NON-LINEAR IMAGE ENHANCEMENT FOR DIGITAL TV APPLICATIONS USING GABOR FILTERS

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ABSTRACT

We propose a non-linear image enhancement method based on Gabor filters, which allows selective enhancement based on the contrast sensitivity function of the human visual system. We also propose an evaluation method for measuring the performance of the algorithm and for comparing it with existing approaches. The selective enhancement of the proposed approach is especially suitable for digital television applications to improve the perceived visual quality of the images when the source image contains less satisfactory amount of high frequencies due to various reasons, including interpolation that is used to convert standard definition sources into high-definition images.

1. INTRODUCTION

Enhancing the perceptual sharpness of an image is a well-studied topic that has found many applications. A typical image enhancement scheme can be illustrated by the diagram in Fig. 1, where the enhancement is achieved by adding back to the original image a high-pass image derived from the original image, after proper post-processing (including linear or non-linear operations). This is the basic principle behind *unsharp masking* and *high-boost filtering* [1]. The methods proposed in [2] and [3] follow similar strategy except that the high-pass image is post-processed by different non-linear operations.

Non-linear processing can presumably generate new frequency components and thus it is attractive in some applications. The method of [2] is a global approach, which uses the Laplacian pyramid representation of an image to extract the high-frequency components of the original image. After proper nonlinear mapping, those components are then added back to the original image to achieve the enhancement. The major nonlinear step involves clipping and scaling the extracted components. The method of [3] can be viewed as a local approach, where the best result is achieve by first detecting the orientation of the edges in the image and then applying a similar non-linear processing along the perpendicular directions of the edges. A global approach has some advantages such as easier implementation of the algorithm and simpler control of the algorithmic parameters.

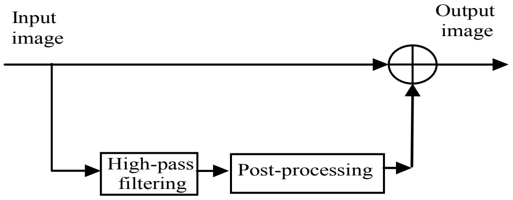

Figure 1. A typical scheme for image enhancement, where Post-processing could be simple scaling (linear) or other complex non-linear operations.

In this paper, we propose a new global technique for non-linear image enhancement by using Gabor filters. In particular, we show that the proposed method allows orientation-selective enhancement based on the contract sensitivity function (CSF) of the human visual system, so that we can sharpen the image while keeping the subjective ringing effect to a minimum, making the technique especially suitable for digital television (DTV) applications. Furthermore, we systematically evaluate the proposed method and compare it with the method proposed in [2].

2. PROPOSED ENHANCEMENT METHOD

2.1 Basic Strategy

The basic strategy of the proposed approach shares the same principle of the methods in [2,3] and the structure illustrated in Fig. 1. That is, assuming that the input image is denoted by I, then the enhanced image O is obtained by the following processing

$$O = I + NL(HP(I))$$

where $HP()$ stands for high-pass filtering and $NL()$ is a nonlinear operator. As will become clear in subsequent sections, the non-linear processing includes a scale step and a clipping step, similar to [2] and [3]. The $HP()$ step is based on a set of Gabor filters. (While Gabor filters are typically viewed as band-pass filters, in this work, due to the particular selection of the parameters, the corresponding Gabor filters are effectively of high-pass nature).

2.2. Gabor Filters

Gabor filters have found applications in the enhancement and processing of fingerprint images and texture images, object and face recognition, etc. (e.g., see [4-7]). The frequency-selective and orientation-selective properties combined with the optimal joint resolution in both spatial and frequency domains make Gabor filters a good choice for image enhancement. The Gabor filter can be defined as a form of a plane wave restricted by a Gaussian envelope. Following the notations of [5], we define the Gabor filter as

