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Estimation of Blur and Depth_Map of a De-focused Image by Sparsity using Gauss Markov Random Field Convex-Prior

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Abstract: ***In this work, we propose a new method for blur-map and depth estimation from de-focused observations using just noticeable blur (JNB) [1] method. Using JNB, we find the blur-map and then estimate the depth of the image in the depth from de-focus setting. We use a novel regularization based optimization framework, wherein we assume the blur-map as Gauss Markov random field. We initially obtain robust estimates of the blur-map then depth of the scene using a convex prior [2]. We show that JNB and clear dictionaries are not replaceable when conducting sparse patch reconstruction. We also show that the estimated blur-map which is utilized for efficient restoration of latent image by de-blurring.***

Keywords: Space-variant Blur-map, Just Noticeable Blur, Gradient Descent, GMRF, Convexity

1. Introduction

One of the fundamental problems of imaging systems is that the depth information is lost when projecting a three-dimensional (3D) scene onto a two-dimensional (2D) image plane. 3D shape reconstruction is a fundamental problem in computer vision applications Currently available vision-based, techniques can be broadly classified into active and passive. In case of active, artificial lighting device illuminates the scene while in case of passive, the scene illumination is provided by natural light. Passive range-finding techniques are image-based methods. Monocular image based techniques include gradient analysis of texture, photometric methods, occlusion cues, focus and defocus based ranging. Methods based on motion or multiple relative positions of the camera include reconstruction from multiple views, stereo disparity analysis, and structure from motion.

Most of the active ranging techniques less to do with the human visual system as they depend on artificial lighting. Their main aim is to provide an accurate range map to be used in a given application. Passive methods are more preferable because natural outdoor scenes fall within this category. These are specifically appropriate for military or industrial applications where security or environmental constraints prevent the use of light sources such as lasers or projectors. However, active ranging methods based on structured lighting sources are certainly acceptable in indoor environments.

2. Previous Work and Literature Survey

The first method of determining the depth-map is based on measuring the blur at known image characteristics like edges. Pentland [8] was the first to explore the DFD problem. He suggested two methods to recover the depth from blurred observations. The second method is based on comparing two images locally, one formed with a very small (pinhole) aperture, and the other image formed with a normal aperture. Since Pentland [8], different related techniques have been developed for recovering depth from defocused images. In [9] suggested a more general method in which he removed the limitation of one image being formed with a pinhole aperture by allowing several images with camera parameters (depth, DOF, focal length, aperture and lens to image plane distance) to be varied at the same time. In [10], vasantha M V et al presents a two-phase algorithm for recovering depth using Context Based Adaptive Variable Length Coding [21] and deblocking Filter of H. 264 standard [6]. During the calibration phase, a robust estimate of the camera parameters is determined using a least squares method. In the depth recovery phase, a gaussian blurring function is assumed, and the blur parameter over a local region is estimated. In [11] Nayar and Y. Nakagawa, devise the Shape from focus as DFD problem for a 3D image restoration problem. In [12], A. Chakrabarti et al. present a depth estimation algorithm in which the raw image data in the proximity of an edge is used to estimate the depth. In [13], T. Zickler, and W. T. Freeman presents analyzing spatially-varying blur method that disintegrates the 2D image into a 1D image sequence and estimates the depth using the Fourier coefficients of 1D sequence. In [14], Latha H N, et al. Presents blur map estimation of a single space-variantly defocused image gives a dynamic referencing approach that consists of an initial blurring by a gaussian convolution followed by Laplacian filtering. And the problem is resolved as a regularized pixel to pixel deconvolution problem. The regularization is with respect to the shape of the PSF [14]. In [15], S. Dai and Y. Wu, showed Removing partial blur in a single image and presented a maximal similarity estimation method that reduce the window effect in DFD. In [16]. the dissimilarity in blurring between the two defocused images is refined iteratively by blurring one image to resemble the other in the proximity of one pixel. Our objective in this is to estimate the blur-map initially and then depth-map of the object in the given blurred image after retrieving the original focused image. Microscopic cameras can be used for obtaining the defocused images. We use blurred images and the focused image is estimated using JNB[1] as well as Gauss Markov Random field algorithm. Then, from the focused image, the blur map is estimated and subsequently the depth of the image. Our main contributions to this work is a new method to detect and estimate blur using just noticeable blur [1] has been proposed. We use this method as a base to retrieve the focused image. Using the all-in-focus image and the blurred observation we estimate the depth map. We use gradient descent with discontinuity adaptive Markov random field [5] prior along with graduated non-convexity (GNC) algorithm to estimate depth, thus preserving fine details and solving the optimization problem.

