Fusing Frame and Event data for High Dynamic Range Video

Robert Mahony

THE AUSTRALIAN NATIONAL UNIVERSITY

Systems Theory and Robotics group

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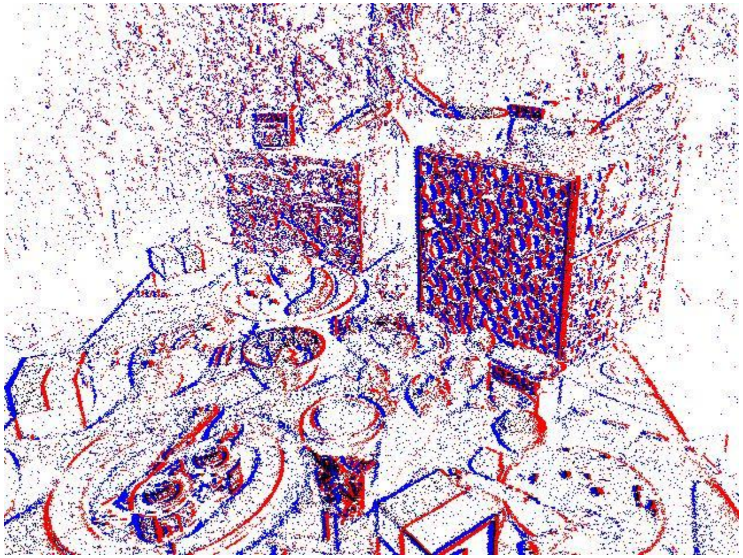
Event versus Frame Cameras

Event Camera

- Asynchronous events
- Temporally dense information
- No image blur.
- High dynamic range

Frame camera

- Synchronous images
- Spatially dense information
- Adjustable exposure
- Images absolute intensity
- Images static scenes.



Events and Frame data from picnic dataset

By fusing event and frame data it should be possible to have it all

- Images that are spatially and temporally dense
  - Full image available at any time stamp.
- Images with High Dynamic Range (HDR) in absolute intensity scale.
- Able to image both static scenes and highly dynamic scenes without blur.

High Dynamic Range Reconstruction

Raw
Frame

E2VID
Event
only

Asynchronous
Kalman
Filter
Event-Frame

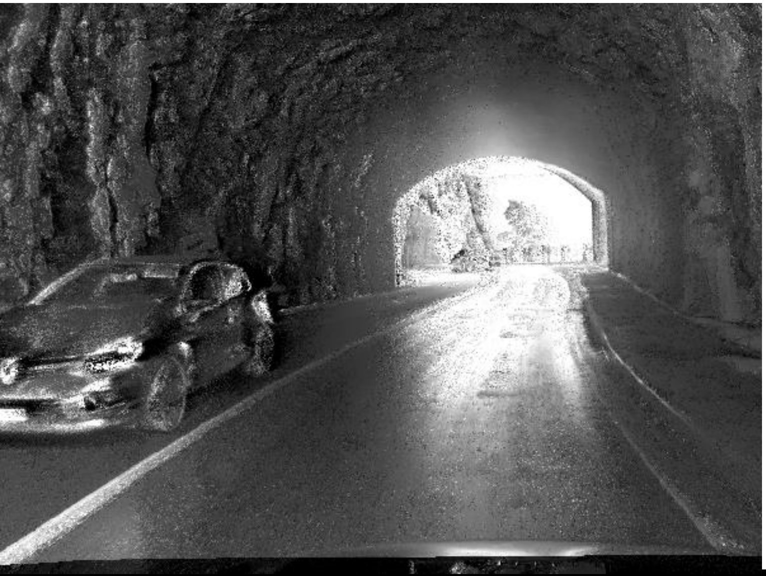
ECNN
Event
only

DSEC dataset
Gehrig et. al

High Dynamic Range Reconstruction

Raw Frame

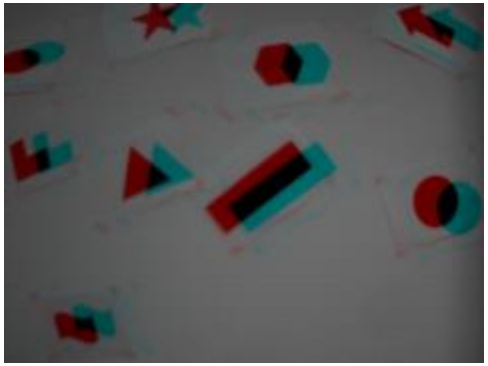
E2VID Event only



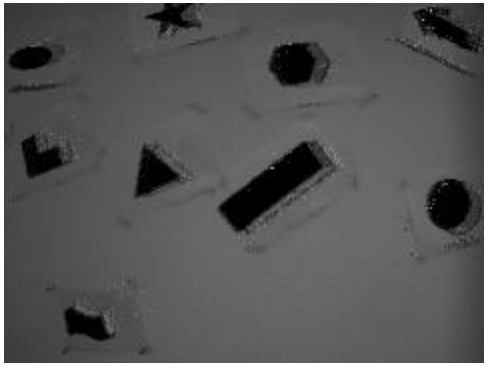
Asynchronous Kalman Filter Event-Frame

ECNN Event only

DSEC dataset
Gehrig et. al



Raw
Frame



Event-based
Double
Integral (EDI)

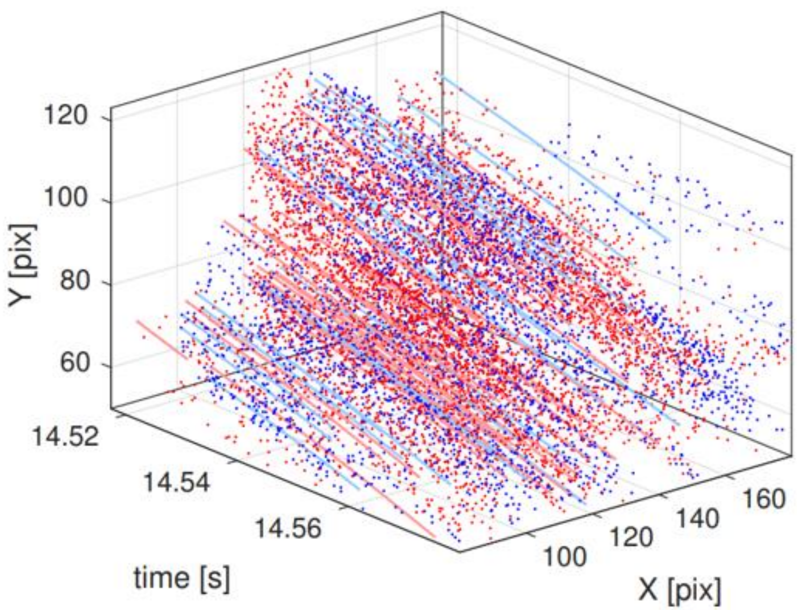
Asynchronous
Kalman
Filter
Event-Frame

Shapes data set
Mueggler et al

An event camera yields a series of events $\{e_k\}$

$$e_k = (\sigma_k, t_k, u_k, v_k)$$

where $(\sigma_k, t_k, u_k, v_k)$ are the polarity, time stamp and pixel location of event k.



