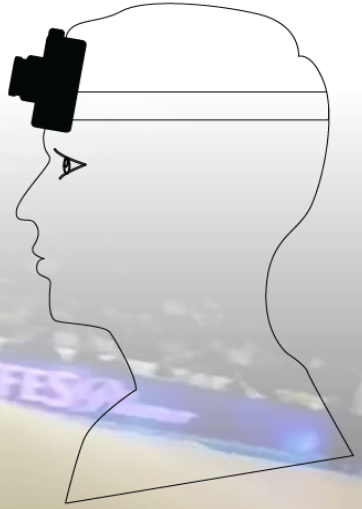
Social and Physical Interactions from First Person Cameras

Hyun Soo Park



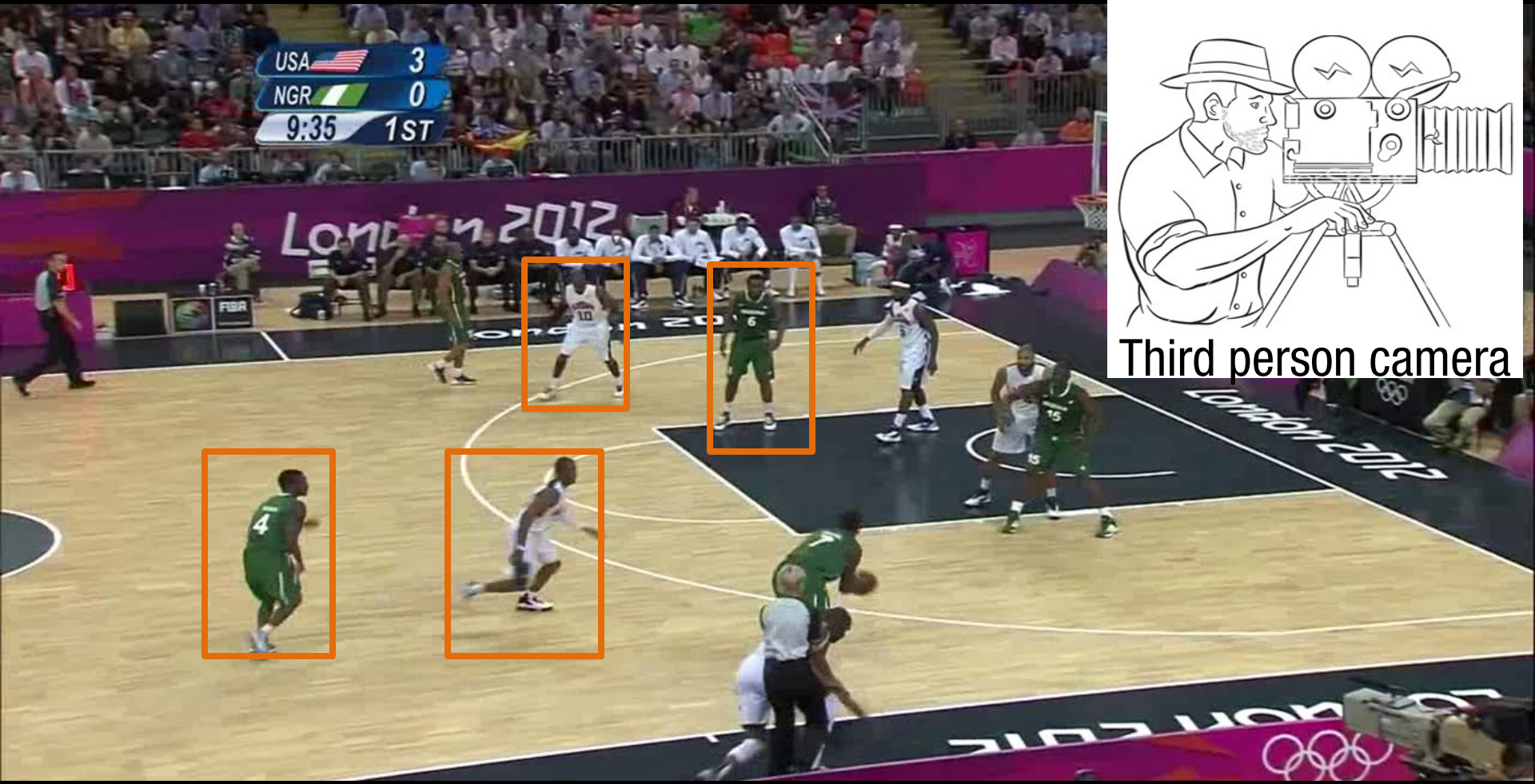
INSIDE OUT: *Riley's First Date?*, PIXAR

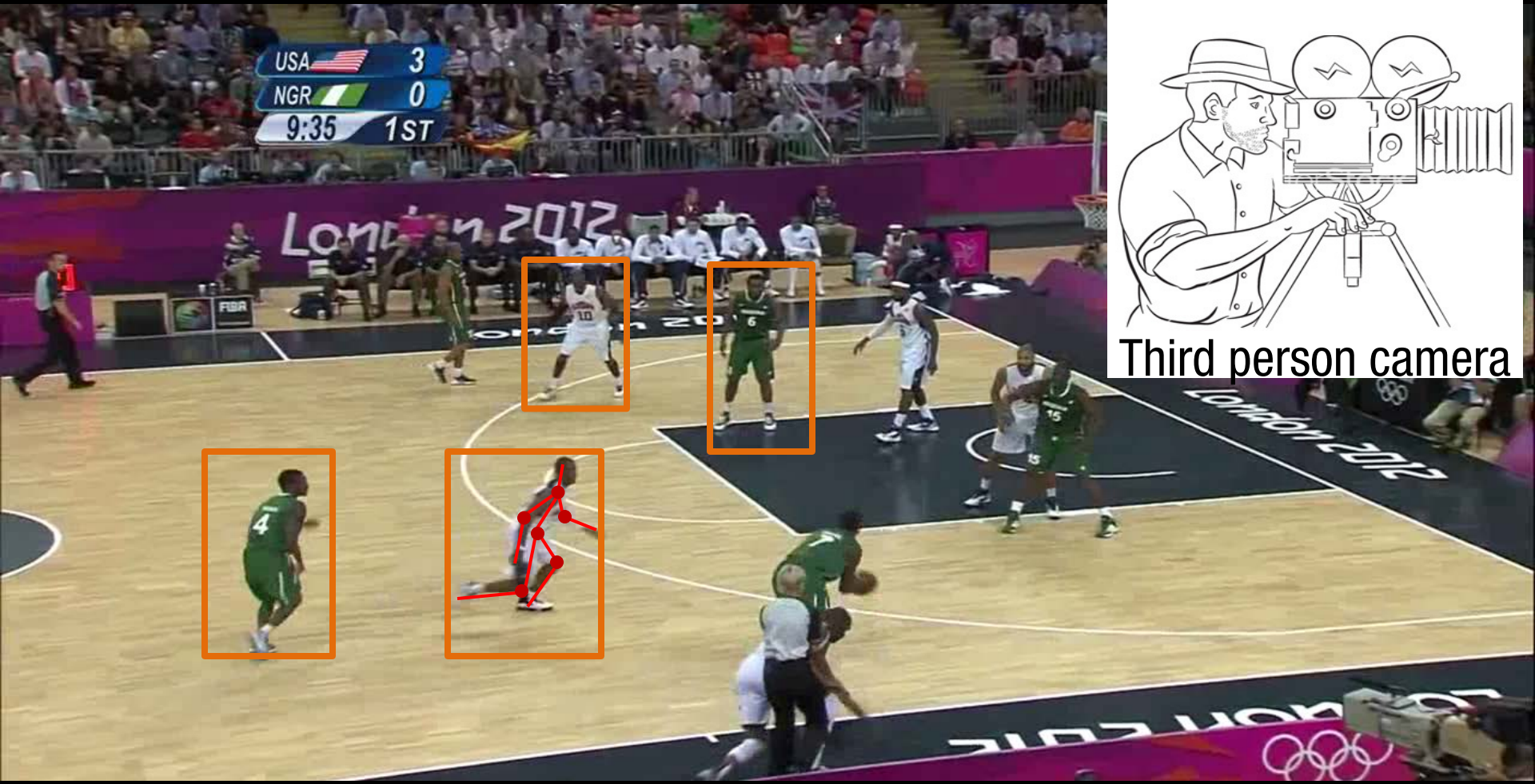
INSIDE OUT: *Riley's First Date?*, PIXAR