3. Problem Definition and Proposed Method

A new approach to understand slight image blur via sparse representation based on external data is shown in Fig [1] (a) and (b). It is discovered that Fig [1] (a) clear and (b) JNB dictionaries show quantitatively and visually different results when local image patches are decomposed into dictionary atoms in an additive manner. The split effect exhibits that dictionary atoms can absolutely identify structure in just noticeable blur images, thus increasing the intrinsic difference between small blur and clear regions. The main contributions of the method are as follows. First, introduction of a new scheme for small blur recognition. Second, a sparsity based feature, which can generate useful results in estimation of blur strength. The scheme is verified on two blur detection image datasets [21] with one having all JNB images. The results can also be used in problems of image focusing, image refocusing, and relative depth estimation, to demonstrate its prospective usage.

a) Just Noticeable Blur

Just Noticeable Blur (JNB) is caused by blur across a small number of pixels in images [1]. This type of blur is very common during photography due to dissimilarity in depth. Although it is not severe, the small edge blurriness contains informative indicators related to depth. It is difficult to detect this type of negligible blur authentically from focused structures using existing blur descriptors, based on local information. So, a basic yet powerful blur feature is presented via sparse representation and image decomposition.

b) Clear and JNB Dictionaries

Elementary dictionary atoms can be obtained by decomposing each image patch via sparse representation. Tests have been conducted to verify that these atoms represent clear and JNB input differently or not.

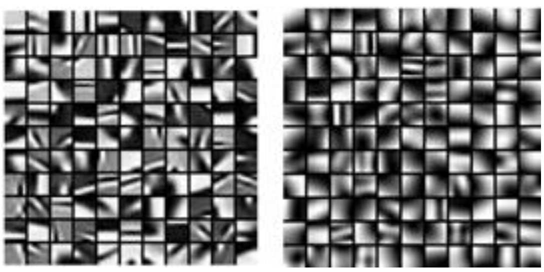

Figure 1: (a) Clear natural image dictionary (b) JNB Dictionary [1]

This method takes out image patches each of size 8x8, forming 64D vector. Following the procedure training of dictionary containing natural images with 128 atoms is carried out using clear images. The resulting dictionary is illustrated in Fig. 2 (a). Each atom is an edge-like component, acceptably representing natural image structure. Similar procedure is used to train a dictionary on slightly blurred images with σ = 2. The corresponding image dictionary is shown in Fig. 2 (b), which presents various structures containing almost no sharp patterns. The dissimilarity between dictionaries shows how small blur affects the basic atoms in decomposition of image. It also indicates that JNB and clear dictionaries are not replaceable when conducting sparse patch reconstruction. After blurring the clear dictionary, the atoms generated are different from atoms.

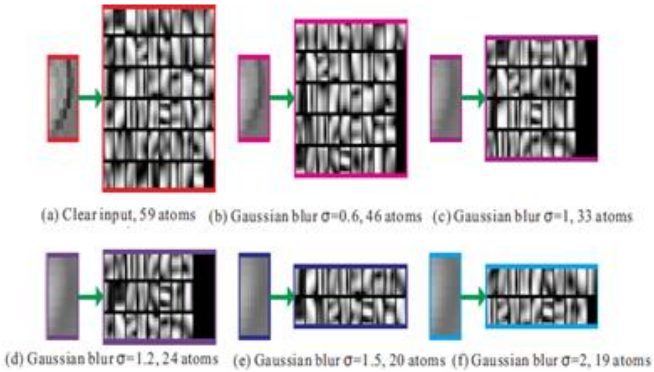

Figure 2: Sparsity features for different blur degrees. Blur is inversely proportional to variation of patches. So, the number of atoms used to represent images decreases sharply. [1]

In Fig. 3 Sparsity values and the corresponding blur strength is shown. And work similarly well in our tests. It is because the current blur dictionary expresses more elementary information to represent JNB images.

