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Rudin-Osher-Fatemi (ROF) Model for Blurring Removal in Digital Images

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Abstract— The use of image is everywhere, from selfie to medical imaging. The quality of an image not only depends on camera type but also on the way it is captured. In real time applications quality of images, is not of that much important. But, in applications such as medical imaging and biometrics, where some information needs to be extracted from the images, quality of images becomes important. In images blurring and noise are two degrading processes, and they need to be suppressed before meaningful information can be extracted. In this paper, we concentrate on the blurring removal in images. For removal of the blurring Rudin-Osher-Fatemi model is considered, and obtained results found to be good.
Keywords— Image, Noise, Degradation, Blurring, Filters

I. INTRODUCTION

The computer vision system organization is very much dependent on application. A few systems are stand-alone applications which unfolds a particular estimation or the problem of detection, though other constitute a sub-system of a bigger design which, like, in the same manner comprises sub-systems for control of mechanical actuators, information databases, planning, man-machine interfaces, and so on. The particular execution of a computer vision system also relies upon in the case of its functionality is pre-specified or if some part of it can be learned or adjusted at the time of operation. There are, although, typical functions which are found in numerous computer vision systems [3-6].

It is generally mandatory to process the data in order, prior to applying a computer vision method on image data to get some particular information, to assure that it fulfils some assumptions implied by the technique. Examples are

Re-sampling to make sure that the image coordinate system is correct.

Reduction in noise to assure that sensor noise does not introduce false information.

Contrast improvement to assure that relevant information can be detected.

Scale space representation to improve image structures at locally appropriate scales.

II. IMAGE BLURRING

The blurring, or degradation, of an image can be due to by factors:

Movement during the process of capturing of image, by the camera or, when long exposure times are used, Out-of-focus optics, use of a wide-angle lens, atmospheric turbulence, or a short exposure time, which decreases the number of photons captured Scattered light distortion in confocal microscopy

A degraded or blurred image can be probably expressed by the equation $G = HF + N$, where

G: The blurred image

F: The original true image

N: Additive noise, introduced at the time of image acquisition that causes the image corruption.

H: The distortion operator, also known as the point spread function (PSF). In the spatial domain, the PSF states the extent to which an optical system blurs (spreads) a point of light [18]. The PSF is the inverse Fourier transform of the optical transfer function (OTF). In the frequency domain, the OTF explains the response of a linear, position-invariant system to an impulse. The OTF is the Fourier transform of the point spread function (PSF). The distortion operator, when convolved with the image, makes the distortion. Distortion brought on by a point spread function is only one kind of distortion.

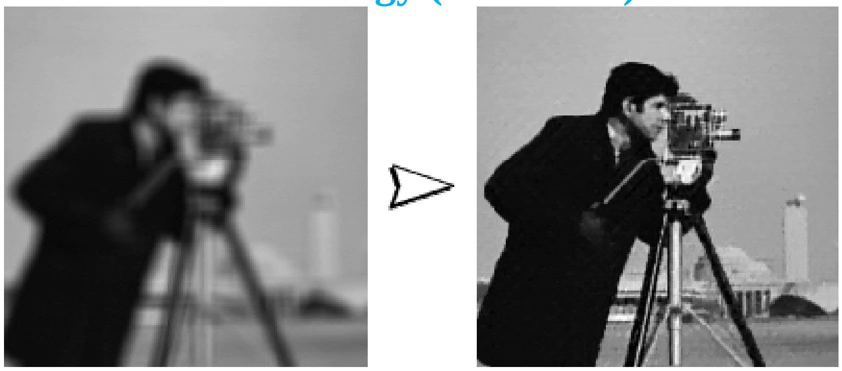

Figure 1 Blurred Image Representation

III. IMAGE DEGRADATION AND RESTORATION

A large number of images are influenced to some degree by noise, which is unexplained variation in data. Analysis of image is generally simplified if this noise can be eliminated. In the similar way as filters are used in chemistry to free fluids from suspended impurities by making them to pass through a layer of sand or charcoal; signal processing engineers have increased the extent of the term filter to incorporate operations which accentuate elements of interest in data.

Applying this more extensive definition, image filters may be used to concentrate edges that is, boundaries between objects or objects parts in images. Filters give a guide to visual interpretation of images, and can also be used as a precursor to following digital processing, like segmentation. Restoration of image or Denoising is the method of getting the original image from the corrupted image given the knowledge of the degrading factors as demonstrated in Figure 2. It is utilized to evacuate noise from the degraded image without affecting and maintaining the edges and other details.