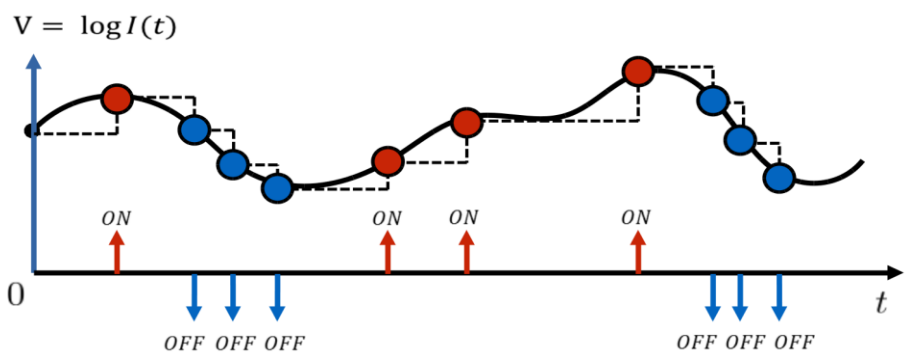
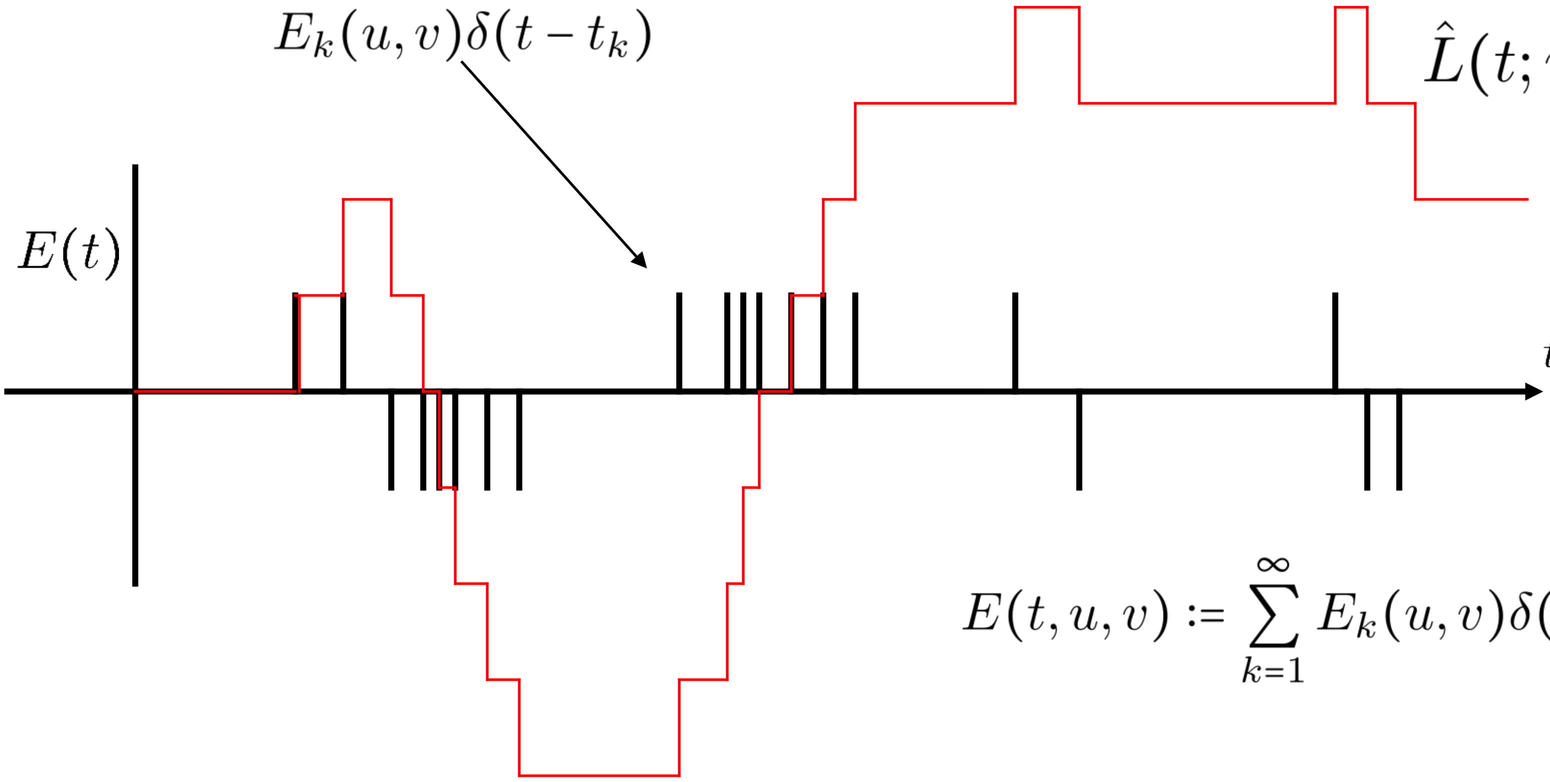


Image reconstruction



$$E(t,u,v) := \sum_{k=1}^{\infty} E_k(u,v)\delta(t-t_k)$$

$$\boxed{\hat{L}(t;u,v) = \sum_{\{k \mid t_k \le t\}} E_k(u,v) = \int_{-\infty}^{t} E(\tau,u,v)\mathrm{d}\tau}$$

Direct integration

$$\hat{L}(t; u, v) = \int_{-\infty}^{t} E(\tau, u, v) \mathrm{d}\tau$$

$$E_{(u,v)}(t) \longrightarrow \boxed{\frac{1}{s}} \longrightarrow \hat{L}_{(u,v)}(t)$$

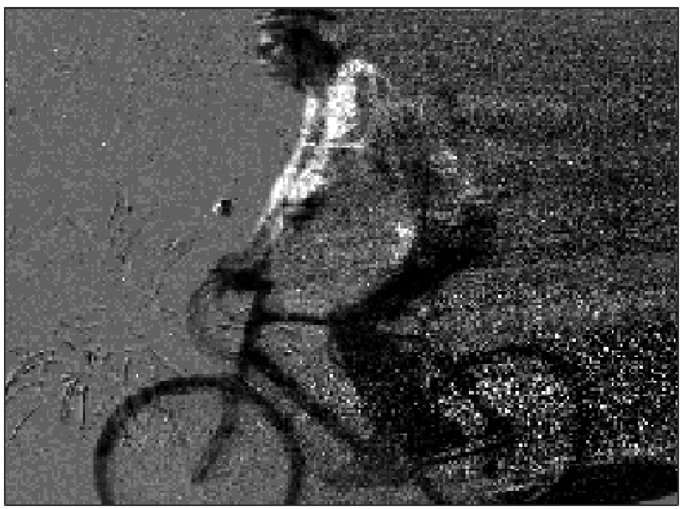
Transfer function interpretation of direct integration

High levels of noise in the event stream stay in the image stream and make direct integration impractical.