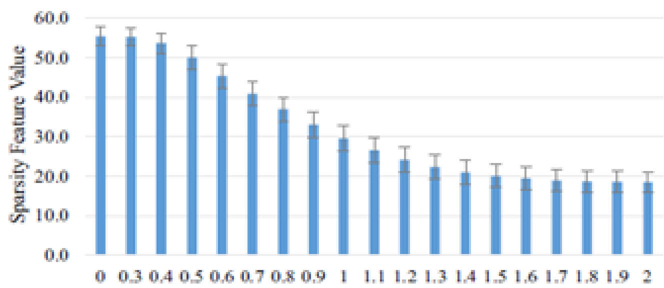

Figure 3: Sparsity values v/s blur strength. The standard deviation is represented by short gray lines. [1]

The blur map results can be applied to several applications such as image focusing, image refocusing, depth estimation, etc.

4. Methodology / Approach

We get the blur estimate by reducing feature map 'f' values and is given by relations

$$\sigma = \frac{\log_e\left(\frac{a}{f-d} - 1\right) - c}{b} \qquad (1)$$

Where f is given by

$$f = \frac{a}{1+\exp(b\sigma + c)} + d \qquad (2)$$

where a, b, c and d are constants with values 39.49, 4.535, -3.538, and 18.53 respectively. Using JNB for ramp blur we get a good blur estimate in the range of (0.4 to 0.95) for both increasing and decreasing ramp as shown in Fig 4 (a) and Fig.4(b). So, we assume it to be almost focused image (near focus) in this range since the blur is very small. Now, we take two blur images one with increasing and other with decreasing ramp in the range of (0.4 to 1.5). So, one image has less blur on the left side and more blur on the right side and vice versa for the other image. This simulates depth from defocus (DFD) setting for two images with different aperture setting. In one image, left side is near focused (almost focused) and right side is far focused (severely blurred) and vice versa in other image.

Since, we get good blur estimate in 0.4 to 1.5 range from image and deblur them separately using Algorithm 1, and Algorithm 2 respectively and get deblurred images. Now, we have the blur map of the observed image which we get from Algorithm 1 and 2 respectively. Finally, we estimate depth of the image using sigma estimate model.

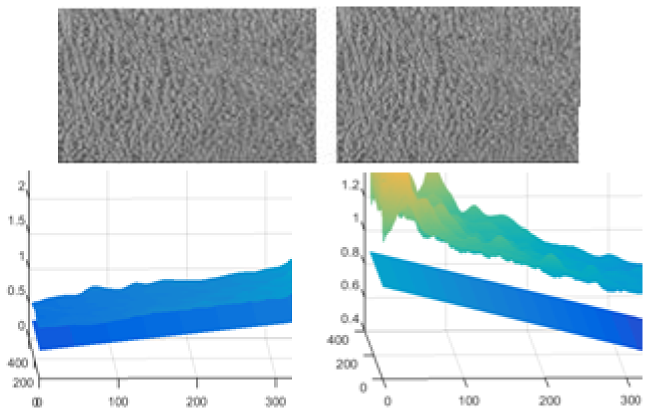

Figure 4: (a) Blur-map with sigma (0.4 to 1.5) increasing ramp [14] (b) Blur-map with sigma (1.5 to 0.4) decreasing ramp

