# Handling Noise in Single Image Deblurring using Directional Filter

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***Abstract*— This project is an implementation of the image deblurring algorithm proposed by Zhong *et. al* [4] in CVPR 2013. This project is done as part of the Computer Vision course at IIIT Hyderabad.**

## I. Objective

While taking a picture, camera shake is likely to happen and this can produce blurry pictures. To restore the quality of the image, the camera blur and noise introduced in the captured image needs to be removed. To do this, we model the image and the blur in the form of a convolution operation using a blur kernel and addition of some random noise. We use this model to estimate the blur kernel and then perform deconvolution to get the de-blurred image.

## II. Theory

In general, a blurred image is modeled as follows:

$$b = (l * k) + n \tag{1}$$

where l is the unblurred sharp image, k is the blur kernel and n is added noise. In this project, the goal is to estimate the blur kernel k and then do deconvolution to try and retrieve the unblurred image l or latent image. There are a number of ways the blur kernel k is estimated, the most recent and state of the art method(Non deep learning based) proposed was:

1) Remove noise from the blur image by using standard denoising operations.
2) Estimate the blur kernel by optimising:

$$k* = argmin_k||b - (k * l)|| + P(k) \tag{2}$$

where b is the blurred image, k is the blur kernel and l is the unblurred image and P(k) is the regularization term. Both k and l are iteratively estimated until they are converged.

But there are issues with this algorithm, mainly that the denoising step hugely biases the kind of kernel that is estimated. The reason behind this is that essential edge information is lost/corrupted during denoising. This edge information is essential to kernel estimation.

We can prove that the denoising step biases the kernel by using Gaussian denoising to remove the noise. In the case of Gaussian, suppose we use a Gaussian kernel $G_g$ to remove noise from the blurred image. We then try and find the blur kernel $k_g$ as:

$$\begin{aligned} k_g &= argmin_{k_g}||b * G_g - l * k_g||^2 \\ &= argmin_{k_g}||(l * k + n) * G_g - l * k_g||^2 \\ &\approx argmin_{k_g}||l * (k * G_g - k_g)||^2 = k * G_g \end{aligned} \tag{3}$$

This shows that the kernel estimated $k_g$ is biased from the actual blur kernel $k$. To overcome this bias, the proposed method uses Radon Transform to reconstruct the original $k$ from the biased $k_\theta$

## III. Proposed Method

The method proposed in the paper follows a similar approach as mentioned earlier: remove noise by denoising the image, estimate the blur kernel, deconvolve to get latent image.

We know that the kernel estimation is biased because of the denoising step, therefore the paper proposes using directional filtering as the denoising step to prevent the kernel from being biased.

Directional filtering is defined as:

$$I(p) * f_\theta = \frac{1}{c}\int_{-\infty}^{\infty} w(t)I(p + tu_\theta)dt \tag{4}$$

Where $w(t)$ is the Gaussian kernel, defined by $w(t) = e^{-t^2/2\sigma_f^2}$. $I(p)$ is the intensity value at point $p$ and $u_\theta = [sin\theta, cos\theta]^T$ is the direction vector.
Since we use a Gaussian kernel, filtering this image as $b_\theta = b * f_\theta$, this gives us the blur kernel as:

$$k_\theta = k * f_\theta \tag{5}$$

We now want to retrieve the actual blur kernel $k$ from $k_\theta$, to do this we use the Radon transform. The Radon transform has the property that a projection orthogonal to the direction of the image, will have almost no effect on the projection. Therefore, we project the estimated blur kernel $k_\theta$ at $\theta' = \theta + \frac{\pi}{2}$. The projection is formulated as:

$$R_{\theta'}(k_\theta) = R_{\theta'}(k * f_\theta) = R_{\theta'}(k) * R_{\theta'}(f_\theta) = R_{\theta'}(k) \tag{6}$$

We can then compute the inverse Radon transform to get the actual blur kernel $k$.

