IMAGE SHARPENING WITH BLUR MAP ESTIMATION USING CONVOLUTIONAL NEURAL NETWORK

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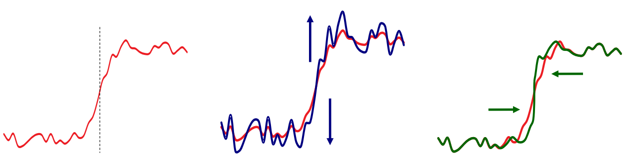
ABSTRACT:

We propose a method for choosing optimal values of the parameters of image sharpening algorithm for out-of-focus blur based on grid warping approach. The idea of the considered sharpening algorithm is to move pixels from the edge neighborhood towards the edge centerlines. Compared to traditional deblurring algorithms, this approach requires only scalar blur level value rather than a blur kernel. We propose a convolutional neural network based algorithm for estimating the blur level value.

1. INTRODUCTION

Blur estimation is a very challenging problem for image deblurring. Many effective image deconvolution algorithms have been developed over the years, but they are highly dependent on the accuracy of blur kernel estimation. Various artifacts and quality degradation may appear in the case of inaccurate blur kernel estimation. This is common for natural images with high noise level and non-uniform blur.

A grid warping has been developed to overcome the problems related to blur kernel estimation (Arad and Gotsman, 1999). Pixel transform is computed from the solution of a differential equation derived from the warping process constraints. In (J. Prades-Nebot et al., 2003) the transformation is calculated directly using the values of partial derivatives. Grid warping can be also expressed as a variant of morphology-based sharpening (Schavemaker et al., 2000) and shock filters (Weickert, 2003). In all of these methods, the warping vectors are proportional to image gradient. It results in insufficient sharpening of blurry and low contrast edges and oversharpening of already sharp and high contrast edges. The work (Nasonova and Krylov, 2015) proposes a grid warping based image sharpening algorithm (GWIS) that solves this problem. Its idea is to transform the areas near image edges so that the pixels move closer towards the edge centerlines (see Figure. 1). It results in thinner edges and overall image sharpness improvement.



(a) Edge profile | (b) Typical image enhancement approach | (c) Warping approach: pixels are shifted

Figure 1. The idea of edge sharpening by grid warping.

It has been shown that the GWIS does not introduce artifacts and does not amplify noise. It also does not need the blur kernel estimation. Instead, it uses a scalar value — the blur level that can be defined for each pixel independently. It has been also shown that GWIS is robust to blur level estimation errors (Krylov et al., 2017).

The application of GWIS algorithm is limited to smooth circular blur kernels, for example, out-of-focus blur. Also GWIS is applied only to edge areas while keeping textured areas almost intact. Therefore, it is effective to apply GWIS as a post-processing step to improve the results of existing deconvolution-based algorithms.

In this paper, we solve the problem of finding the optimal parameter values for GWIS algorithm in each pixel using a convolutional neural network.

2. GRID WARPING

The grid warping algorithm is described in detail in (Nasonova and Krylov, 2015, Krylov et al., 2017, Nasonov et al., 2018). We present here a brief explanation of this algorithm.

2.1 Edge sharpening

Consider a one-dimensional profile $g(x)$ of a blurred edge centered at $x = 0$. In order to make the edge sharper, we shrink its transient width by a warping transform W with a displacement function $d(x)$ that defines the pixel offset for each pixel x (see Figure. 1c):

$$W[g, d](x + d(x)) = g(x)$$

The restrictions for the displacement function $d(x)$ are the following:

1. The transform should be monotonic:

$$x_1 < x_2 \Rightarrow x_1 + d(x_1) \leq x_2 + d(x_2),$$

so the derivative of the displacement function should match the following constraint:

$$d'(x) \geq -1. \quad (1)$$

2. Pixels should be affected only in the neighborhood of the edge:

$$d(x) \to 0, \qquad \text{as } |x| \to \infty. \tag{2}$$

The result of image sharpening by grid warping greatly depends on the choice of the displacement function $d(x)$. In the work (Nasonov et al., 2018), the following displacement function has been suggested:

$$d(x,\sigma) = \begin{cases} -x, & |x| \le \sigma, \\ (3\sigma - 2|x|)\operatorname{sign} x, & \sigma < |x| \le \frac{3}{2}\sigma, \\ 0, & |x| > \frac{3}{2}\sigma. \end{cases}$$

$$\operatorname{sign} x = \begin{cases} -1, & x < 0, \\ 0, & x = 0, \\ 1, & x > 0. \end{cases}$$

Here the parameter σ is the scale factor — the size of area to be shrinked. It is correlated with the blur level.

