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Multi Scale Patch Based Image Restoration Technique

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Abstract: Image restoration is used to in the Prior information of an image can often be used to restore the sharpness of edges. De-blurring is the process of removing blurring artefacts from images, such as blur caused by defocus aberration or motion blur. Motion blur is the apparent streaking of rapidly moving objects in a still image. A Gaussian blur is the result of blurring an image by a Gaussian function. The success of recent single-image methods partly stems from the use of various sparse priors, for either the latent images or motion blur kernels. In this thesis, we propose a novel scheme based on sparse representation to identify the blur kernel. By analyzing the sparse representation coefficients of the recovered image, we determine the angle of the kernel based on the observation that the recovered image has the most sparse representation when the kernel angle corresponds to the genuine motion angle. Then, we estimate the length of the motion kernel with Radon transform in Fourier domain. Our scheme can well handle large motion blur even when the license plate is unrecognizable by human.

Keywords: Image Restoration, Deblurring, Radon Transform.

I. INTRODUCTION

Image restoration is one of the fundamental problems in image processing. It aims at reconstruction of true image from the degraded image. There are two main types of blurring one is motion blur, which is caused by the relative motion between the camera and object during image capturing; the other is defocus blur, which is due to the inaccurate focal length adjustment at the time of image capturing. Blurring means the degradation of image quality, specifically for sharp images where the high frequency information can be easily lost due to blur. The RGB color model is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. RGB uses additive color mixing and is the basic color model used in television or any other medium that projects color with light.

In image processing, a Gaussian blur also known as Gaussian smoothing is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. The visual effect of this blurring technique is a smooth blur resembling that of viewing the image through a translucent screen. Motion blur is the apparent streaking of rapidly moving objects in a still image or a sequence of images such as a movie or animation. It results when the image being recorded changes during the recording of a single exposure, either due to rapid movement or long exposure.

Fig. 1 a) Blurred Image b) Restored Image

We propose a novel scheme based on sparse representation to identify the blur. By analyzing the sparse representation coefficients of the recovered image, we determine the angle of the kernel based on the observation that. the recovered image has the most sparse representation when the kernel angle corresponds to the genuine motion angle. Then, we estimate the length of the motion kernel with Radon transform in Fourier domain.

II. LITERATURE REVIEW

Several studies and researches have been done in the last few years for the deblurring of image Following are the some researches and studies to detect blur of image and deblurring methods.
I. Ram, M Elad and I. Cohen [1] proposed an image processing scheme based on reordering of its patches. For a given corrupted image, we extract all patches with overlaps, refer to these as coordinates in high-dimensional space, and order them such that they are chained in the "shortest possible path," essentially solving the traveling salesman problem. The obtained ordering applied to the corrupted image implies a permutation of the image pixels to what should be a regular signal. This enables us to obtain good recovery of the clean image by applying relatively simple one-dimensional smoothing operations (such as filtering or interpolation) to the reordered set of pixels. We explore the use of the proposed approach to image denoising and in painting and show promising results in both cases.
P. Chatterjee and P. Milanfar [3] proposed a denoising method motivated by our previous analysis of the performance bounds for image denoising. Insights from that study are used here to derive a high-performance practical denoising algorithm. We propose a patch-based Wiener filter that exploits patch redundancy for image denoising. Our framework uses both geometrically and photo metrically similar patches to estimate the different filter parameters. We describe how these parameters can be accurately estimated directly from the input noisy image. Our denoising approach, designed for near-optimal performance (in the mean-squared error sense), has a sound statistical foundation that is analyzed in detail. The performance of our approach is experimentally verified on a variety of images and noise levels. The results presented here demonstrate that our proposed method is on par or exceeding the current state of the art, both visually and quantitatively.
Ophir, M. Lustig and M. Elad [4] proposed a multi-scale dictionary learning paradigm for sparse and redundant signal representations. The appeal of such a dictionary is obvious-in many cases data naturally comes at different scales. A multi-scale dictionary should be able to combine the advantages of generic multi-scale representations (such as Wavelets), with the power of learned dictionaries, in capturing the intrinsic characteristics of a family of signals. Using such a dictionary would allow representing the data in a more efficient, i.e., sparse, manner, allowing applications to take a more global look at the signal. In this paper, we aim to achieve this goal without incurring the costs of an explicit dictionary with large atoms. The K-SVD using Wavelets approach presented here applies dictionary learning in the analysis domain of a fixed multi-scale operator. This way, sub-dictionaries at different data scales, consisting of small atoms, are trained. These dictionaries can then be efficiently used in sparse coding for various image processing applications, potentially outperforming both single-scale trained dictionaries and multi-scale analytic ones. In this paper, we demonstrate this construction and discuss its potential through several experiments performed on fingerprint and coastal scenery images.
J.Mairal, M.Elad and G.Sapiro [5] Sparse representations of signals have drawn considerable interest in recent years. The assumption that natural signals, such as images, admit a sparse decomposition over a redundant dictionary leads to efficient algorithms for handling such sources of data. In particular, the design of well adapted dictionaries for images has been a major challenge. The K-SVD has been recently proposed for this task and shown to perform very well for various grayscale image processing tasks. In this paper, we address the problem of learning dictionaries for color images and extend the K-SVD-based grayscale image denoising algorithm that appears in . This work puts forward ways for handling non homogeneous noise and missing information, paving the way to state-of-the-art results in applications such as color image denoising and in painting.
G. Plonka and J. Ma [6] Denoising is always a challenging problem in natural imaging and geophysical data processing. In this paper, we consider the denoising of texture images using a nonlinear reaction-diffusion equation and directional wavelet frames. In our model, a curvelet shrinkage is used for regularization of the diffusion process to preserve important features in the diffusion smoothing and a wave atom shrinkage is used as the reaction in order to preserve and enhance interesting oriented textures. We derive a digital reaction-diffusion filter that lives on graphs and show convergence of the corresponding iteration process. Experimental results and comparisons show very good performance of the proposed model for texture-preserving denoising.