INSIDE OUT: *Riley's First Date?*, PIXAR


USA 3
NGR 0
9:43 1ST
Third person camera

Third person camera


USA 3
NGR 0
9:35 1ST
London 2012
Third person camera


USA 3
NGR 0
9:35 1ST
London 2012
Third person camera

Third person camera

Internal state:
intention, attention, and memory

Internal state:
intention, attention, and memory

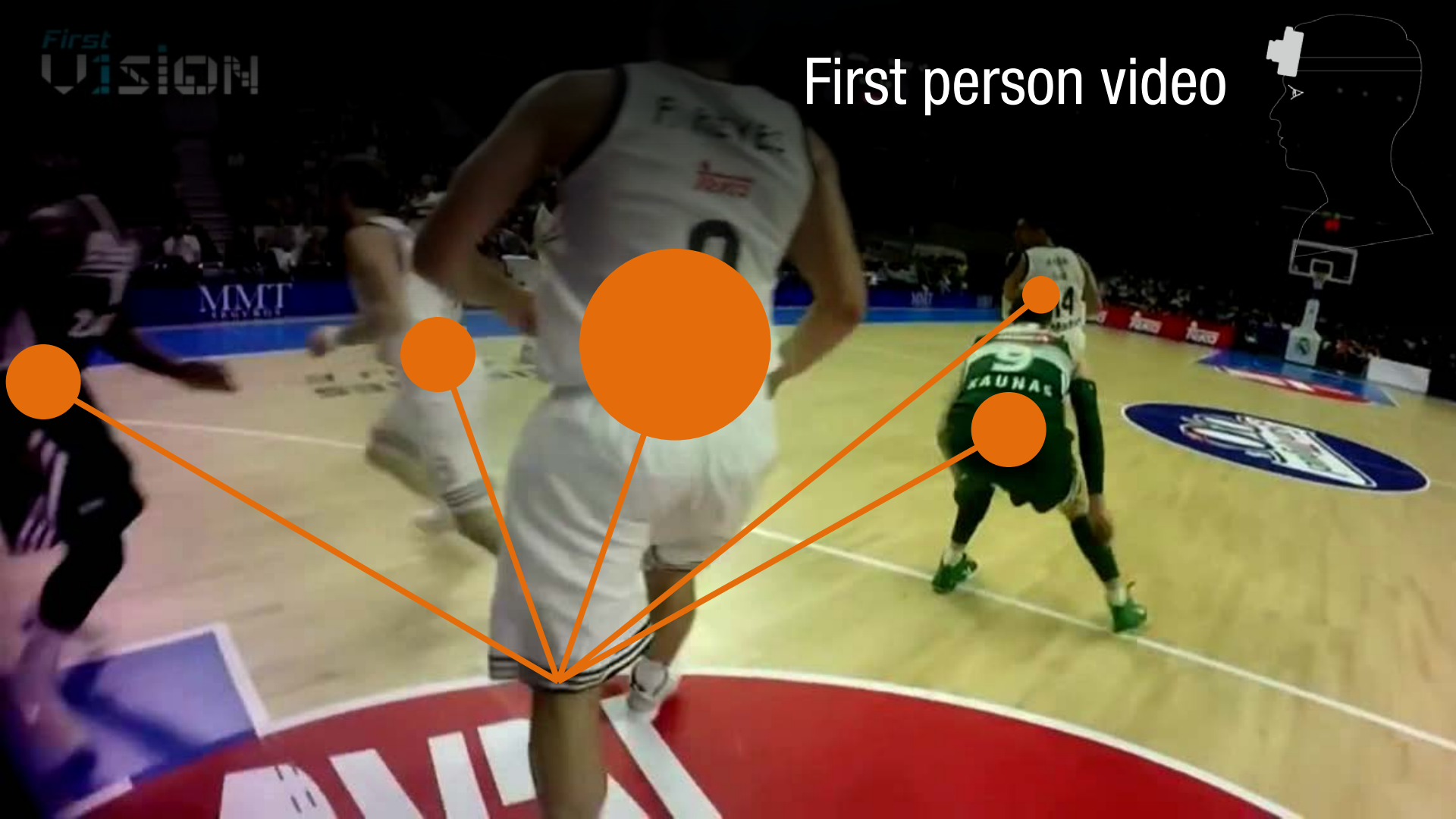
Can we recover the <u>internal states</u> from a video?


First
VISION


First person video
Vanishing line
First Vision
MMT
9
KAUNAS

First person video

First person video

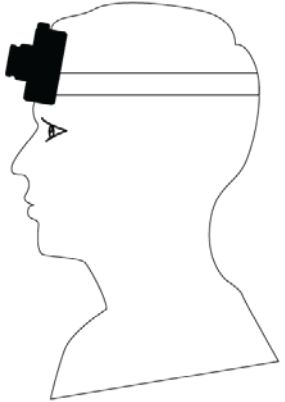


First person video

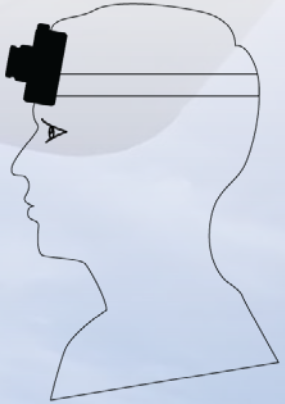
First person video

First person video tells us about me.

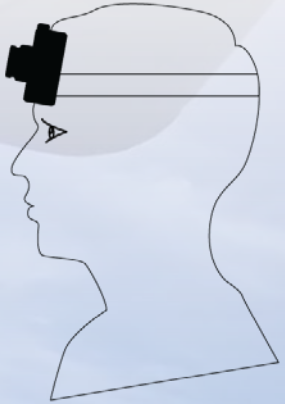
What can first person video tell us?

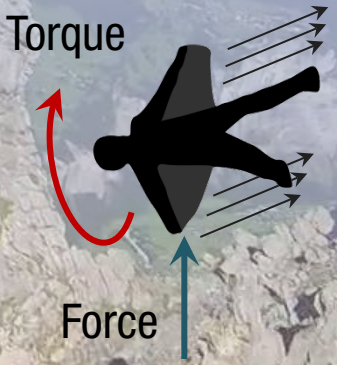


What can first person video tell us about my physical interactions with scene?

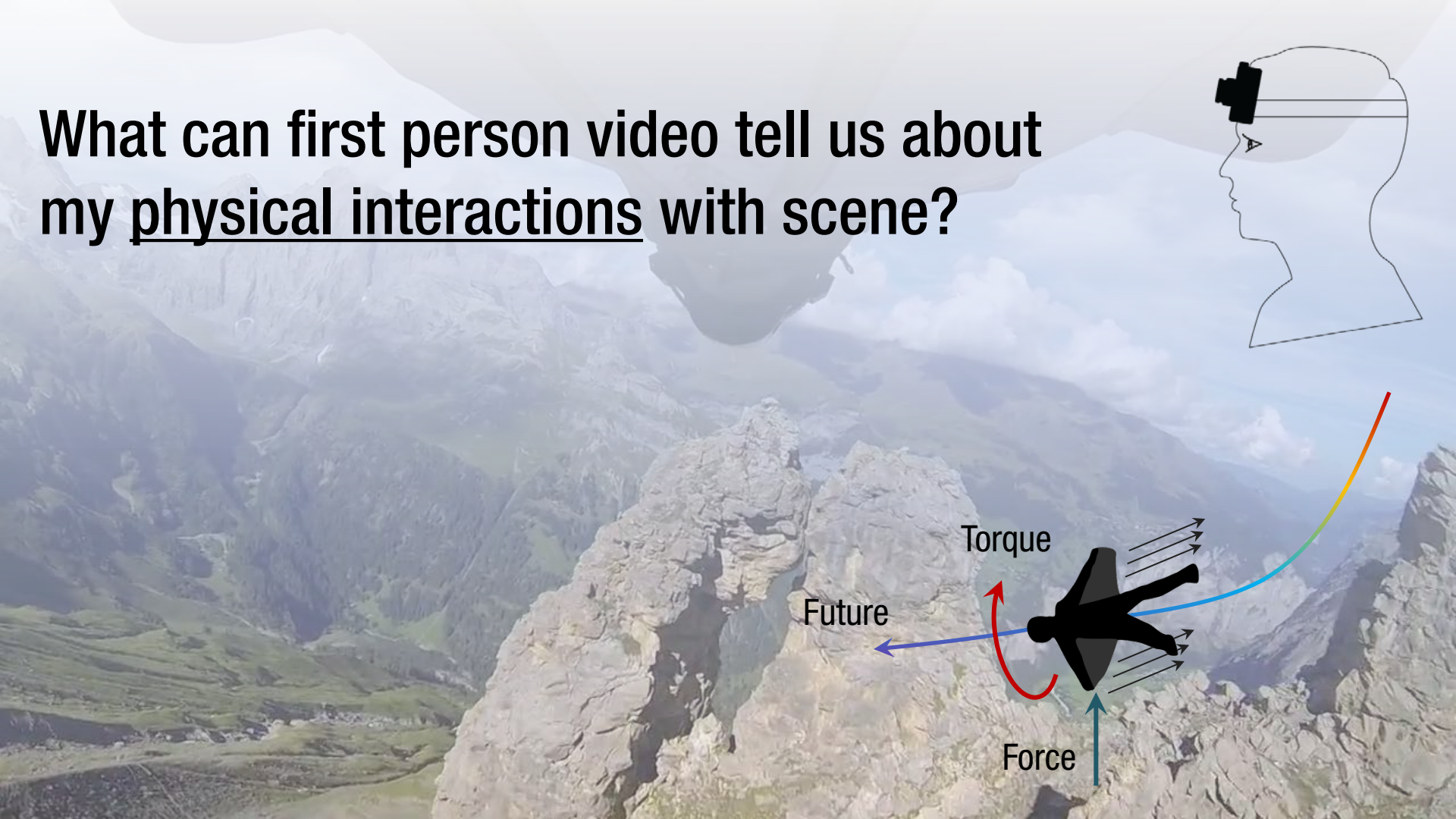


What can first person video tell us about my physical interactions with scene?





What can first person video tell us about my <u>physical interactions</u> with scene?




Biker


Biker

Can we understand activity?

Mountain biking

Can we understand detailed activity?

Mountain biking

Can we understand physics of activity?

1. Gravity

Gyroscope

Can we understand physics of activity?

2. Speed

Accelerometer

Can we understand physics of activity?