5. Estimation of Focused Image

The formation of space variantly blurred images $y_p(i, j)$ is given by

$$y_p(i,j) = \sum_k \sum_l x(k,l) h_p(i,j;k,l) + \eta \qquad (3)$$

Here the x(k, l) is the focused image, η is the AWGN given by [6], $h_p(i, j; k, l)$ is the point spread function (PSF) of the lens used setup modeled as a 2D Gaussian function given by

$$h_p(i,j;k,l) = \frac{1}{2\pi\sigma_p^2(i,j)} \exp\left(-\frac{(i-k)^2+(j-l)^2}{2\sigma_p^2(i,j)}\right) \qquad (4)$$

where the standard deviation of the gaussian function $\sigma_p(i, j)$ is the space varying blur parameter at (i, j) in the observation [14] . The gaussian PSF $h_p(i, j)$ spans the rectangle defined by $(i - 3\sigma(i, j), j - 3\sigma(i, j))$ to $(i + 3\sigma(i, j), j + 3\sigma(i, j))$ centered at (i, j). So, the image blurring can also be modelled as

$$y_p(i,j) = \sum_k \sum_l x(k,l) h_{k_p}(i,j;k,l) + \eta \qquad (5)$$

The formation of a space variant blurred image can be modeled as

$$y = X h_{k_p} + \eta \qquad (6)$$

where X is the focused image, h is the blur kernel and η is the additive white zero mean gaussian noise [6]. The results of both equations must be identical. The problem of structure estimation can be formulated as the minimization of the energy function given by

$$e = \frac{1}{2}\|y - X h_{k_p}\|_2^2 \qquad (7)$$

For solving this ill-posed problem, we need to add regularizer or prior term to smoothen the outliers and to make it well-posed problem.

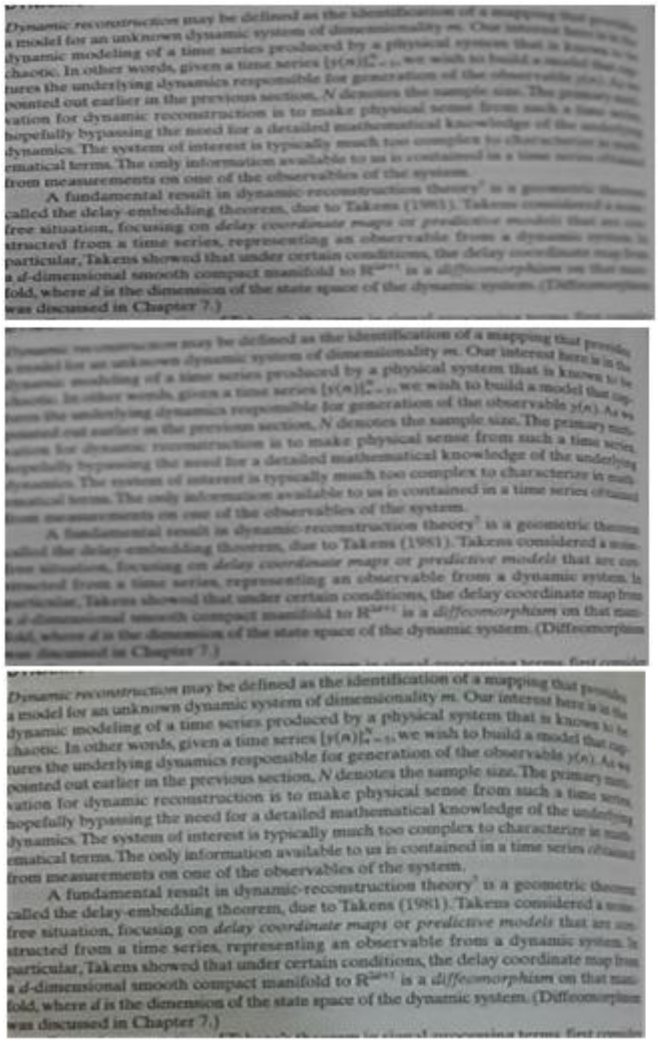

Figure 5: (a) Space variantly blurred text image with increasing ramp sigma from 0.4 to 1.5 (b) Space variantly blurred text image with Decreasing ramp sigma from 1.5 to 0.4 (c) de-blurred latent image.

