

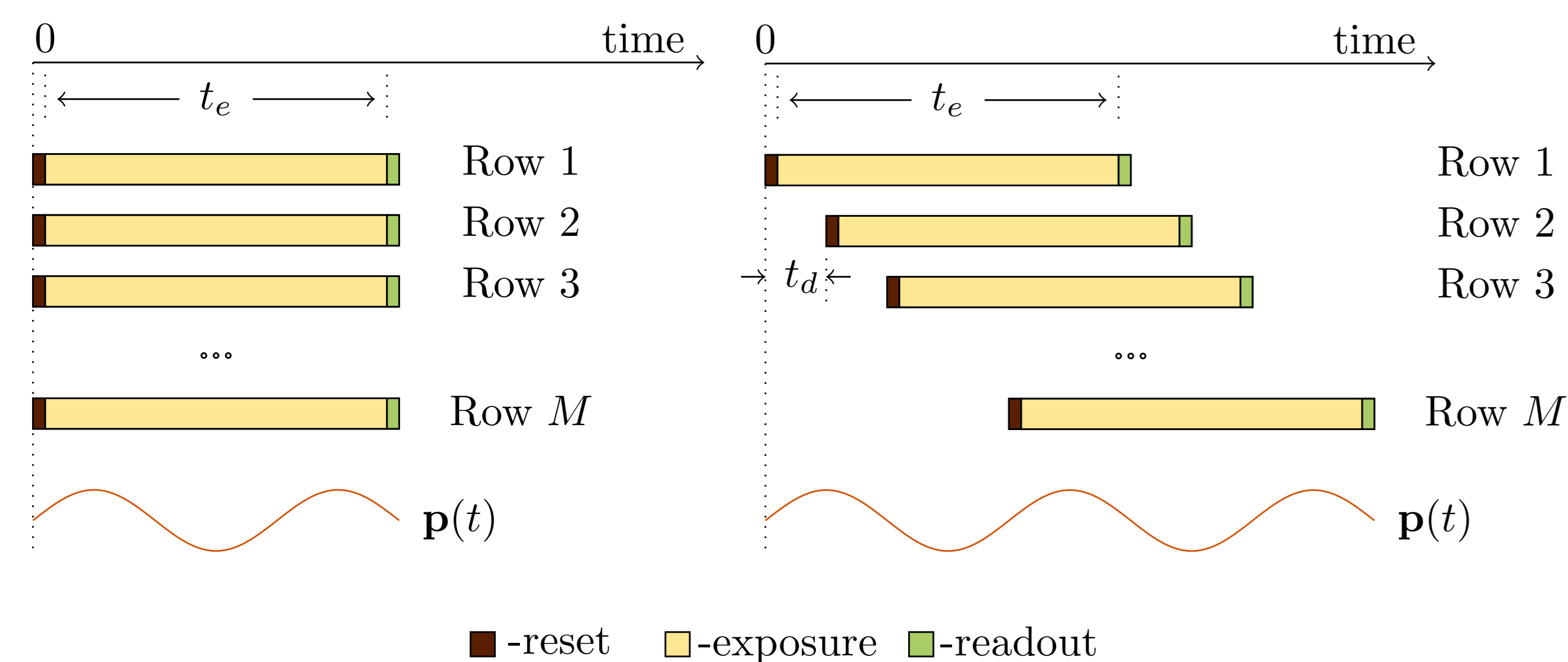


1 Introduction

- CMOS sensors are prevalent nowadays, especially in mobile phones, due to their low cost and power consumption
- Sequential exposure of rows in CMOS sensors causes both motion blur (MB) and rolling shutter (RS) effect
- Change detection in such images is a challenging task
- A joint framework is proposed to register a reference image and a distorted image, and to also simultaneously detect occlusions
- Assumption: The reference image is clean and free from artifacts

2 Motion Blur in Rolling Shutter Cameras

- Each row in a rolling-shutter camera experiences different camera motion during its own unique exposure time
- This is unlike global shutter (GS) cameras, where all the pixels are exposed during the same period
- Induced motion blur is thus different



(a) Global shutter

(b) Rolling shutter

- Due to the camera motion trajectory $\mathbf{p}(t)$, every row of the observation \mathbf{g} is equal to the corresponding row in the weighted average of warps of \mathbf{f}