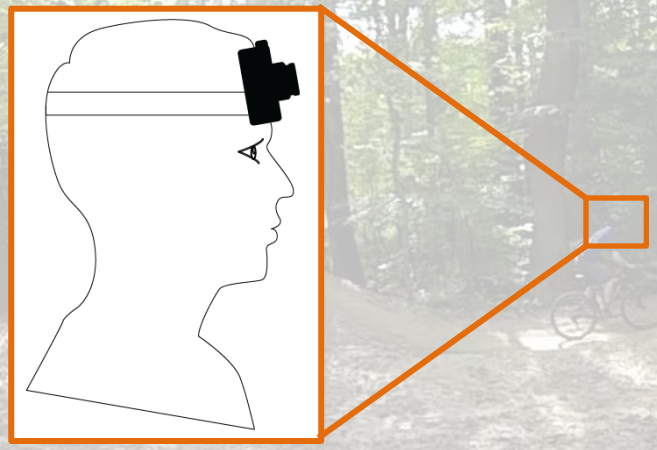
Pedaling Braking

Braking

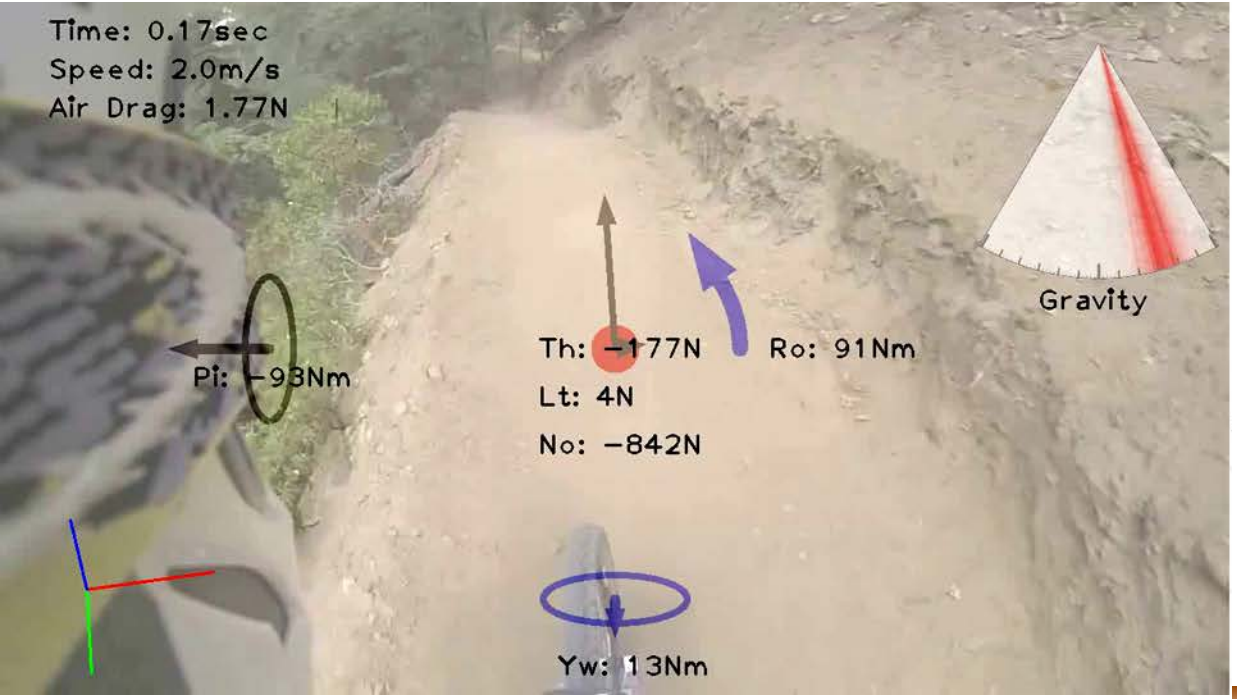
Pedaling

3. Control

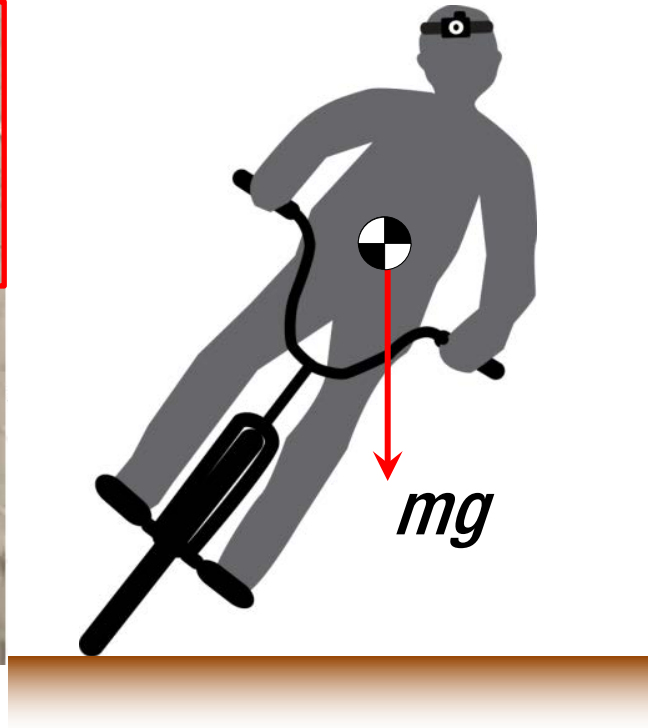
Can we understand physics of activity?



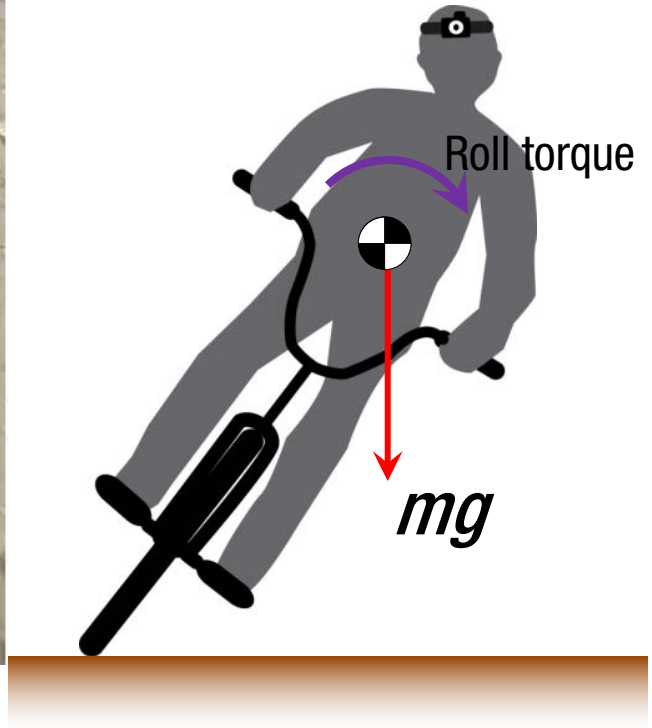
First person camera


Time: 0.17sec
Speed: 2.0m/s
Air Drag: 1.77N
Gravity
Th: -177N
Ro: 91Nm
Pi: -93Nm
Lt: 4N
No: -842N
Yw: 13Nm


Time: 0.17sec
Speed: 2.0m/s
Air Drag: 1.77N
Gravity
Th: -177N
Ro: 91Nm
Pi: -93Nm
Lt: 4N
No: -842N
Yw: 13Nm


mg


Time: 0.17sec
Speed: 2.0m/s
Air Drag: 1.77N
Gravity
Th: -177N
Ro: 91Nm
Pi: -93Nm
Lt: 4N
No: -842N
Yw: 13Nm

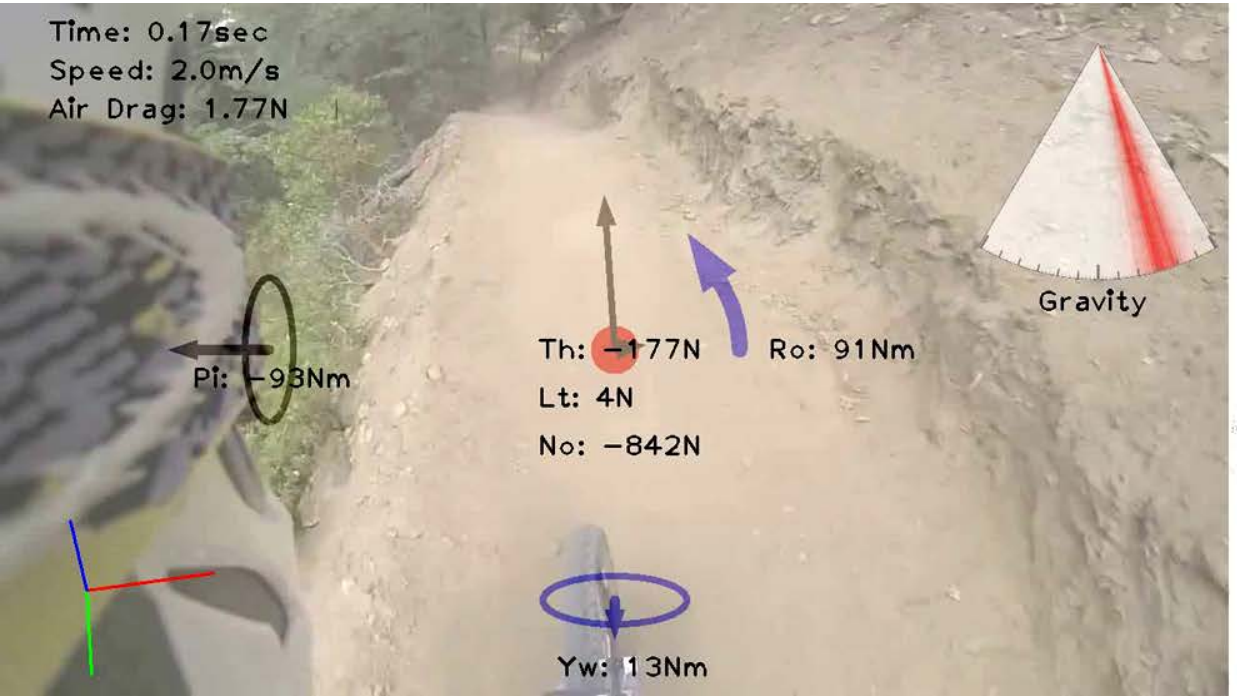

Roll torque
mg

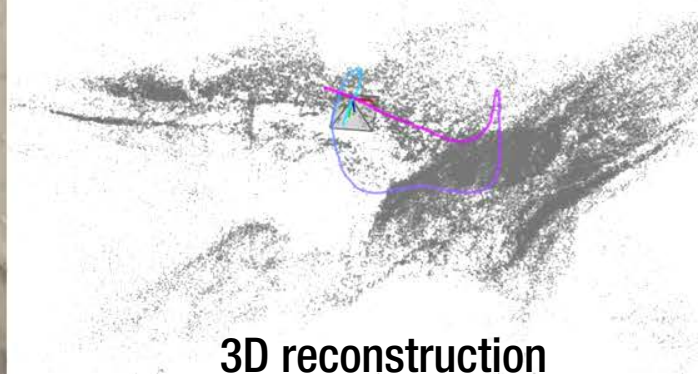

Time: 0.17sec
Speed: 2.0m/s
Air Drag: 1.77N
Gravity
Th: -177N
Ro: 91Nm
Pi: -93Nm
Lt: 4N
No: -842N
Yw: 13Nm


