fixed m sharpening, $m=5$ was most preferred (55.6 %).

B. Discussion

The experimental result showed that the difference of

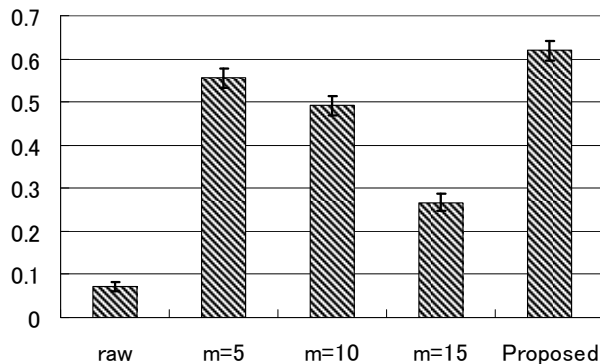


Figure 5. The result of the subjective evaluation.

preference of the proposed method and the image sharpened by $m=5$ was small. This seems natural, since m_{\min} for $M_3(i, j)$ is 5, and image regions where long lines are not present are filtered with that magnitude. If a large proportion of the image is filtered with m_{\min} , the image processed with the proposed algorithm looks similar to the image processed homogeneously with $m=5$. It might be better if we could use more such images that contained various regions with different properties to evaluate our new algorithm. In the images used, there were images with one homogeneous property. We would like to conduct another experiment in the near future.

V. CONCLUSIONS

We applied the feature X for Natural-Object/Artifact discrimination to determine the sharpening magnitude, and found the relation between the preferred sharpening magnitude and the feature. The feature X was the ratio of short lines to all lines in the image.

However, the feature is not useful for sharpening an image adaptively to image local regions. Hence, we developed a novel image sharpening method, which can control the sharpening magnitude adaptively to the local property of the image.

The proposed method showed the best result with statistical significance in the subjective evaluation experiment. We are now planning to apply this algorithm to image processing modules for digital image input/output devices: e.g. cameras, printers, etc.

ACKNOWLEDGMENT

Part of this work was supported by Common Platform Software Res. Labs., NEC Corporation. We deeply acknowledge the support.

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