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

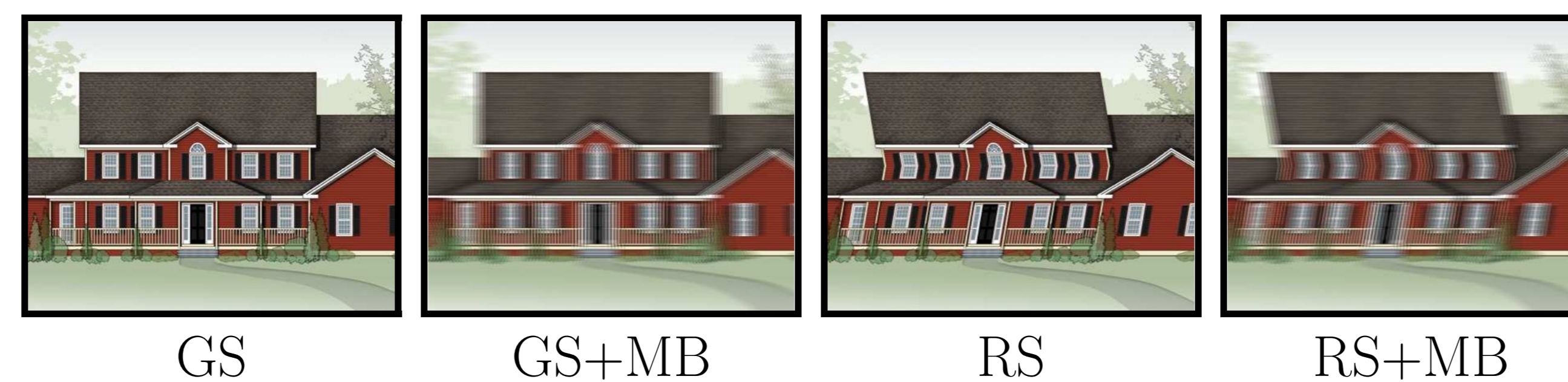
$\mathbf{f}_{\mathbf{p}(t)}^{(i)}$ represents the i th row of the warped version of \mathbf{f} due to the camera pose $\mathbf{p}(t)$

- Discretisation with respect to a camera pose space $\mathcal{S}^{(i)} = \{\tau_k\}$

$$\mathbf{g}^{(i)} = \sum_{\tau_k \in \mathcal{S}} \omega_{\tau_k}^{(i)} \mathbf{f}_{\tau_k}^{(i)} \quad (2)$$

- $\omega_{\tau_k}^{(i)}$ is the pose weight vector of the i th row, and each element $\omega_{\tau_k}^{(i)}$ represents the fraction of the row exposure time that the camera has stayed in the pose τ_k

Type	Inter-row delay	Pose weight vector ($1 \leq i \leq M$)
GS	$t_d = 0$	$\omega_{\tau_k}^{(i)} = \begin{cases} 1 & \text{for } k = k_0 \\ 0 & \text{otherwise} \end{cases}$ where k_0 is independent of i
GS+MB	$t_d = 0$	Same $\omega^{(i)}$ for all i
RS	$t_d \neq 0$	$\omega_{\tau_k}^{(i)} = \begin{cases} 1 & \text{for } k = k_i \\ 0 & \text{otherwise} \end{cases}$
RS+MB	$t_d \neq 0$	Different $\omega^{(i)}$ for each i



3 Joint Estimation of Camera Motion and Occlusion

Equivalent representation of (2): $\mathbf{g}^{(i)} = \mathbf{F}^{(i)} \omega^{(i)}$ (3)

Occlusion model: $\mathbf{g}_{\text{occ}}^{(i)} = \begin{bmatrix} \mathbf{F}^{(i)} & \mathbf{I}_N \end{bmatrix} \begin{bmatrix} \omega^{(i)} \\ \chi^{(i)} \end{bmatrix} = \mathbf{B}^{(i)} \xi^{(i)}$ (4)