Thrust force
braking
Pedaling

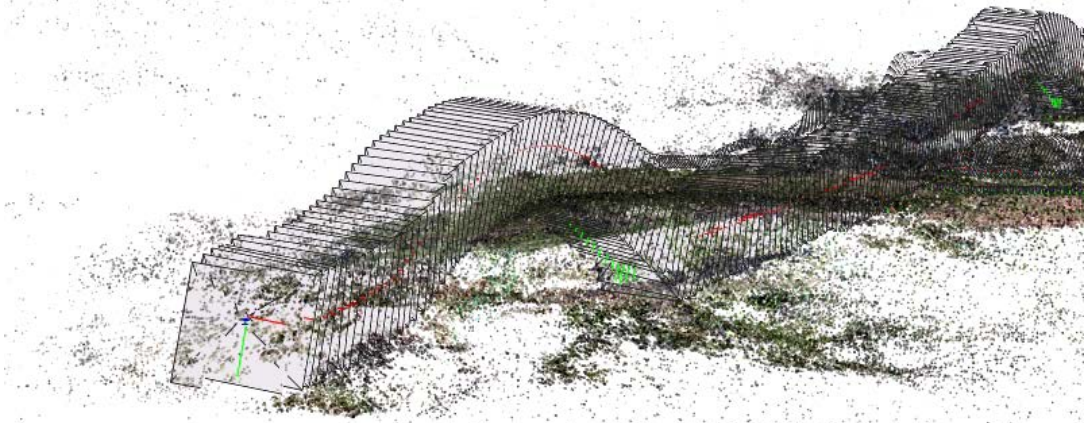

Time: 0.17sec
Speed: 2.0m/s
Air Drag: 1.77N
Gravity
Th: -177N
Ro: 91Nm
Pi: -93Nm
Lt: 4N
No: -842N
Yw: 13Nm


Air drag
Thrust force
braking
Pedaling

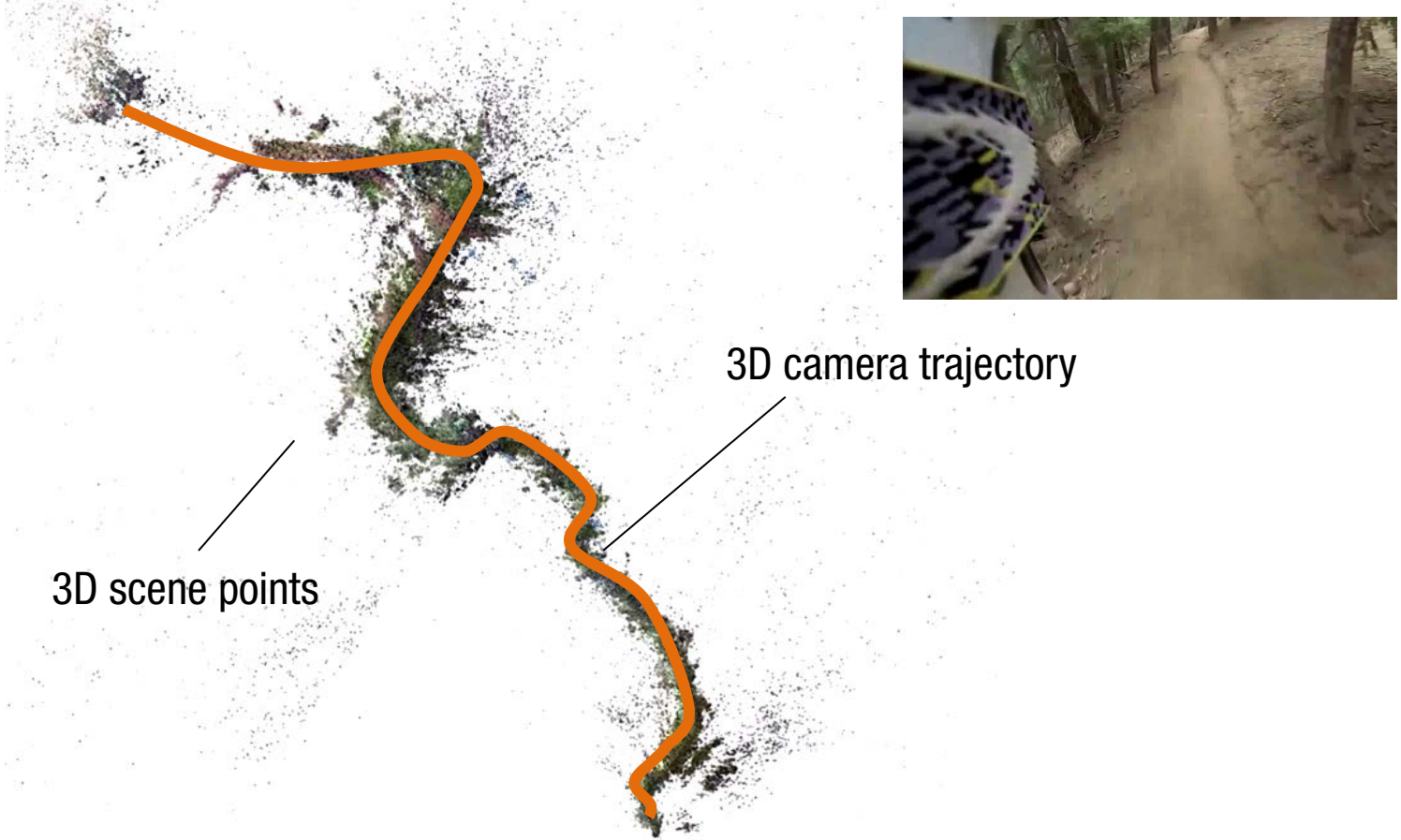




3D reconstruction



3D reconstruction



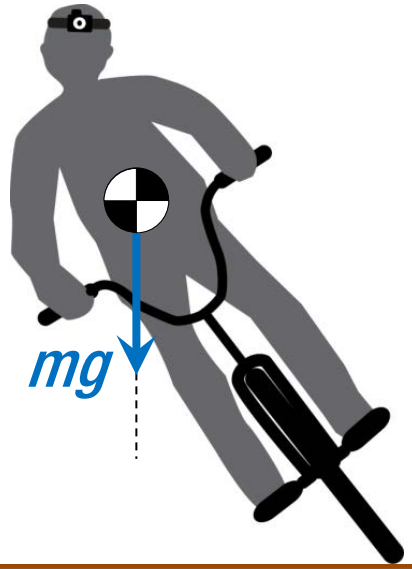
3D reconstruction

Is <u>geometry</u> or <u>kinematics</u> enough to understand the biker's behaviors?

What causes motion?

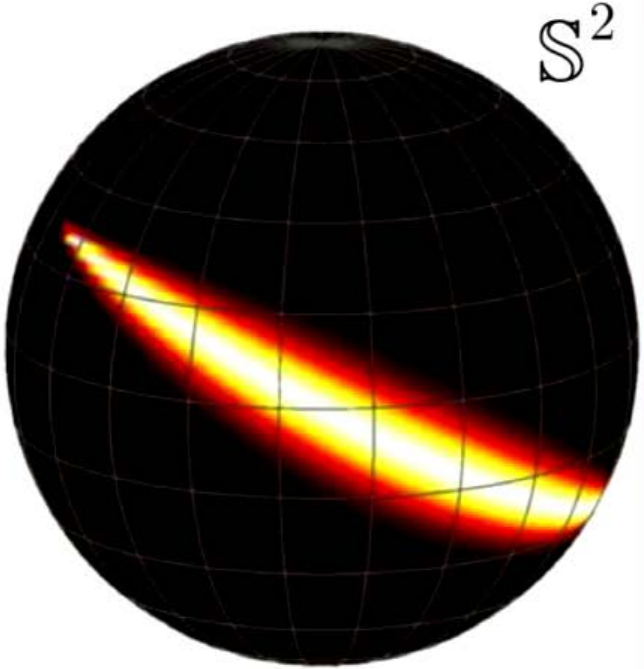
3D reconstruction

1. Compute Gravity




Tree
Water
Horizon

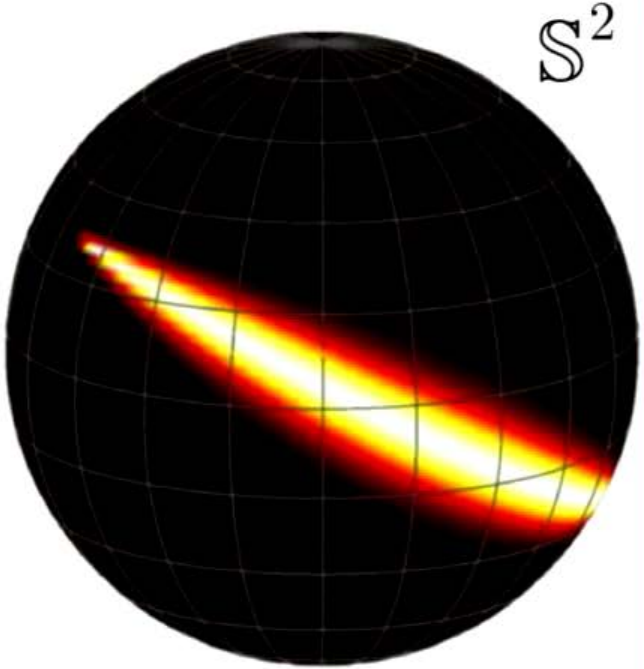

$p(\mathbf{g} \mid \mathcal{I})$
Prediction via CNN
Ground truth
Prediction error: 0.5 degree