High pass the state estimate filter

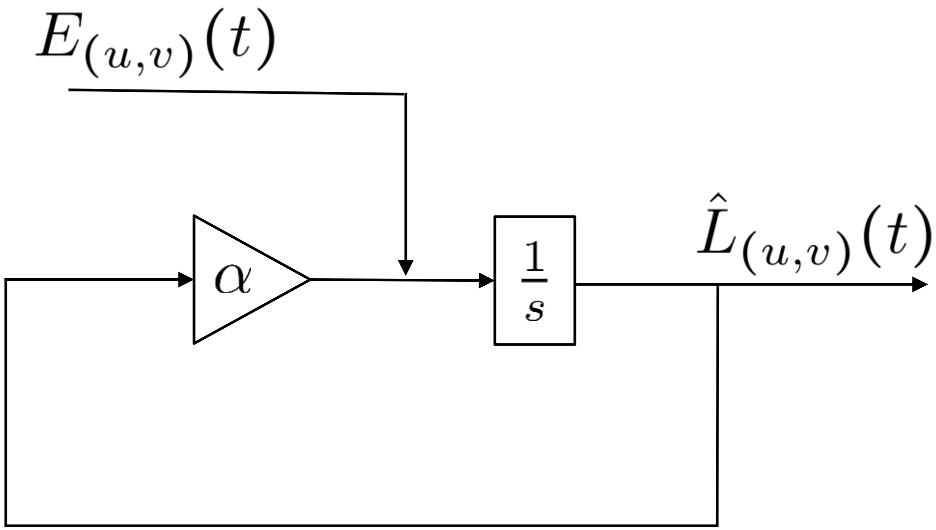
$$E_{(u,v)}(t) \longrightarrow \boxed{\frac{1}{s}} \longrightarrow \boxed{\frac{s}{s+\alpha}} \longrightarrow \hat{L}_{(u,v)}(t)$$

Integration High pass filter



Integration without high pass

Integration with high pass



Transfer function realisation

$$\hat{L}_{(u,v)}(s) = \frac{s}{s+\alpha}\frac{1}{s}E_{(u,v)}(s)$$

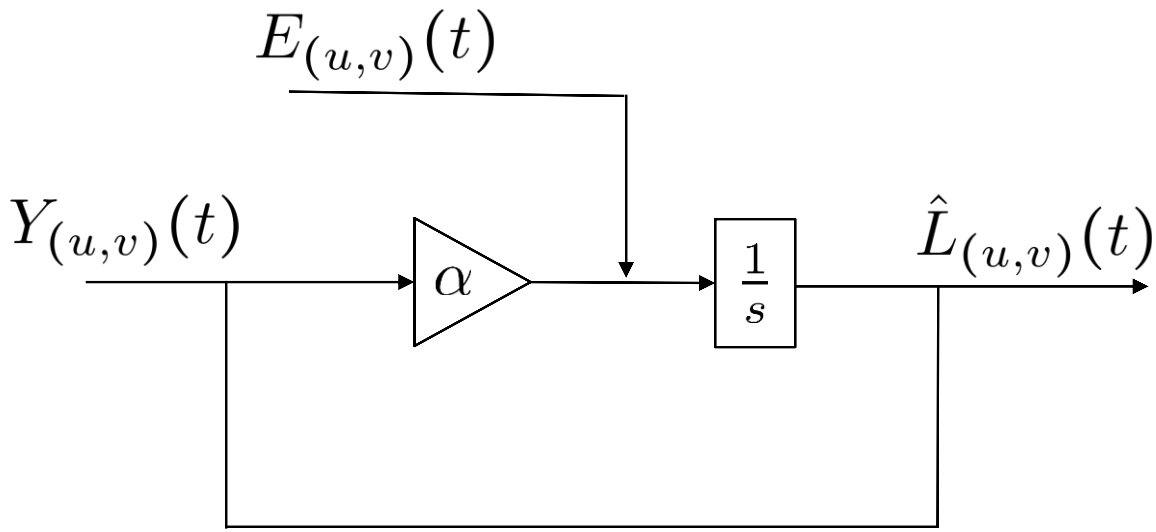
ODE system realisation

$$\frac{\mathrm{d}}{\mathrm{d}t}\hat{L}_{(u,v)}(t) = -\alpha\hat{L}_{(u,v)}(t) + E_{(u,v)}(t)$$

Image state:
$\hat{L}_{(u,v)}(t)$ is the internal state of the filter.

Complementary filter

If an estimate $Y_k(u,v)$ of the conventional image is available



Transfer function realisation

$$\hat{L}_{(u,v)}(s) = \frac{s}{s+\alpha}\frac{1}{s}E_{(u,v)}(s) + \frac{\alpha}{s+\alpha}Y_{(u,v)}(s)$$

