Causal Motion Segmentation in Moving Camera Videos

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Motion Segmentation

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- M Narayana, A Hanson, E Learned–Miller, ICCV13:
  “Coherent motion Segmentation in moving camera videos using optical flow”

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- P Bideau, E Learned–Miller, ECCV16:
  "It's Moving! A probabilistic Model for Causal Motion Segmentation"
- P Bideau, E Learned–Miller, Workshop:
  "Moving Object Segmentation using Statistics of Optical Flow"

Overview

Goal: Segmentation of static environment and moving objects

- compute dense optical flow
- find j different motion models M from optical flow
- Segmentation: assign pixels to different motion models

ICCV Paper

- **only camera translation**
- **angle field**

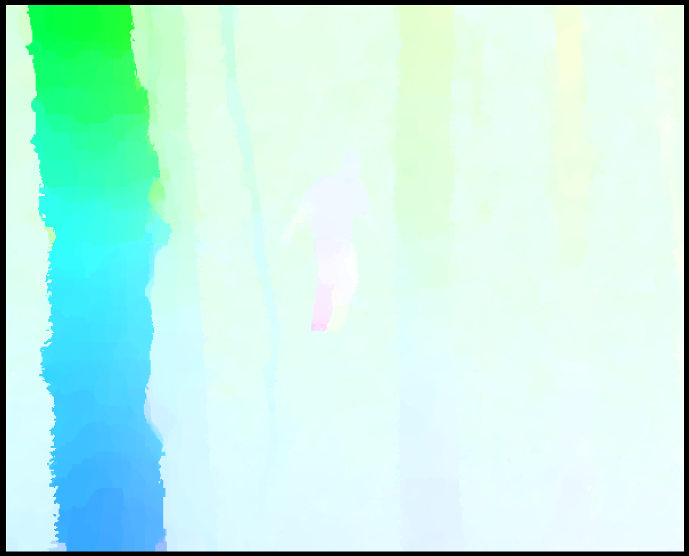
ECCV Paper

- **arbitrary camera motion**
- **angle likelihood**

ECCV Workshop

- **arbitrary camera motion**
- **flow likelihood**
- **incorporating statistics of optical flow**

Modeling Motion



Modeling Motion

contributions to the motion field:

- camera motion
    - A. translation
    - B. rotation
- object motion

Modeling Motion

camera rotation only:

camera translation only:

Modeling Motion

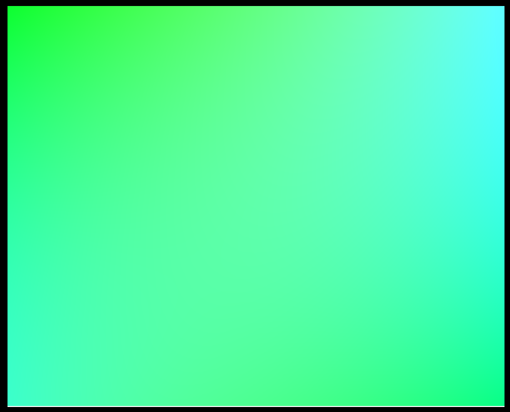
camera rotation only:

optical flow is independent of scene depth

camera translation only:

Modeling Motion

camera rotation only: **optical flow is independent of scene depth**

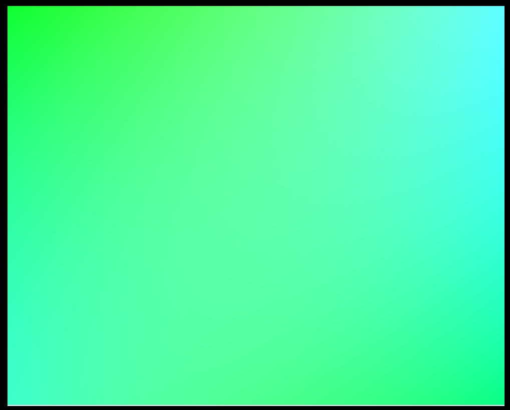


camera translation only: **flow magnitude is dependent on scene depth**

Modeling Motion

camera rotation only:

optical flow is independent of scene depth

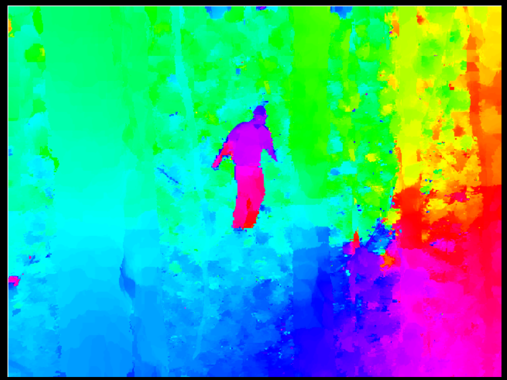


camera translation only:

