Efficient Change Detection for Very Large Motion Blurred Images

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The Problem

- Detect changes between a clean reference image and an observed image
- Observed image is affected by motion blur and contains occlusions
- Image dimensions are very large

Outline

- Joint estimation of camera motion and occlusion
    - Motion blur model
    - Camera motion estimation
    - Occlusion model
- Tackling very large motion blurred images
    - Camera motion estimation from sub-image
    - Choosing a good sub-image
    - Effect of occlusion
- Algorithm and Results

Motion Blur

- Camera sees multiple images of the scene during exposure time due to its motion
- Resultant image is the average of all of them

$$\mathbf{g} = \frac{1}{T_e} \int_0^{T_e} \mathbf{f}_{\mathbf{p}(t)} \; dt,$$

where $\mathbf{p}(t)$ is the camera path defined for $0 \leq t \leq T_e$

- Discretise with respect to a finite camera pose space $\mathcal{P} = \{\mathbf{p}_i\}_{i=1}^{|\mathcal{P}|}$

$$\mathbf{g} = \sum_{\mathbf{p}_k \in \mathcal{P}} \omega_{\mathbf{p}_k} \; \mathbf{f}_{\mathbf{p}_k}$$

Camera Motion Estimation

- Blurred image as matrix-vector multiplication

$$\mathbf{g} = \sum_{\mathbf{p}_k \in \mathcal{P}} \omega_{\mathbf{p}_k} \, \mathbf{f}_{\mathbf{p}_k} \iff \mathbf{g} = \mathbf{F}\boldsymbol{\omega}$$

- **F** contains the warped copies of the reference image **f** in its columns for the camera poses in $\mathcal{P}$
- Estimate camera pose weights

$$\widetilde{\boldsymbol{\omega}} = \arg\min_{\boldsymbol{\omega}} \|\mathbf{g} - \mathbf{F}\boldsymbol{\omega}\|_2^2 + \lambda \, \|\boldsymbol{\omega}\|_1 \text{ subject to } \boldsymbol{\omega} \succeq 0$$

- sparsity of camera motion
- fraction of exposure time for a pose

Occlusion Detection

Additive occlusion model:

$$\mathbf{g}_{\text{occ}} = \mathbf{g} + \chi$$

$$\mathbf{g}_{\text{occ}} = \begin{bmatrix} \mathbf{F} & \mathbf{I}_N \end{bmatrix} \begin{bmatrix} \omega \\ \chi \end{bmatrix} = \mathbf{A}\xi$$

Joint registration and occlusion detection:

$$\widetilde{\boldsymbol{\xi}} = \arg\min_{\boldsymbol{\xi}} \|\mathbf{g}_{\text{occ}} - \mathbf{A}\xi\|_2^2 + \lambda \|\boldsymbol{\xi}\|_1 \text{ subject to } \mathbf{C}\xi \succeq 0$$

$$\text{where } \mathbf{C} = \begin{bmatrix} \mathbf{I}_{|\mathcal{P}|} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}$$

- sparsity of both camera motion and occlusion
- non-negativity only on pose weights

Camera Motion in Sub-images

- Any subimage (of size $S \times S$) observes the same camera motion as the original large image
- Estimate camera motion from a sub-image instead of the large image

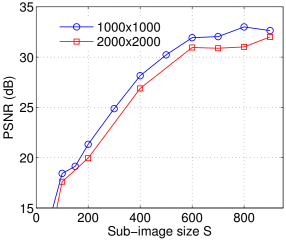

Figure : Reconstruction PSNR in dB vs. sub-image size S

- Reconstruction PSNR: estimate camera motion from sub-image, reblur the large image, compare with the original blurred image

Choosing a good sub-image

- Sub-image should contain ample blur variation
- Blur kernels at different locations inside a sub-image - an indicator of the quality of camera motion estimate

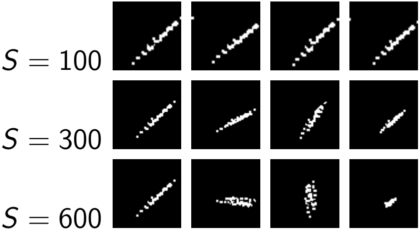

Figure : Estimated blur kernels for different sub-image sizes S. The blur kernels are displayed as binary images with non-zero values shown in white colour