ODE system realisation

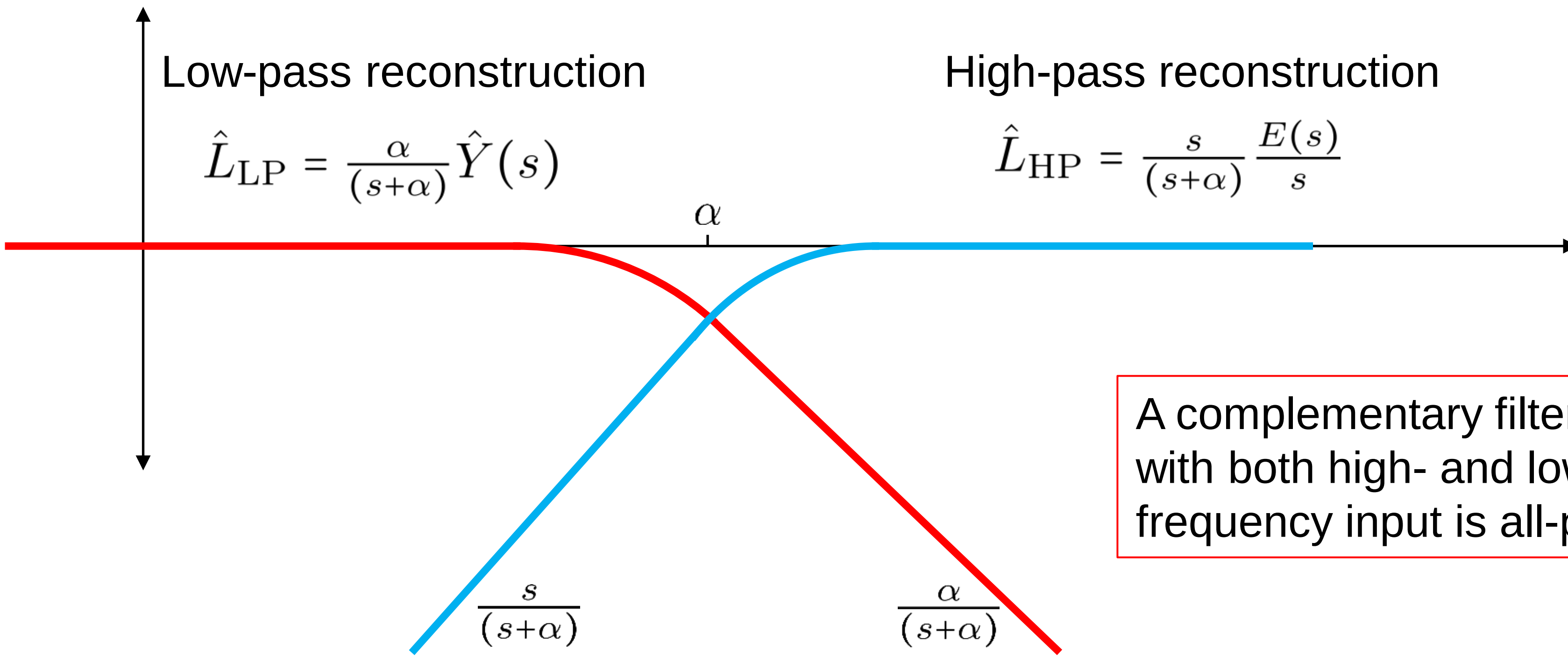
$$\frac{\mathrm{d}}{\mathrm{d}t}\hat{L}_{(u,v)}(t) = -\alpha(\hat{L}_{(u,v)}(t) - Y_{(u,v)}(t)) + E_{(u,v)}(t)$$

If

$$\begin{aligned}\int_{-\infty}^{t_k} E(\tau,u,v)\mathrm{d}\tau &\approx L(t_k,u,v)\\ &\approx Y_k(u,v)\end{aligned}$$

$$\begin{aligned}\hat{L}(s,u,v) &\approx \left(\frac{s}{s+\alpha} + \frac{\alpha}{s+\alpha}\right)L(t,u,v)\\ &\approx L(t,u,v)\end{aligned}$$

Frequency interpretation



A complementary filter with both high- and low-frequency input is all-pass

$$\hat{L}(s) = \hat{L}_{\mathrm{LP}} + \hat{L}_{\mathrm{HP}} = \frac{\alpha}{(s+\alpha)}\hat{Y}(s) + \frac{s}{(s+\alpha)}\frac{\hat{E}(s)}{s}$$

Ordinary differential equation

$$\frac{\mathrm{d}}{\mathrm{d}t}\hat{L}_{(u,v)}(t) = -\alpha(\hat{L}_{(u,v)}(t) - Y_{(u,v)}(t)) + E_{(u,v)}(t)$$

Solve on the time period $t \in (t_k, t_{k+1})$ for $\hat{L}_{(u,v)}(t_k)$ known.
For $Y_{(u,v)}(t)$ constant (zero-order-hold) and $E_{(u,v)}(t) \equiv 0$ then

A $$\boxed{\hat{L}_{(u,v)}(t_{k+1}) = e^{-\alpha(t_{k+1}-t_k)}\hat{L}_{(u,v)}(t_k) + (1 - e^{-\alpha(t_{k+1}-t_k)})(\hat{L}_{(u,v)}(t_k) - Y_{(u,v)}(t_k))}$$

Solve on the time period $t \in [t_{k+1}, t_{k+1}]$ for $\hat{L}_{(u,v)}(t^-_{k+1})$ known.
Integrate through the Dirac delta function

B $$\boxed{\hat{L}_{(u,v)}(t^+_{k+1}) = \hat{L}_{(u,v)}(t^-_{k+1}) + \sigma_k \delta_{(u_k,v_k)}(u,v)}$$

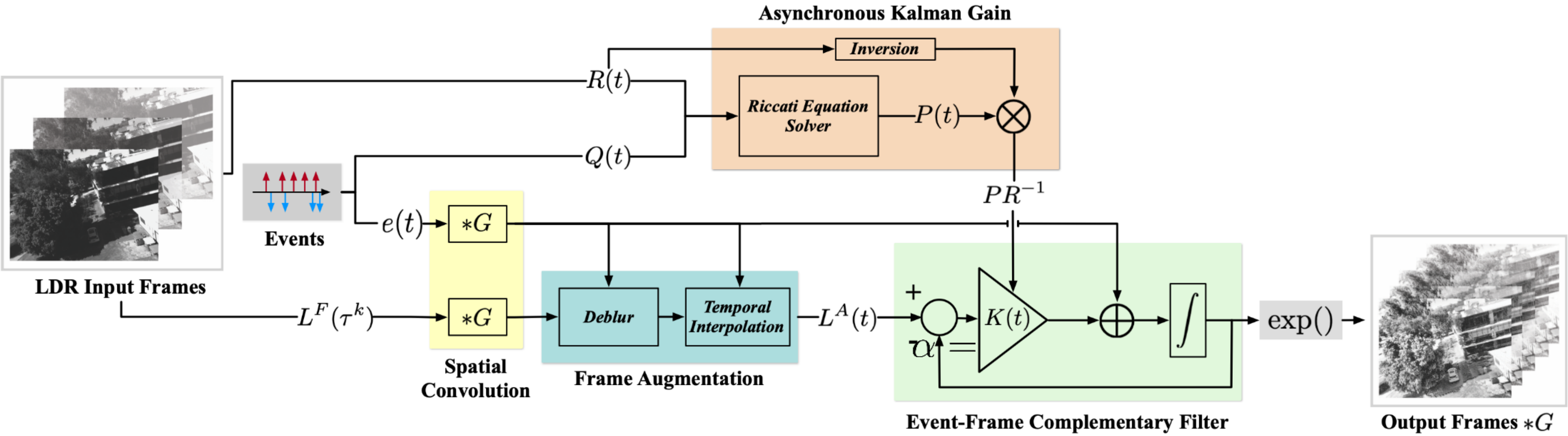
- Asynchronous: Only compute when an event arrives.
- Computationally efficient: One scalar exponential.
- Image state: Estimate $\hat{L}(t,u,v)$ is stored in memory and can be accessed whenever required.