$$\phi_{\vec{k}}(\vec{x}) = \frac{\vec{k}^2}{\sigma^2}\exp\left(-\frac{\vec{k}^2\vec{x}^2}{2\sigma^2}\right)\left[\exp(i\vec{k}\vec{x}) - \exp\left(-\frac{\sigma^2}{2}\right)\right]$$

where $\vec{x}$ and $\vec{k}$ are the spatial and frequency vectors, respectively. The Fourier transform of the above filter is give by

$$F\{\phi_{\vec{k}}(\vec{x})\}(\vec{k}_0) = \exp\left(-\frac{\sigma^2(\vec{k}_0-\vec{k})^2}{2\vec{k}^2}\right) - \exp\left(-\frac{\sigma^2(\vec{k}_0^{\,2}+\vec{k}^2)}{2\vec{k}^2}\right)$$

From the Fourier transform of the filter we can see that the first term of the function is a band pass Gaussian filter centered at the frequency given by $\vec{k}_0$.

2.3. Non-linear Enhancement Using Gabor Filters

The first step of the proposed method is to use Gabor filters to extract directional high frequency components from the original image. We choose four directions for the enhancement: vertical, horizontal, diagonal at 45º and 135º respectively. Let H_i denote the output of Gabor filter G_i, at the above four orientations respectively, we have

$$H_i = G_i(I) \qquad i = 1,2,3,4$$

These four different high frequency components are then clipped to obtain four new images C_i, i=1,…,4:

$$C_i = clip\,(H_i)$$

where the clipping function *clip*() is defined as

$$clip\,(x) = \begin{cases} T & x \geq T \\ x & -T \leq x \leq T \\ -T & x \leq -T \end{cases} \qquad (1)$$

with T being a threshold defined according to the maximum value of corresponding H_i. The clipping is the source of nonlinearity.

The second step is to scale these clipped high frequency components by a constant greater than *1*, and then we add them back to the original image:

$$O = I + s_1 C_1 + s_2 C_2 + s_3 C_3 + s_4 C_4 \qquad (2)$$

where s_i, $i=1,\ldots,4$, are the scale factors.

2.4. Selective Boosting Based on Human CSF

Adding high-frequency components to the original image may creates noticeable ringing effects, especially when the high-frequency components are harmonics of some low frequencies of the original image. Therefore, on one hand, we may want to use large values for s_i to get a sharper visual effect; on the other hand, the values of s_i cannot be too high in order to avoid significant ringing effects. Thus the choice of is s_i critical, as is the case in [2]. From Eqn. (2), we can easily control the contribution of the directional high-frequency components C_i. This is an advantage that the existing methods such as [2] do not have. In applications such as DTV, where the relative orientation between the shown image and the viewer is in general fixed, we can exploit the difference contrast sensitivity of human visual system at different spatial orientations to determine the best set of scaling parameters in Eqn. (2). In this paper, according to the CSF of the human visual system (e.g., see [8]), we propose to defined the scale parameters as follows,

$$s_i = s,\ i = 1,2 \quad \text{and} \quad s_i = 1.5 \times s, \quad i = 3,4$$

That is, we enhance the two diagonal orientations *1.5* times more than the horizontal/vertical orientations. The rationale is that, since human CSF is smaller along the diagonals, we may be able to sharpen the image more along those directions without creating too much noticeable ringing artifacts.

This strategy of selective boosting has also another potential advantage in the DTV applications where the source image is compressed by block-based methods, since the relatively less strong enhancement along the vertical and horizontal directions will cause less ringing artifacts along the block boundaries.

3. PROPOSED EVALUATION METHOD

The performance of a perceptual image enhancement algorithm is typically judged through a subjective test. In most current work in the literature, such as [2,3], this subjective test is simplified to simply showing an enhancement image along with the original to a viewer. While a viewer may report that a blurry image is indeed enhanced, this approach does not allow systematic comparison between tow competing methods. Furthermore, since the ideal goal of enhancement is to make up the high-frequency components that are lost in the imaging or other processes, it would be desired to show whether an enhancement algorithm indeed generates the desired high-frequency components. The tests in [2,3] do not answer this question. (Note that, although showing the Fourier transform of the enhanced image may illustrate whether high-frequency components are added, as in [2], this is not an accurate evaluation of a method, due to the fact that the Fourier transform provides only a global measure of the signal spectrum. For example, disturbing ringing artifacts may appear as false high-frequency components in the Fourier transform.)