2.2 Two-dimensional image sharpening

In the case of 2D sharpening, pixels are shifted towards the weighted average of the individual directions corresponding to edge profiles for each edge point:

$$\vec{d}(\mathbf{x}) = \sum_{\mathbf{p}\in E} \frac{w(\mathbf{p},\mathbf{x})\vec{n}(\mathbf{p})d(\mathrm{Pr}_{\vec{n}(p)}(\mathbf{x}-\mathbf{p}),\sigma_{\mathbf{p}})}{w(\mathbf{p},\mathbf{x})},$$

$$w(\mathbf{p},\mathbf{x}) = |\nabla I(\mathbf{p})| \exp\left(-\frac{\mathrm{Pr}_{\perp\vec{n}(\mathbf{p})}(\mathbf{x}-\mathbf{p})^2}{2\sigma_{\mathbf{p}}^2}\right),$$

where:

- E is the set of edge points;
- I is the image, and $\vec{\nabla} I$ is image gradient;
- $\vec{n}(\mathbf{x}) = \frac{\vec{\nabla} I(\mathbf{x})}{|\vec{\nabla} I(\mathbf{x})|}$ is the normalized image gradient direction;
- $\perp \vec{n}(\mathbf{p})$ is the direction orthogonal to $\vec{n}(\mathbf{x})$;
- $\sigma_{\mathbf{p}}$ is the blur level at point $\mathbf{p}$;
- $w(\mathbf{p},\mathbf{x})$ is the weight coefficient;
- $\mathrm{Pr}_{\vec{n}(p)}(\mathbf{x}-\mathbf{p}) = (\vec{n}(\mathbf{p}), \mathbf{x}-\mathbf{p})$ is projection of vector $\mathbf{x}-\mathbf{p}$ onto edge profile direction $\vec{n}(\mathbf{x})$;
- $\mathrm{Pr}_{\perp\vec{n}(\mathbf{p})}(\mathbf{x}-\mathbf{p})$ is projection of vector $\mathbf{x}-\mathbf{p}$ onto edge profile orthogonal direction $\perp \vec{n}(\mathbf{x})$:
  $\mathrm{Pr}_{\perp\vec{n}(\mathbf{p})}(\mathbf{x}-\mathbf{p})^2 = |\mathbf{x}-\mathbf{p}|^2 - \mathrm{Pr}_{\vec{n}(\mathbf{p})}(\mathbf{x}-\mathbf{p})^2$.

3. BLUR MODEL

We consider image sharpening for images affected by out-of-focus blur. The shape of typical out-of-focus blur kernel is close to circular shape with small deformation due to optical aberrations. Examples of real out-of-focus blur kernels are shown in Fig. 3.

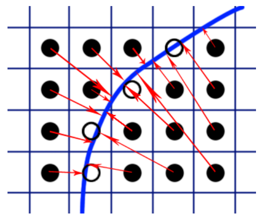
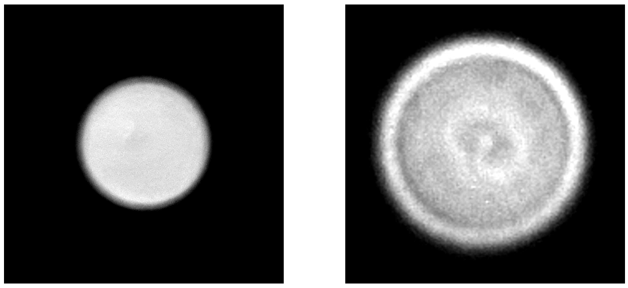


Figure 2. Displacements for two-dimensional grid warping. Thick blue line represents the exact edge location, white circles represent edge pixels, black circles represent pixels from the edge neighborhood.



(a) Blur kernel for an object in front of the focal plane

(b) Blur kernel for an object behind the focal plane

Figure 3. Examples of real out-of-focus blur kernels.