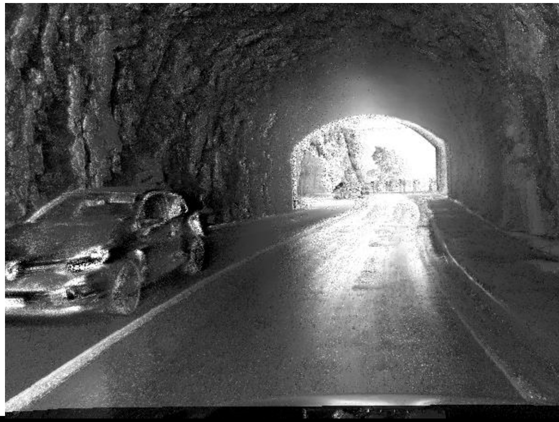
The gain α used in the image reconstruction filter is tuned by hand. Typical value $\alpha = 6\text{rad/s}$.

However, adaptively tuning the gain will produce much better response across the full image.

- Pixels where the conventional camera is properly exposed should trust the conventional camera response.
- Pixels where the conventional camera is under or over exposed should trust the event camera response.

How should the gain α be adaptively tuned.

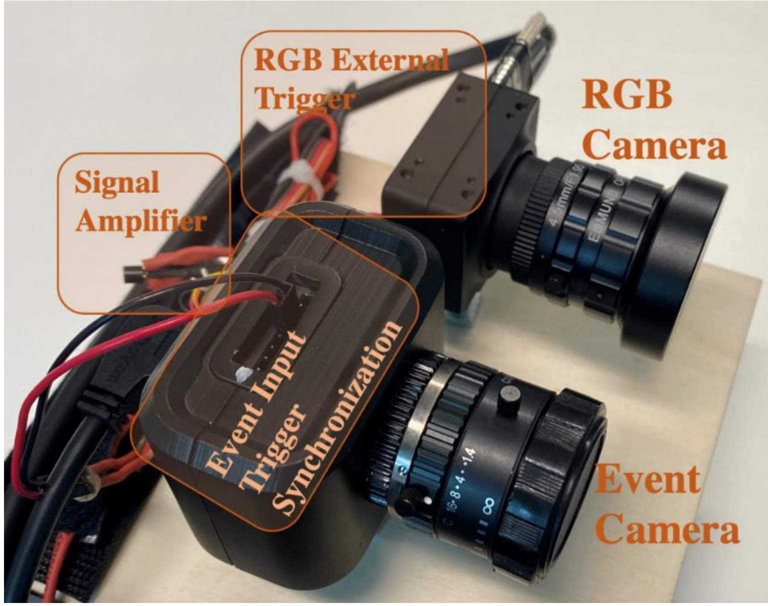

Asynchronous Kalman Gain
Inversion
Riccati Equation Solver
$R(t)$
$Q(t)$
$P(t)$
PR^{-1}
LDR Input Frames
Events
$e(t)$
$*G$
$*G$
$L^F(\tau^k)$
Spatial Convolution
Deblur
Temporal Interpolation
Frame Augmentation
$L^A(t)$
+
$-\alpha$
$K(t)$
$\int$
exp()
Event-Frame Complementary Filter
Output Frames $*G$



Results

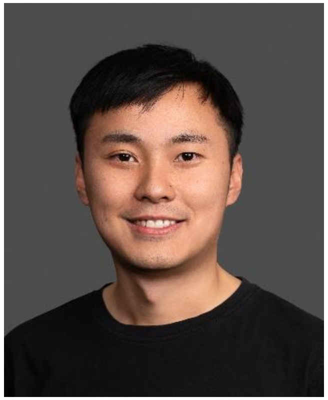
Asynchronous Kalman filter (AKF)

- Exploit the asynchronous nature of the sensor with algorithm design and implementation.
- Use both frame and event data.



- A shallow algorithm (no deep learning)

As the quality of event camera sensors improves so will the output of the AKF



Yonhon Ng

System Theory and Robotics group

THANKS

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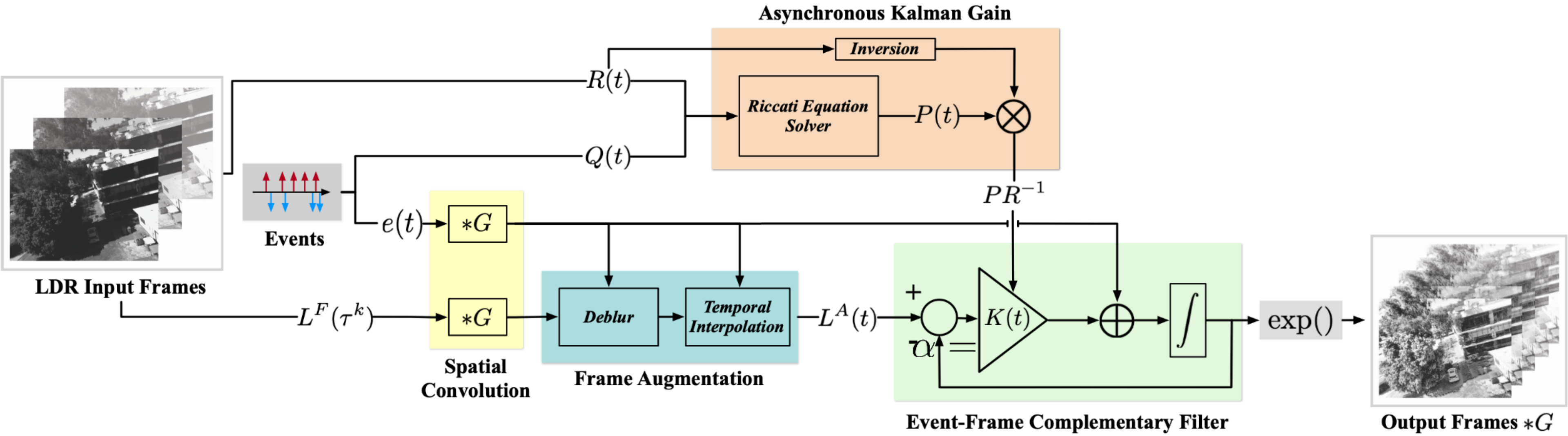
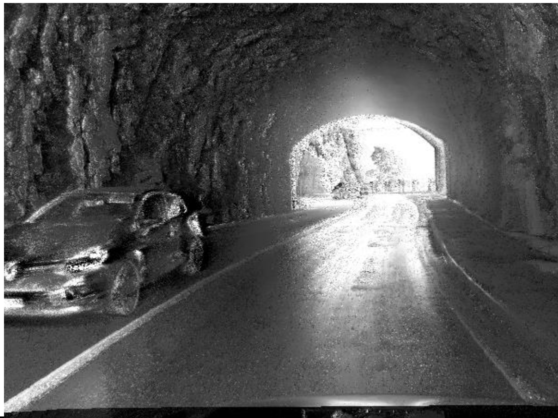
Asynchronous Kalman Filter