Probability of gravity direction in 3D

$p(\mathcal{I} \mid \mathbf{g})$

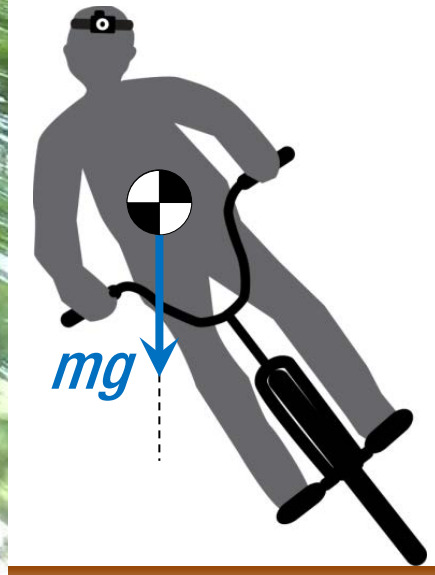
Visual Gravity Prediction

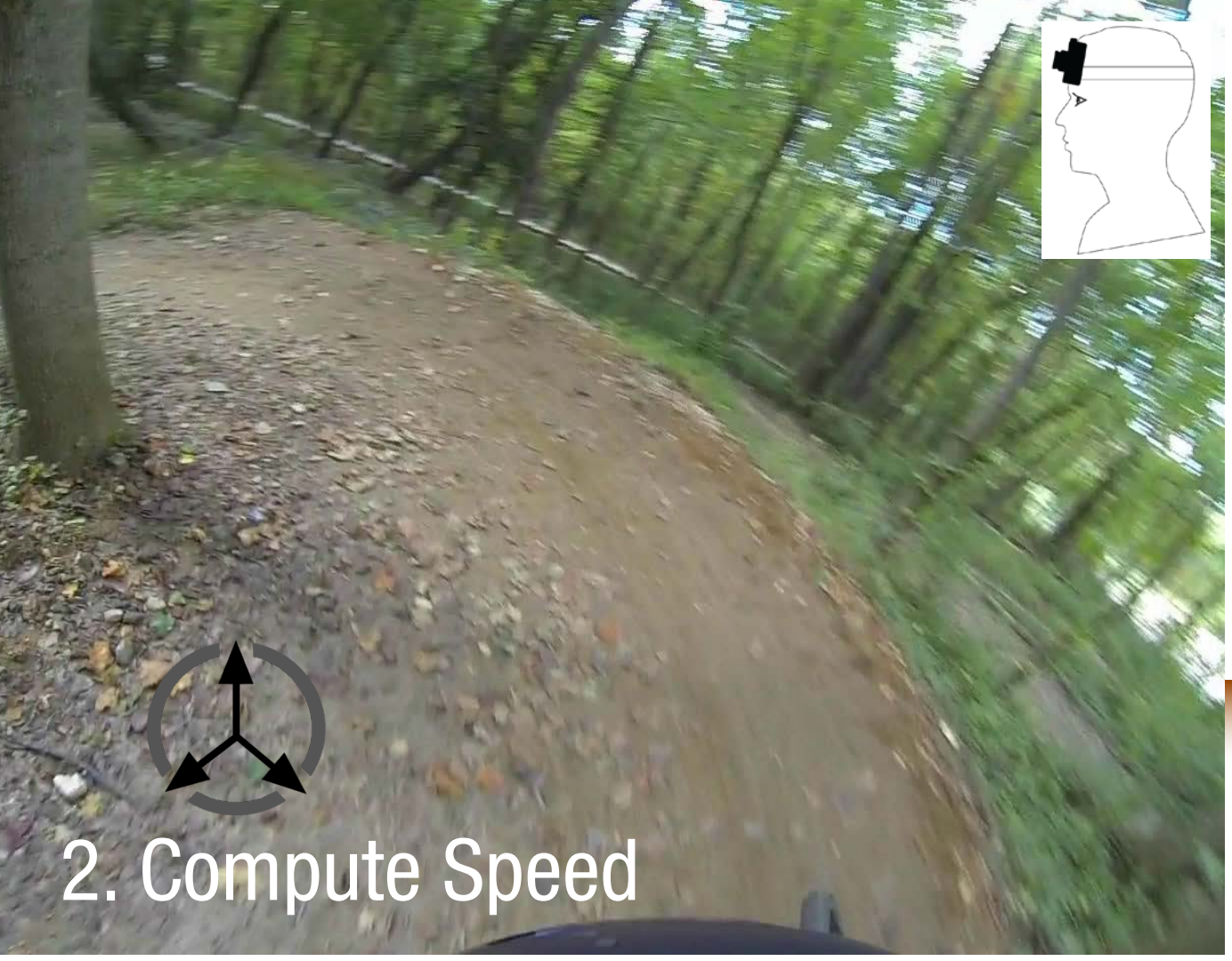


Probability of gravity direction in 3D

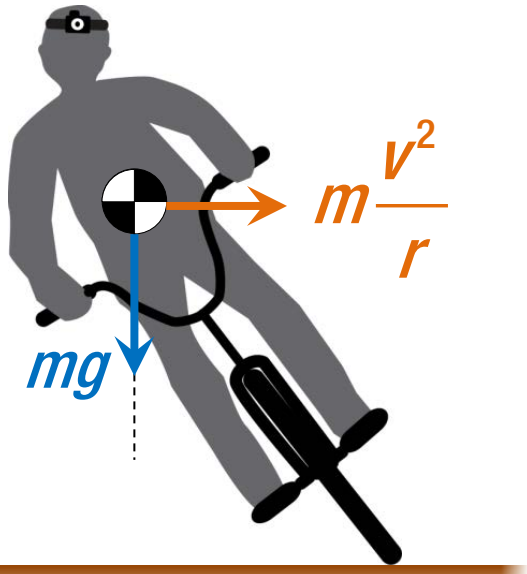
$$p(\hat{\mathrm{g}} \mid \mathcal{I}_1, \cdots, \mathcal{I}_N) \propto p(\hat{\mathrm{g}}) \prod_i^N p(\mathcal{I}_i \mid \hat{\mathrm{g}})$$