III. PROPOSED WORK

A. *Input/Dataset image*
An image is a rectangular array of values (pixels). Each pixel represents the measurement of some property of a scene measured over a finite area. The property could be many things, but we usually measure either the average brightness (one value) or the bright nesses of the image filtered through red, green and blue filters (three values).The values are

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normally represented by an eight bit integer, giving a range of 256 levels of brightness. We talk about the resolution of an image this is defined by the number of pixels and number of brightness values.

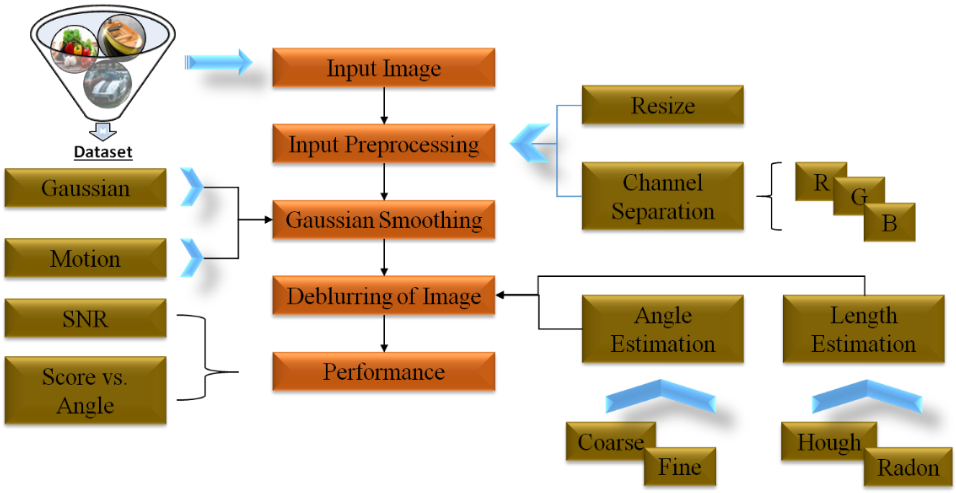

Fig. 2 Block Diagram of Proposed System

B. Image Resize

Not all of our images are the exact size we need them to be, so it's important to understand how to properly resize an image and how resizing works. When an image is resized, its pixel information is changed. For example, an image is reduced in size, any unneeded pixel information will be discarded by the editor (Photoshop). When an image is enlarged, the photo editor must create and add new pixel information based on its best guesses.