In this paper, we propose to use a new evaluation method, combining peak-signal-to-noise-ratio (PSNR) based evaluation with well-designed psychophysical tests, to systematically compare two competing approaches.

3.1 PSNR-based Evaluation

The first step of the proposed evaluation consists of PSNR-based comparison. We use high-resolution images with rich details as the test images. We blur the test images (ground truth) with a low-pass filter to simulate the blurring degradation. We then enhance the artificially-blurred image with the proposed method and a competing method, and then compare the enhanced image against the ground truth, in terms of PSNR. (In addition, the resultant images can be tested via the subjective tests described in Sect. 3.2.)

Although PSNR is not deemed as a good measure for subjective quality, in the designed experiments, since we have high resolution images, we can use PSNR to measure how close the enhanced image is to the original one, and thus PSNR in this case provides a metric for comparing two competing methods by evaluating how much *real* high-frequency components (instead of false “details” due to noise) are added by a given method, through comparing against a true high-frequency image. This process is illustrated in Fig. 2.

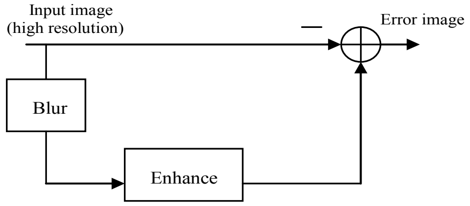

Figure 2. Evaluation based on PSNR.

3.2 Comparative Subjective Evaluation

In the second step of the proposed evaluation, psychophysical tests are adopted to perform comparative, subjective evaluation. Viewers are asked to compare the outputs of different methods. The enhanced images from competing methods are presented to a viewer at random order (so that only the operator but not the viewer knows which method was used to obtain the shown image). The viewers also know nothing about the enhancement methods. They are only asked to vote for the better image when comparing two images. Further, the images are presented at the same location on the screen at alternating order (i.e., the viewer only sees one image at a time, but he/she can switch between the two images being compared). Since the compared images are display in the same location on the screen, this enables the comparison of even a tiny difference. We believe that this is a much better and more accurate way of evaluating two methods, compared with simply presenting the results side-by-side, as is normally done in the literature.

4. EXPERIMENTAL RESULTS

Based on the evaluation method discussed in Sect. 3, we can perform two kinds of experiments. In the first kind of test, we begin with a high resolution image, blur it with low pass filter, and then enhance the blurred image. PSNR is then computed based on the ground truth and the enhanced image. In the following, results from two images are presented. The images are named "Calendar" and "Lady", respectively..

In our comparative experiments, we have chosen the method of [2] as the competing approach, since it is similarly a global approach. The best set of parameters recommended in [2] are used (S=5, C=0.4). For our method, we also choose a set of fixed parameters with s =1.2. The variance of the Gabor filter is 0.7. To save computation, the clipping is achieved by simply limiting the enhanced pixels within [0,255], without invoking Eqn. (1).

In the following, Method 0 refers to the method of [2] with the recommended parameter setting given by the authors in the paper. Proposed method I is used to stand for the basic algorithm described in Sect. 2.3, while Proposed method II refers to the variant of the basic algorithm with selective boosting, as described in Sect. 2.4.

4.1 The Tests Results Based on PSNR

The two high-resolution images are illustrated in Fig. 3, and the PSNR results from the three methods are given in Table 1. From the table, it is clear that the proposed methods outperform Method 0. Also, in terms of PSNR, the selective boosting method (Proposed method II) only lags the proposed method I slightly, but it gives a sharper image than the latter.