flow magnitude is dependent on scene depth

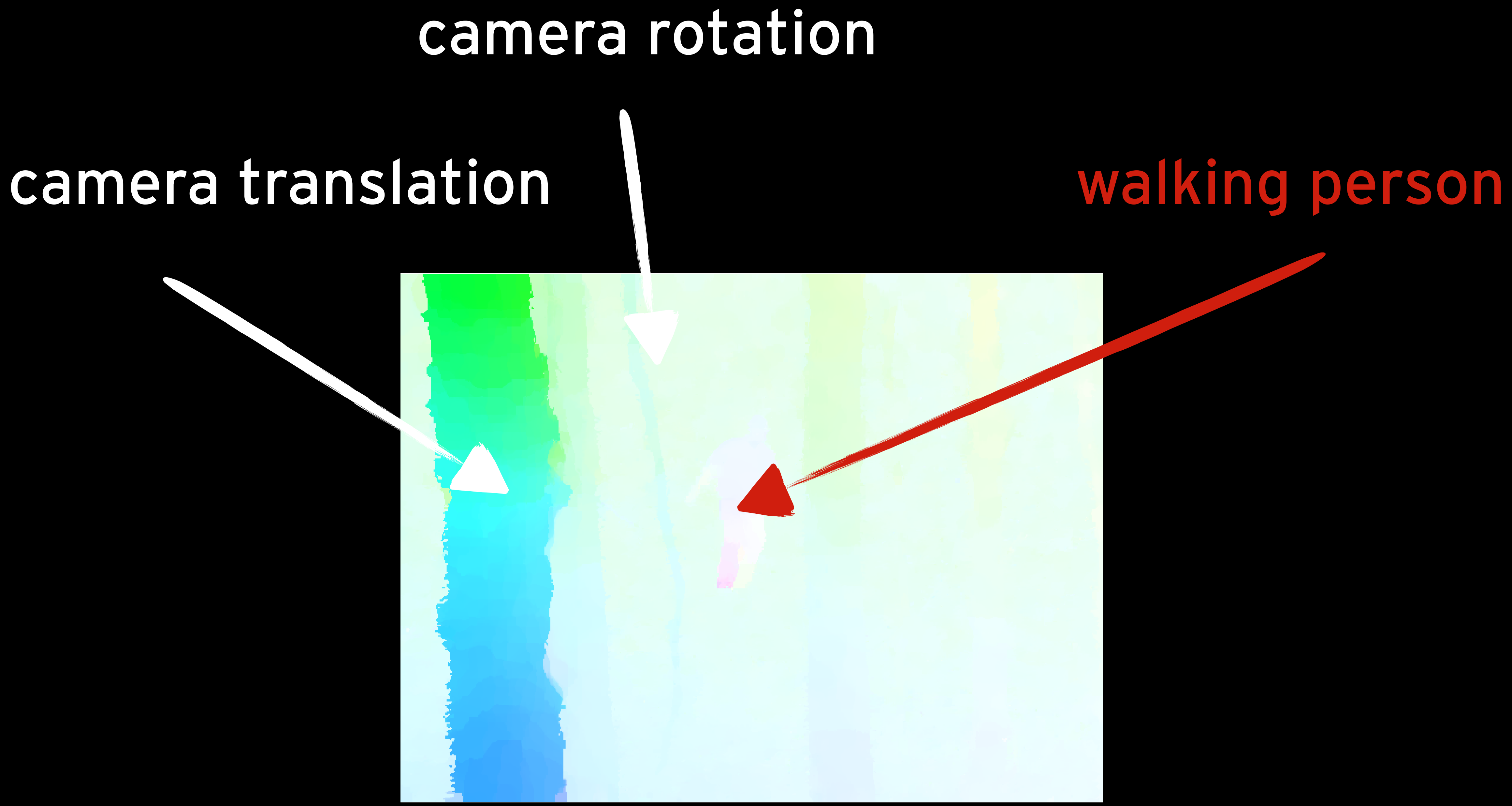
flow angle

flow angle is independent of scene depth



Modeling Motion

each motion component is approximated with a motion model



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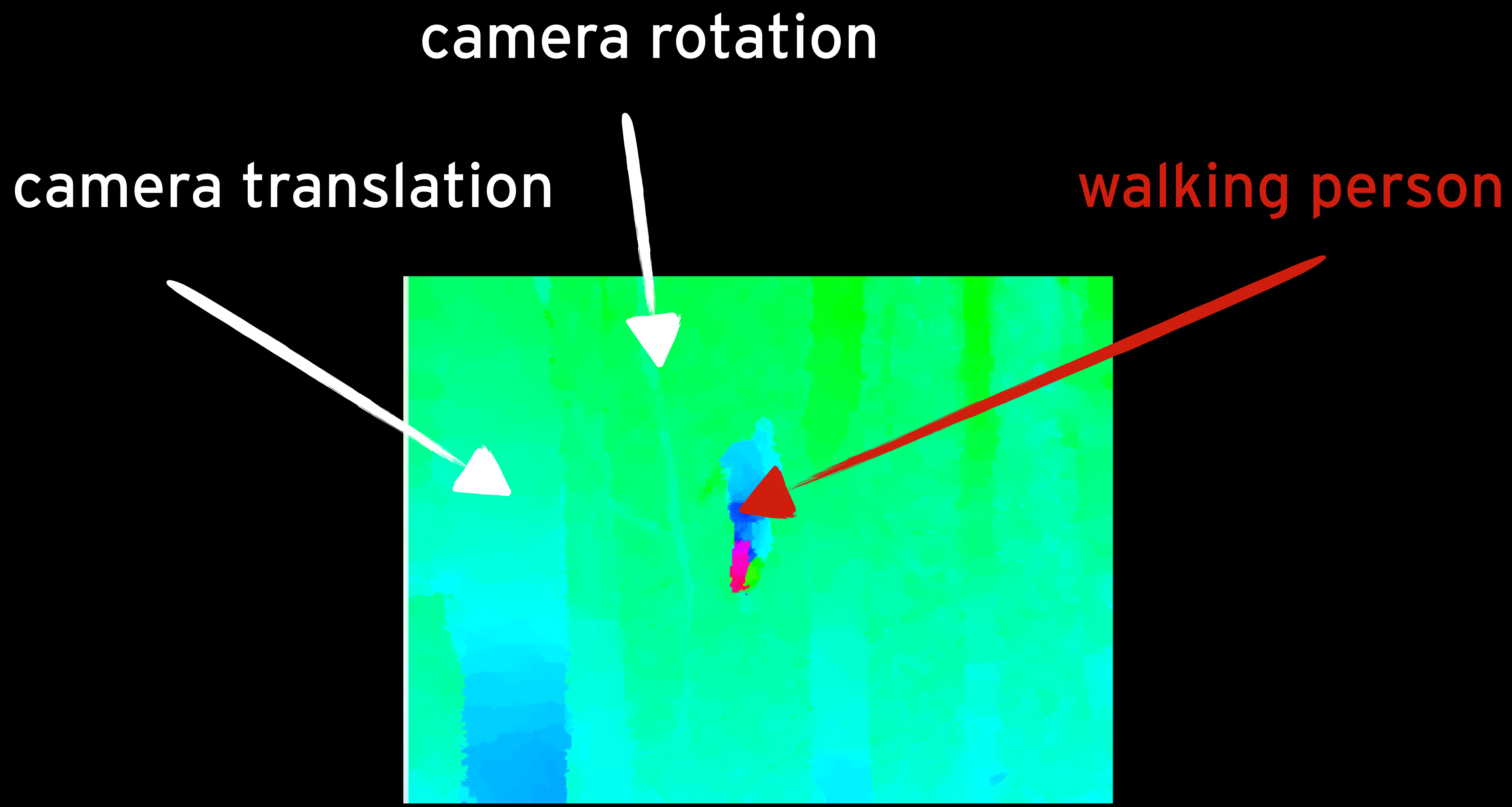


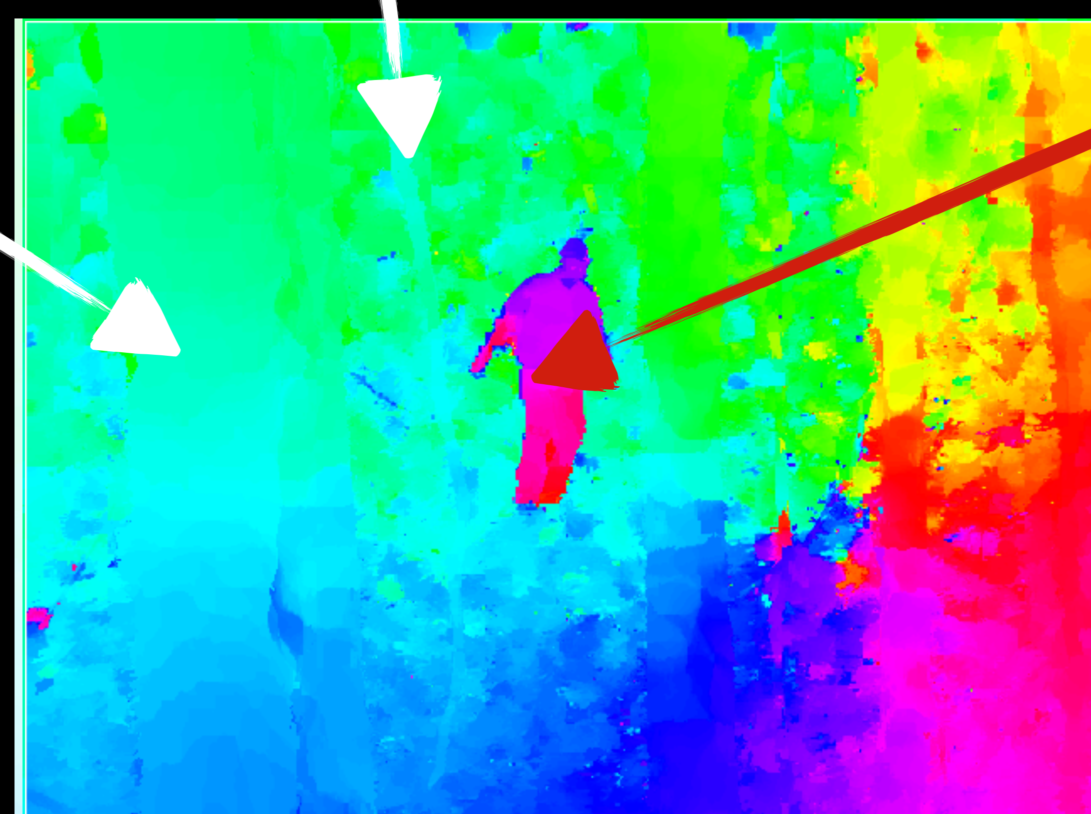
Modeling Motion

each motion component is approximated with a motion model

~~camera rotation~~

camera translation

walking person



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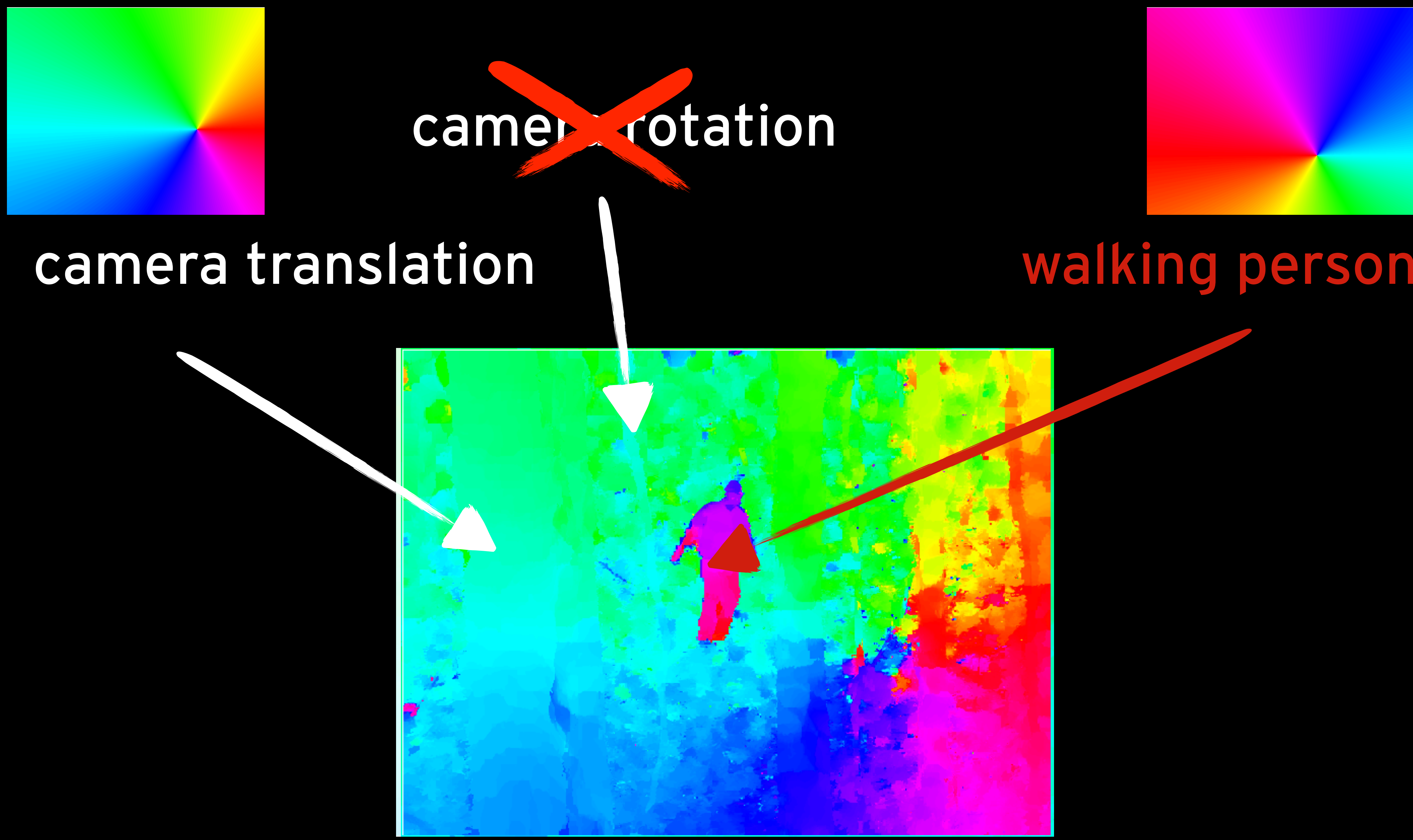