This type of blur is effectively suppressed by grid warping. We consider three types of modeled blur:

1. Gaussian blur

$$G_\sigma(\mathbf{x}) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{|\mathbf{x}|^2}{2\sigma^2}\right)$$

2. Disk blur

$$D_r(\mathbf{x}) = \begin{cases} 1, & |\mathbf{x}| \le r, \\ 0, & \text{otherwise.} \end{cases}$$

3. Ring blur

$$R_r(\mathbf{x}) = \begin{cases} 0.25, & |\mathbf{x}| \le 0.75r, \\ 1, & 0.75r < |\mathbf{x}| \le r, \\ 0, & \text{otherwise.} \end{cases}$$

Some examples of these blur kernels in shown in Fig. 4.

4. BLUR ESTIMATION

Blur estimation is a challenging problem. Both variational and learning-based methods are developed to solve this problem.

A method based on the analysis of first- and second-order derivatives in edge points has been proposed in (Elder and Zucker, 1998). In the work (Zhuo and Sim, 2011), a blur estimation is performed using the analysis of the Gaussian gradient ratio. The authors have shown that their method is robust to noise, inaccuracy

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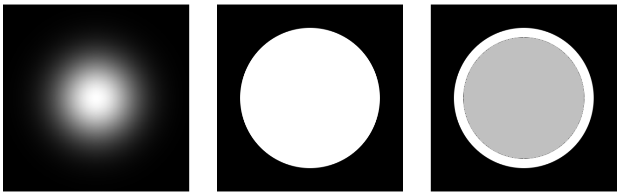


(a) Gaussian kernel (b) Disk kernel (c) Ring kernel

Figure 4. The considered modeled blur kernels.

of edge detection and influence of the surround edges. A spectrum analysis of the blurred edges has been suggested in (Tang et al., 2013). The blur map defined at edge points is then interpolated to the entire image (Bae and Durand, 2007, Levin et al., 2008).

General purpose blur estimation methods can also be used for sparse defocus map construction problem. The method (Hu and de Haan, 2006) is based on the assumption that the blur of the image is close to Gaussian. The image is divided into blocks, and the blur kernel is supposed to be uniform inside the block. The estimation of the blurriness of the block is based on the maximum of difference ratio between an original image and its two re-blurred versions. Block-based approach provides good blur estimation for highly textured areas but it shows inadequate results for blocks not containing edges, for example, flat areas.

Convolutional neural network based approaches have recently gained popularity for blur and defocus estimation from a single image (Suzuki et al., 2003, Park et al., 2017, Anwar et al., 2017).

In our application, we need to find the optimal parameters for the image sharpening algorithm by analysing the blur level. Instead of finding the blur level followed by parameter estimation, we develop an algorithm that estimates the sharpening parameters directly using the input image.

4.1 CNN architecture

We use a convolutional neural network (CNN) to estimate the blur level at each pixel. The architecture of CNN is the following:

Layer	Size	Count	Activation
Conv + bias	5×5	32	ReLU
Conv + bias	$5 \times 5 \times 32$	32	ReLU
MaxPooling	2×2	—	—
Conv + bias	$11 \times 11 \times 32$	64	ReLU
Conv + bias	$1 \times 1 \times 64$	17	ReLU
Conv + bias	$1 \times 1 \times 17$	1	ReLU

Thus, a patch of 31×31 pixels is mapped to a scalar value — the optimal blur parameters for GWIS algorithm.

4.2 Training dataset

We created a dataset that consists of reference images, corresponding blurred and noisy images and the results of image sharpening with different parameters. The reference images were taken from TID2013 database (Ponomarenko et al., 2015). We used the considered types of blur: Gaussian blur, disk blur and ring blur. Each reference image was uniformly blurred with each type of blur with 10 random combinations of blur level within $[0, 6]$ range and Gaussian noise with a variance within $[0, 10]$ range. Each blurry and noisy image was sharpened using GWIS algorithm with blur parameter within $[0.5, 8]$ range with a step of 0.5. The blur parameter was constant for whole images. Examples of blurred and noisy images are shown in Fig. 5 and Fig. 6.