Table 1. PSNR for the three methods

	Calendar image PSNR(dB)	Lady Image PSNR(dB)
Method 0	23.5843	28.8002
Proposed method I	26.3994	30.2453
Proposed method II	25.9031	30.0346

In Figures 4 and 5, close-up views of the enhanced images are given, along with the original image (all at 100% of the original zoom factor). It is noticed that, in Fig. 4, while (c) looks sharper, it contains noticeable artifacts (e.g., the color of the digits is distorted). On the other hand, in Fig. 5, the result in (c) shows too much ringing effects, resulting wrinkles and black spots that do not exist in the original image.

It is interesting to note that, when performing subjective tests with these two images, although Method 0 gets three out of total six votes from the three viewers initially, after presented with the original high-resolution image as a reference, the viewers inevitably voted for the proposed method II.

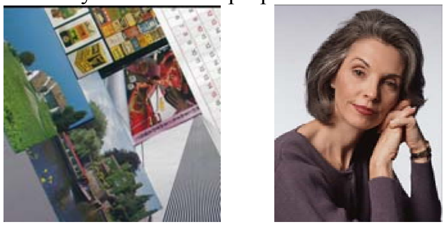

Figure 3. Partial view of the two high-resolution images. The original sizes of images are 720x1280 and 1218x975, respectively.

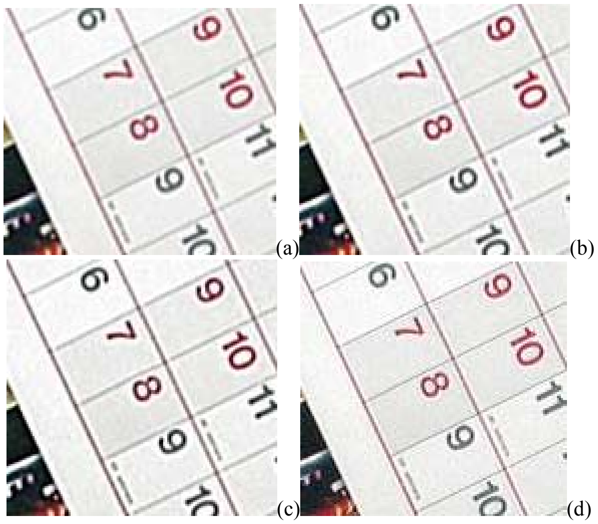

Figure 4. A close look (at the native resolution) at the enhanced images: (a) by Proposed method I; (b) by Proposed method II; (c) by Method 0; (d) original image.

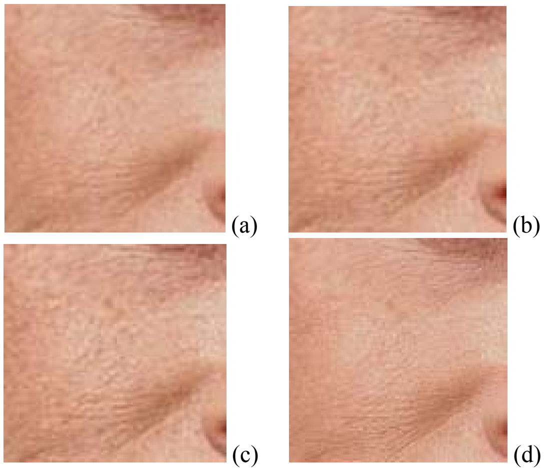

Figure 5. A close look (at the native resolution) at the enhanced images: (a) by Proposed method I; (b) by Proposed method II; (c) by Method 0; (d) original image. The strong artifacts in (c) are obvious, especially when the original (d) is given as a reference.

4.2 Results of Comparative Subjective Tests

In the experiments based on the psychophysical test described in Sect. 3.2, three viewers were asked to evaluate the results from the three methods for four test images, which contain different level of details, as illustrated in Fig. 6. These are JPEG-compressed images. We intentionally select JPEG-compressed images in this case, since in the TV application, many types of sources may subject to similar DCT-based compression (e.g., MPEG video from a DVD).

Figure 6. Four JPEG-encoded test images with different levels of details (the original resolution: ~768x512).