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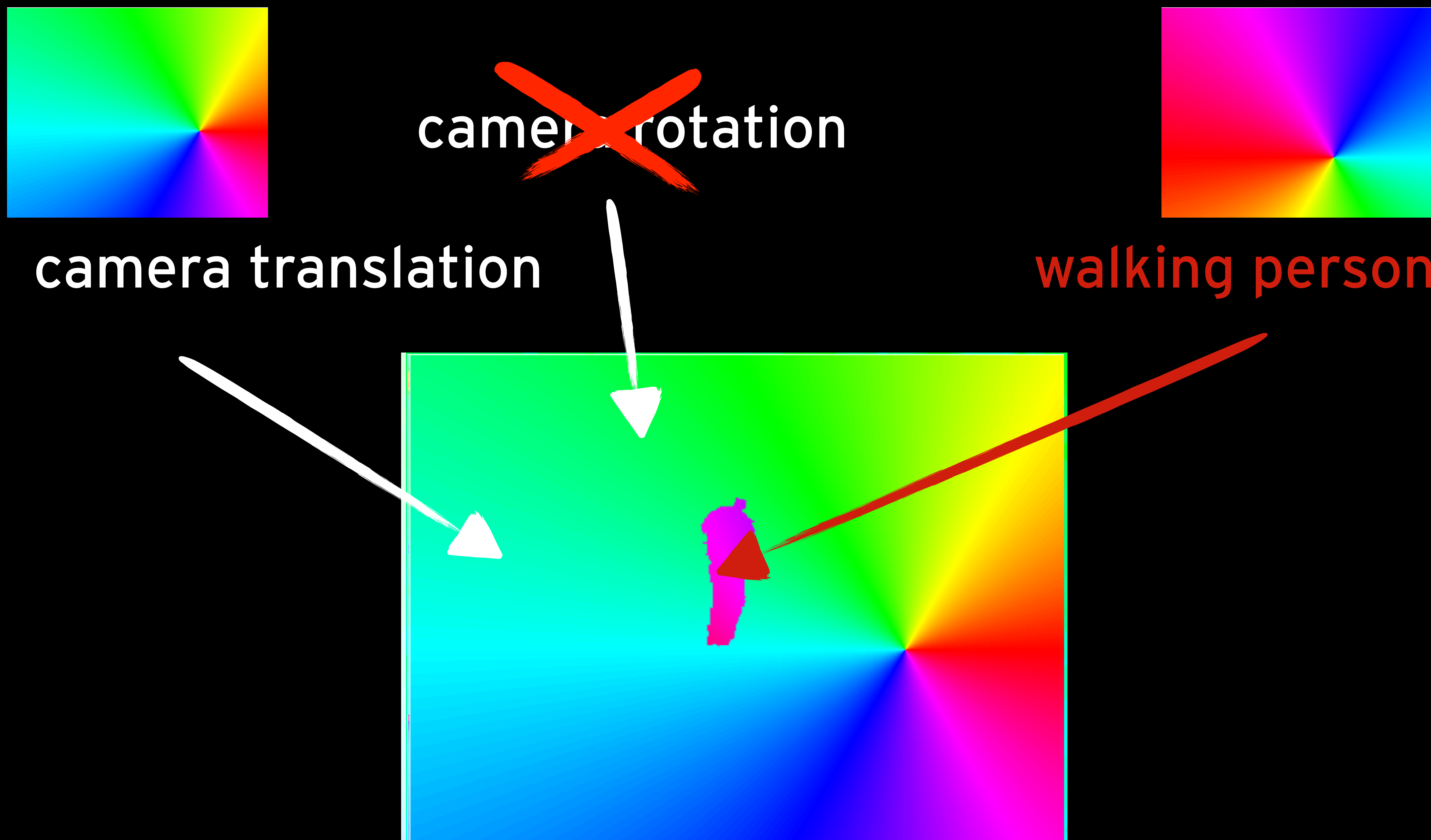


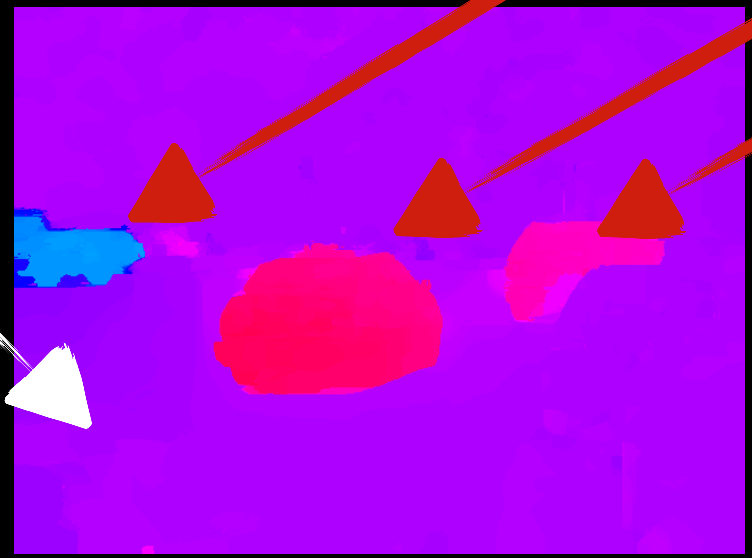
Modeling Motion

each motion component is approximated with a motion model

camera rotation

camera translation

3 cars



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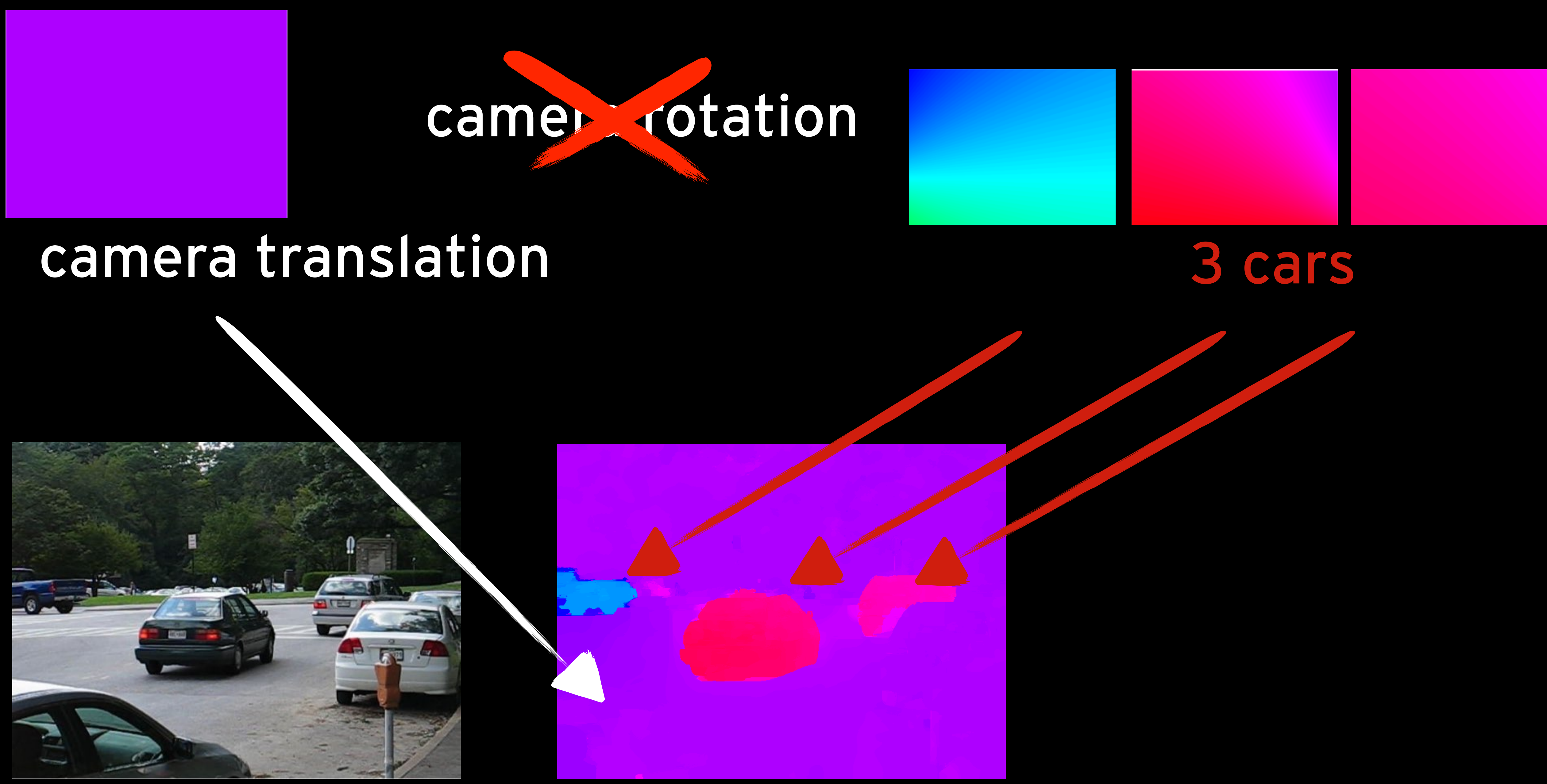


Segmentation: Bayes' rule

$$p(M_j \mid \boldsymbol{v_t}) \propto p(\boldsymbol{v_t} \mid M_j) \cdot p(M_j)$$

posterior

likelihood

prior

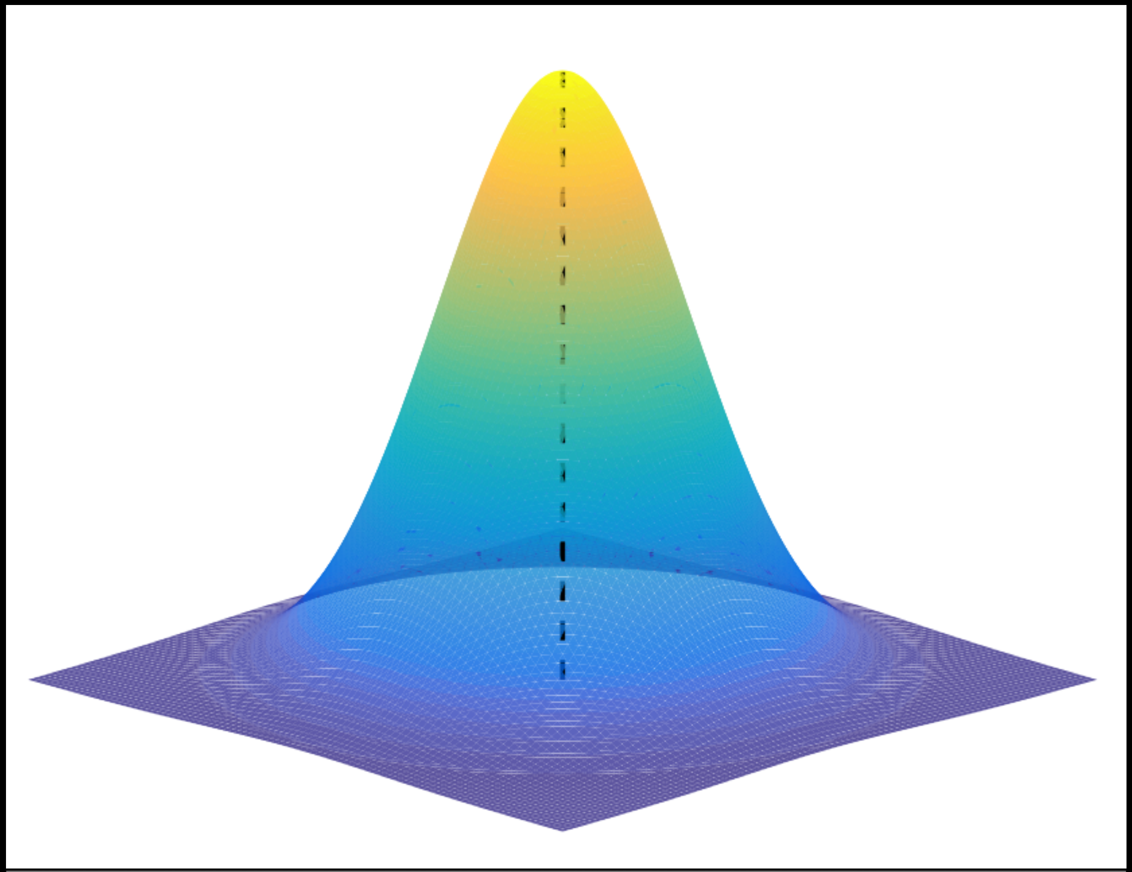
M_j motion model (angle field)

v_t observed trans. flow

Assumption 1

motion field vectors are Gaussian distributed

$$q \sim \mathcal{N}(0, \Sigma_2)$$



M_j motion model (angle field)