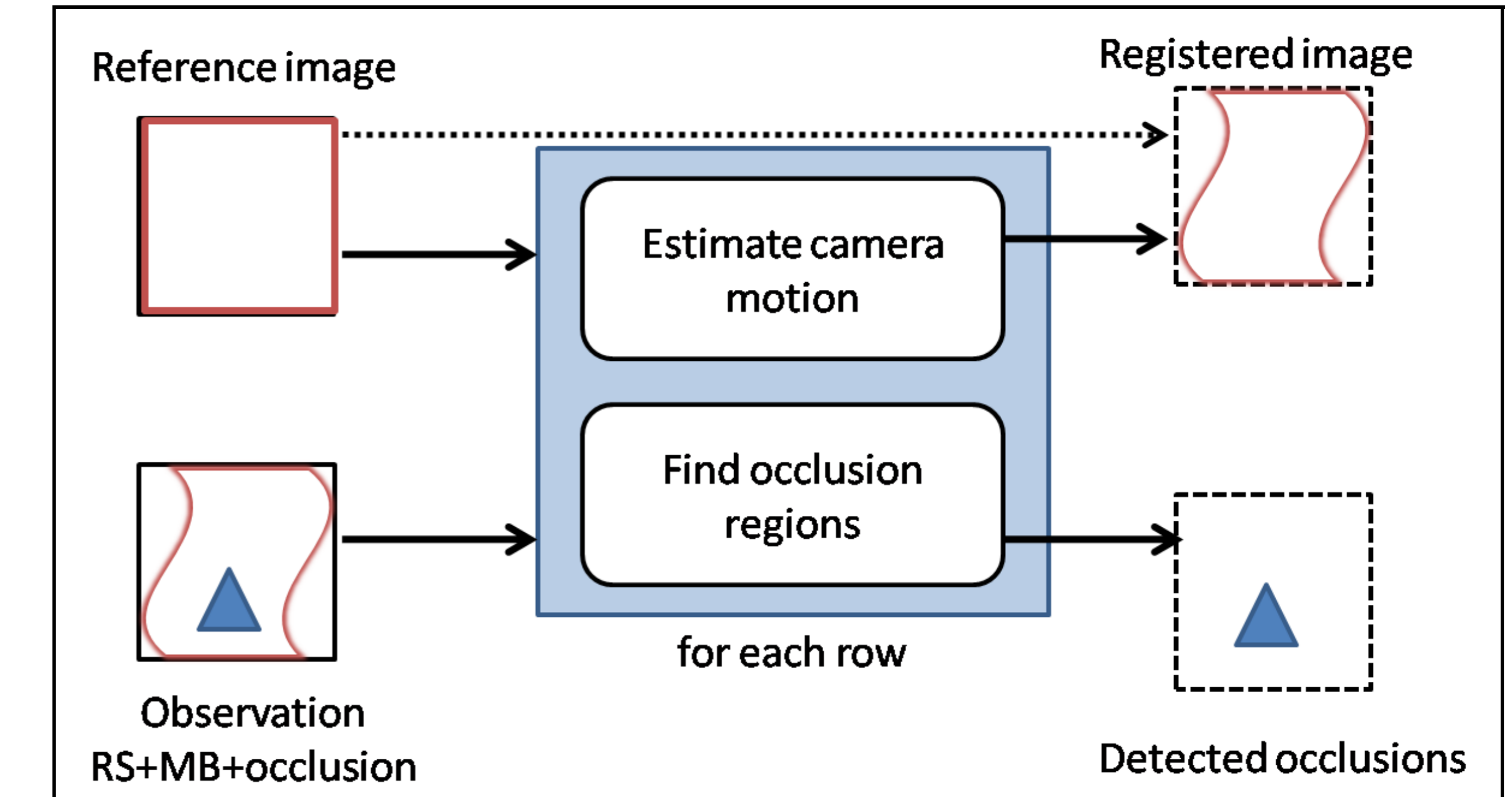
■ sparsity of both camera motion and occlusion

■ non-negativity only on pose weights

$$\tilde{\xi}^{(i)} = \arg \min_{\xi^{(i)}} \left\{ \|\mathbf{g}_{\text{occ}}^{(i)} - \mathbf{B}^{(i)} \xi^{(i)}\|_2^2 + \lambda_1 \|\omega^{(i)}\|_1 + \lambda_2 \|\chi^{(i)}\|_1 \right\} \quad (5)$$

subject to $\omega^{(i)} \succeq 0$

Block diagram of our change detection method



Pose space adaptation:

