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# Shift-Variant Restoration of Defocused Images Using Shift-Invariant Wavelet Transform

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## Abstract

In this paper, we restore a blurred image caused by defocus of a lens using the shift-invariant Wavelet transform realized by the RI-Spline Wavelets. In a defocus blurred image, the blurring kernel becomes shift-variant, so the positional frequency representation such as the Wavelet space is necessary for deblurring them. For restoring the defocusing blur, we assume that the blurring kernel of any position in a image can be obtained. In the experiments using synthesized images, our method using the shift-invariant Wavelet transform shows the better deblurring performance than the method using the ordinary Wavelet transform. We also show that our method can be applied to real images with the help of additional range data.

## 1 Introduction

A lens camera creates a blurred image when a object is not placed in the focused position. Generally the blurring effect is expressed in the Frequency domain as decreases of higher frequency components. In theory, by restoring these decreased frequency components in the Frequency domain, we can restore blurred images. However, when a image contains noise this restoration is not easy, because restoring higher frequency components also accentuates noise. It can be saied that a blurring restoration problem is the problem how to treat with noise, and many methods to restore a blurred image have been proposed[2]. Among them Wiener filtering is one of the best known approaches to linear image restoration. The Wiener filter, which is formulated in the Frequency domain, assumes that the blurring kernel is shift-invariant. The second problem for restoring defocusing blur is that the blurring kernel varies depending on the image position, which violates the assumption that the Wiener filter and many other methods depend on. So the rate of decreases of the frequency components also varies depending on the image position. For this reason we need a positional frequency representation such as the Wavelet space to restore defocusing blur[4].

In this paper, we restore a blurred image caused by defocus of a lens using the shift-invariant Wavelet transform realized by the RI-Spline Wavelets proposed by Zhang *et al.*[5][6]. We assume that we have enough information to calculate the blurring kernel, which is approximated in this paper by a Gaussian, on each image point. This information includes the focused position, aperture size, approximated distances to objects and so on. On this point our approach is different from that of Hashimoto & Saito's which uses the blind deconvolution approach[4]. In the experiments using synthesized images, we show that our method using the shift-invariant Wavelet transform has better performance in shift-variant restoration than the method using the ordinary Wavelet transform. We also show that our method can be applied to real images with the help of additional range data.

## 2 Shift-Variant Restoration of Defocusing Blur

In this section, we briefly explain the shift-invariant Wavelet transform realized by the RI-Spline Wavelets. Then we explain the restoration method of defocusing blur using the shift-invariant Wavelet transform.

### 2.1 Shift-Invariant Wavelet Transform

The Wavelet transform is a frequency-space analysis method for which a very efficient computation algorithm has been proposed. However, the Wavelet transform has a shift variance problem[3]. To realize the shift-invariant Wavelet transform, Zhang *et al.* proposed the RI-Spline Wavelets[5], then extended to 2-dimensions[6]. Although we briefly explain the requisite information for the succeeding sections, interested readers should refer to [5][6] for details.

The shift-invariant Wavelet transform using the RI-Spline Wavelets consists of even (m=4) Spline Wavelets and odd (m=3) Spline Wavelets. For extension to 2-D, these two type Wavelets are applied in both column and row directions. We denote a real (even) transform in the row direction and an imaginary (odd) transform in the column direction as RI and so on, then we obtain RR, RI, IR, and II type transformed results (or coefficient images). These four coefficient images constitute the shift-invariant representation.

### 2.2 Deblurring in the Wavelet Space

In this paper, we assume that the blurring kernel can be approximated by a 2D Gaussian $\frac{1}{2\pi\sigma^2}e^{-(\frac{x^2}{2\sigma^2}+\frac{y^2}{2\sigma^2})}$.

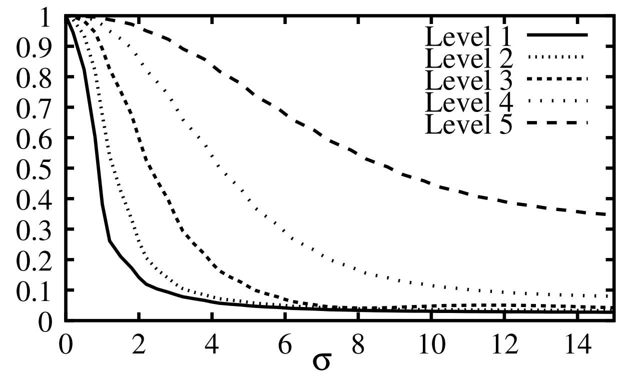



Figure 1: Decreasing of Wavelet coefficients of the image blurred by the Gaussian with varying sigma