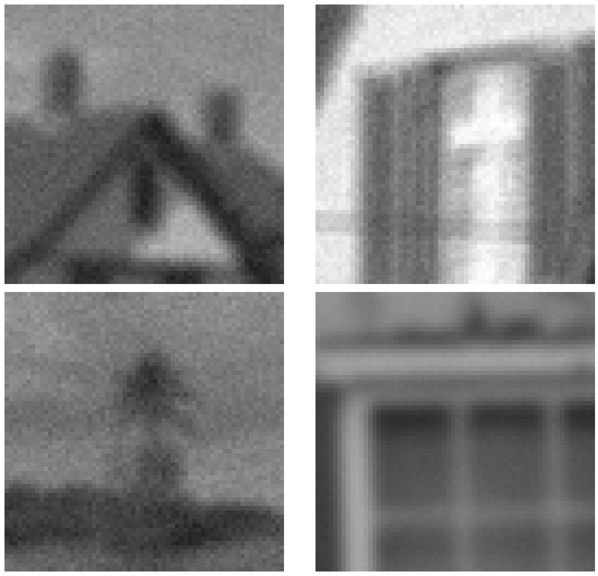
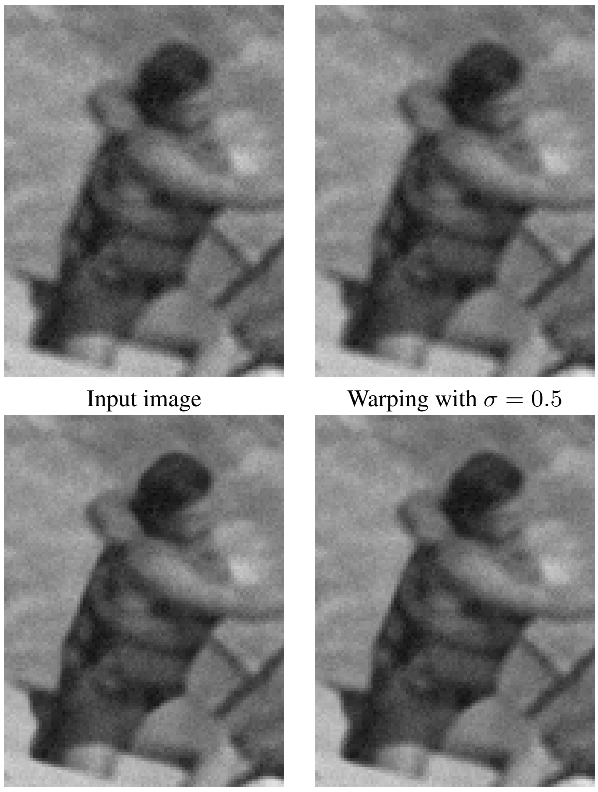


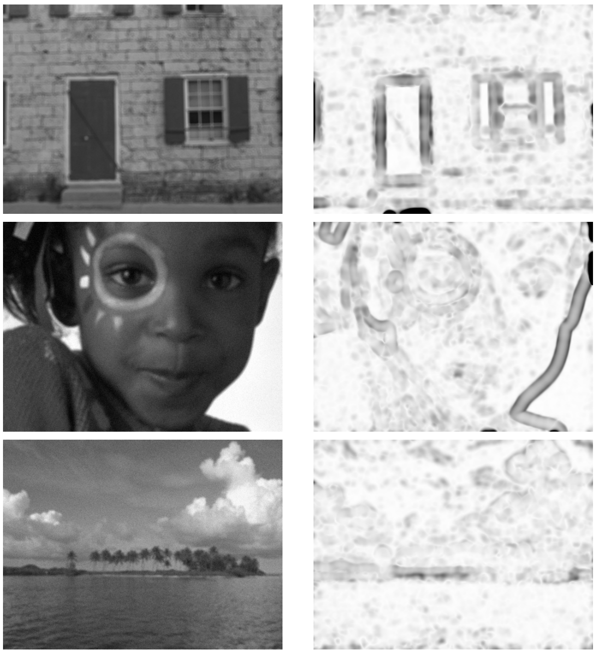
Figure 5. Examples of blurred and noisy images from the dataset.



Input image / Warping with $\sigma = 0.5$ / Warping with $\sigma = 1.5$ / Warping with $\sigma = 2.5$

Figure 6. Examples of image sharpening by the grid warping algorithm with different parameters.

For each pixel of each blurred and noisy image, we find the optimal parameter for the sharpening algorithm. We take a small rectangular neighborhood of the considered pixel (11×11 pixels)



Input image Patch importance map

Figure 7. A visualization of the importance measure of image patches. Darker areas are considered as more important.

and calculate SSIM values between corresponding patches from the reference image and images sharpened with different parameters. Then we find a parameter that maximizes SSIM value.