C. Channel Separation

An RGB image has three channels: red, green, and blue. RGB channels roughly follow the color receptors in the human eye If the RGB image is 24-bit,each channel has 8 bits, for red, green, and blue in other words, the image is composed of three images (one for each channel), where each image can store discrete pixels with conventional brightness intensities between 0 and 255. If the RGB image is 48-bit (very high color-depth), each channel is made of 16-bit images. Display devices commonly use the Red, Green, Blue (RGB) additive color system. Resized images are converted from RGB to its red, green and blue components.

D. Gaussian Blur

In image processing, a Gaussian blur (also known as Gaussian smoothing) is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. The visual effect of this blurring technique is a smooth blur resembling that of viewing the image through a translucent screen, distinctly different from the bokeh effect produced by an out-of-focus lens or the shadow of an object under usual illumination. Gaussian smoothing is also used as a pre-processing stage in computer vision algorithms in order to enhance image structures at different scales

E. Motion Blur

Motion blur is the apparent streaking of rapidly moving objects in a still image or a sequence of images such as a movie or animation. It results when the image being recorded changes during the recording of a single exposure, either due to rapid movement or long exposure. When a camera creates an image, that image does not represent a single instant of time. Because of technological constraints or artistic requirements, the image may represent the scene over a period of time. Most often this exposure time is brief enough that the image captured by the camera appears to capture an instantaneous moment, but this is not always so, and a fast moving object or a longer exposure time may result in blurring artifacts which make this apparent. As objects in a scene move, an image of that scene must represent an integration of all positions of those objects, as well as the camera's viewpoint, over the period of exposure determined by the shutter speed. Motion length estimation should take the benefit of the fact that, when motion length increases, the parallel dark lines of the Fourier spectrum get closer to each other. For estimating the motion length, we can measure the distance (d) between parallel dark lines from each other, then using these distances motion blur length can be predicted. Our scheme can well handle large motion blur even when the license plate is unrecognizable by human. We evaluate our approach on real-world images and compare with several popular state-of-the-art blind image de-blurring algorithms. Experimental results demonstrate the superiority of our proposed approach in terms of effectiveness and robustness

F. ESTIMATIONN OF PARAMETERS

If we transform the uniform motion blurred image in frequency domain, we can extract the motion blur parameters from frequency spectrum To find the line direction, we can apply any line fitting method like Radon transform, Hough transform method. Motion length estimation should take the benefit of the fact that, when motion length increases, the parallel dark lines of the Fourier spectrum get closer to each other. For estimating the motion length, we can measure the distance (d) between parallel dark lines from each other, then using these distances motion blur length can be predicted.

G. Hough Transform Method

The Hough transform can be applied to find global patterns such as lines, circles, and ellipses in an image in a parameter space. It is especially useful in line detection because lines can be easily detected as points in Hough transform space, based on the polar representation of line.

$$p = x\cos\Theta + y\sin\Theta$$

where (x,y) are cartesian coordinates of a point on the line θ is the angle between the perpendicular from the origin to the given line and the x-axis and ρ is the length of the perpendicular. Thus, a pair of coordinates (ρ, θ) can describe a line in polar domain. Fig shows transformation of line parameters from image domain to polar domain. Peak in Hough transform corresponds to the motion blur angle.

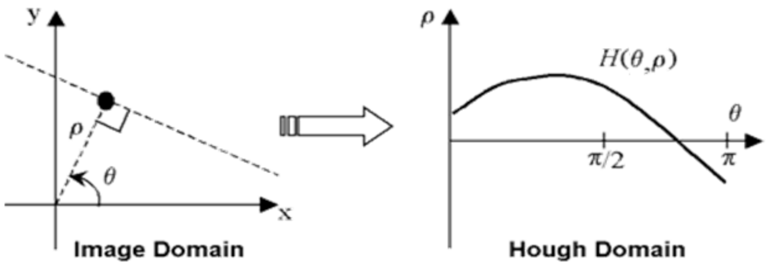

Figure 3 Hough transform

H. Radon Transform Method

Radon transform is competent to transform two dimensional images with lines into a domain of possible line parameters Θ & p which have the same meaning as given in above section. Each line in the image will give a peak positioned at the corresponding line parameters. It computes the projections of an image matrix along specified directions. A projection of a two-dimensional function *f(x, y)* is a set of line integrals. The Radon function computes the line integrals from multiple sources along parallel paths, or beams, in a certain direction.