Markov Random Field Regularization Term

When we try to solve equation for X for observations y, it becomes an ill-posed inverse problem [19]. So in this case, regularizer or prior term is required which introduces some assumptions on the solution and guide the energy term towards minimization leading to a plausible solution. We have used Bayesian MAP inference for incorporation of prior [20] knowledge about X so as to improve robustness during estimation process.

We proposed a model to de-focuse [18] image as a Markov random field [5] and the MAP estimate of X given y, is given by

$$X = \underset{X}{argmax}\{p(X|Y_1, Y_2, ..., Y_m)\} \quad (8)$$

Using Bayes' rule,

$$\hat{X} = \underset{X}{argmax}\{p(Y_1, Y_2, ..., Y_m|X)p(X)\} \quad (8)$$

Taking logarithm of the posterior probabilities, the MAP estimate of X is given by

$$X = \underset{X}{argmax}\{\log p(Y_1, Y_2, ..., Y_m|X) + \log p(X)\}$$

From the MRF-Gibbs equivalence, we can write

$$P(X) = \frac{1}{Z}\exp\{-\sum_{c\in C} V_c(X)\} \quad (9)$$

MAP estimate can be equivalently written as

$$\hat{X} = \underset{X}{argmax}\left[\sum_i \|y_i - Xh_i\| + \sum_{c\in C} V_c(X)\right]$$

In case of applying Markov random field (MRF), the energy function modifies according to the class of MRF being applied

For MRF,

$$E = \frac{1}{2}\|y - Xh_{k_p}\|_2^2 + \lambda R(d) \quad (11)$$

The first term in the energy function (E) is the data term and the second term is the prior. The term R(d) or Vc(X) imposes regularization and λ is the regularization parameter.

Gaussian Markov random field prior (GMRF)

For Gaussian MRF

$$R(d) = \eta^2 \quad (12)$$

Where η is neighbour clique potential. The gradient of the Gaussian MRF is

$$\frac{\partial R}{\partial x} = \frac{\partial \eta^2}{\partial x} \quad (13)$$

$$= \frac{\partial}{\partial x}\Big(\sum_i\sum_j [x(i,j) - x(i,j-1)]^2 + [x(i,j) - x(i,j+1)]^2 + [x(i,j) - x(i-1,j)]^2 + [x(i,j) - x(i+1,j)]^2\Big)$$

$$= \sum_i\sum_j 2[x(i,j) - x(i,j-1)] + 2[x(i,j) - x(i,j+1)] + 2[x(i,j) - x(i-1,j)] + 2[x(i,j) - x(i+1,j)]$$

$$\frac{\partial R}{\partial x} = 2\eta \quad (14)$$

It is known that blur kernel h_{kp} is a function of sigma which in turn is a function of depth d. So, these relations can be used to find the gradients required in each case.

a) Image deblurring model

In this case, blurring is modeled for unknown image x as:

$$y = Hx + \eta \quad (15)$$

The problem of structure estimation can be formulated as the minimization of the

$$E = \frac{1}{2}\|y - Hx\|_2^2 + \lambda R(d) \quad (16)$$

energy function given by

$$\frac{1}{2}\|y - Hx\|_2^2 = \frac{1}{2}(y^T y - 2y^T Hx + x^T H^T Hx) \quad (17)$$

The gradient descent update is

$$x_{new} = x_{old} - \alpha\frac{\partial E}{\partial x}$$
$$x_{old} = x_{new} \quad (18)$$

where a is the learning rate or the step size.

Algorithm 1 Image deblurring

1: σ_1 = input sigma map (known)
2: σ_2 = estimated sigma map using JNB
3: x_{old} = initial estimate of focused image
4: x_{new} = deblurred image
5: y = blurred image using σ_1
6: α = learning rate or the step size
7: λ = regularization parameter
8: $i \leftarrow 1$
9: $\alpha \leftarrow 0.5$
10: $\lambda \leftarrow 5e-8$
11: **while** $(i \leq Iter)$ **do**
12: $\quad x_{new} = x_{old} - \alpha\frac{\partial E}{\partial x}$
13: $\quad x_{old} = x_{new}$
14: **end while**