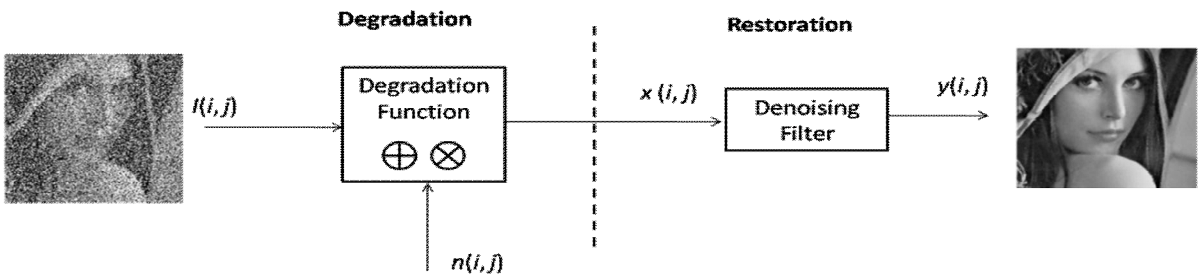

Figure 2 Image Degradation and Restoration Process

In figure 2 image degradation and restoration process is shown. O(i,j) is an input object n(i,j) is degrading term (may include noise, blurring or both) so x(i,j) is

$$x(i,j)= I(i,j)+ n(i,j) \tag{1}$$

or

$$x(i,j)= I(i,j)\times n(i,j) \tag{2}$$

$$y(i,j)=\mathbf{L}\,[x(i,j)] \tag{3}$$

L is filter operator.

In past, different techniques have been proposed for the purpose of image filtering. Linear filtering methods have been given most preference over the years.

$$y(t)=\int_{-\infty}^{\infty} x(\tau)h(t-\tau)d\tau$$

Where x(t) is input image, h(t) is filter impulse function and y(t) is the output image. The design of such filters is an important engineering problem. When blurring occurs due to independent and identical sources, using central limit theorem, process can be modelled as Gaussian.

IV. RUDIN -OSHER-FATEMI (ROF) MODEL

A novel version of the popular Rudin-Osher-Fatemi (ROF) model is presented in this work to restore image. The crucial point of the model is that it could recreate images with blur and non-uniform distributed noise.

In numerous applications, the images we acquire are contaminated by added blur and noise. This procedure is frequently modeled by

$$g(x) = (k * f)(x) + n(x) \tag{4}$$

where f(x) is the original clean image, g(x) is the noticed noisy blurred image, k is the point spread function (PSF) and also termed as the blur kernel, n(x) is the additive noise and *refers to the usual convolution. In this paper we are only concentrating on blurring, then noise term can be set to zero.

$$g(x) = (k * f)(x) \tag{5}$$

The issue of reconstruction of image is to recover f(x) from the degraded image g(x). Traditional image recovery approaches are chiefly on the basis of variational techniques [2, 3, 4,6, 8, 9, 10, 11, 13, 17], of which the most renowned one is the ROF model, proposed by Rudin, Osher and E.Fatemi [3, 17]. A regularized solution is obtained in that model by minimizing the energy functional.

$$T(f) = \frac{1}{2}\|k * f - g\|^2 + \lambda J_\beta(f) \tag{6}$$

$$J_\beta(f) = \int \sqrt{|\nabla f|^2 + \beta}\, dx \tag{7}$$

k is a known blur kernel, β > 0 is referred to as the stabilizing parameter, and λ > 0 is the regularization parameter. A number of experimental results (ref.[3, 4, 10, 12, 17]) have illustrated the impact of these processes in eliminating Gaussian and uniform distributed white additive noise. In the above expression (7) maximum gradient is obtained in a particular direction, thus help in minimizing equation 6.

A. A orithm 1

Choose initial values of f^0 and $\left(\sigma^2\right)^0$. For different values of n=1,2,3,4…….so on

Evaluate f^{n+1}, under the condition

$$f^{n+1} = \arg\min E(f, (\sigma^2)^n)$$

Evaluate $\left(\sigma^2\right)^{n+1}$, under the condition

$$\left(\sigma^2\right)^{n+1} = \arg\min E(f^{n+1}, (\sigma^2))$$

Check for the convergence, if converges STOP, else go to STEP 1.

V. RESULTS

Experimental results are obtained on Lena image as shown in Figure 3. Lena image is corrupted with Gaussian Blur with mean 25, and variance as 1, 5 and 7 respectively and obtained images are shown in Figure 4(a), 4(b) and 4(c) respectively.

Figure 3 Lena image

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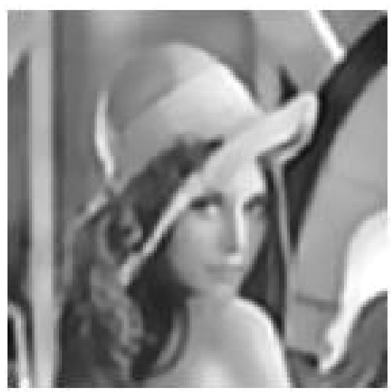
(a) (b) (c)

Figure 4 Blurred Lena image

It should be remember that, the blurring is affected by variance only; mean does not play any significant role.