Details



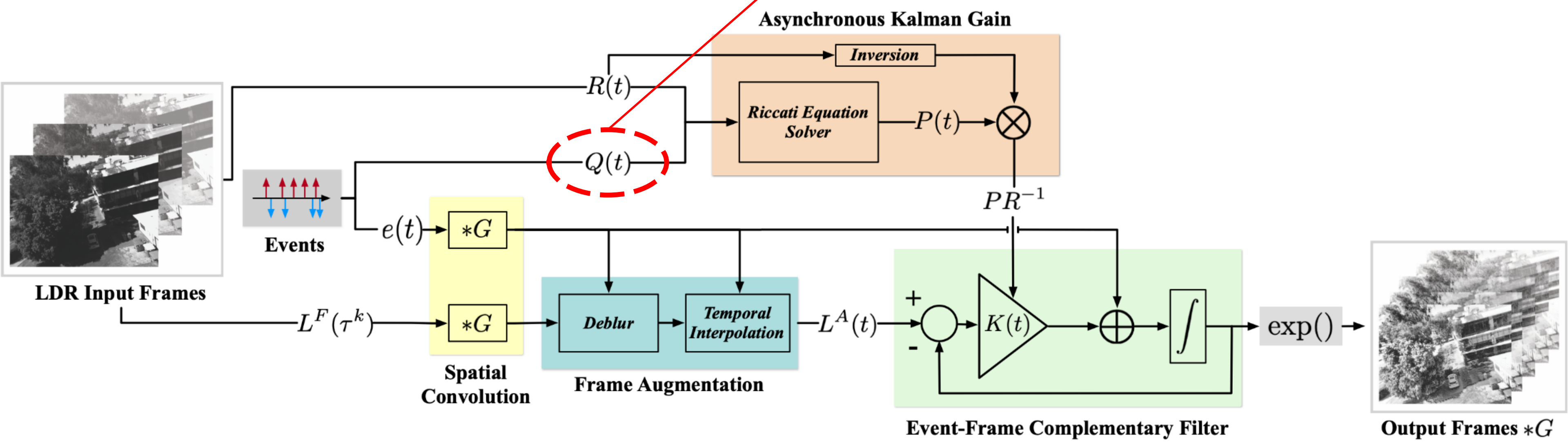
Noise in the event data

$$e_{\vec{p}}(t) = \sum_{i=1}^{\infty} (c\sigma^i_{\vec{p}} + \eta^i_{\vec{p}})\delta(t - t^i_{\vec{p}}), \qquad \eta^i_{\vec{p}} \sim \mathcal{N}\left(0, Q^{\text{proc.}}_{\vec{p}}(t) + Q^{\text{iso.}}_{\vec{p}}(t) + Q^{\text{ref.}}_{\vec{p}}(t)\right)$$

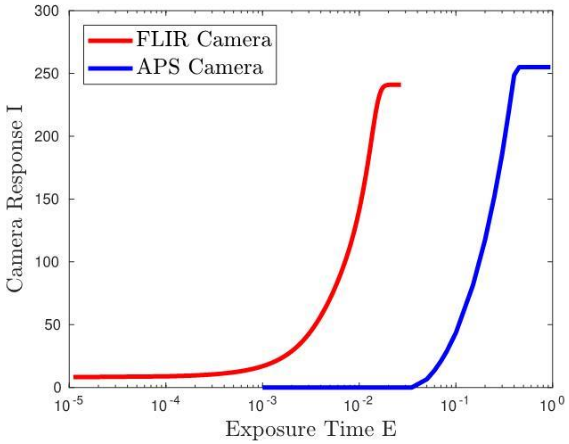
Process noise: $Q^{\text{proc.}}_{\vec{p}}(t^i_{\vec{p}}) = \sigma^2_{\text{proc.}}(t^i_{\vec{p}} - t^{i-1}_{\vec{p}})$

Isolated pixel noise: $Q^{\text{iso.}}_{\vec{p}}(t^i_{\vec{p}}) = \sigma^2_{\text{iso.}} \min\{t^i_{\vec{p}} - t^*_{N(\vec{p})}\}$

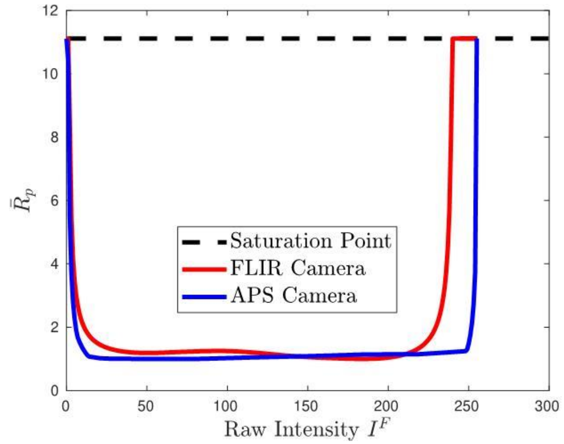
Refractory period noise: $Q^{\text{ref.}}_{\vec{p}}(t^i_{\vec{p}}) = \begin{cases} 0 & \text{if } t^i_{\vec{p}} - t^{i-1}_{\vec{p}} > \bar{\rho} \\ \sigma^2_{\text{ref.}} & \text{if } t^i_{\vec{p}} - t^{i-1}_{\vec{p}} \leq \bar{\rho}, \end{cases}$

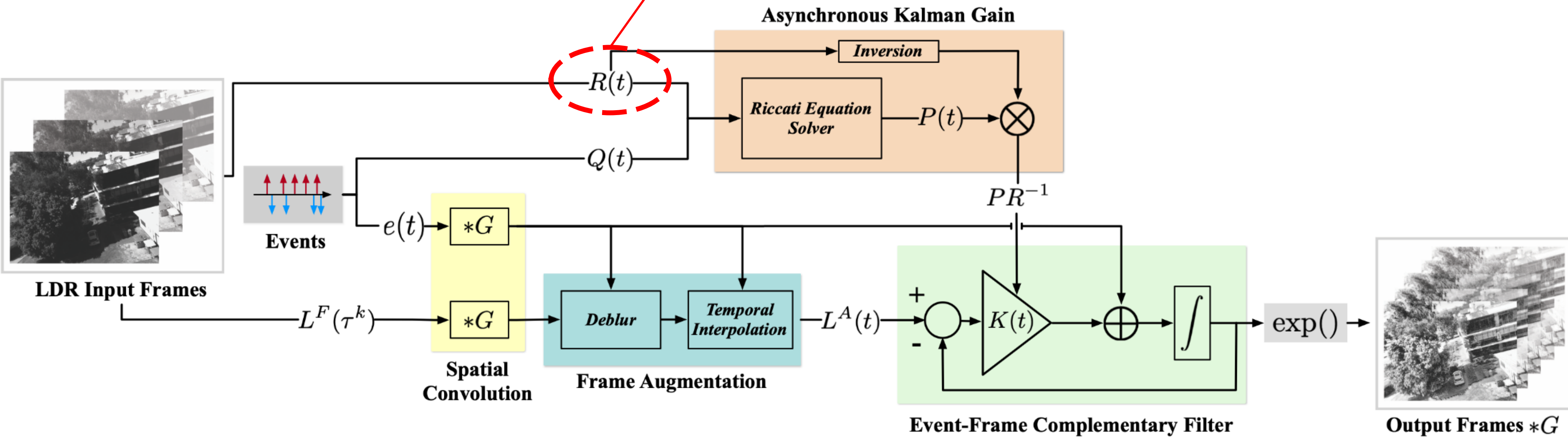


Noise in frame data



$$I^F_{\vec{p}}(\tau^k) = CRF^{-1}\lfloor I_{\vec{p}}(\tau^k)\rfloor + \mu^k_{\vec{p}},$$
$$\mu^k_{\vec{p}} \sim N(0, \bar{R}_{\vec{p}}(\tau^k)),$$