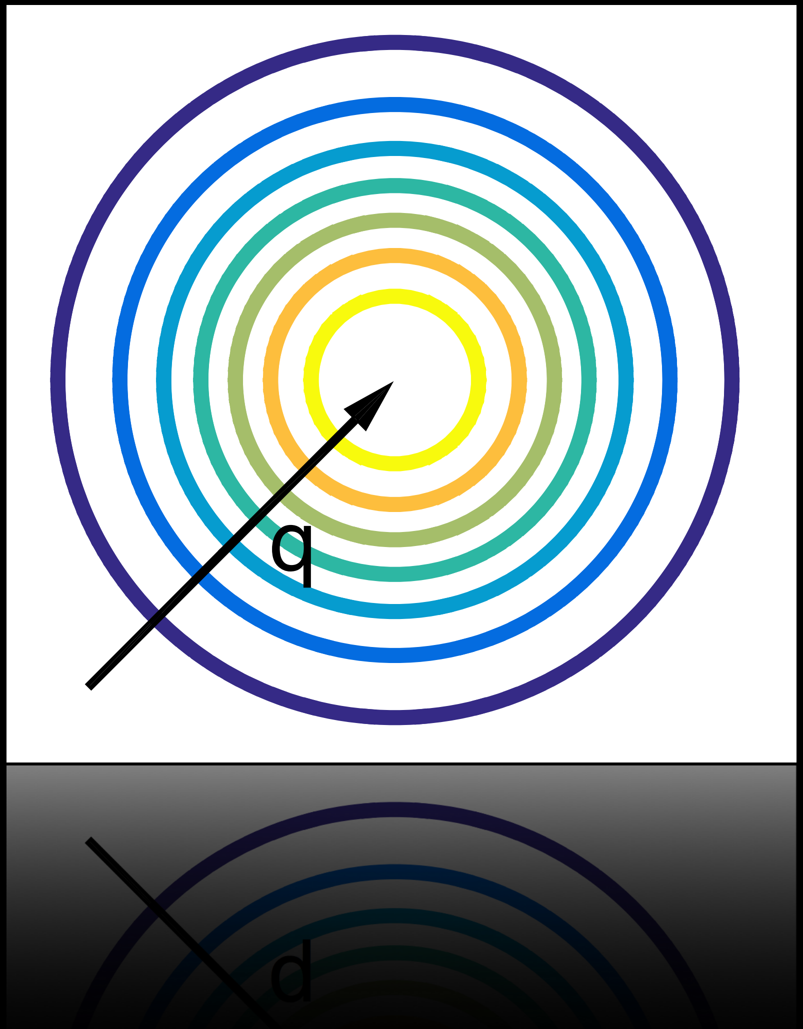
v_t observed trans. flow

q true trans. flow

Assumption 2

flow noise *n* is Gaussian distributed conditioned on the flow magnitude

$$\boldsymbol{n} \sim \mathcal{N}(0, \Sigma_1(r))$$



M_j motion model (angle field)

v_t observed trans. flow

q true trans. flow

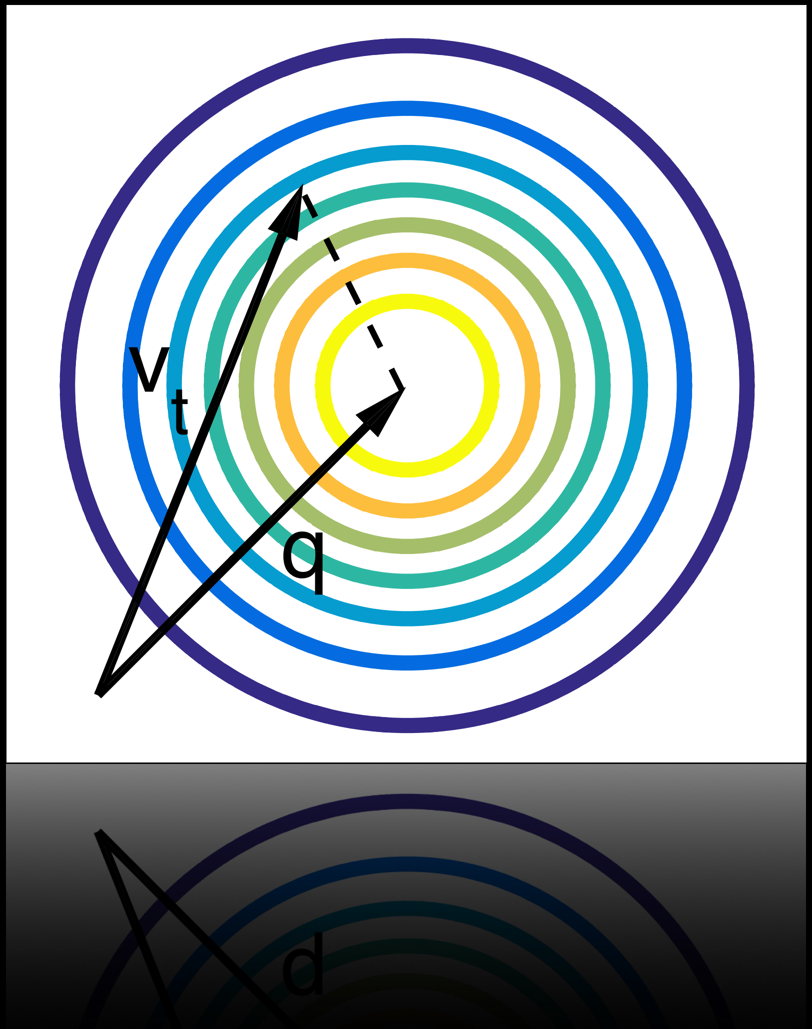
n flow noise

r unknown true flow magnitude

Assumption 3

translational optical flow vectors are noisy observations of the true trans. motion vectors

$$v_t = q + n$$



M_j motion model (angle field)

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Segmentation: Bayes' rule

likelihood:

$$
\begin{aligned}
p(\boldsymbol{v_t} \mid M_j) &= \int p(\boldsymbol{v_t}, r \mid M_j)\, dr \\
&= \int p(\boldsymbol{v_t} \mid r, M_j) p(r \mid M_j)\, dr
\end{aligned}
$$

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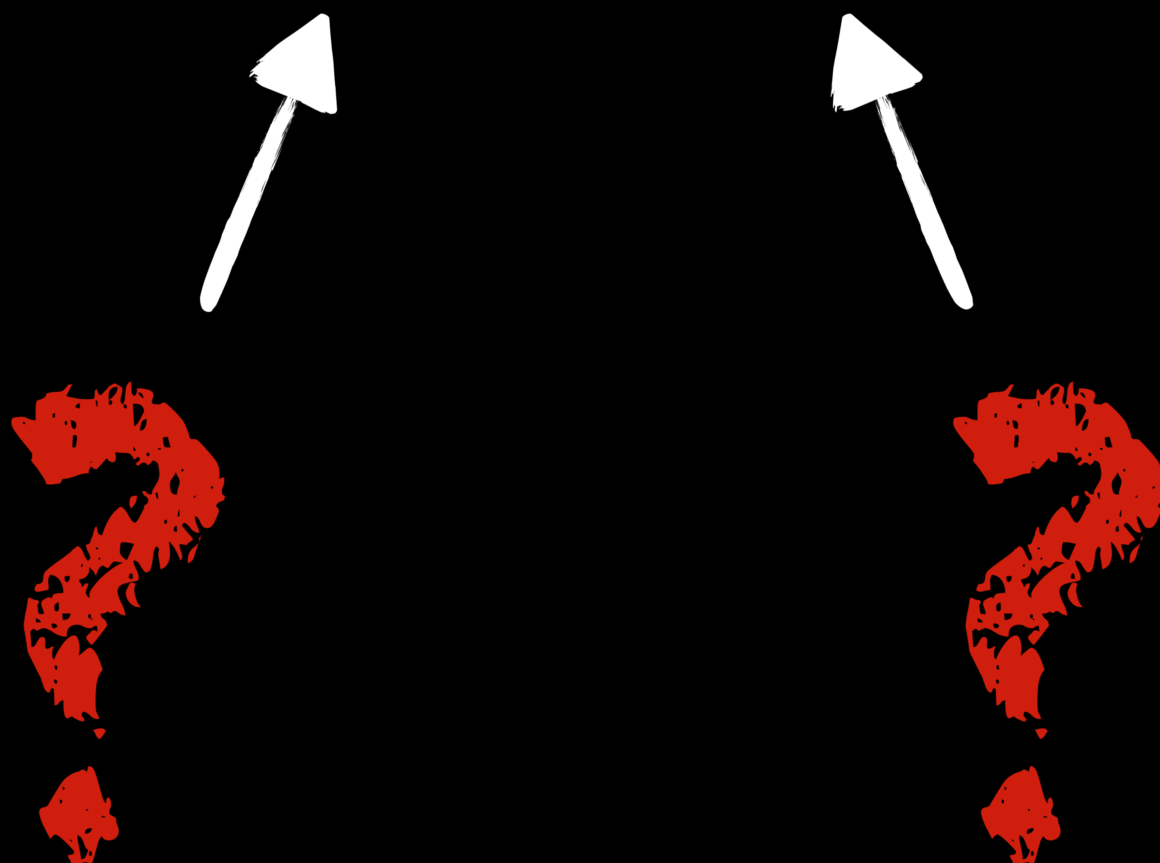

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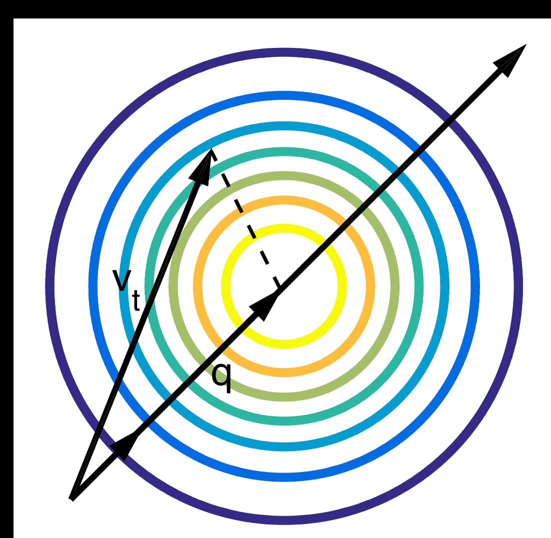