(a)

In figure 5(a), blurred image is shown, with variance of 7. In figure 5(b) the recovered image is shown after 91 iterations is hown. It is clear form the figure, that there is significant reduction in image blurring in the obatined image.



(b)

Fig.5 (a) Blurred and (b) Recovered Lena image

VI. CONCLUSIONS

Blurring is a phenomenon that degrades the quality of images. In many applications where image processing is done to extract meaningful information, blurring removal becomes essential. In this paper, Rudin, Osher and E.Fatemi is used for the removal of blurring, which is based on the minimization of energy function. Experiment is performed on the Lena image and obtained results are produced. It is found that, using the Rudin, Osher and E.Fatemi model blurring can be reduced significantly.

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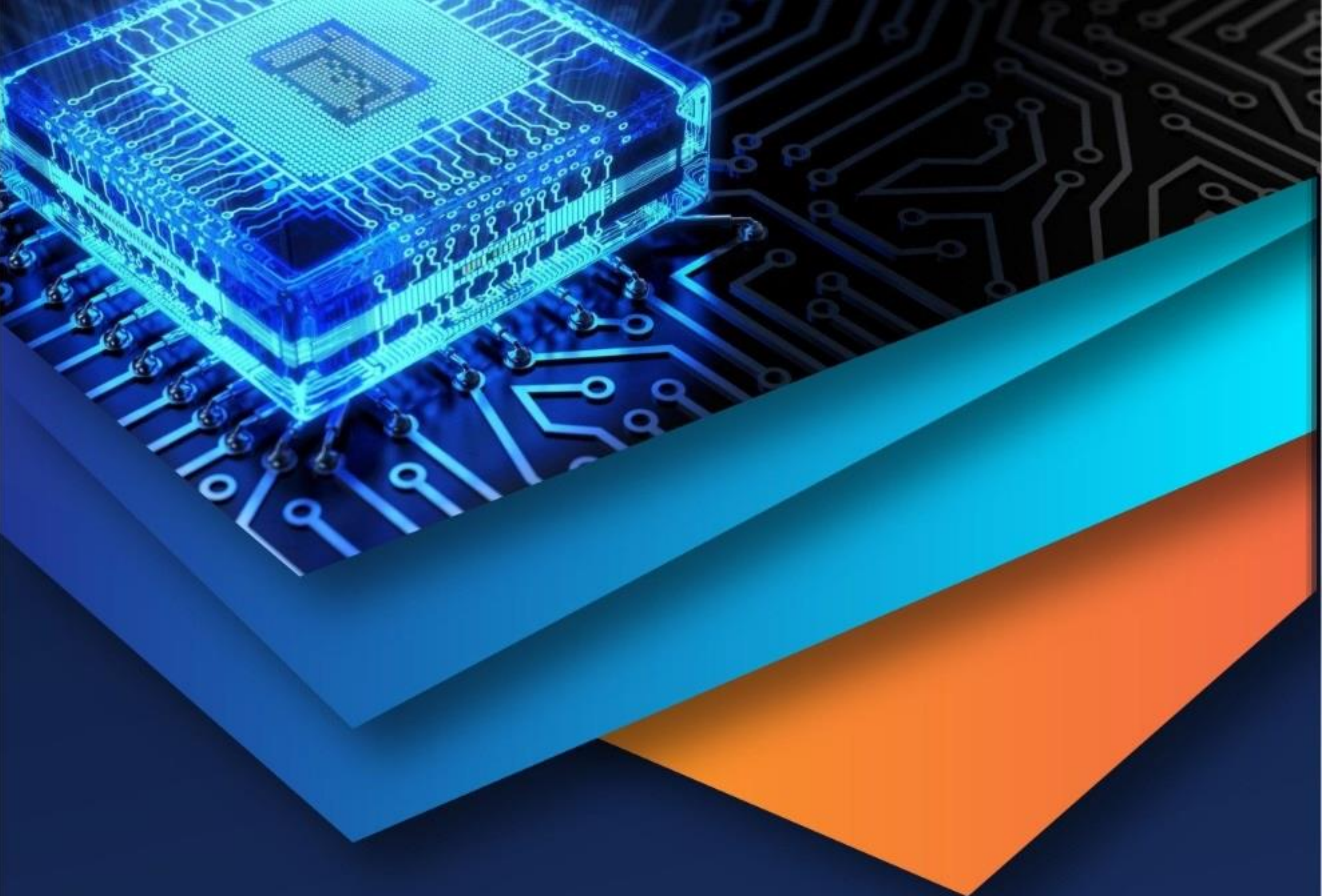

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