Algorithm 2 Blur estimation

1: $\sigma_{p_{old}}$ = initial estimate of sigma map
2: $\sigma_{p_{new}}$ = estimated sigma map
3: x = focused image
4: y = blurred image using sigma ground truth
5: α = learning rate or the step size
6: λ = regularization parameter
7: $Iter$ = Maximum number of iterations
8: $i \leftarrow 1$
9: $\alpha \leftarrow 1e-5$
10: $\lambda \leftarrow 1e4$
11: **while** $(i \leq Iter)$ **do**
12: $\quad \sigma_{p_{new}} = \sigma_{p_{old}} - \alpha\frac{\partial E}{\partial \sigma_p}$
13: $\quad \sigma_{p_{old}} = \sigma_{p_{new}}$
14: **end while**

b) Blur estimation model

In this case, blurring is modeled for unknown sigma as :

$$y = Xh_{k_p} + \eta \quad (19)$$

X is the focused image. The problem of structure estimation can be formulated as the minimization of the energy function and

The gradient of the energy function E with respect to σ_p is and prior term is given by

$$\frac{\partial E}{\partial \sigma_p} = \frac{\partial E}{\partial \sigma_p} + \lambda\frac{\partial R}{\partial \sigma_p} \quad (20)$$

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The gradient descent update is

$$\sigma_{p_{new}} = \sigma_{p_{old}} - \alpha \frac{\partial E}{\partial \sigma_p}$$

$$\sigma_{p_{old}} = \sigma_{p_{new}}$$

where a is the learning rate or the step size.

6. Results

The blur-map estimation obtained by our proposed framework using GMRF prior for text image is shown in Fig 6. (c) and (d). Ground truth Image is shown in Fig 6. (a) and (b).

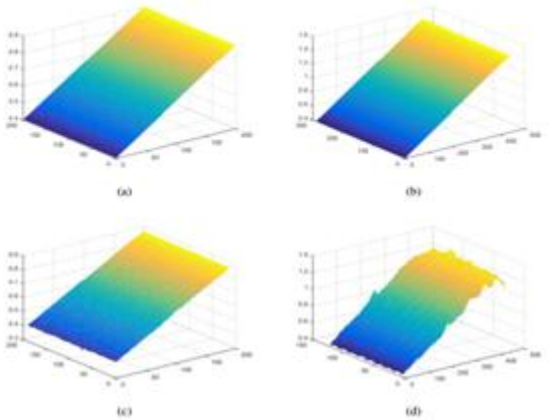

Figure 6: Ground truth (a), (b) and estimated blur-map (c),(d) of calf and text image respectively .

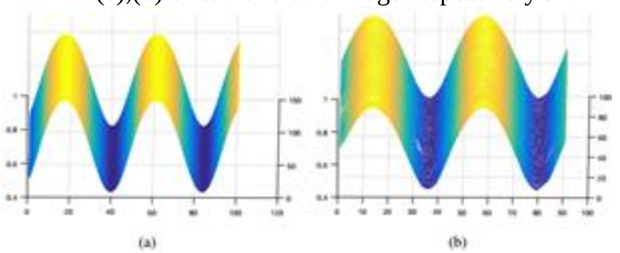

Figure 7: (a) Ground truth sin wave blur map for calf image (b) Estimated sin wave blur map for calf image

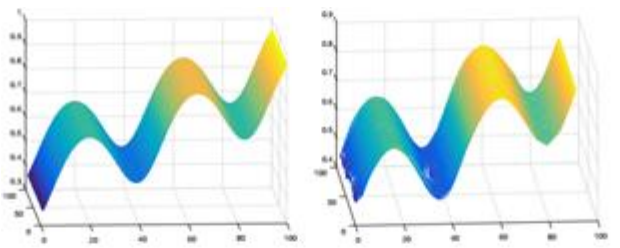

Figure 8: (a) Ground truth shifted sin wave blur map for calf image (b) Estimated shifted sin wave blur map for calf image

The estimated blur-map of the non-uniform sine sigma and shifted sine wave is given in Fig 8. (b) and Fig 8. (d) respectively. The corresponding ground truth Blur-map of sine sigma and shifted sine sigma used for obtaining the space variant bulrred synthetic image is as shown in Fig 8. (a) and Fig 8. (c).