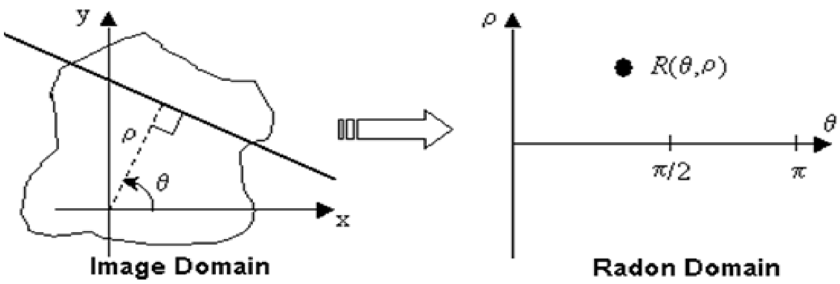

Figure 4 Radon Transform

I. PSNR

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the quality of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR of an image is the ratio between original image and compressed image the higher PSNR is better quality of image.

$$PSNR = 10.\mathrm{Log}_{10}\,(MAX_1^2/MSE)$$

Where MAX=maximum pixel value of image

J. Mean Square Error

In statistics, the mean squared error (MSE) or mean squared deviation (MSD) of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors or deviations that is, the difference between the estimator and what is estimated. MSE is a risk function, corresponding to the expected value of the squared

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error loss or quadratic loss. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

$$\text{MSE}=1/mn \sum_{i=0}^{m-1} \quad \sum_{i=0}^{n-1}[I(i,j)-K(i,j)]$$

K. Relation between Angle And Length

Sparse representation show great potential in the angle estimation of linear uniform kernel. A natural extension is to apply it to the length inference. however sparse representation coefficient do not show such qausi convex characteristic with the variation of length. the relation between A and L when the angle is fixed, where the sparse representation coefficient show the monotonic increasing property with the increase of L.

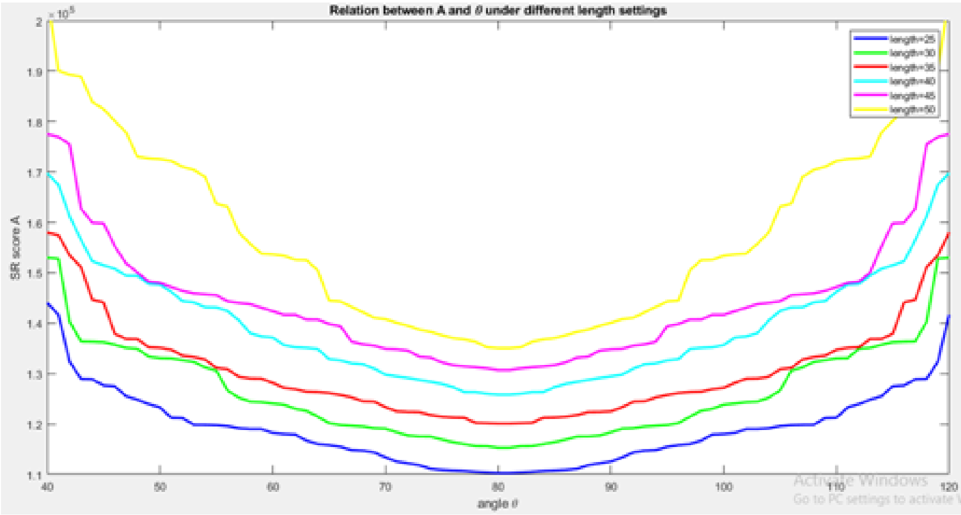

Fig 5 Relation between Angle and length

IV. RESULTS AND DISCUSSIONS

Our databases contain link http://www.gti.ssr.upm.es/~jal/download.html. [17] Two problems (Sketch photo and NIR-VIS) and three databases are selected to evaluate the proposed method. CASIA HFB and NIR-VIS 2.0 databases. The proposed technique has been implemented using MATLAB version R2015a environment and implemented using Intel core i3-6006U processor speed at 2.00 GHz with 4 GB RAM.