How the Gaussian $\sigma$ will affect the decreases of the RR,IR,II and RI coefficients is investigated experimentally in advance. These experimental results are shown in Fig.1. In this experiment, we used a image contains only Gaussian white noise with standard deviation of 10.0, then blurred this image using 2D Gaussian with varying $\sigma$. In Fig1, the abscissa expresses the Gaussian $\sigma$. Next, we applied the RI-Spline Wavelets to this blurred image to obtain 5 level decomposition, then estimated how the RR,IR,II and RI coefficients value of each level decreased in terms of coefficients' standard deviation, which are shown as the ordinate of Fig.1. From Fig1, we see that all the coefficients values decrease monotonically with increasing of the Gaussian $\sigma$. The level 1 coefficients, which contain higher frequency components, decrease more rapidly than any other level coefficients.

In order to restore a blurred image, we restore these decreased coefficients values in the Wavelet space. To accomplish this, in this paper we assume $\sigma$ of the Gaussian blurring kernel on each image point is known. Under this assumption, we can restore the decreased RR,IR,II and RI coefficients values following Fig.1. After the restoration operation applied to the RR,IR,II and RI coefficients, the inverse Wavelet transform is applied to the RR,IR,II and RI coefficient images. In this way, we can shift-variantly restore the blurred image caused by defocus of a lens.

Using a synthesized images, we experimentally show that this method can really restore defocusing blur. The upper image of Fig.2(a) shows a synthesized image which simulates a check-patterned plane tilted 60 degree to the image plane with defocusing blur. The second row shows the horizontal profile along a section near the lowermost part of the upper image. The size of the original synthesized image is 512 × 512, but only central 128 × 384 part is shown. As both blurring by image processing and deblurring by the Wavelet transform have a boundary problem, so the areas near boundaries should be eliminated to avoid this problem. In Fig.2 (a)∼(f), all the upper images show 128 × 384 part of images, and all the second row show the horizontal profiles along the same section of the upper images. The image shown in Fig.2(a) has a defocusing blur simulating a lens where the central horizontal line is in-focus. In this setup, the farther from the central horizontal line, the larger the Gaussian $\sigma$ becomes. Near the uppermost part, the Gaussian $\sigma$ becomes 2.13 (pixel). Near the lowermost part, the Gaussian $\sigma$ becomes 1.87 (pixel).

Fig.2(b) shows the deblurred image of Fig.2(a) with 5 level decomposition of the shift-invariant Wavelet transform. Although we see overshootings around edges, the appearance can be perceived to be almost identical to the synthesized image before adding defocusing blur, which is omitted in this paper. So we can say that the Wavelet coefficients restoration method can restore the defocusing blur quite well when noise is not contained.

### 2.3 Denoising Method

An actual image captured by a camera contains noise. So we should take noise into consideration. By adding Gaussian white noise with standard deviation of 3.0 on the image of Fig2(a), we obtain the noisy synthesized image shown in Fig2(c). The added noise is so subtle that it is nearly imperceptible in the image. However the profile clearly shows that noise is contained in the image. Fig.2(d) shows the deblurred image of Fig.2(c) using the Wavelet coefficients restoration method explained in Sec.2.2. In Fig.2(d), the defocusing blur is well restored, however at the same time noise is so much accentuated that contaminates the restored image. Fig.2(d) calls back the fact that how to treat noise is very important in blurring restoration.

For removing noise, in this study, we also use the shift-invariant Wavelet transform, by which the *Wavelet Shrinkage*[1] is empowered. We express each coefficient of RR,IR,II and RI coefficient images as $d_{RR}$,$d_{IR}$,$d_{II}$,$d_{RI}$ respectively. For simplicity, we omit the suffixes which express the decomposed level and the position in the coefficient images. Here we make a new coefficient $d_{TI}$ defined by the next equation.