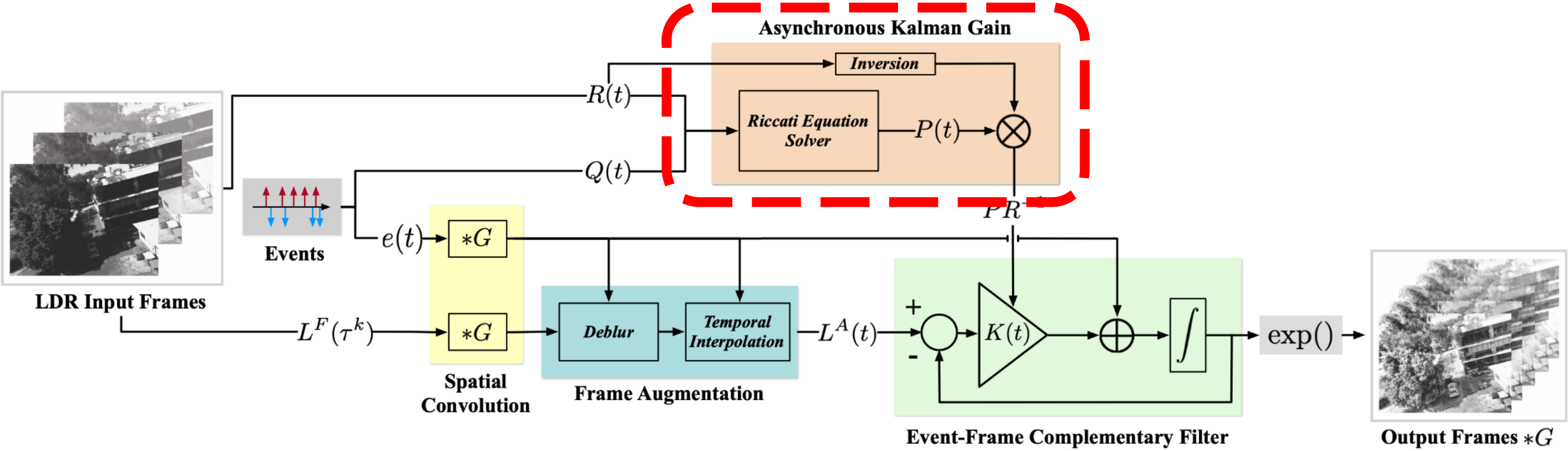


Riccati computation

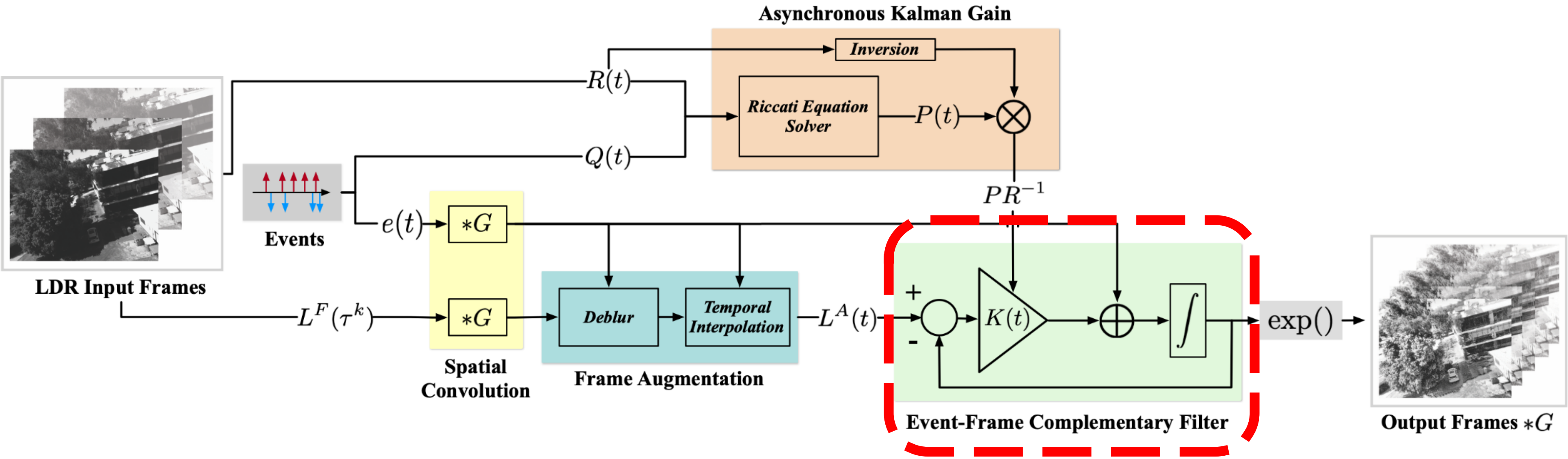
$$P_{\vec{p}}(t) = \frac{1}{P_{\vec{p}}^{-1}(t_{\vec{p}}^{i}) + R_{\vec{p}}^{-1}(t)\cdot(t - t_{\vec{p}}^{i})} \quad \text{for } t \in [t_{\vec{p}}^{i}, t_{\vec{p}}^{i+1})$$

$$\boxed{\dot{P}_{\vec{p}} = -P_{\vec{p}}^{2} R_{\vec{p}}(t) + Q_{\vec{p}}(t)}$$

$$P_{\vec{p}}(t_{\vec{p}}^{i}) = P_{\vec{p}}(t_{\vec{p}}^{i-}) + Q_{\vec{p}}(t_{\vec{p}}^{i})$$