- Normalized cross correlation

$$\mathbf{NCC}(\mathbf{h}_i, \mathbf{h}_j) = \frac{\mathbf{corr}(\mathbf{h}_i, \mathbf{h}_j)}{\|\mathbf{h}_i\|_2 \|\mathbf{h}_j\|_2}$$

- Correlation measure $m(\mathbf{h}_i, \mathbf{h}_j) = \max\ \mathbf{NCC}(\mathbf{h}_i, \mathbf{h}_j)$
- $\mathbf{h}_i$ and $\mathbf{h}_j$ are blur kernels from the sub-image

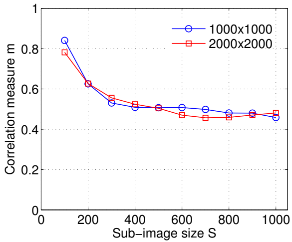

Figure : Correlation measure vs. sub-image size S

Effect of Occlusion

- Chosen sub-image may contain occluding objects
- Our joint estimation tackles occlusions too

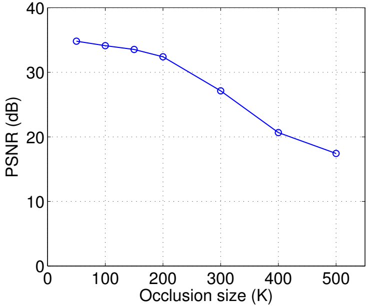

Figure : PSNR in dB for $S = 600$ vs. occlusion size K

Algorithm

1. Pick a sub-image of size S
   - Extract γ blur kernels
   - Calculate $\overline{m}_S$ by averaging out the correlation values found out for all kernel pairs
   - If $\overline{m}_S < 0.6\ \overline{m}_{100}$, goto Step 4 (joint estimation)
2. If a particular S is chosen α times at different locations, declare this S to be unsuitable to estimate motion
   - Update $S \leftarrow S + 100$
   - Goto Step 1
3. If $S > S_{\text{max}}$, declare blur to be space-invariant
   - Use one of the estimated blur kernels itself as the camera pose weight vector
   - Goto Step 5 (reblurring)

Algorithm (contd.)

4. Estimate jointly the pose weight vector and occlusion weight vector for the selected sub-images $\mathbf{f}^{(S)}$ and $\mathbf{g}^{(S)}$
   - If the number of non-zero elements in the occlusion weight vector $\|\boldsymbol{\chi}\|_0 > \frac{2}{3}S^2$, then go to Step 1
5. Reblur the original reference image $\mathbf{f}$ using the estimated pose weight vector $\widetilde{\boldsymbol{\omega}}$
6. Detect the changes by differencing the reblurred image and the observation $\mathbf{g}$

Results

(a) (b) (c) (d)

Figure : (a) Reference image, (b) synthetically blurred and occluded observation from a different view point, (c) sub-image from (a), (d) sub-image from (b),

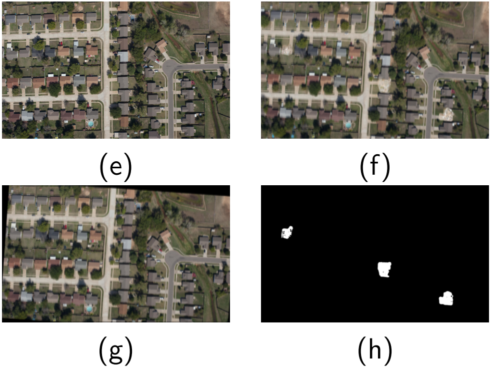

Figure : (e) Reference image, (f) synthetically blurred and occluded observation from a different view point, (g) reference image reblurred using the estimated camera motion, and (h) detected occlusion

Results

Imaged using an 18MP Canon DSLR camera


(a) (b)


(c) (d)

Figure : (a) Reference image, (b) real blurred and occluded observation, (c) registered image, and (d) detected dynamic occluder

Results

Imaged using an 8MP Google Nexus 4 camera

(a) (b) (c)

Figure : (a) Reference image, (b) real blurred and occluded observation, and (c) detected changes

Conclusions

- Traditional deblurring techniques fail to cope with large image sizes
- Feature-based approaches for change detection are rendered invalid in the presence of blur
- Devised an algorithm to choose good sub-images from the large observations to estimate the camera motion
- Developed an optimisation problem which would perform registration in the presence of blur and detect occlusions simultaneously