$$d_{TI} = \sqrt{d_{RR}^2 + d_{IR}^2 + d_{II}^2 + d_{RI}^2} \qquad (1)$$

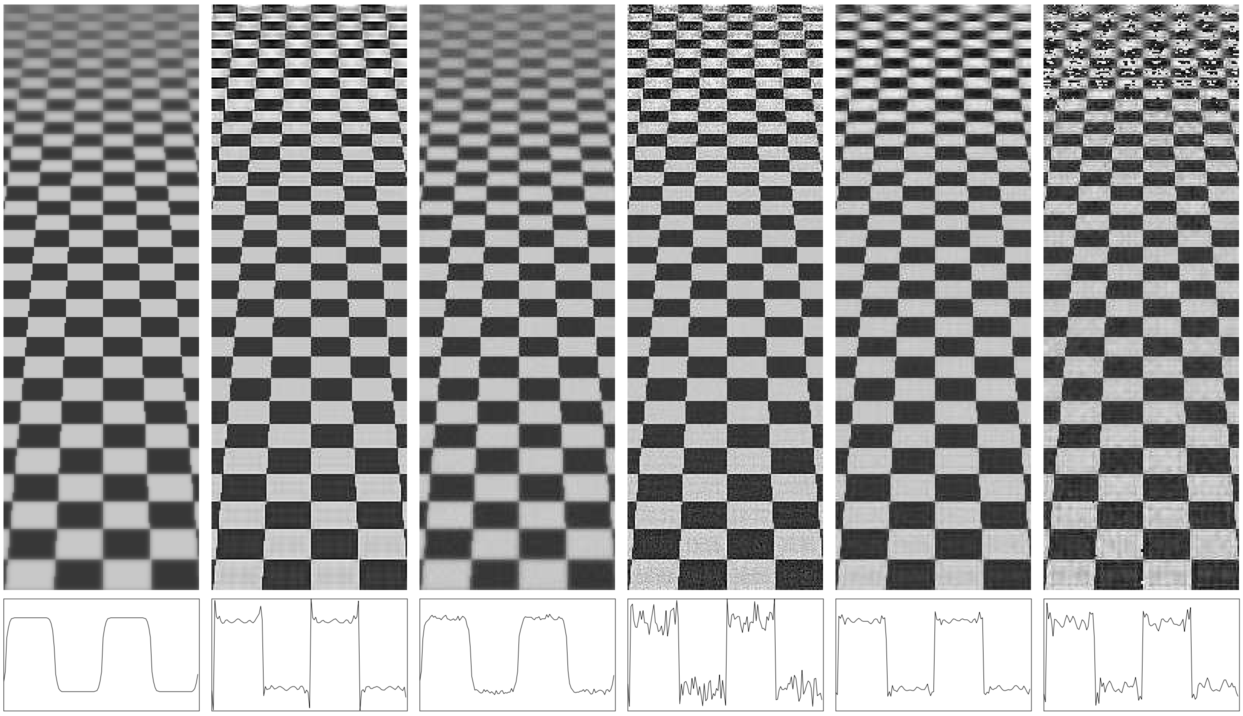
In this way, we obtain the TI coefficient image which consists of $d_{TI}$. Then, the thresholding operation expressed in Eq.(2) is applied to every coefficient of the RR,IR,RI and II coefficient images.

$$\eta_\lambda(x) = \begin{cases} x(d_{TI} - \lambda(L))/d_{TI} & \text{if } d_{TI} > \lambda(L) \\ 0 & \text{if } d_{TI} \leq \lambda(L) \end{cases} \qquad (2)$$

Here, $L$ means the decomposition level to which a coefficient $x$ belongs. As Spline Wavelets are not the orthonormal Wavelets, which are assumed in [1], but the bi-orthogonal Wavelets, we vary $\lambda(L)$ depending on the decomposition level following Eq.(3).

The $\lambda(L)$ in Eq.(2) controls denoising ability, in this study which is evaluated by the standard deviation of the reconstructed image when the original image contains only Gaussian white noise Apparently the higher $\lambda(L)$ we use, the better denoising ability we have. However, at the same time the higher $\lambda(L)$ also reduces signal components, which makes the reconstructed image overly smoothed. As our aim is deblurring, this oversmoothing is not desirable. In this study, we experimentally decide the optimal $\lambda(L)$ following the next equation.

$$\lambda(L) = aS(L)\sigma \qquad (3)$$



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

(a)Synthesized tilted image with defocus blurring
(b)Deblurred image of (a) by the S-I WT
(c)Adding noise on (a)
(d)Deblurred image of (c) by the S-I WT
(e)Denoised & deblurred image of (c) by the S-I WT
(f)Denoised & deblurred image of (c) by the ordinary WT

Figure 2: Experimental results using synthesized images

Here, $\sigma$ means the standard deviation of noise estimated in the original image. And $S(L)$ means the standard deviations of coefficients in each decomposed level, when the original contains only Gaussian white noise whose standard deviation is 1.0. The higher we gradually raise $a$ in Eq.(3) from 0, the better denoising ability we get. However, after reaching the certain value $a_0$, we can barely improve denoising ability. We used this $a_0$ value for the following experiments.