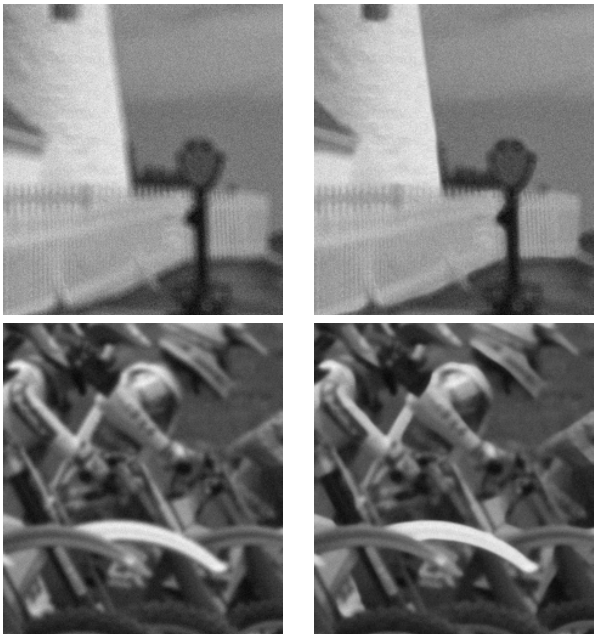
For parts of the image containing textures and flat areas, the difference between sharpening with different parameters is usually insignificant. In order to avoid overfitting problem in the proposed CNN, we exclude these areas from the dataset and keep only patches where the accuracy of the chosen blur parameter is crucial. We use the difference between the maximal and the minimal SSIM values for the considered blur parameter range as the importance measure of the patch. For each image, we extract 1% of patches with the highest importance value. An example of this is shown in Fig. 7.

The dataset is randomly splitted into training set and testing set: 80% of the reference images are used as the training set and the remaining 20% are used as the testing set.

4.3 Improvements

It has been shown that GWIS algorithm is robust to blur estimation errors (Krylov et al., 2017), and the decrease of image quality due to inaccurately estimated blur parameter is proportional to the relative difference between the estimated and the optimal blur parameters but not to the absolute difference between them.

Therefore, we replace the blur level with the logarithm value in the dataset and choose the loss function as squared difference between the expected value and actual outcome of the CNN.



Input blurred and noisy images

The result of GWIS with the proposed parameter estimation algorithm

Figure 8. The results of deblurring by GWIS algorithm with the proposed blur parameter estimation algorithm for the testing dataset.

	PSNR	SSIM
Blurred and noisy images	24.87	0.7022
GWIS with the best parameters	25.22	0.7207
GWIS with proposed parameter estimation	25.16	0.7192

Table 1. Objective results for the testing dataset.

5. RESULTS

After training the convolutional neural network, we evaluated it on the testing dataset. We have also applied it to real images with objects at different focus planes.

Table 1 and Figure 8 show the results for the testing dataset. The blurred and noisy images have been sharpened using GWIS algorithm with the best parameters and the parameters estimated by the proposed no-reference algorithm. The best parameters are obtained by maximizing SSIM between sharpened and reference images.

It can be seen that the obtained metrics values are close to optimal values, and the proposed algorithm can be used as a no-reference parameter estimation for GWIS algorithm.

Fig. 9 demonstrates an application of the proposed algorithm for the image with variable blur. A reference image was blurred with Gaussian filter with gradually increased parameter from 0 at the top to 6 at the bottom of the image. Then the proposed algorithm was executed and two sharpened by GWIS images were generated: one with constant average blur parameter and another with variable blur parameter. The average blur parameter was 2.34. The most improvement is observed in areas where the real blur level differs from the average blur level.

GWIS algorithm can be effectively used as a post-processing step after existing image deconvolution algorithms. The problem of