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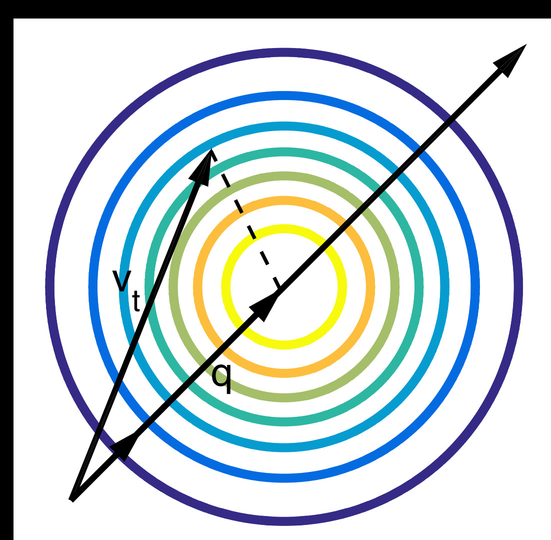

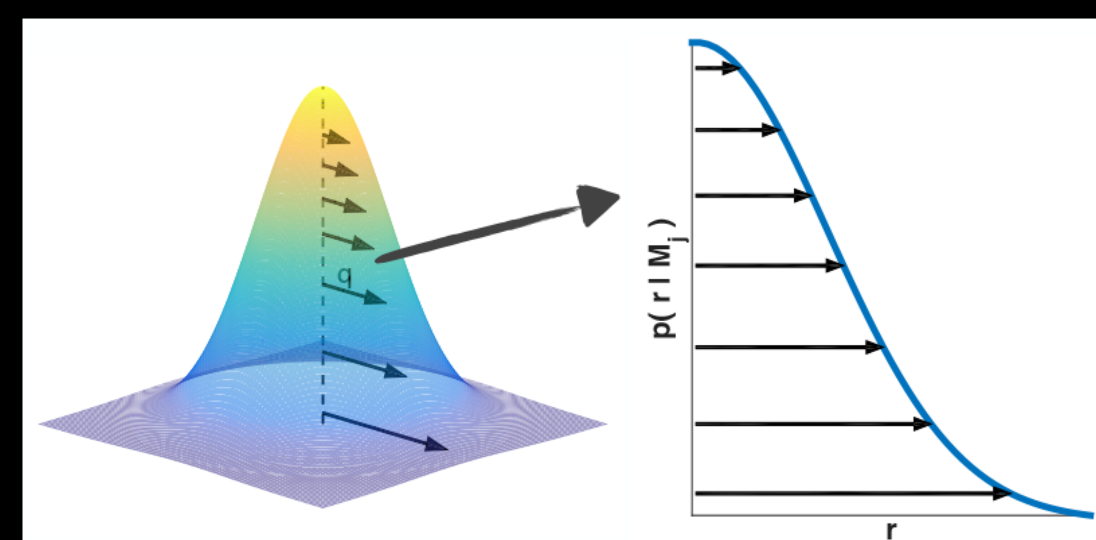

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How can we incorporate
"true" statistics of optical flow?