Fig.2(e) shows the denoised and deblurred image of Fig.2(c) using the shift-invariant Wavelet transform. In this experiment, we first applied the denoising method explained in this section, then applied the Wavelet coefficients restoration method explained in Sec.2.2. Compared with Fig.2(d), noise is much reduced. We can observe that edges are blurred near the uppermost part. This is because near the uppermost part coefficients are attenuated so much that even small noise deteriorates signal-noise-ratio, which makes it difficult to remove noise without affecting signal components. However, as a whole the deblurred image is perceived to be proximate to the synthesized non-blurred image, which is omitted in this paper.

In this paper, we use the shift-invariant Wavelet transform for shift-variant restoration of defocusing blur. However, the crucial point in achieving shift-variant restoration is to use the Wavelet transform in which positional frequency information is represented. Here we have a question. How shift-invariance of the Wavelet transform affects the performance of shift-variant restoration of defocusing blur? To ascertain this point, we conducted a comparative experiment using the ordinary Wavelet transform which lacks shift-invariance.

Fig.2(f) shows the denoised and deblurred result using the $m = 4$ Spline Wavelets as the ordinary Wavelet transform. In conducting this experiment, we adjusted the noise-removing ability of the ordinary Wavelet Shrinkage becomes equal to that of the method using the shift-invariant Wavelet transform. For this we adjusted the standard deviation of the denoised image which originally contains only Gaussian white noise to be equal. For the details of the ordinary Wavelet Shrinkage, interested reader is directed to [1]. As the coefficients decreasing of the $m = 4$ Spline Wavelets is almost equal to that of the $m = 3, 4$ RI-Spline Wavelets shown in Fig.1, we used Fig.1 for coefficients restoration in the Wavelet space. In Fig.2(f), we perceive that the overall image is more noisy. However this is not noise remained and accentuated in the deblurring process, but rather pattern noise happened around edges. In addition, in near the uppermost part the restoration result is deteriorated. As these deteriorations are not observed in Fig.2(e), we think that the shift-variance of the Wavelet transform causes these deteriorations. From these experiments, we see that the shift-invariance of the Wavelet transform steadily improves the performance of shift-variant restoration of defocusing blur.

(a) In-focus image (iris 16) (b) Defocused image (iris 4) (c) Deblurred image of (b)

Figure 3: Experimental results using real images

## 3 Experiments Using Real Images

We applied the shift-variant restoration method using the shift-invariant Wavelet transform explained in the previous section to real images. Fig.3(a) shows the $256 \times 256$ in-focus image of the scene where a "Daimajin" figure, which is 60cm distant from the camera, a "Haniwa" figure, which is 135cm distant from the camera, and a book "Digital Image Processing with MATLAB", which is 220cm distant from the camera, are placed. Fig.3(a) is captured with iris of 16, which deepens depth of focus. Fig.3(b) shows the defocused image of the same scene, which is captured with iris of 4. In this image, the "Daimajin" figure is in-focus, and the book contains so much blur that we can not read the book title any more.

In order to apply the method in the previous section, we need to know the Gaussian $\sigma$ on each image point. For this, we complemented with range data captured by EKL3101, of which the resolution is about 12 times coarser than that of the image data. We omit the details of the calibration experiments to convert the range data into the Gaussian $\sigma$. We estimated the noise level of the camera; the standard deviation of noise is 1.19.

Fig.3(c) shows the deblurred image of Fig.3(b) with 5 level decomposition of the shift-invariant Wavelet transform. Although the readability of the title of the book is not as well as that of Fig.3(a), we see that the overall deblurring result becomes acceptable level, except the strong ringings happened near the head of the "Daimajin" figure. We think that these ringings happened because the resolution of the range sensor EKL3101 is so coarse that we can not get the exact range information near object boundaries in level 1,2 and 3 decompositions. In order to eliminate these ringings, we think, we have to get the range data as fine as the level 1 decomposition.

## 4 Conclusions

In this paper, we proposed the shift-variant restoration method for a blurred image caused by defocus of a lens using the shift-invariant Wavelet transform. In the experiments using synthesized images, we showed that our method using the shift-invariant Wavelet transform outperformed the method using the ordinary Wavelet transform. We also showed that our method restored real defocused images with the help of additional range data.

In this paper, we assume that the blurring kernel of any position on a image is known. A digital camera of late date automatically records some of camera parameters. In addition, a digital camera which can get range information on several points by auto-focusing mechanisms, has appeared recently. Although, this range data is much coarser than the image data, we can compensate this coarseness by segmenting image data. So we think this assumption has come within reason. Future work is to realize the shift-variant restoration of defocusing blur within the scope of information that we can get through an actual digital camera.

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