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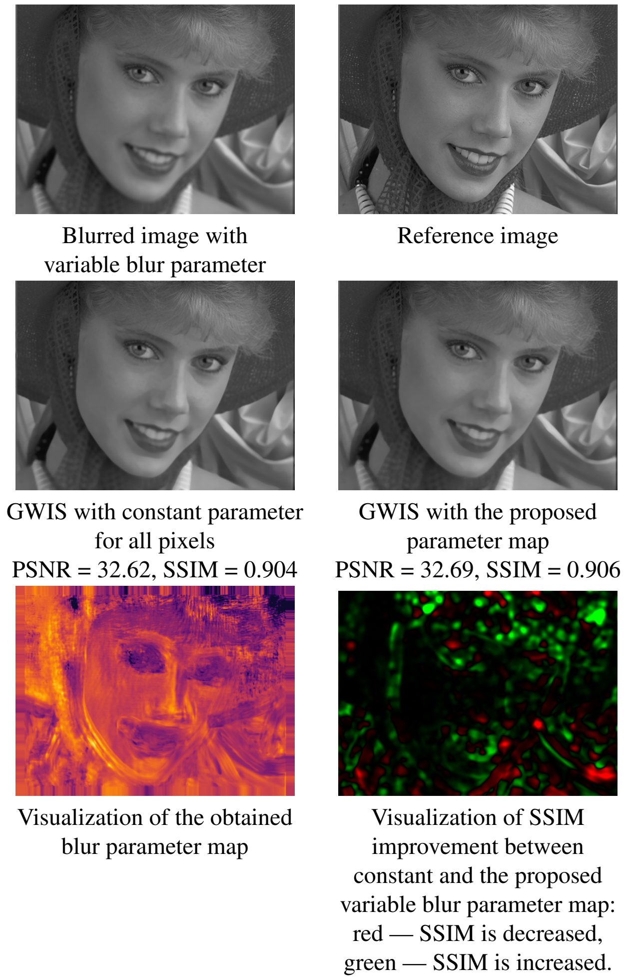

Figure 9. The application of the proposed algorithm for the image with non-uniform blur.

blur kernel estimation for image deconvolution leads to a trade-off between high probability of artifacts and incomplete sharpening that can be controlled by tuning the deconvolution algorithms. Since GWIS algorithm does not introduce artifacts, it can be used in a scenario where image deconvolution algorithms produce stable result with some blur effect remaining. The results of post-processing by GWIS algorithm for this case are shown in Fig. 10.

6. CONCLUSION

A convolutional neural network based method for blur parameter estimation for image sharpening by grid warping algorithm has been developed. The application of the proposed method of the CNN-based local blur estimation for grid warping image sharpening method showed the visible and numerical enhancement of the results comparing with other existing classical methods of blur level estimation.

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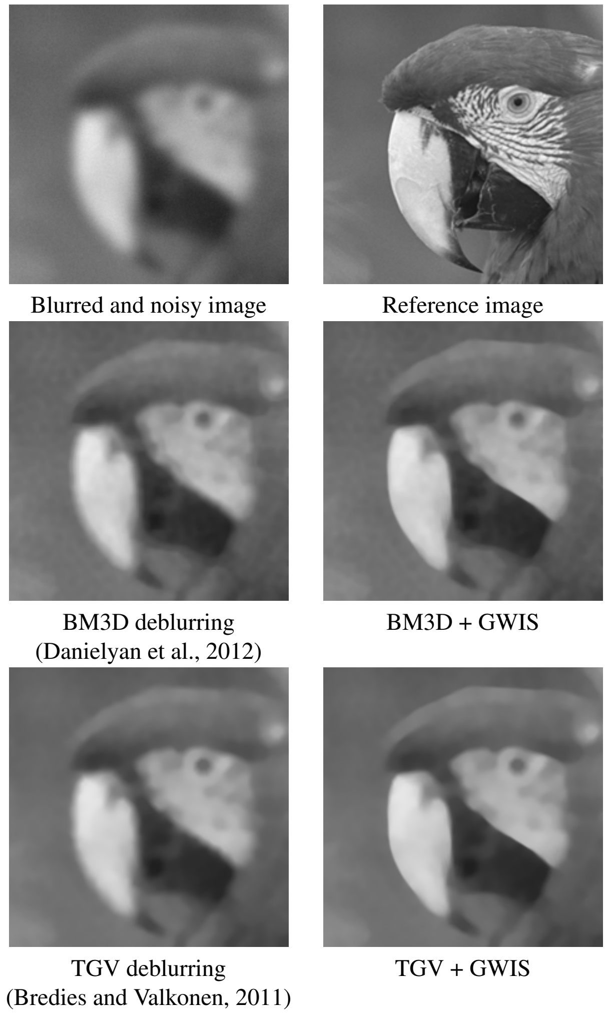

Figure 10. The results of post-processing by GWIS algorithm after deblurring with the proposed blur parameter estimation algorithm

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