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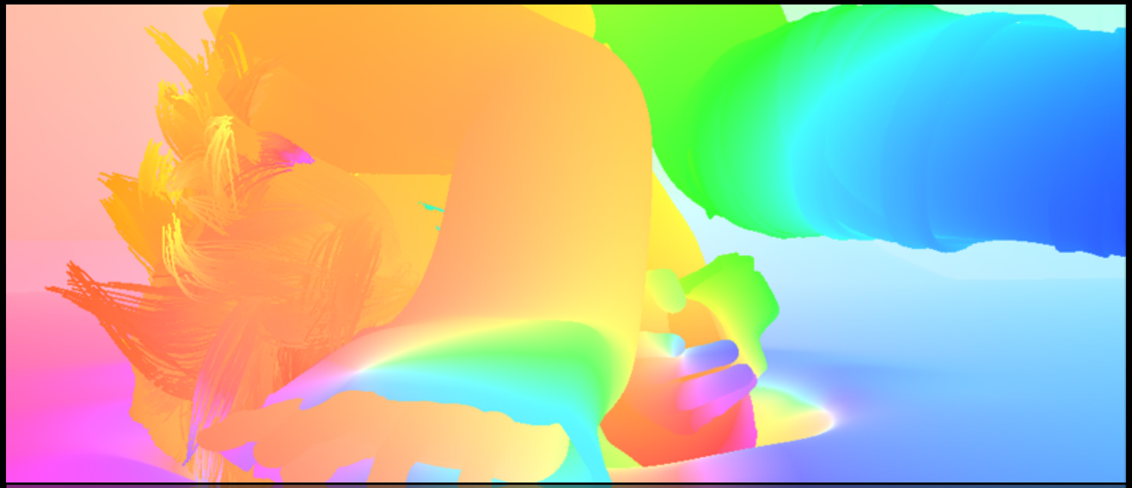
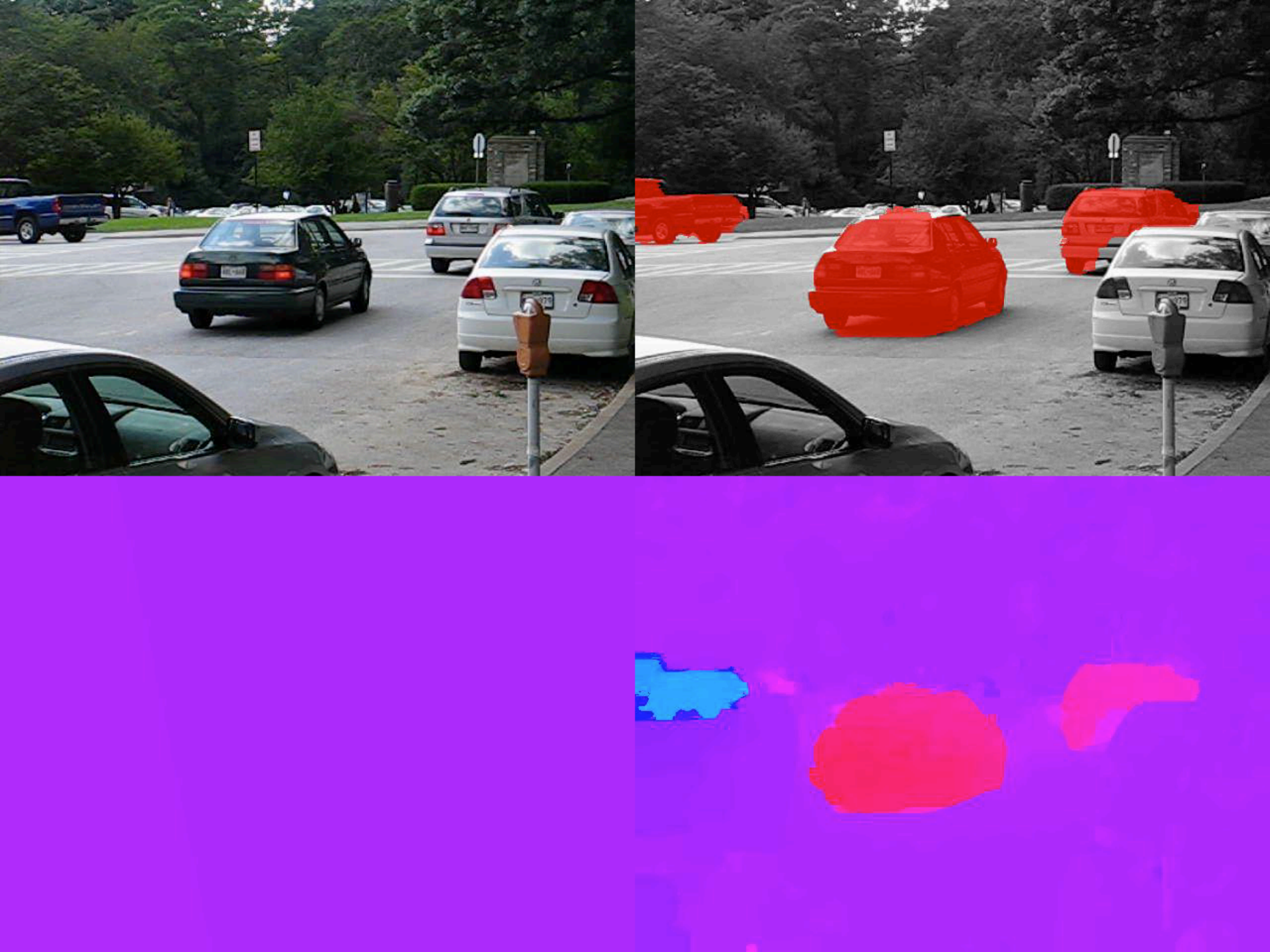
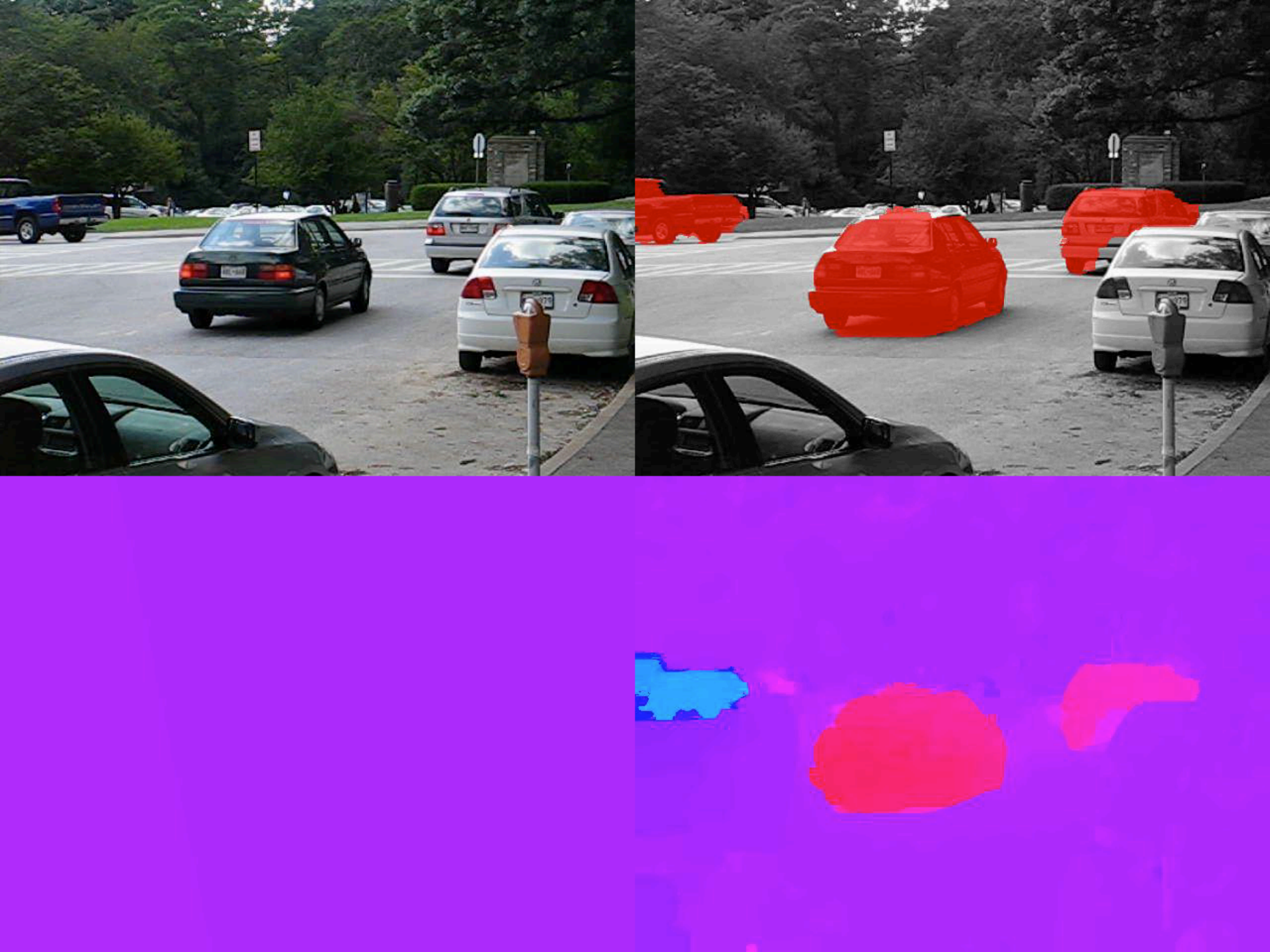
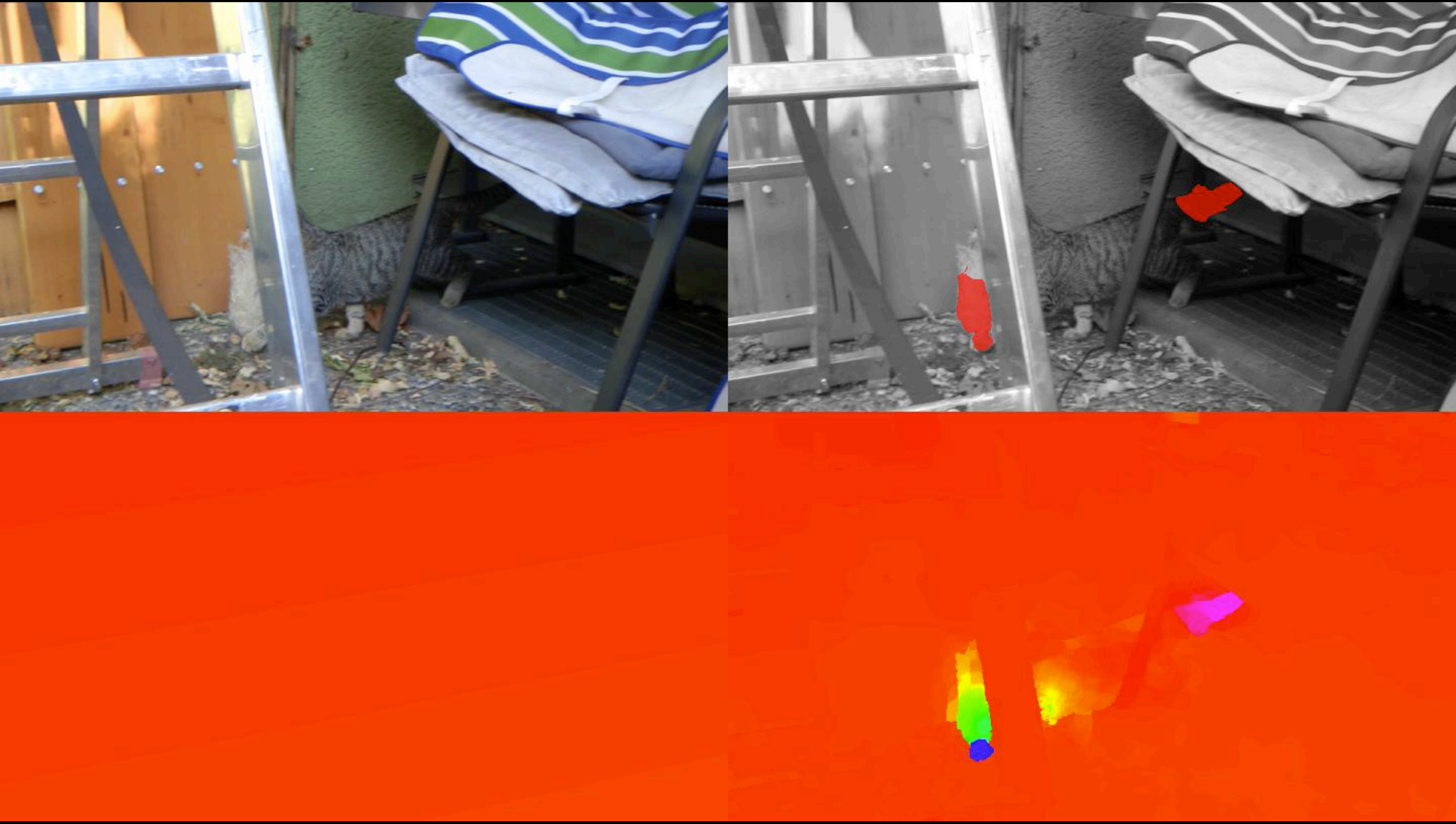
ground truth flow: Sintel