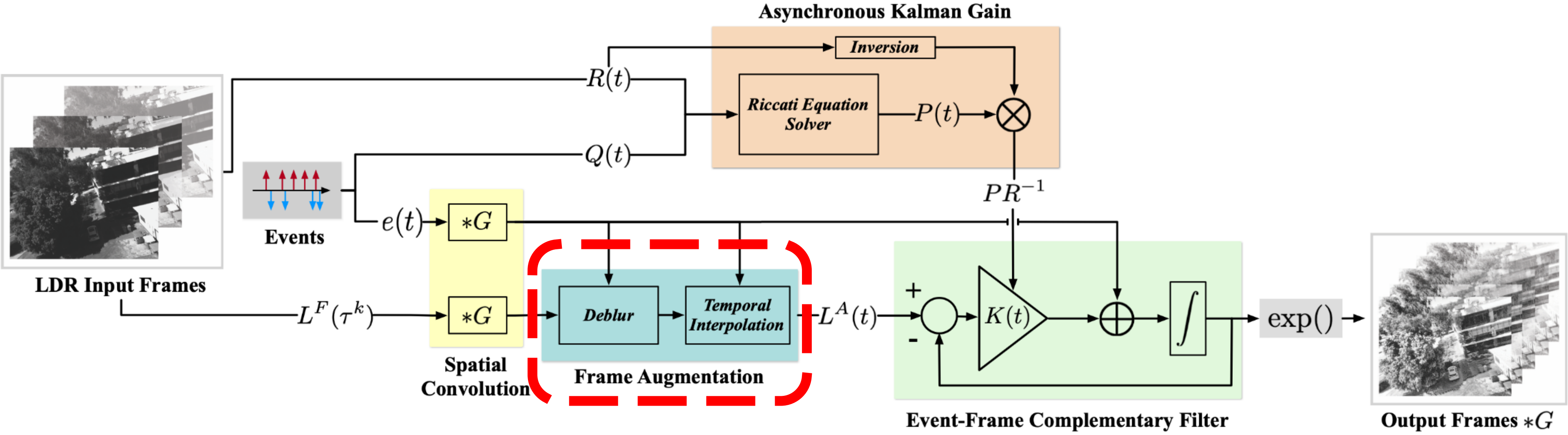
Filter update



$$\hat{L}_{\vec{p}}(t) = \frac{[\hat{L}_{\vec{p}}(t^i_{\vec{p}}) - L^A_{\vec{p}}(t^i_{\vec{p}})] \cdot P^{-1}_{\vec{p}}(t^i_{\vec{p}})}{P^{-1}_{\vec{p}}(t^i_{\vec{p}}) + R^{-1}_{\vec{p}}(t) \cdot (t - t^i_{\vec{p}})} + L^A_{\vec{p}}(t)$$

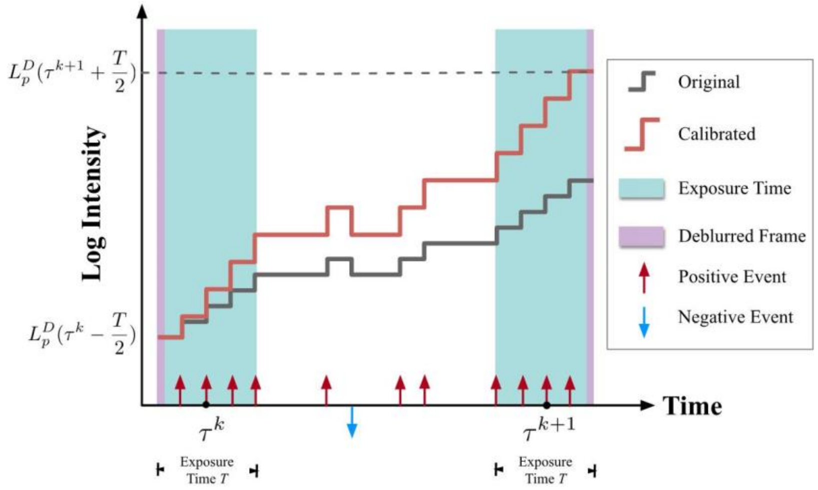
$$\boxed{\dot{\hat{L}}_{\vec{p}}(t) = e_{\vec{p}}(t) - K_{\vec{p}}(t)[\hat{L}_{\vec{p}}(t) - L^A_{\vec{p}}(t)]}$$

$$L_{\vec{p}}(t^i_{\vec{p}}) = \hat{L}_{\vec{p}}(t^{i-}_{\vec{p}}) + e_{\vec{p}}(t^i_{\vec{p}})$$

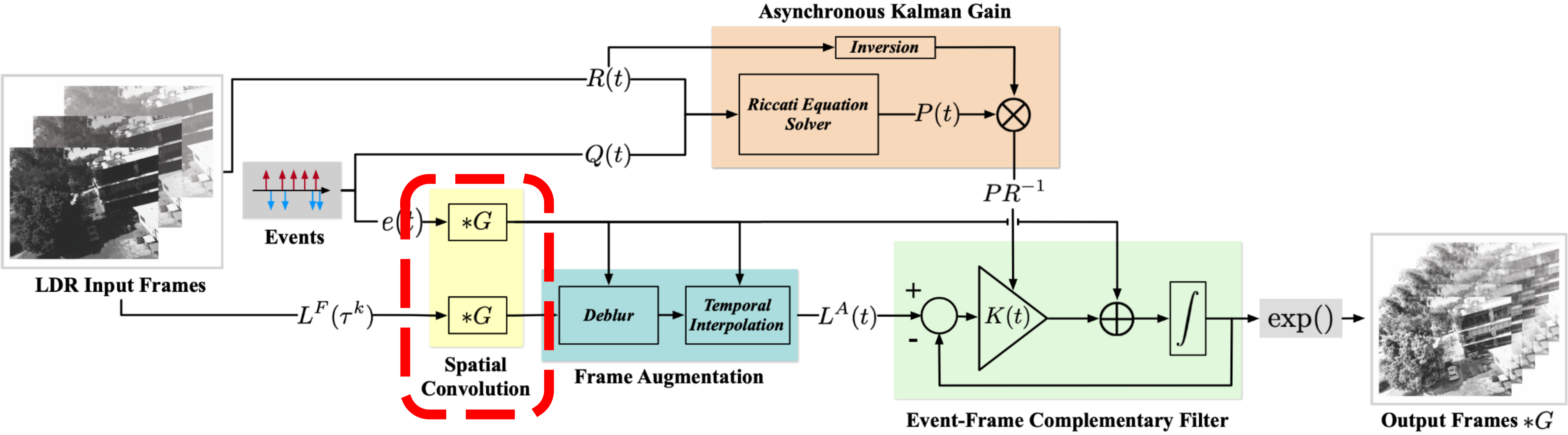


Conventional computer vision image processing:

- Use events to deblur conventional frames
- Use events to interpolate between conventional frames



Linear convolution



e_k ⇒ $K \star e_k = \{K_{ij}\sigma_k\delta_{(u_k-i,v_k-j)}(u,v)\delta(t-t_k)\}$

Each event #(K) events

Results