1] Result of 1st Image: Tiger

		RED	GREEN	BLUE
Gaussian Blur	Initial PSNR	23.09	23.41	23.6
	Final PSNR	23.72	23.92	24.06
	MSE	2.75	2.63	2.55

		RED	GREEN	BLUE
Motion Blur	Initial PSNR	26.48	26.8	26.97
	Final PSNR	28.4	28.57	28.66
	MSE	0.93	0.9	0.88

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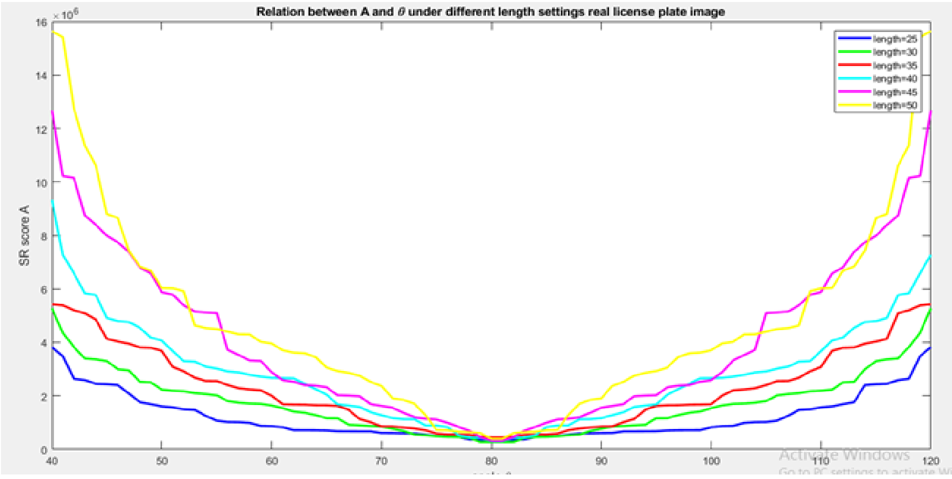
Relation between Angle and Length

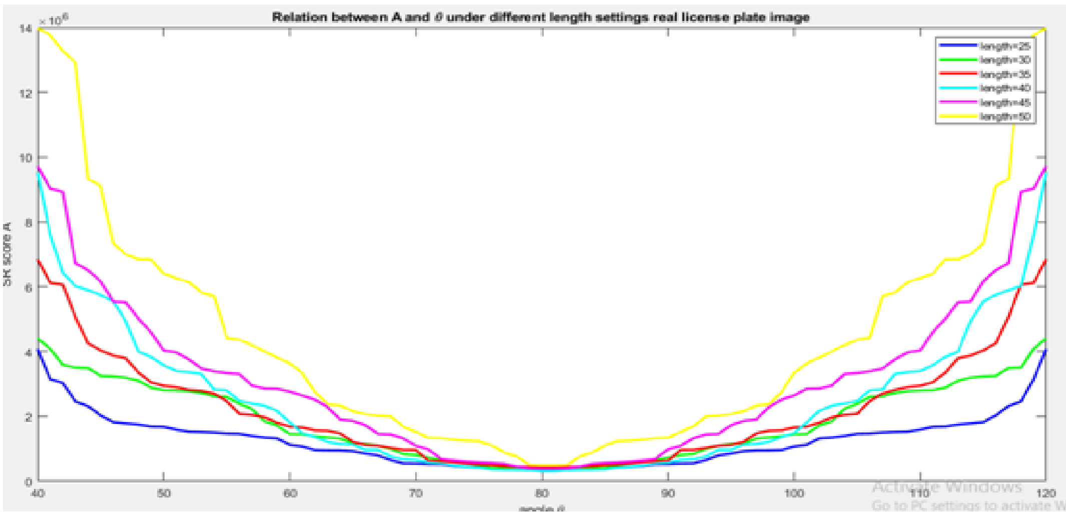


2] Result of 2nd Image: Vegetables

Gaussian Blur		RED	GREEN	BLUE
	Initial PSNR	22.02	21.91	21.73
	Final PSNR	22.93	22.82	22.72
	MSE	3.3	3.39	3.46

Motion Blur		RED	GREEN	BLUE
	Initial PSNR	25.28	25.45	25.22
	Final PSNR	28.55	28.73	28.67
	MSE	0.9	0.87	0.88

Relation between Angle and Length



Comparative Performance Parameters

Parameter	Ref[11]	Ref[2]	Proposed
PSNR	25.81	26.88	28.73
MSE	-	-	0.9
Sigma	5	5	5

Higher PSNR of image is better quality of image.