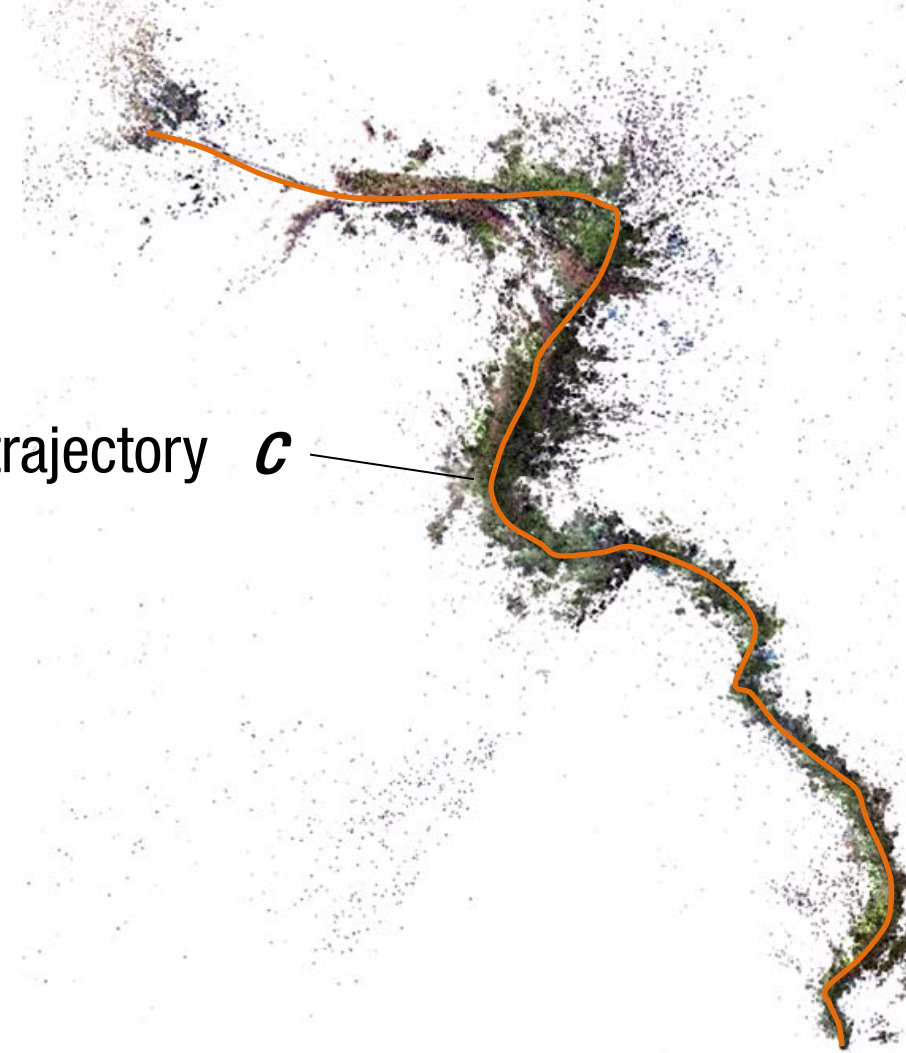

mg


mg



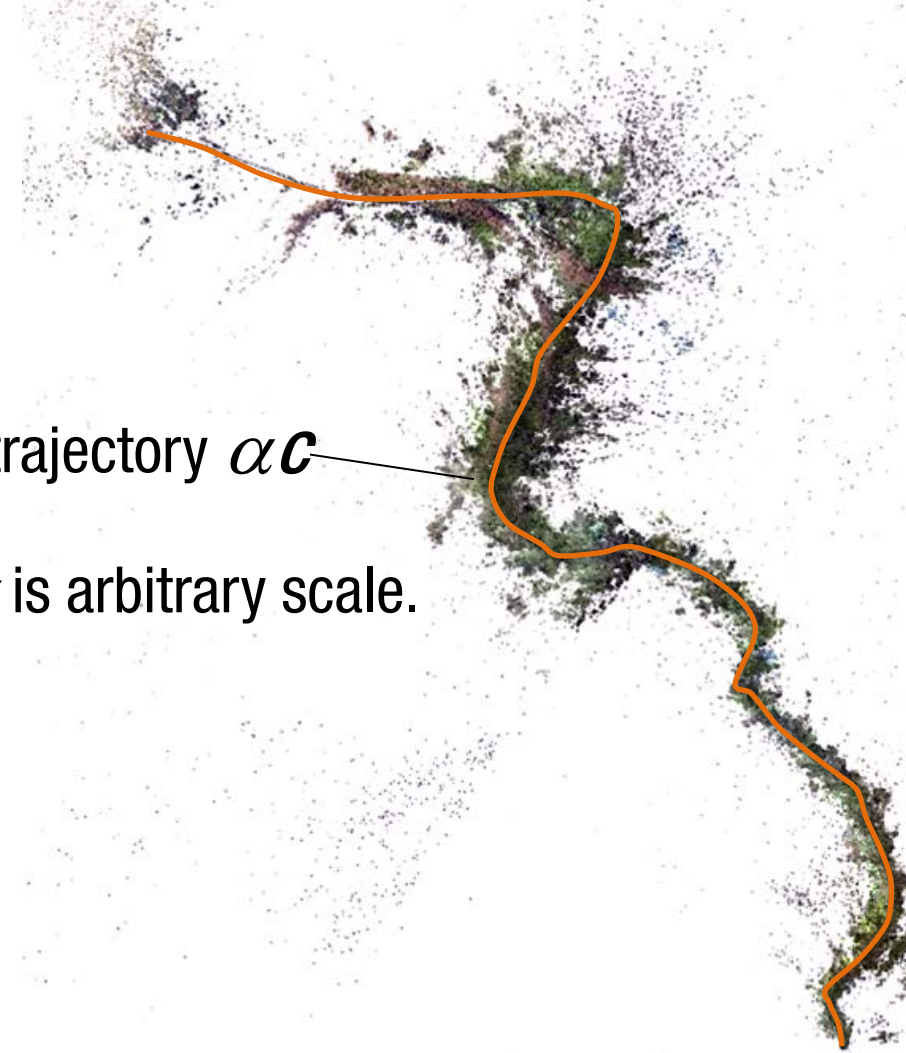
2. Compute Speed





Camera trajectory $\boldsymbol{c}$

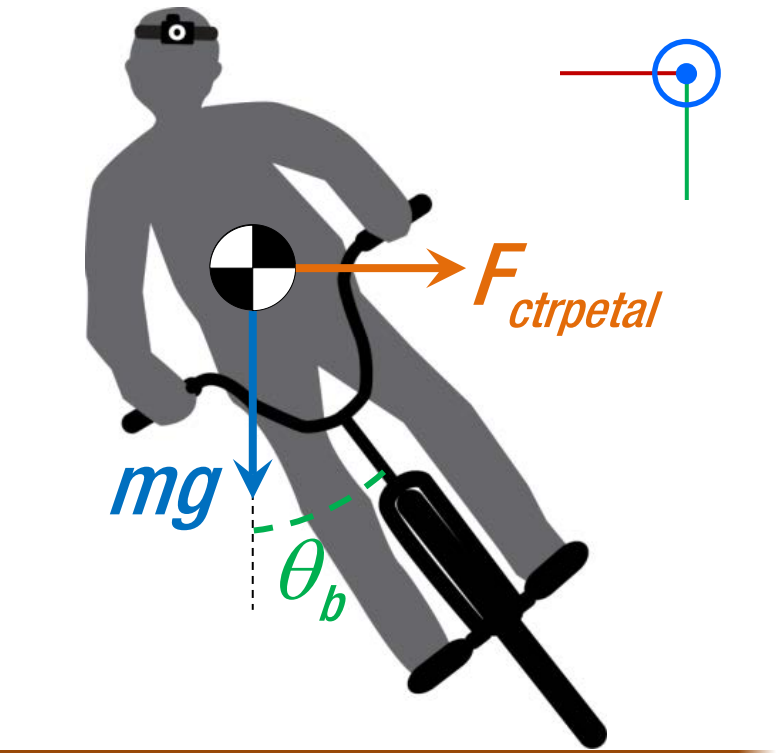
Velocity: $\boldsymbol{v} = \dfrac{\mathrm{d}\boldsymbol{c}}{\mathrm{d}t}$



Camera trajectory $\alpha \boldsymbol{c}$

where α is arbitrary scale.

Velocity: $\boldsymbol{v} = \alpha \dfrac{\mathrm{d}\boldsymbol{c}}{\mathrm{d}t}$



Banked turn

Dynamic balance:

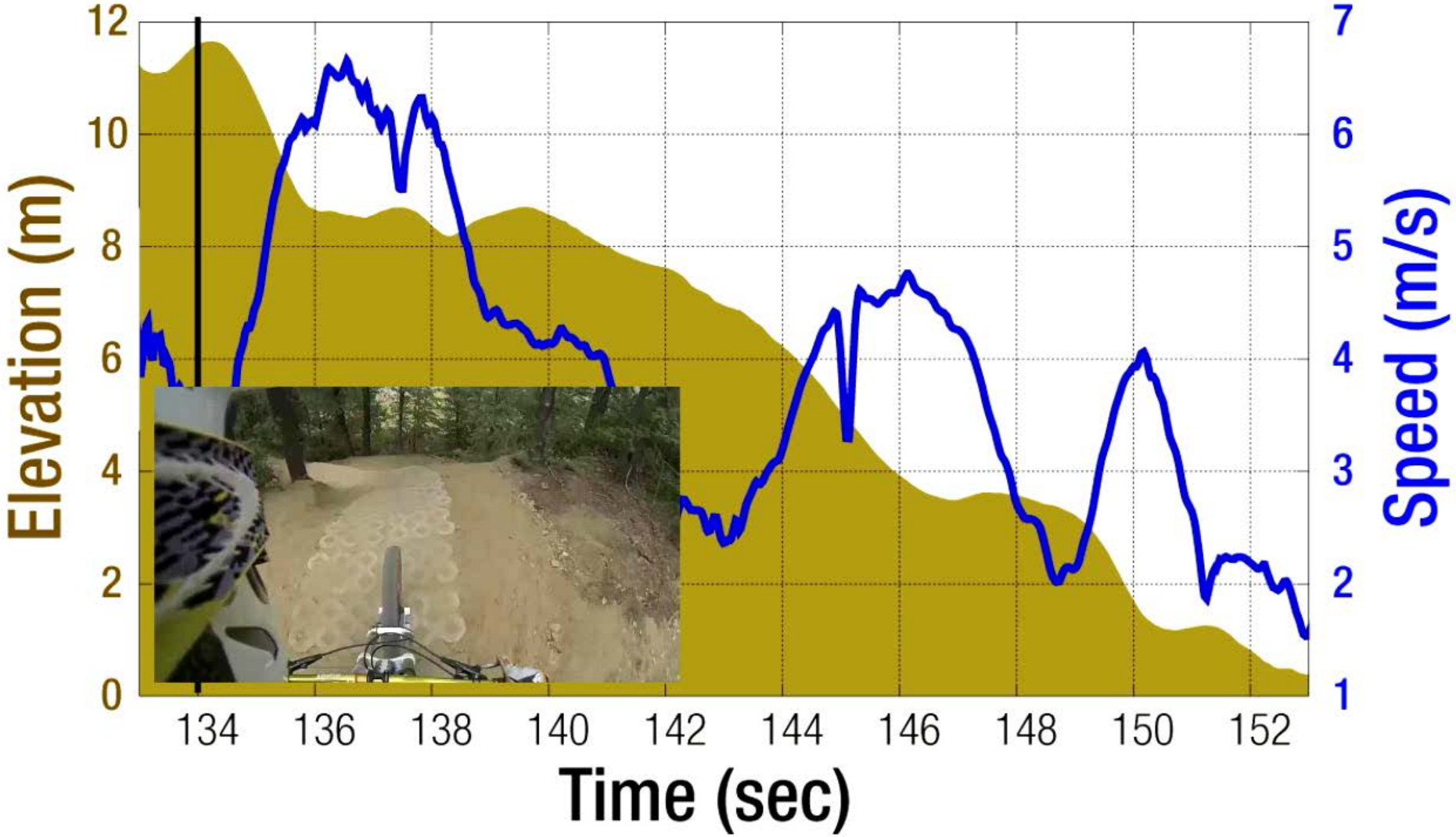
mg

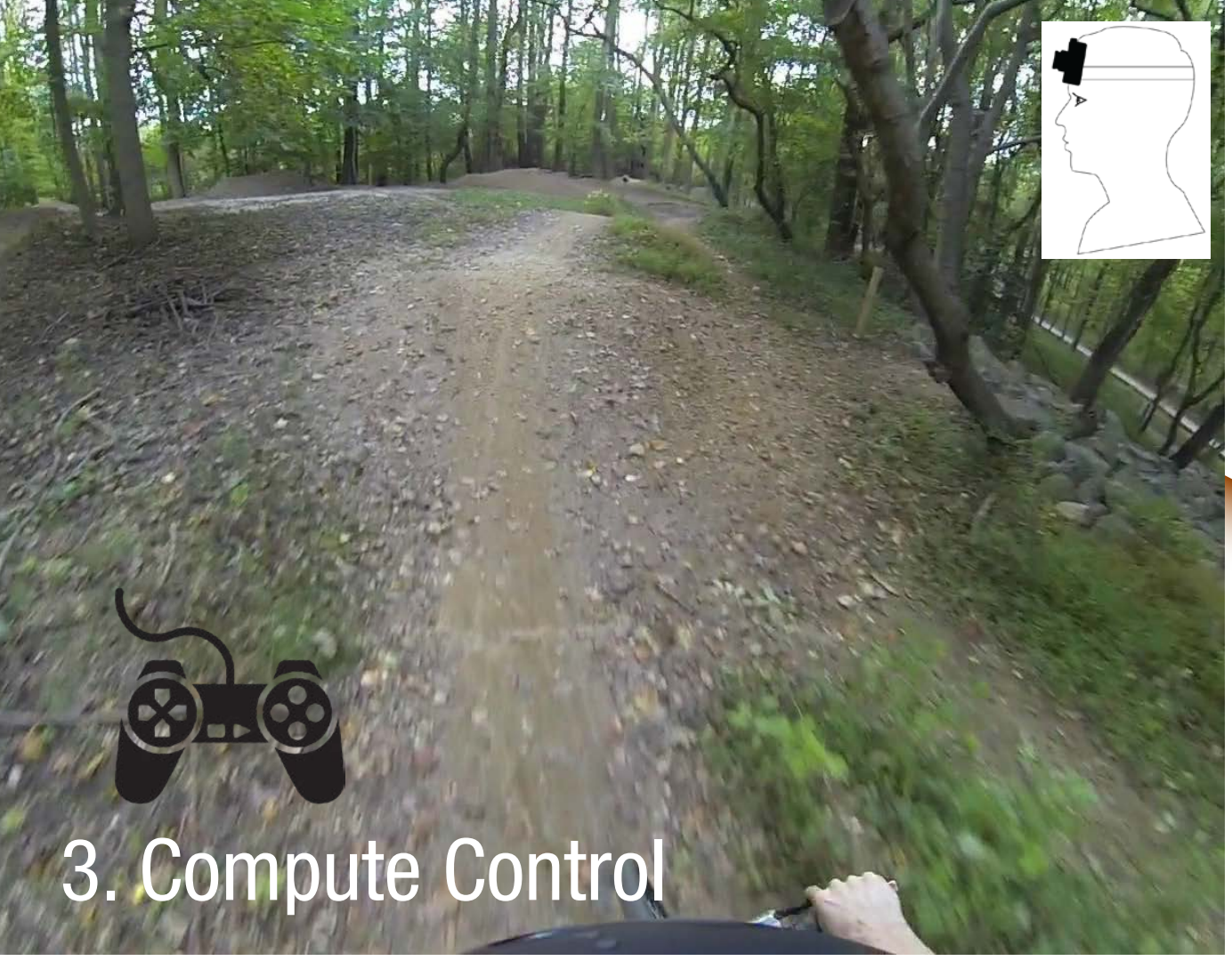
Scale factor:

$$\alpha = \frac{g}{a_{ctrpetal}} \tan \theta_b$$

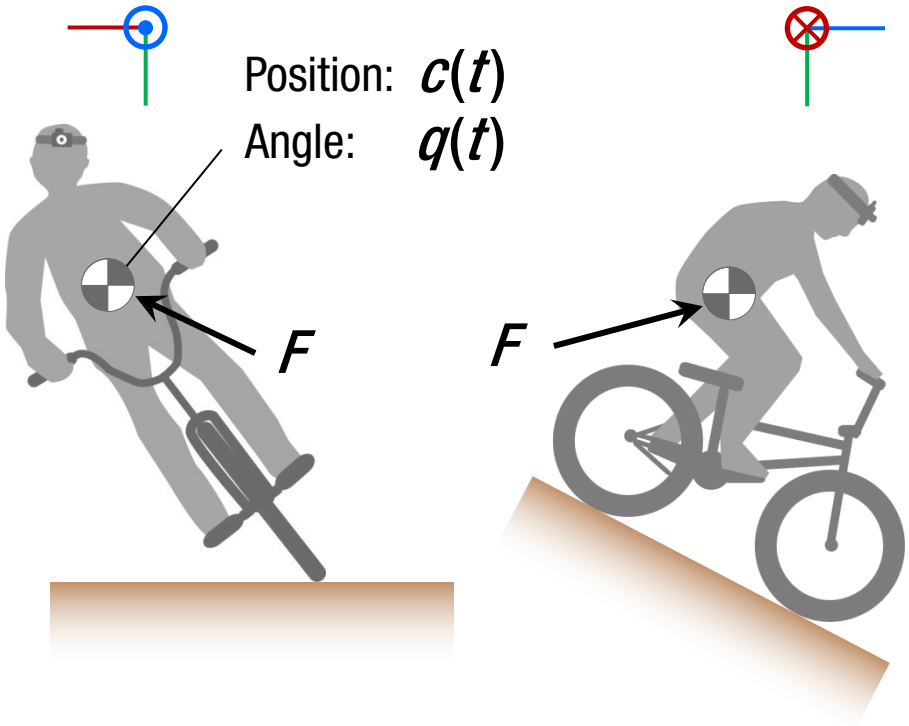
g: 9.81 m/s^2

$a_{ctrpetal}$: Measured by 3D reconstruction


Elevation (m)
Speed (m/s)
Time (sec)
0
2
4
6
8
10
12
1
2
3
4
5
6
7
134
136
138
140
142
144
146
148
150
152

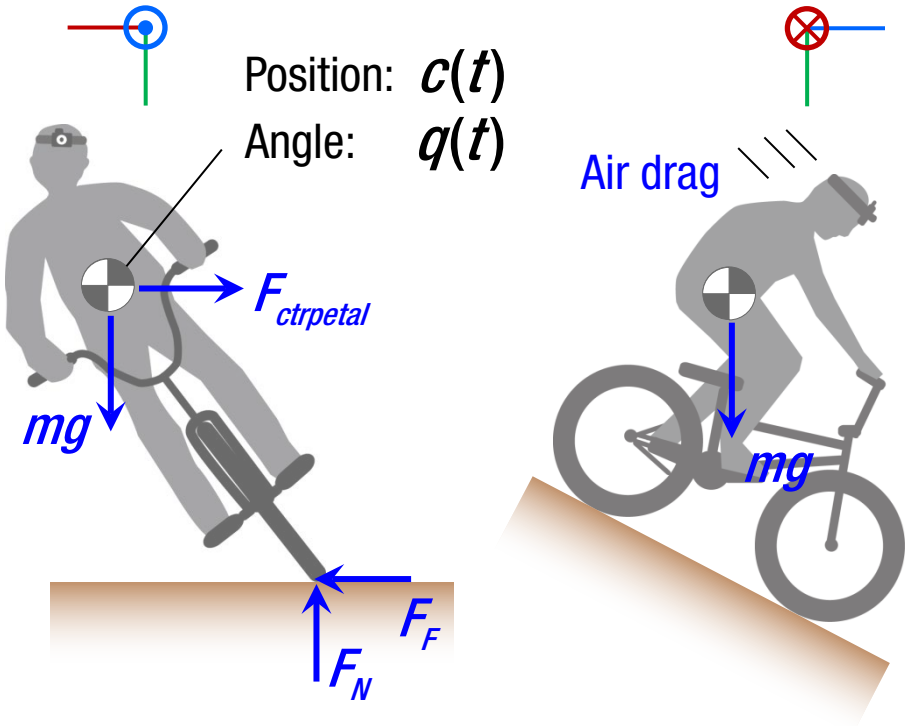


3. Compute Control



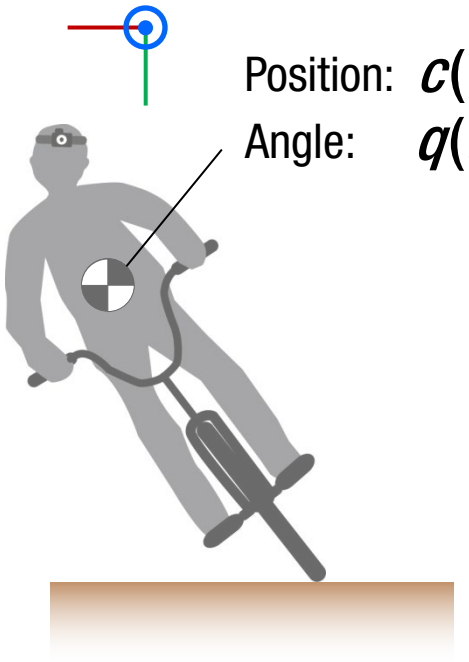
Linear force:

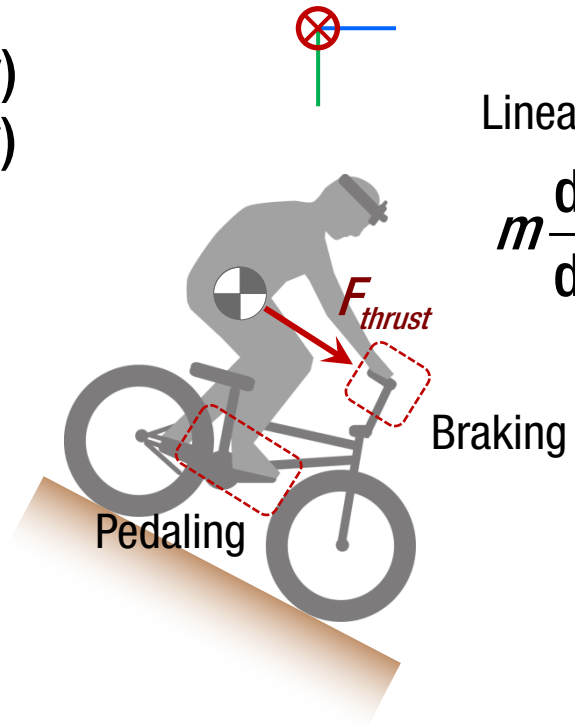
$$m\frac{\mathrm{d}^2 c}{\mathrm{d}t^2} = \underline{F}$$



Linear force:

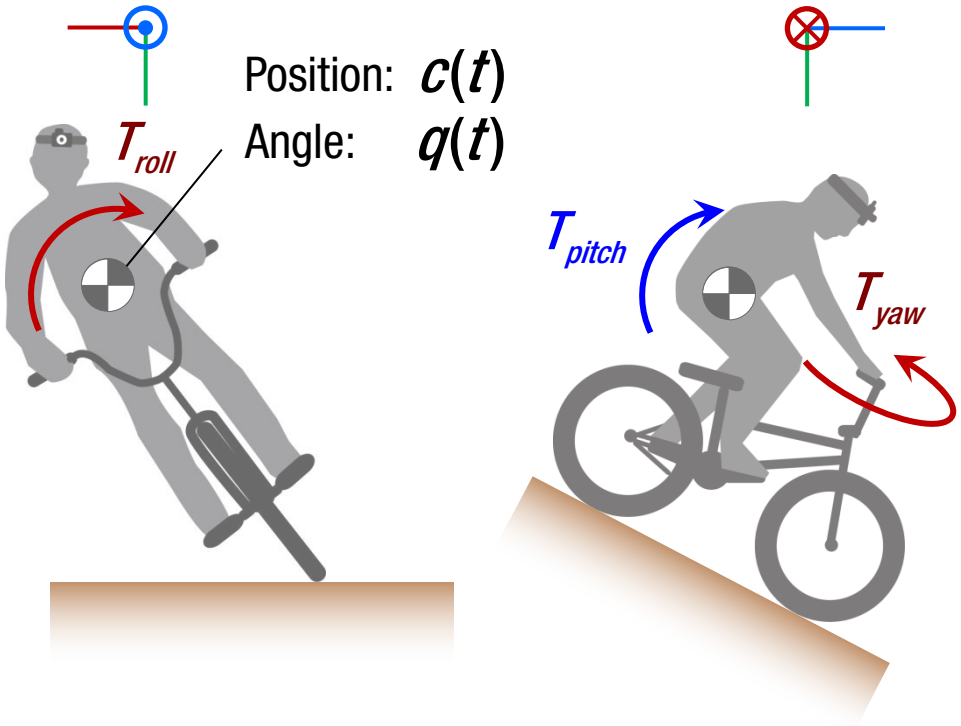
$$m\frac{\mathrm{d}^2 c}{\mathrm{d}t^2} = F = \underline{\sum F_{\text{passive}}} + \sum F_{\text{active}}$$





