Get out of my Picture!

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CS 603 - Computational Photography
Project Presentation

Outline

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Inpainting

- Image inpainting generally is the process of filling up lost(or deliberately masked) regions of the scene.
- There are a wide variety of techniques that have been developed to address this issue

A few Inpainting techniques

- Diffusion tehcniques based on PDE's [?]
- Exemplar based image inpainting techniques [?]
- Texture based image inpainting [?]
- Structure based image inpainting [?]
- But methods have the limitation that the size of the patch that need to be filled has to be small and also most of these use information from the some other part in the same image to fill the patch. These methods are ideal for removing small objects like wires etc.

A few Inpainting techniques

Inpainting using images of semantically similar scenes [?]

This technique uses information from other semantically similar scenes to fill the patch

This does not give us the true scene

Our method

- Inpainting using images of same scene taken from different views [?]
- This technique uses information from other images of the same scene taken from a different view, to fill the patch
- The information occluded in one view might be visible from another view and thus can be used to fill the patch.

Image equation

Outline

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Given a blurred image y, and a filter f our problem now is to find the sharp image x.

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Proposed Approach

Some methods to solve for x include Richardson-Lucy algorithm, deconvolution using a gaussian prior, and deconvolution using a spare prior.

Outline

Proposed Approach

- If we consider convolution as a linear operator, the previous equation can be rewritten as,

$$y = C_f x \tag{1}$$

where C_f is an $N \times N$ convolution matrix, the images x, y are written as $N \times 1$ element vectors.

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- In frequency domain, the convolution formula is as follows.

$$Y(v, \omega) = F(v, \omega)X(v, \omega) \tag{2}$$

where X, Y are frequency domain representations of x, y and v, w are their coordinates in frequency domain.

Proposed Approach

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- And in frequency domain by the following equation.

$$X(v, \omega) = \frac{Y(v, \omega)}{F(v, \omega)} \tag{4}$$

but the above equation won't be defined in the cases where $F(v, \omega) = 0$.

Proposed Approach

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- This will be a problem in those case when we have noise in imaging process.

$$Y(v, \omega) = F(v, \omega)X(v, \omega) + n \tag{5}$$

$$\frac{Y(v, \omega)}{F(v, \omega)} = X(v, \omega) + \frac{n}{F(v, \omega)} \tag{6}$$

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- If we observe the above equation, the noise contribution will be increased when $F(v, \omega)$ is small.

Proposed Approach

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$$x = argmax_x P(x|y) \propto P(y|x)P(x) \tag{7}$$

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- If we assume that we have independent and identically distributed gaussian noise with variance η, then we can express the likelihood as follows,

$$P(y|x) \propto e^{-\frac{1}{2\eta^2}\|x - C_f y\|^2} \tag{8}$$

and priori on x can be defined as

$$P(x) = e^{-\alpha \sum_{i,k} \rho(g_{i,k} * x)} \tag{9}$$

where $g_{i,k}$ is the k^{th} filter centered at pixel i of the image and i sums over image pixels. The fucntion ρ is either sparse or heavy tailed function and in the paper they used

Proposed Approach

- The general selection of filters g_k is the vertical and horizontal derivative filters namely $g_x = [1, -1]$ and $g_y = [1, -1]^T$.

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- If we take the log of equations 8, 9 and 10, the maximum a-posteriori explanation of x is given by

$$x = argmin_x \parallel y - C_f x \parallel^2 + W \sum_{i,k} \rho(g_{i,k} * x) \qquad (11)$$

where $W = \alpha\eta^2$ and $\parallel y - C_f x \parallel^2$ is called the reconstruction error.

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- The above equation can be solved using various techniques out of which we will specifically focus on deconvolution using a gaussian prior and deconvolution using a sparse prior.

Outline

Deconvolution using a gaussian prior

- Differentiate the equation 12 with respect to x and equate the derivative to zero.