V. CONCLUSIONS AND FUTURE SCOPE

The process of regularizing an unknown blur kernel largely determines the success of blind image restoration. In this process, we propose a novel approach to regularization in which a blur kernel is modeled as a representation of a tensor dictionary comprising basic 2-D patterns. The advantage of this approach is that it can be customized for a variety of applications simply by altering the design of the dictionary. To demonstrate, we constructed a dictionary with atoms formed by the Kronecker product of two 1-D scaled Gaussian functions. We also demonstrated that the solution of the approach can be derived by using the variable splitting method for image estimation and the proximal gradient method for blur kernel estimation.

Future Scope:

- Orthogonal parabolic exposures for motion de-blurring:

In the future work, we address spatially variant blur induced by moving objects. Removing subject motion blur is challenging because one has to locally estimate the motion. Even if the motion is successfully identified, blur inversion can still be unstable because the blur kernel attenuates high frequency image content. Hence by using the orthogonal parabolic we can eliminate the blur more when compared with the other methods.

REFERENCES

[1] I. Ram, M. Elad, and I. Cohen, "Image processing using smooth ordering of its patches," Image Processing, IEEE Transactions on, vol. 22, no. 7, pp. 2764–2774, 2013.
[2] Vardan Papyan, and Michael Elad, Multi-Scale Patch-Based Image Restoration Fellow, IEEE,2015
[3] P. Chatterjee and P. Milanfar, "Patch-based near-optimal image denoising," Image Processing, IEEE Transactions on, vol. 21, no. 4, pp. 1635–1649, 2012.
[4] B. Ophir, M. Lustig, and M. Elad, "Multi-scale dictionary learning using wavelets," Selected Topics in Signal Processing, IEEE Journal of, vol. 5, no. 5, pp. 1014–1024, 2011.
[5] J. Mairal, M. Elad, and G. Sapiro, "Sparse representation for color image restoration," Image Processing, IEEE Transactions on, vol. 17, no. 1, pp. 53–69, 2008
[6]G. Plonka and J. Ma, "Nonlinear regularized reaction-diffusion filters for denoising of images with textures," Image Processing, IEEE Transactions on, vol. 17, no. 8, pp. 1283–1294, 2008.
[7] Y. Li and F. Santosa, "A computational algorithm for minimizing total variation in image restoration," in IEEE Trans. on Img. Proc., Vol. 5, No. 6, pp. 987-995, Jun. 1996.
[8] T. Chan and C. Wong, "Total variation blind deconvolution," in IEEE Trans. on Img. Proc., Vol. 7, No. 3, pp. 370-375, Mar. 1998.
[9] M. Bronstein, A. Bronstein, M. Zibulevsky, and Y. Zeevi, "Blind deconvolution of images using optimal sparse representations," in IEEE Trans. on Img. Proc., Vol. 14, No. 6, pp. 726-736, Jun. 2005.
[10] S. Babacan, R. Molina, and A. Katsaggelos, "Variational bayesian blind deconvolution using a total variation prior," in IEEE Trans. on Img. Proc., Vol. 18, No. 1, pp. 12-26, Jan. 2009.
[11] D. Zoran and Y. Weiss, "From learning models of natural image patches to whole image restoration," in Computer Vision (ICCV), 2011 IEEE International Conference on. IEEE, 2011, pp. 479–486.
[12] W. Zhang and W. Cham, "Single-image refocusing and defocusing," in IEEE Trans. on Img. Proc., Vol. 21, No. 2, pp. 873-882, Feb. 2012.
[13] Y. Xu, X. Hu, L. Wang, and S. Peng, "Single image blind deblurring with image decomposition," in ICASSP, pp. 929-932, 2012.
[14] Q. Shan, J. Jia, & A. Agarwala, "High-quality motion deblurring from a single image," in ACM Trans. on Graphics (SIGGRAPH), Vol.27, No.3, Aug. 2008.
[15] Y. Yitzhaky and N. S. Kopeika, "Identification of blur parameters from motion-blurred images," in Graph. Models Image Proc., Vol. 59, No. 5, pp. 310-320, 1997. [16] J. Hui and L. Chaoqiang, "Motion blur identification from image gradients," in CVPR, Jun. 2008.
[17] databases contain link http://www.gti.ssr.upm.es/~jal/download.html .
[18] S. Oh and G. Kim, "Robust estimation of motion blur kernel using a piecewise-linear model," in IEEE Trans. on Img. Proc., Vol. 23, No. 3, pp. 1394-1407, Mar. 2014.