Illumination Robust Change Detection with CMOS Imaging Sensors

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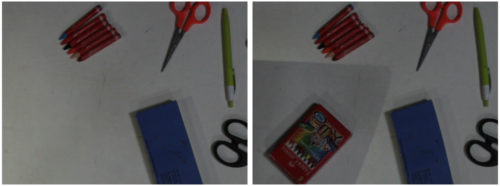
Change Detection

- The goal is to detect changes between two images taken at different times
- Image capture from moving aerial vehicles introduces motion blur (MB)
- If CMOS camera is employed, rolling shutter (RS) effect also occurs
- Illumination (IL) changes, both global and local, pose additional challenges



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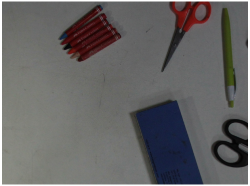


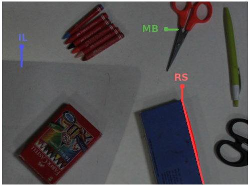
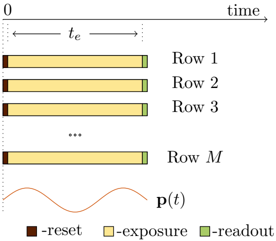
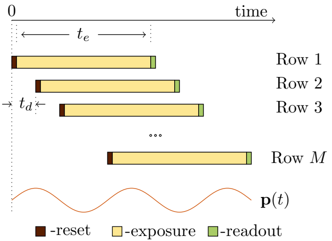


Image Formation Model in a CMOS Camera

CCD camera	CMOS camera
All pixels exposed at the same time	Unique exposure time for every row
Global motion blur model	Row-wise motion blur model





t_e : exposure time for a row

t_d : row-wise exposure delay

$\mathbf{p}(t)$: camera path

Rolling Shutter Motion Blur (RSMB) Model

- Let $\mathbf{f}$ denote the image captured without camera motion and $\mathbf{g}$ denote the image captured under camera motion $\mathbf{p}(t)$
- Each row of $\mathbf{g}$ observes a unique combination of warps of $\mathbf{f}$
- Continuous-time model:

$$\mathbf{g}^{(i)} = \frac{1}{t_e} \int_{(i-1)t_d}^{(i-1)t_d + t_e} \mathbf{f}_{\mathbf{p}(t)}^{(i)} \, dt, \text{ for } i = 1 \text{ to } M,$$

  where the superscript (i) denotes ith row and $\mathbf{f}_{\mathbf{p}(t)}$ is the warped version of $\mathbf{f}$ due to the camera pose $\mathbf{p}(t)$ at a particular time t
- Discrete model:

$$\mathbf{g}^{(i)} = \sum_{\boldsymbol{\tau}_k \in \mathcal{S}} \omega_{\boldsymbol{\tau}_k}^{(i)} \, \mathbf{f}_{\boldsymbol{\tau}_k}^{(i)} \equiv \mathbf{g}^{(i)} = \mathbf{F}^{(i)} \boldsymbol{\omega}^{(i)}$$

  where $\mathcal{S} = \{\boldsymbol{\tau}_k\}$ is a set of 6D camera poses, and $\|\boldsymbol{\omega}^{(i)}\|_1 = 1$ by energy conservation

Illumination Model

- Illumination variation is modelled as a multiplication factor $\boldsymbol{\alpha}^{(i)}$

$$\mathbf{g}^{(i)} = \boldsymbol{\alpha}^{(i)} \circ \mathbf{F}^{(i)} \boldsymbol{\omega}^{(i)}$$

  where $\circ$ is the element-wise multiplication operator
- Global variation:

$$\boldsymbol{\alpha}^{(i)} = \mathbf{a}, \quad \text{where } \mathbf{a} = [a, a, \ldots, a]$$

Hence, $\mathbf{g}^{(i)} = \mathbf{F}^{(i)} \widetilde{\boldsymbol{\omega}}^{(i)}$, where $\widetilde{\boldsymbol{\omega}}^{(i)} = a \cdot \boldsymbol{\omega}^{(i)}$ and $\|\widetilde{\boldsymbol{\omega}}^{(i)}\|_1 = a$

- Local variation: $\boldsymbol{\alpha}^{(i)} = \mathbf{a}_i$ where $\mathbf{a}_i = [a_{i1}, a_{i2}, \ldots, a_{iN}]$