Table 1: Performance evaluation of synthetic image

Image	SSIM value	PSNR value
Calf-ramp	0.7906	14.3377
Text-ramp	0.8648	16.9327
Sine Wave calf	0.9768	29.6948
Shifted Sine calf	0.8996	24.7991
Sine Wave text	0.9243	27.5438
Shifted Sine text	0.8896	23.4191

Evaluation of the de-focused image by sparsity based techniques using a Gauss Markov random field is performed using two qualitative measurement, SSIM and PSNR is given in Table 1.

(a) Depth estimation model

After obtaining blur map of the image using the proposed mosel, we use the relation between sigma (σ) and depth (d) to obtain depth-map of the image. The relation is given as

$$\sigma = \rho R v \left(\frac{1}{\omega_d} - \frac{1}{\omega_d - d + m\Delta d} \right) \quad (21)$$

From this relation we get depth in terms of sigma as

$$d = \omega_d + m\Delta d - \frac{1}{\left(\frac{1}{\omega_d} - \frac{\sigma}{\rho R v} \right)} \quad (22)$$

We can estimate depth-map of the image using the above relation. Here, r=1, R=1, v=0.0259, wd=0.0088, D=0.000025, and m=140.

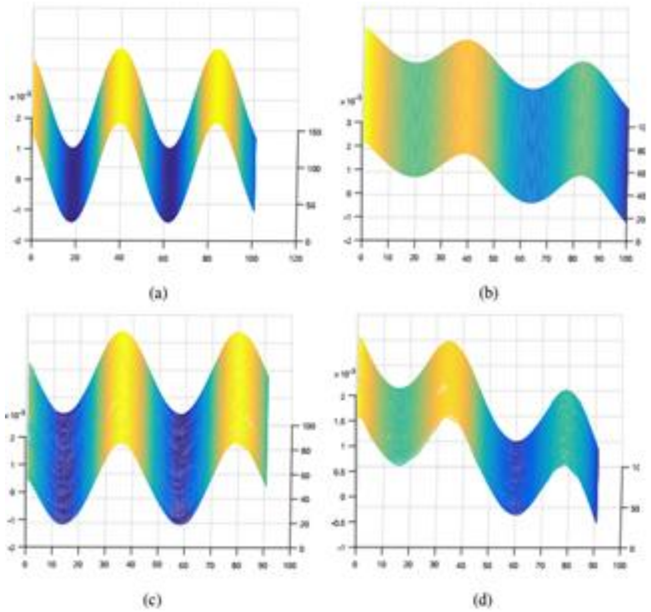

Figure 9: (a) Ground truth depth map for sin wave blur sigma on calf image (b) Ground truth depth map for shifted sin wave blur sigma on calf image (c) Estimated depth- map for sin wave blur on calf image (d) Estimated depth- map for shifted sin wave blur on calf image

The ground truth depth-map of sine sigma and shifted sine sigma used for obtaining space variant blurred image is as shown in Fig 9. (a) and Fig 9. (c). The estimated depth-map of the space variant sine sigma and shifted sine wave is given in Fig 9. (b) and Fig 9. (d) respectively.

7. Conclusion and Future Work

We have proposed a novel work based on sparsity optimization framework capable of estimating blur-map of different shape similar to increasing blur-sigma, decreasing blur-sigma, sine sigma and shifted sine sigma for Broadz Calf image data and DSLR captured text image. The results obtained both in-terms of quality and quantity is better than the few state-of-the art work given the literature. Deblurring of images using gradient descent optimization algorithm with Gaussian Markov random field prior is proposed. Depth-map estimation of images using JNB sigma-map features generated. Future work is extended for large depth map estimation of real images. Presently the proposed work is a very restrictive model since the blur-map estimation works only for $0 < \sigma \leq 2$.

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