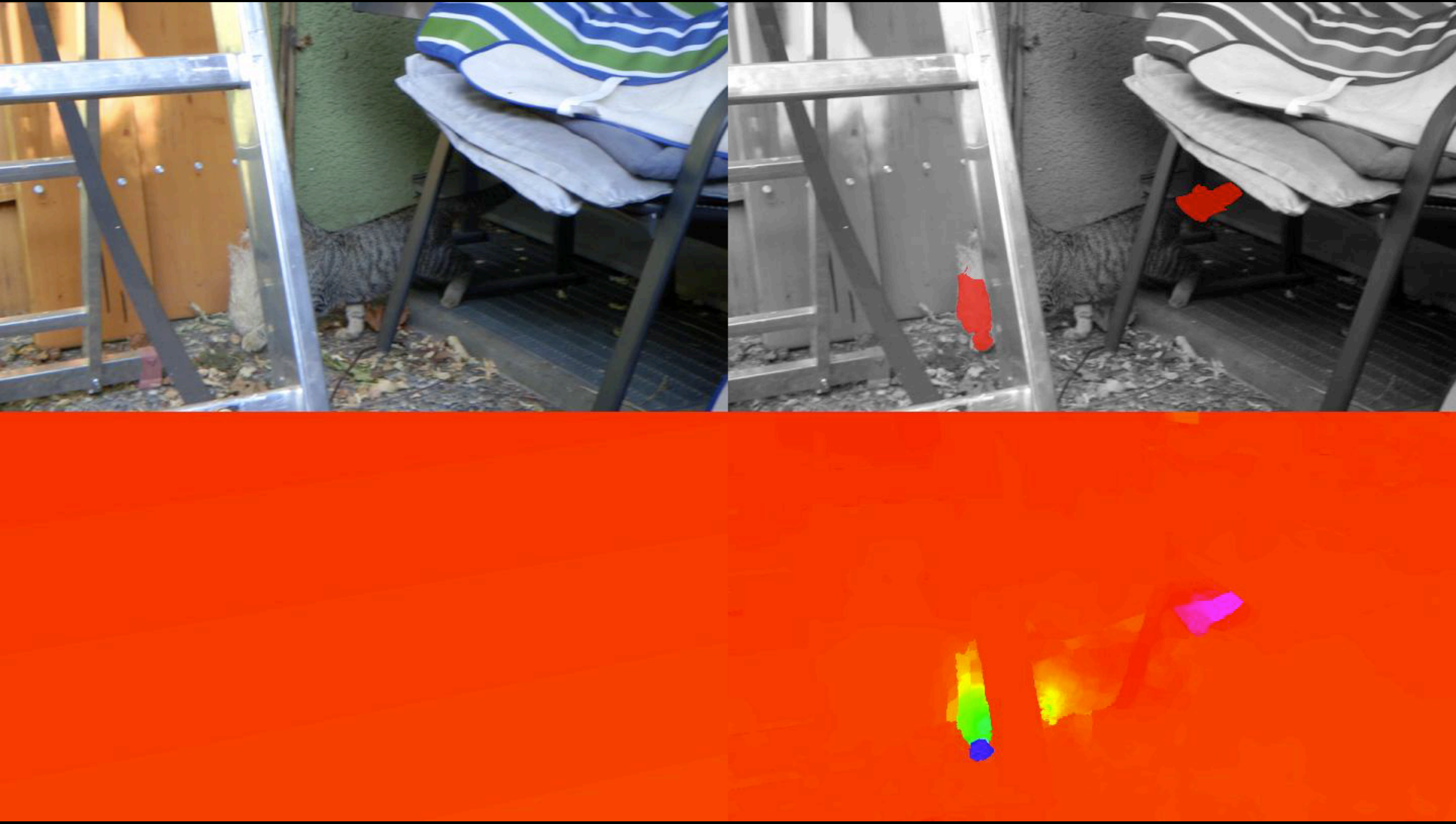


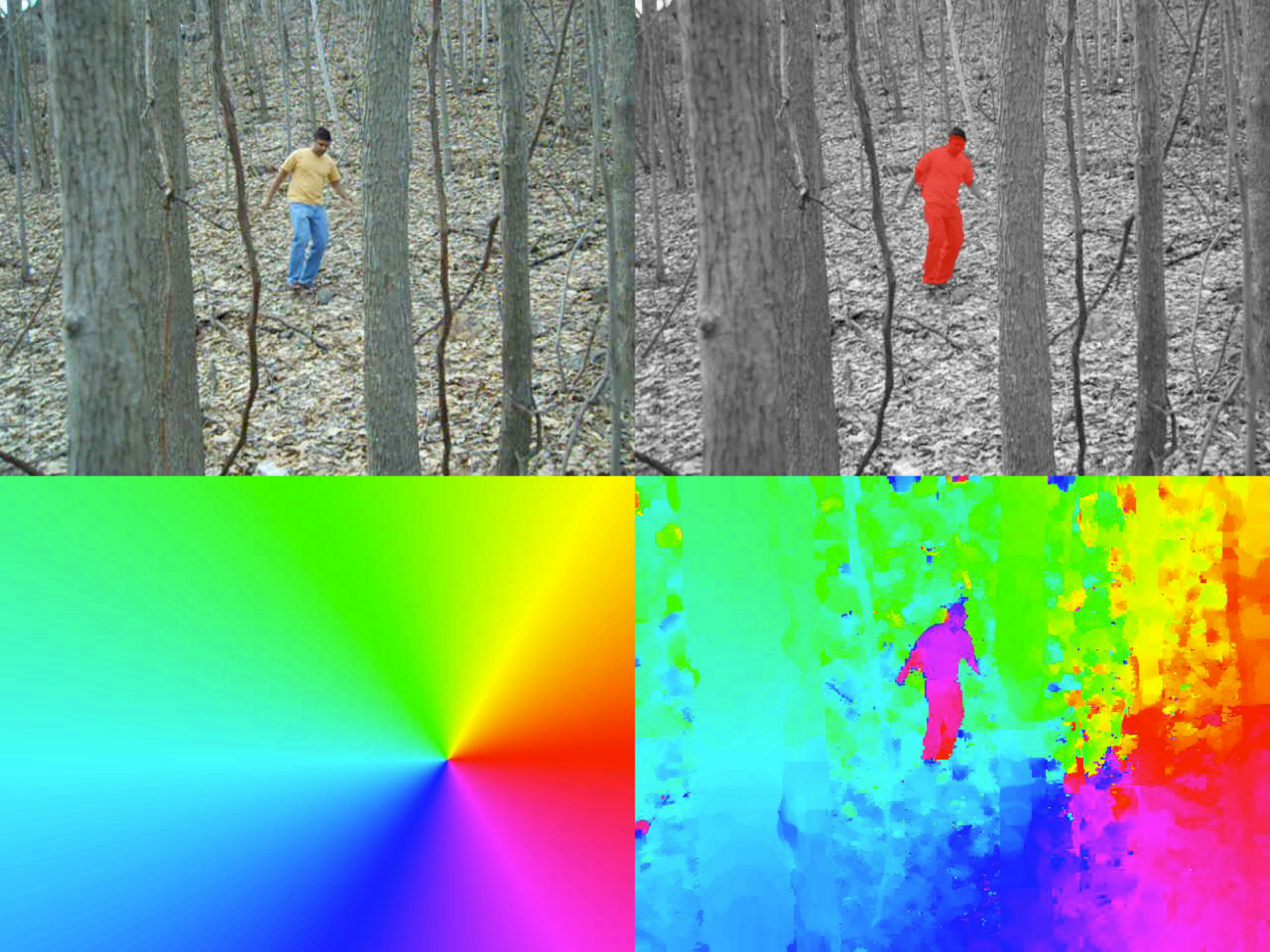
Results: Video

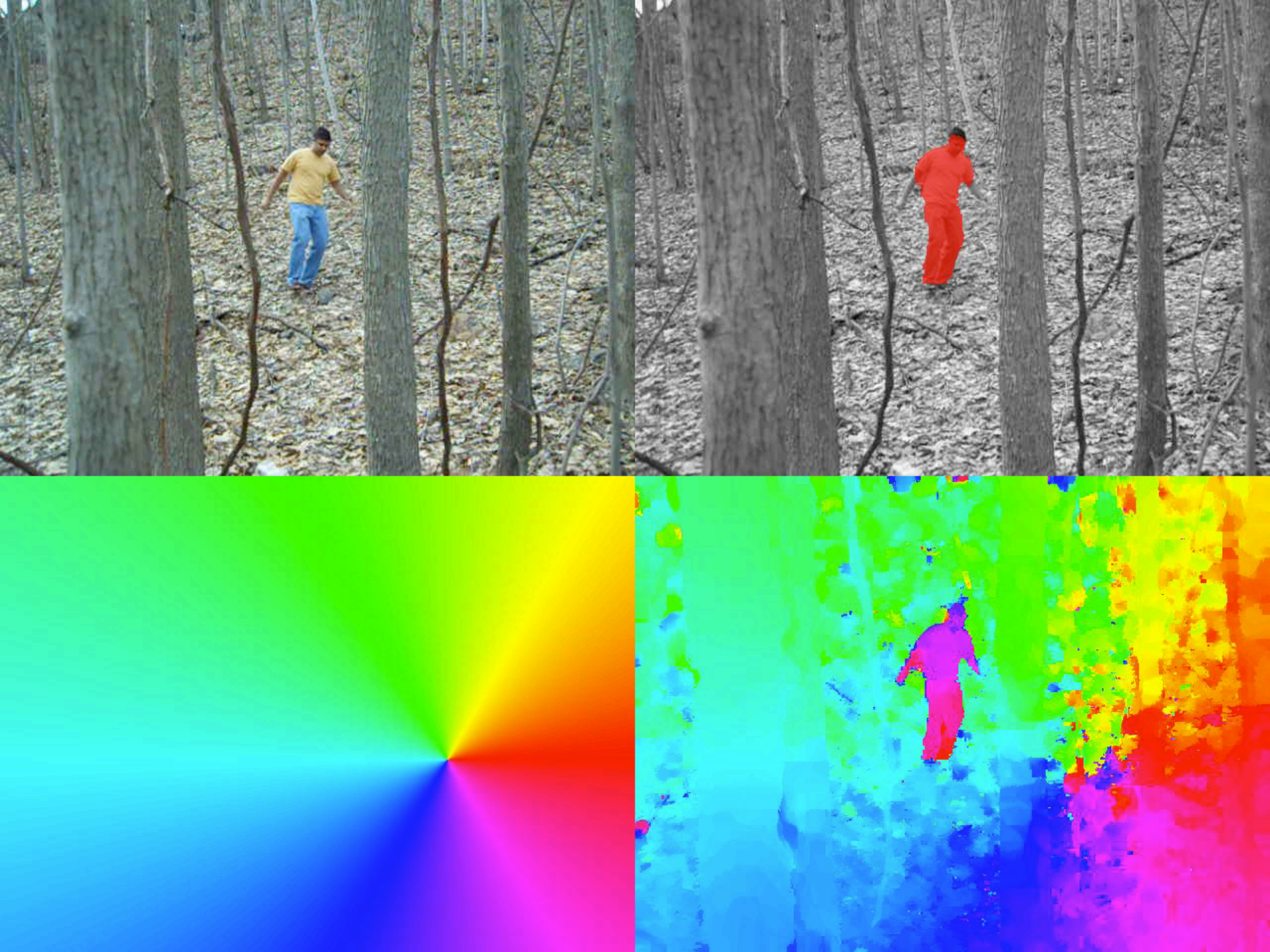


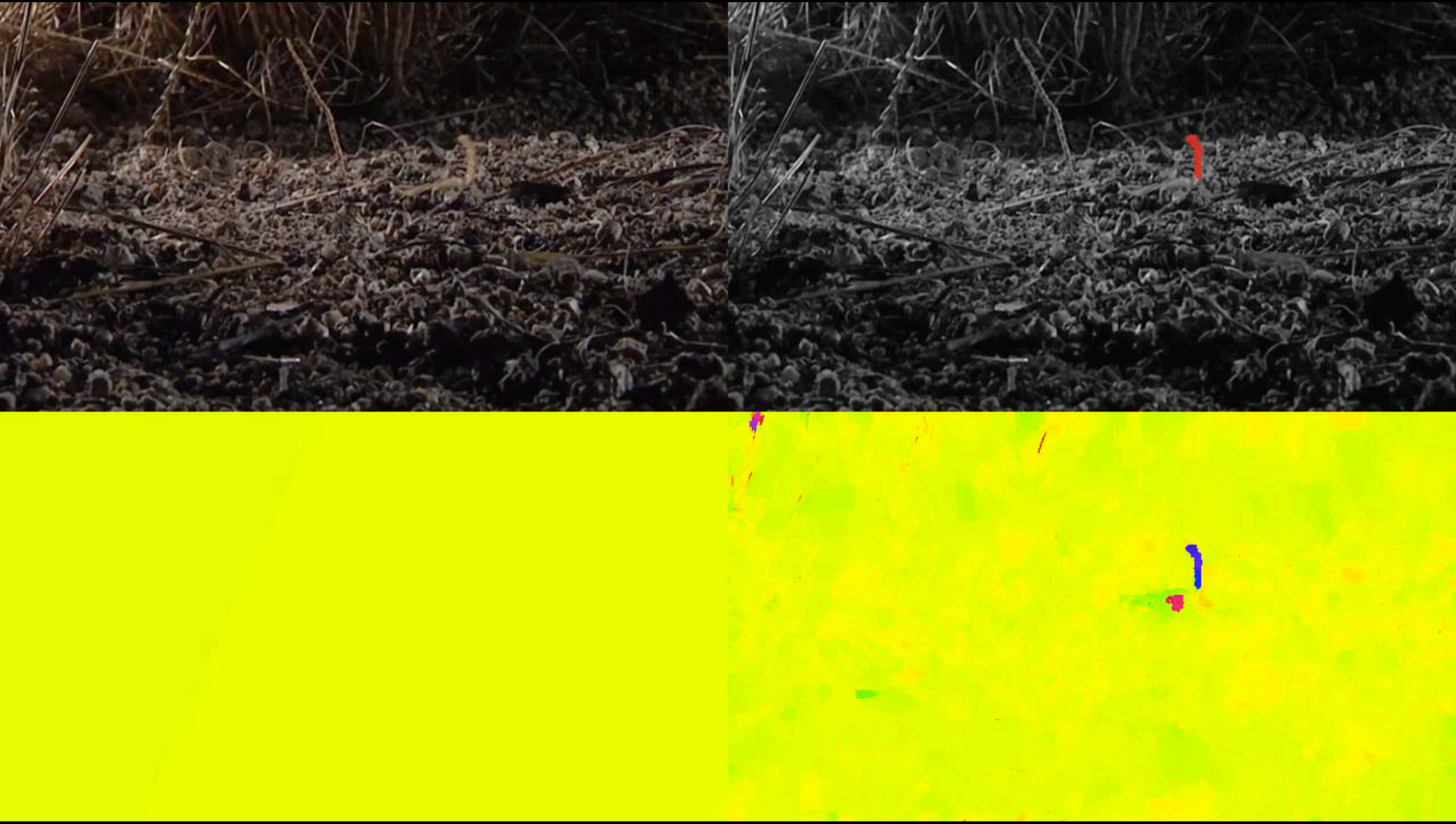






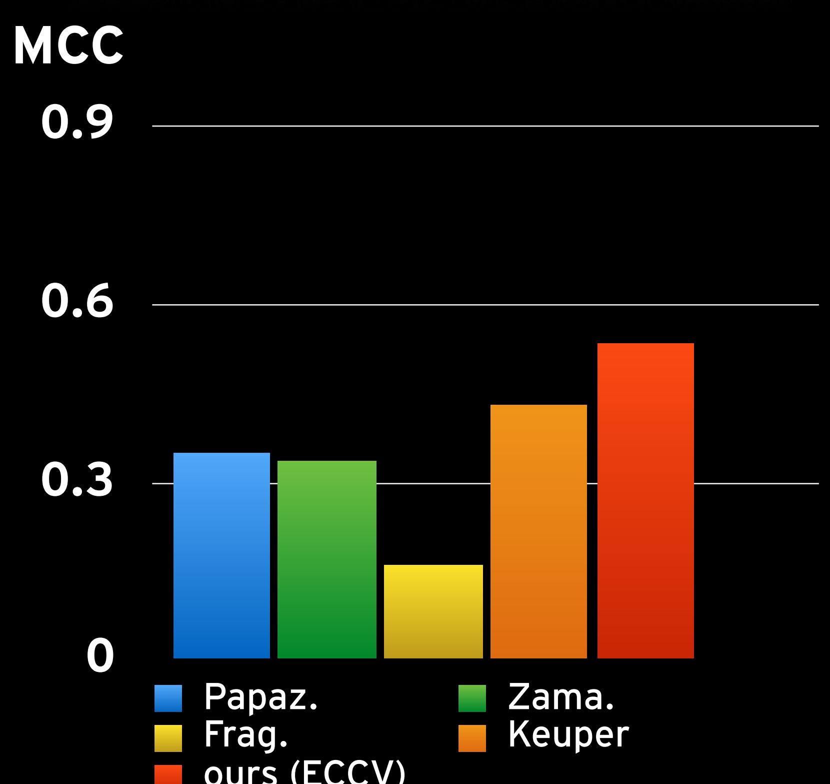




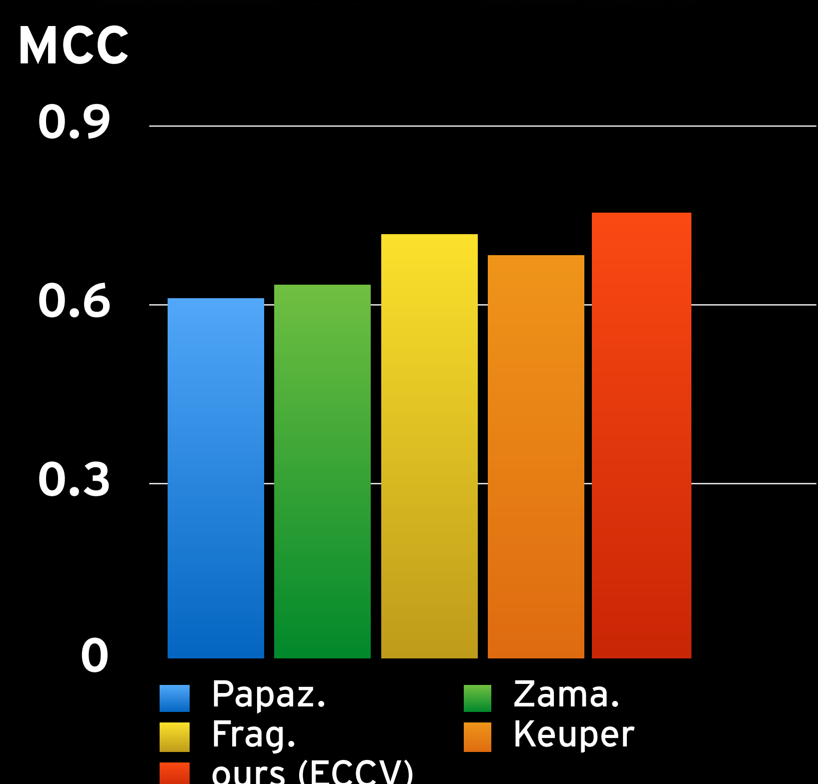


Results