Change Detection in RSMB Model

- Joint motion blur and change model:

$$\mathbf{g}^{(i)} = \begin{bmatrix} \mathbf{F}^{(i)} & I \end{bmatrix} \begin{bmatrix} \boldsymbol{\omega}^{(i)} \\ \boldsymbol{\chi}^{(i)} \end{bmatrix} = \mathbf{B}^{(i)} \boldsymbol{\xi}^{(i)} \quad \text{for } i = 1, 2, \ldots, M$$

row-wise motion blur
changed pixels

- Optimization problem:

$$\widetilde{\boldsymbol{\xi}}^{(i)} = \arg\min_{\boldsymbol{\xi}^{(i)}} \left\{ \|\mathbf{g}^{(i)} - \mathbf{B}^{(i)} \boldsymbol{\xi}^{(i)}\|_2^2 + \lambda_1 \| \boldsymbol{\omega}^{(i)} \|_1 + \lambda_2 \| \boldsymbol{\chi}^{(i)} \|_1 \right\}$$

sparsity of camera motion
sparsity of changes
λ_1 and λ_2 are non-negative regularization parameters

Experiments

Change detection of RSMB image with global illumination variations

Reference image

RSMB image

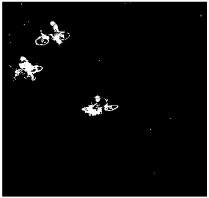
Experiments

Change detection of RSMB image with global illumination variations

Reference image

RSMB image

Registered image



Detected changes

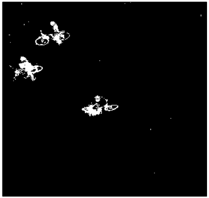
Experiments

Change detection of RSMB image with global illumination variations

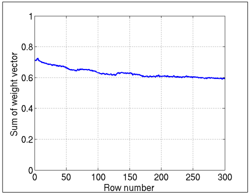
Reference image

RSMB image

Registered image



Detected changes



Plot of $\|\omega^{(i)}\|_1$ vs. i

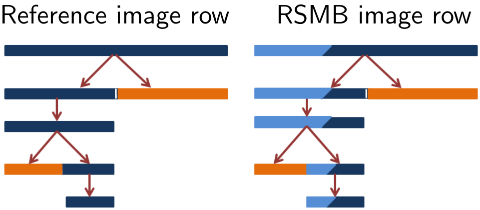
Handling Local Illumination Variations

Algorithm 1 Change detection in the presence of local illumination variations for ith row.

1: Initialize: `block` $=$ `row`
2: Estimate pose weight vector $\boldsymbol{\omega}^{(i)}_{\texttt{block}}$ and occlusion vector $\boldsymbol{\chi}^{(i)}_{\texttt{block}}$ for `block`
3: Let B be the length of `block`
4: Calculate $\mathbf{d} = \mathbf{g}^{(i)}_{\texttt{block}} - \boldsymbol{\omega}^{(i)}_{\texttt{block}} \mathbf{F}^{(i)}_{\texttt{block}}$
5: Calculate $k = \|abs(\mathbf{d}) > \epsilon\|_0$
6: **if** $k > 0.2B$ **or** $B/2 \geq B_{min}$ **then**
7:     Split `block` into two, `block_l` and `block_r`
8:     Repeat from Step 2 for `block_l` and `block_r`
9: **else**
10:     **if** $\|\boldsymbol{\chi}^{(i)}_{\texttt{block}} > \epsilon\|_0 > 0.1B$ **then**
11:         $\boldsymbol{\omega}^{(i)}_{\texttt{block}} = \boldsymbol{\omega}^{(i)}_{\texttt{prev\_block}}$
12:         Realign difference region r
13:     **end if**
14: **end if**

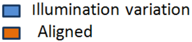
Handling Local Illumination Variations

- Divide recursively the row into blocks until the block has almost uniform illumination



- Align using weights of previous section (which is correctly aligned)

- Realign difference region



$$\min_{\boldsymbol{\omega}_r^{(i)}} \left\{ \|\mathbf{g}_r^{(i)} - \mathbf{F}_r^{(i)} \boldsymbol{\omega}_r^{(i)}\|_2^2 + \lambda_1 \|\boldsymbol{\omega}_r^{(i)}\|_1 \right\} \text{ subject to } \boldsymbol{\omega}_r^{(i)} \succeq 0$$

Experiments

Local illumination variations: Synthetic case

Reference

RSMB

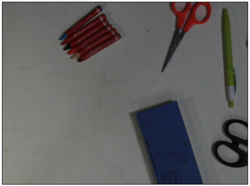
Registered

Change vector

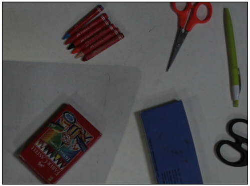
Detected changes

Experiments

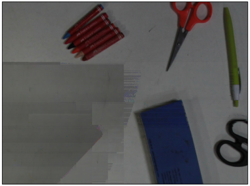
Local illumination variations: Real case



Reference



RSMB



Registered

Detected changes

Conclusions

- Proposed an algorithm to handle jointly, the effects of rolling shutter, motion blur, and illumination variation for the application of change detection
- Framed an optimization problem to handle motion blur and rolling shutter effect, and devised a recursive algorithm to handle local illumination variations

- A possible direction of future work is to do away with the assumption of the reference image being clean