The final votes for these four images are given in Table 2. From the voting results, we can see that the technique of the selective boosting method is on average better than the other two techniques. Also, the only case where Method 0 seems to outperform the proposed methods is when the image is highly-textured (the lower right image in Fig. 6), where the ringing effects of Method 0 invoke the false feeling of richer details. In the close look of the results in Fig. 7, it is easy to notice the excessive rings effects introduced by Method 0, while the proposed methods produce only mild artifacts. Although this initial test was based on only three subjects, the decisive results show the potential of the proposed methods.

Table2. The votes for four test images

	Method 0	Proposed I	Proposed II
Image1	0	3	0
Image2	0	0	3
Image3	0	1	2
Image4	2	0	1

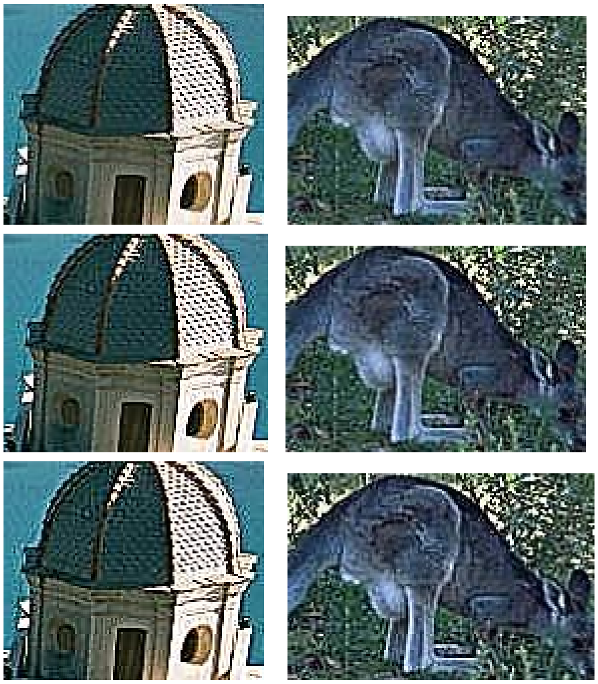

Figure 7. A close look (at the native resolution) at the enhanced images. Top row: by Proposed method I. Center: by Proposed method II. Bottom: by Method 0.

4.3 Testing on Circular Patterns

To test if the directional enhancement causes anisotropic visual effects, we processed a blurred high-resolution zone plate image. Parts of the processed images are listed in Fig. 8. It is found that the proposed methods do not introduce anisotropic visual effects. Also, the proposed method II (selective boosting) produces the most desirable results the voting-based subjective test.

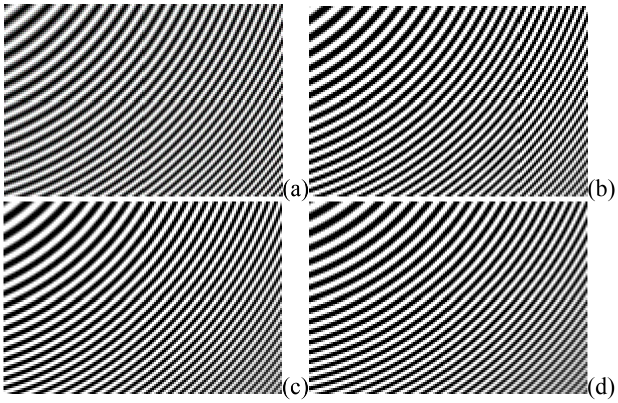

Figure 8. A close look (at the native resolution) at the enhanced images: (a) original image; (b) by proposed method I; (c) by Method 0; (d) by method II (with selective boosting).

5. SUMMARY AND CONCLUSION

We have proposed an image enhancement method using Gabor filters. The proposed method allows orientation-selective enhancement based on human CSF. We also introduced an evaluation method for measuring the performance of the proposed method and for comparing it against an existing method. Results show that the proposed method is promising.

6. REFERENCES

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