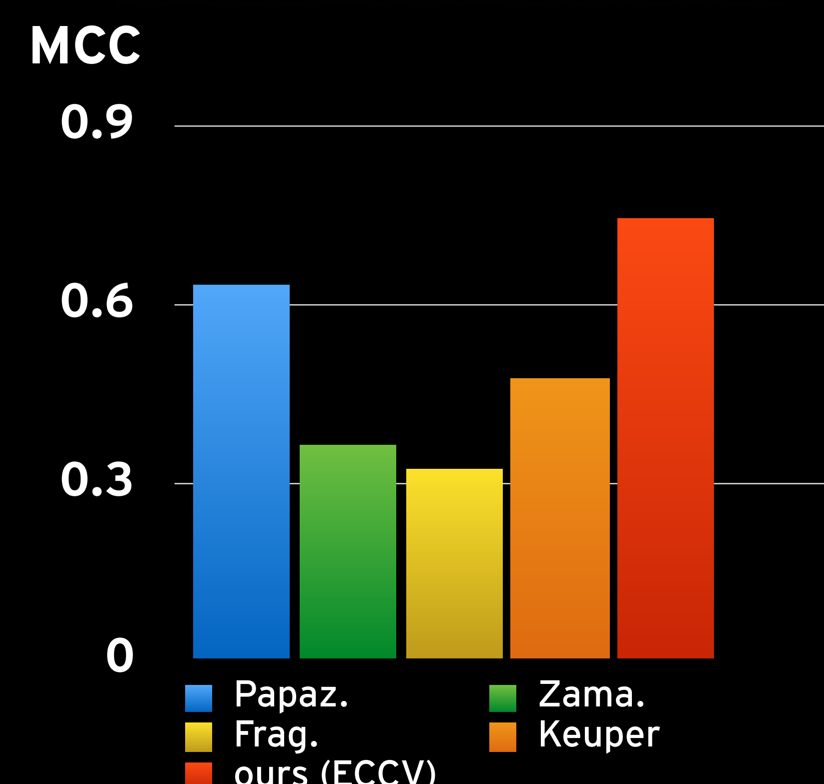
camouflaged Animal



BMS−26



complex background



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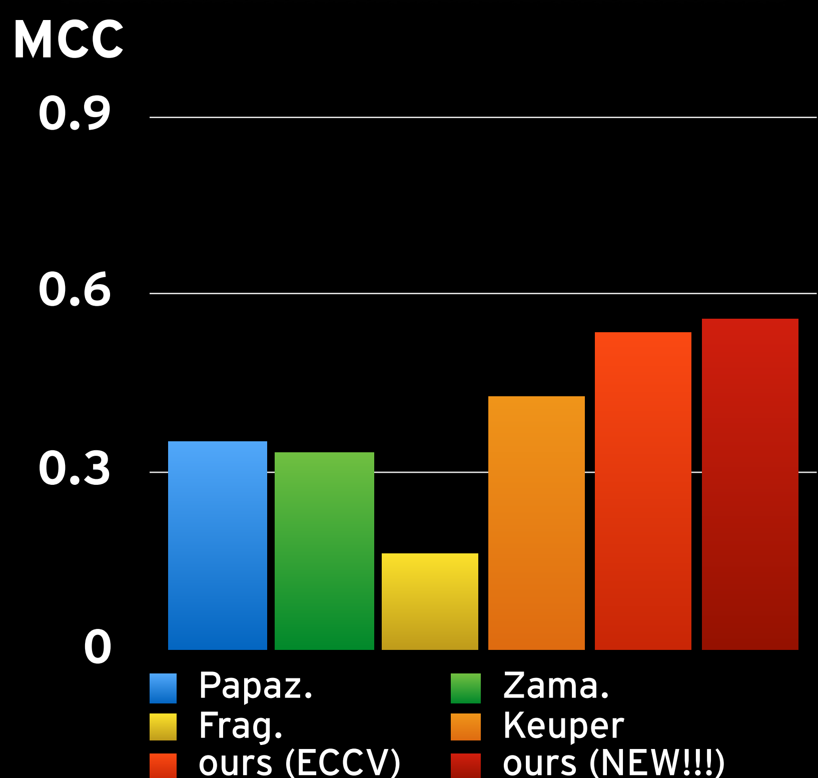
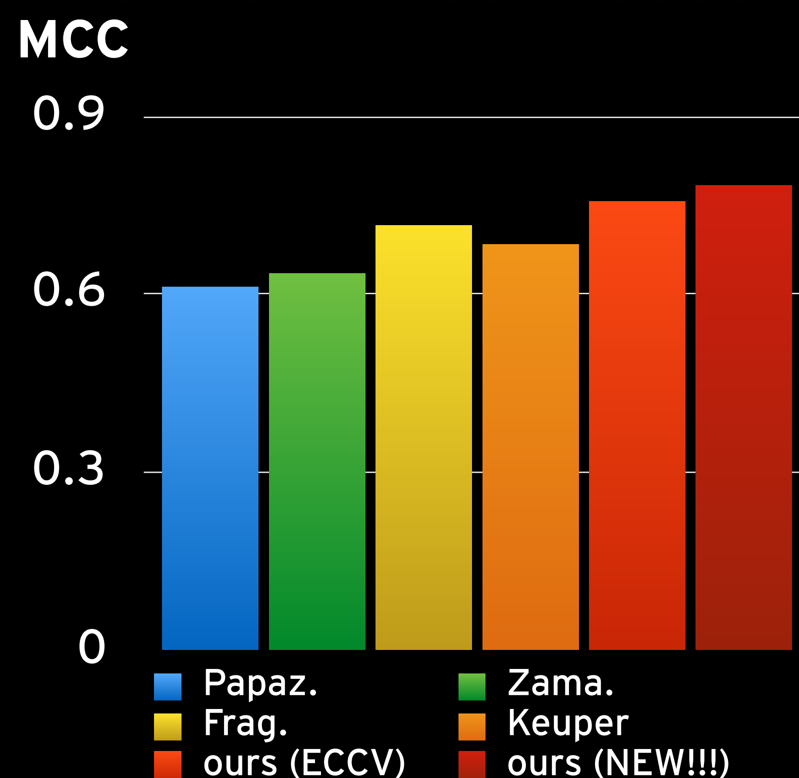


BMS-26



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