The entire algorithm is given as:

**Algorithm 1:** Blur kernel and latent image estimation

**Data:** The pyramid $b_0, b_1, ..., b_n$ by down-sampling the input blurry and noisy image $b$, where $b_0 = b$.

**Result:** blur kernel $k_0$ and latent image $l_0$

Apply an existing nonblind approach [2] to estimate $k_i$ and $l_i$ for $b_i$ , $i = n, ..., 1$

Upsample $l_1$ to generate initial $l_0$

**while** $k_0$ *doesn't converge* **do**

1) Apply $N_f$ directional filters to the input image $b_0$ each filter has a direction of $i\pi/N_f$ , $i = 1, ..., N_f$, where N f is the number of directional filters.
2) For each filtered image $b_\theta$ , use $l_\theta$ as the latent image to estimate $k_\theta$.
3) For each optimal kernel $k_\theta$ , compute its Radon transform $R'_\theta(k_\theta)$, along the direction $\theta = \theta + \pi/2$.
4) Reconstruct $k_\theta$ from the series of $R'_\theta(k_\theta)$ using inverse Radon transform.
5) Update $l_\theta$ based on the new $k_\theta$ using a noise-aware nonblind deconvolution approach.

**end**

With the final estimated kernel $k_\theta$ , use the final deconvolution method described below to generate the final output $l_\theta$.

For estimating $k_\theta$ in step (2), we use the following optimisation:

$$k_\theta = argmin_{k_\theta}\{||\nabla b_\theta - k_\theta * \nabla l_0||^2 + \rho(k_\theta)\} \quad (7)$$

Once we have an estimate for $k_0$, we can estimate $l_0$ by minimising the following energy function:

$$||\nabla l_0 * k_0 - \nabla b_0||^2 + w_1||\nabla l_0 - u(\nabla l_1)||^2 + w_2||\nabla l_0||^2 \quad (8)$$

Where $w_1$ and $w_2$ are regularisation constants and $u(.)$ is the upsampling function.

The final deconvolution step mentioned in the end to obtain the final $l_0$ is defined as optimising the following function:

$$l_0 = argmin_{l_0}||l_0 * k_0 - b_0||^2 + w_3||l_0 - l'_0||^2 \quad (9)$$

Here $l'_0$ is defined as $l'_0 = NLM(l_0)$, where $NLM()$ is the non-local means denoising operation defined in [1].

## IV. WORK DONE

- Implemented module to compute initial estimate of blur kernel and latent image. The reference work uses S.Cho's[2] fast deblurring algorithm to get initial estimates. In this module, we optimize the following equations iteratively.

$$L' = argmin_L||b - (k * l)|| + \rho_L(L) \quad (10)$$

$$K' = argmin_L||b - (k * l)|| + \rho_K(K) \quad (11)$$

The functions $\rho_L(L)$ and $\rho_K(K)$ act as the regularization terms in the above equations. Different functions are used in the reference work. In our work, we use total variation as the regularization factor. The optimal values $L'$ and $K'$ for the above objective functions are learnt using gradient descent in our implementation.

- Implemented module to get the directional filtered images along different directions.
- Implemented module to calculate Radon Transform of a image at a different angles.
- Implemented module to calculate an inverse radon transform for a given series of radon projections.

## V. WORK TO BE DONE

- Module to estimate a latent image for a given $b$ and $k$ using noise aware deconvolution. This step also involves optimizing two objective functions iteratively.
- Module to estimate $k$ along a direction using a blur image $b$ and latent image estimate $l$
- Experiment the performance of this algorithm for different blurred images.
- Will try to compare these results with deep learning based deblurring algorithm results.

## VI. EXPERIMENTS AND DATASET

To test the image blurring algorithm proposed in the reference work, we will run the algorithm on both real images that have natural blur and noise and synthetically generated images. The dataset being used is available at [3]

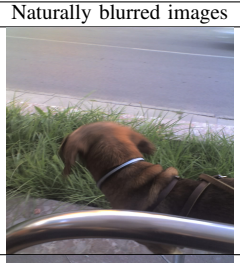
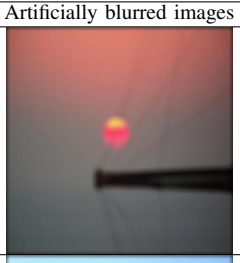
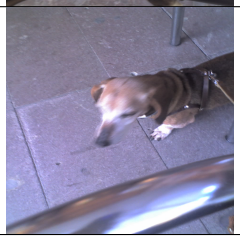
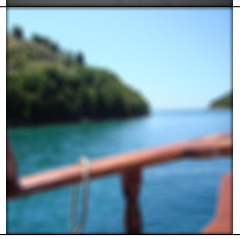
| Naturally blurred images | Artificially blurred images |
|---|---|
|  |  |
|  |  |

TABLE I: First column displays the images with natural blur. Second column shows the images with artificial blur

## REFERENCES


[1] Antoni Buades, Bartomeu Coll, and J-M Morel. A non-local algorithm for image denoising. In *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, volume 2, pages 60–65. IEEE, 2005.

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