Deconvolution using a gaussian prior

- Differentiate the equation 12 with respect to x and equate the derivative to zero.
- Now, we will get the optimal solution by solving the sparse set of linear equations.

$$Ax = b \tag{12}$$

where A and b are given by

$$A = C_f^T C_f + W\sigma_k C_{g_k}^T C_{g_k} \tag{13}$$

$$b = C_f^T y \tag{14}$$

Deconvolution using a gaussian prior

- From equation 14, we can observe that A in frequency domain is nothing but sum of convolution matrices and its diagonal. This can be shown by the following equation.

$$A_F = |F(v,\omega)|^2 + W \sum_k |G_k(v,\omega)|^2 \tag{15}$$

where A_F is the representation of A in frequency domain and similarly we can obtain b_F as

$$b_F = F(v,\omega) * Y(v,\omega) \tag{16}$$

Deconvolution using a gaussian prior

- By using the equations 16 and 17, we can obtain X as follows

$$X(v,\omega) = \frac{F(v,\omega) * Y(v,\omega)}{|F(v,\omega)|^2 + W\sum_k |G_k(v,\omega)|^2} \tag{17}$$

where W is the prior.

Deconvolution using a gaussian prior

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  where W is the prior.
- The prior effect will be larger at higher frequencies. At higher frequencies, the image content will be generally small and noise content will be large.
- In gaussian image prior the optimization problem is convex and optimal solution can be obtained in closed form.

Outline

Deconvolution using a sparse prior

- In natural images, the distribution of derivative filters won't be gaussian but sparse.
- A sparse prior concentrates derivatives at a smaller number of pixels when compared to gaussian prior.
- (Advantages) This will leave majority of image pixels as constant which will produce sharper edges and noise reduction with removal of unwanted artifacts such as ringing.
- (Disadvantages) The optimization problem is not convex, it can't be minimized in closed form. So, the optimization is achieved by iterative re-weighted least squares process (IRLS).

IRLS Algorithm

- In the IRLS approach the cost minimization is approached in the following form.

$$\sum_j \rho(A_{j\to x} - b_j) \tag{18}$$

- If we set the row vectors $A_{j\to}$ as the rows of the convolution matrices in equation 14, C_{gk} and C_f, we will approach to deblurring problem.
- In IRLS problem, each least square in the present step is re-weighted by its solution in the previous step.

IRLS Algorithm

- Initialize: $\psi_j^0 = 1$
- Repeat till convergence:
  - Let $A' = \sum_j A_{j\rightarrow}^T \psi_j^{t-1} A_{j\rightarrow}$ and $b' = \sum_j A_{j\rightarrow}^T \psi_j^{t-1} b_j$. x^t will be the solution for $A'x = b'$.
  - Set $u_j = A_{j\rightarrow} x^t - b_j$ and $\psi_j^t(u_j) = \frac{1}{u_j} \frac{d\rho(u_j)}{du}$ where $\rho(u_j) = |u_j|^{0.8}$ which implies the reweighting term $\psi(u_j) = max(|u_j|, \epsilon)^{0.8-2}$

  where $|u_j|$ is replaced by $max(|u_j|, \epsilon)$ to eliminate division by zero.
- The above algorithm can be implemented only in spatial domain because of re-weighting process.
- The quality of the results will be dependent on the number of iterations we are using for conjugate gradient.

Lucy Deconvolution

images/original.png	images/lucy.png
(a) Original Image	(b) Lucy Deconvolution

Deconvolution using Gaussian Priors

images/freq002.png

(c) Gaussian prior, $w = 0.002$

images/freq005.png

(d) Gaussian prior, $w = 0.005$

images/freq01.png

images/freq05.png

Deconvolution using Sparse Priors

images/sps001.png

(g) Sparse prior, $w = 0.001$

images/sps004.png

(h) Sparse prior, $w = 0.004$

images/sps008.png

images/sps01.png

Applications

images/beer_coke_inp.png

(k) Defocus Image

images/beer_coke_out.png

(l) All-focus Image

images/cups_board_inp.png

images/cups_board_out.png

Summary

- In this project, we have implemented the different deconvolution techniques proposed in the [?].
- We also discussed about the demerits and merits of different convolution techniques and how they are implemented.
- We also discussed about some applications of the proposed approach and how to proceed to those applications from the proposed algorithm.

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