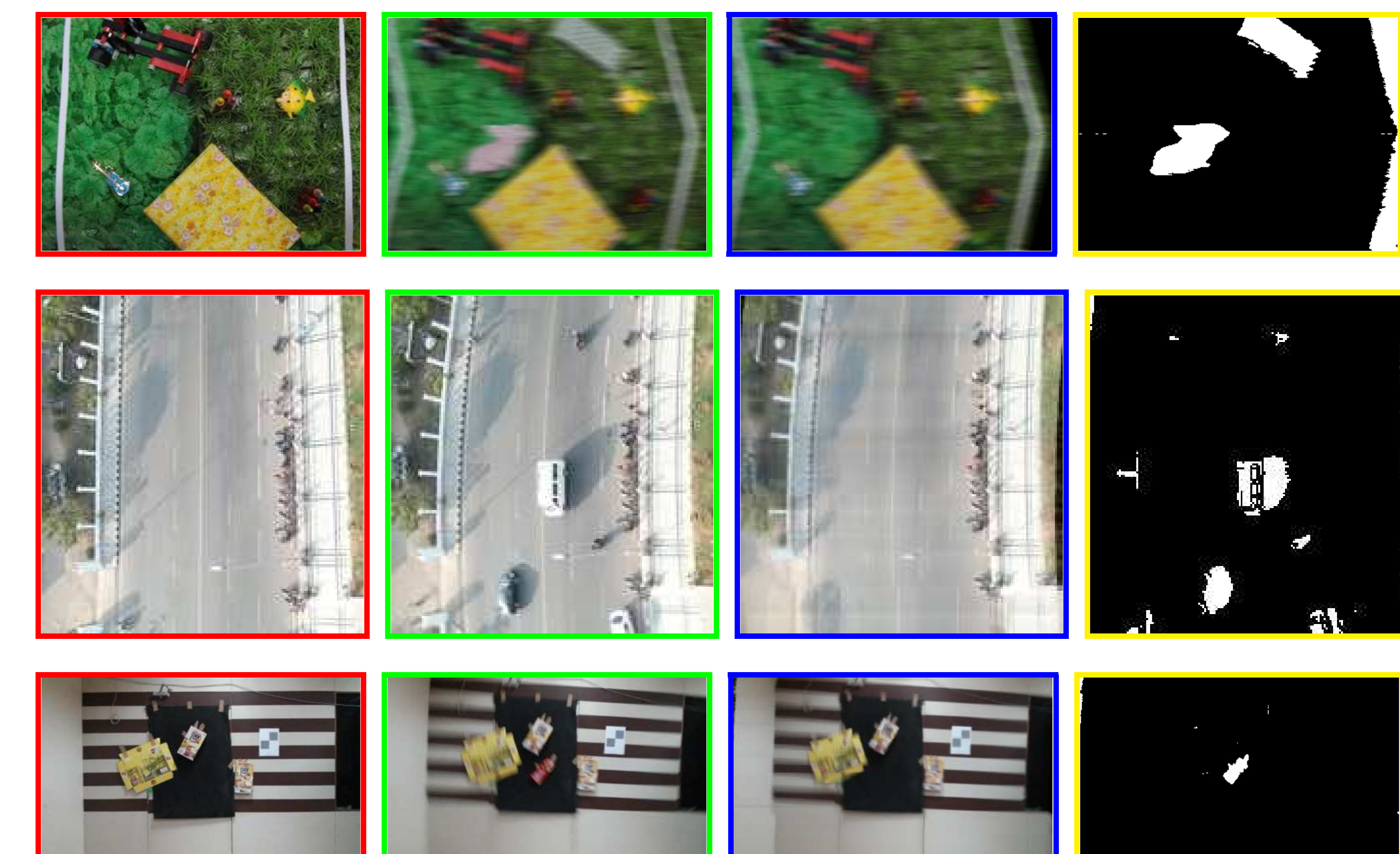
- Start at $i = M/2$ with a pose space $\mathcal{S}^{(M/2)}$. Choose pose space of other rows as neighbourhood of the centroid pose of the nearby row

$$\mathcal{S}^{(i)} = \begin{cases} N(\tau_c^{(i+1)}, \mathbf{b}, \mathbf{s}) & i < M/2 \\ N(\tau_c^{(i-1)}, \mathbf{b}, \mathbf{s}) & i > M/2 \end{cases} \quad (6)$$

$$N(\tau, \mathbf{b}, \mathbf{s}) = \{\tau + q\mathbf{s} : \tau - \mathbf{b} \preceq \tau + q\mathbf{s} \preceq \tau + \mathbf{b}, q \in \mathbb{Z}\} \quad (7)$$

$$\text{Centroid pose, } \tau_c^{(i)} = \frac{\sum_{\tau_k} \omega_{\tau_k}^{(i)} \tau_k}{\sum_{\tau_k} \omega_{\tau_k}^{(i)}}$$

4 Experimental Results



Reference image RSMB image Registered image Occlusion regions