Linear force:

$$m\frac{\mathrm{d}^2 c}{\mathrm{d}t^2} = F = \sum F_{\text{passive}} + \underline{\sum F_{\text{active}}}$$



Position: $c(t)$

Angle: $q(t)$

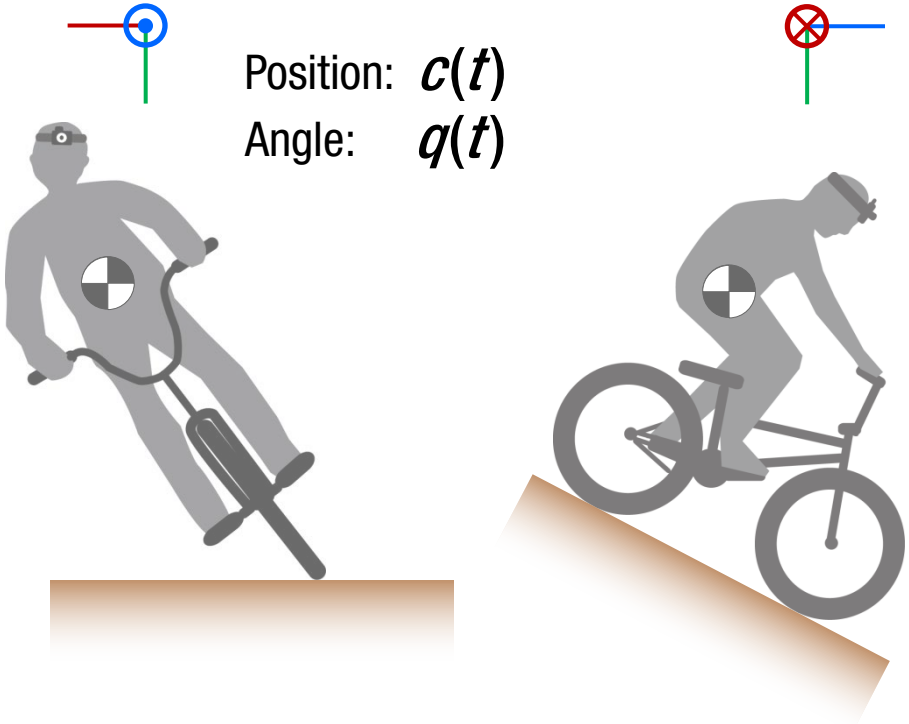
Linear force:

$$m\frac{\mathrm{d}^2 c}{\mathrm{d}t^2} = F = \sum F_{\text{passive}} + \sum F_{\text{active}}$$

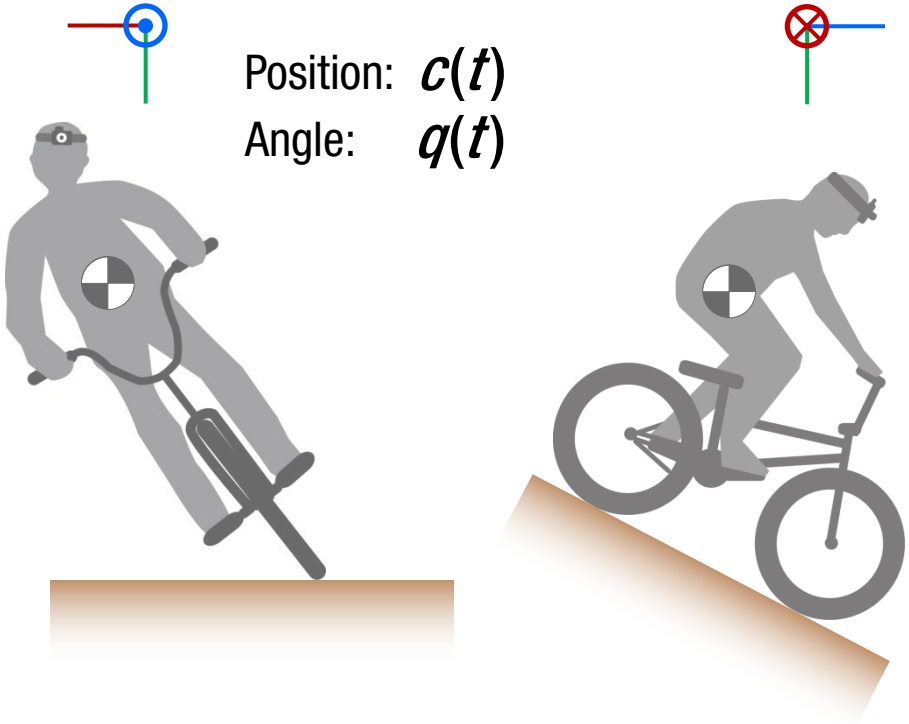
Angular force (torque):

$$J\frac{\mathrm{d}^2 q}{\mathrm{d}t^2} + \frac{\mathrm{d}q}{\mathrm{d}t} \times J\frac{\mathrm{d}q}{\mathrm{d}t} = \sum T_{\text{passive}} + \sum T_{\text{active}}$$

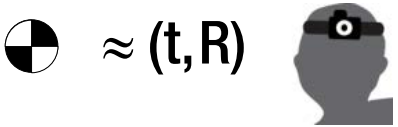
J : Moment of inertia



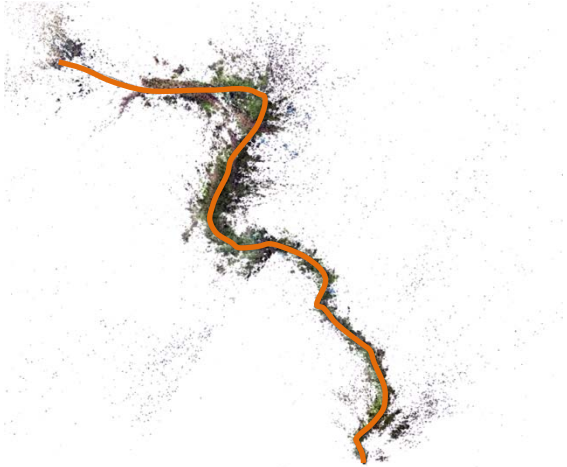
$$(c, q) = \mathrm{ODE}(F_{\text{passive}}, F_{\text{active}}, T_{\text{passive}}, T_{\text{active}})$$

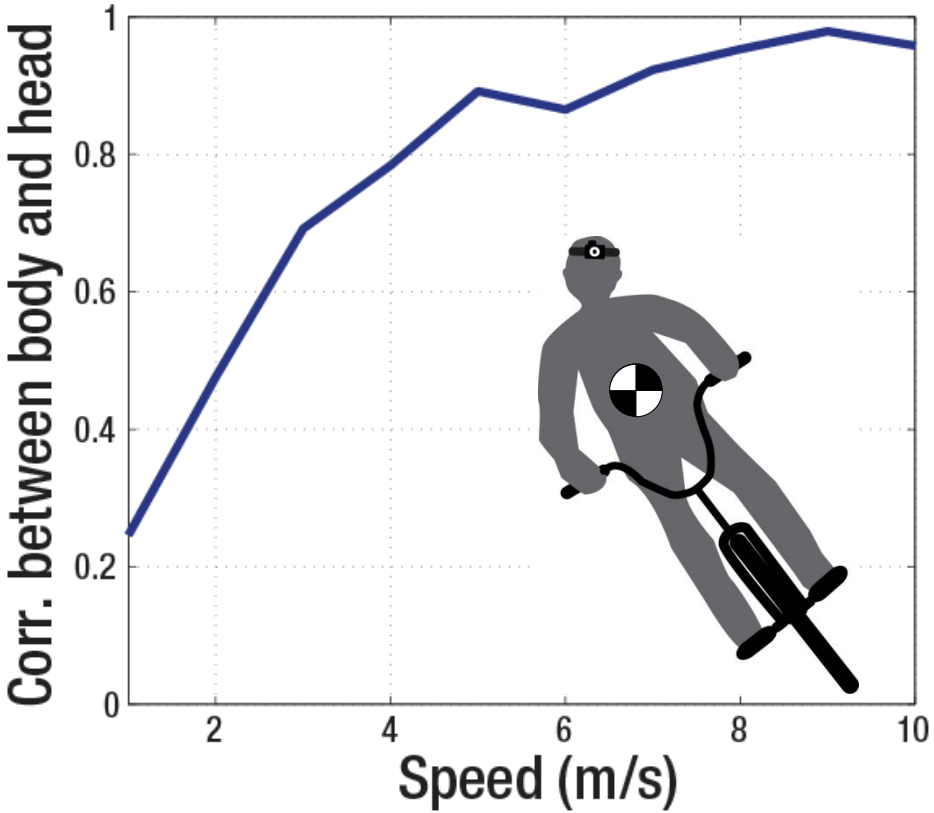


$$(c, q) = \mathrm{ODE}(F_{\text{passive}}, F_{\text{active}}, T_{\text{passive}}, T_{\text{active}})$$

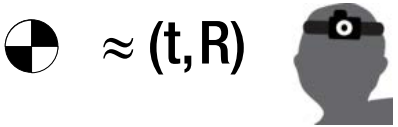


where $P = K[R \quad t]$

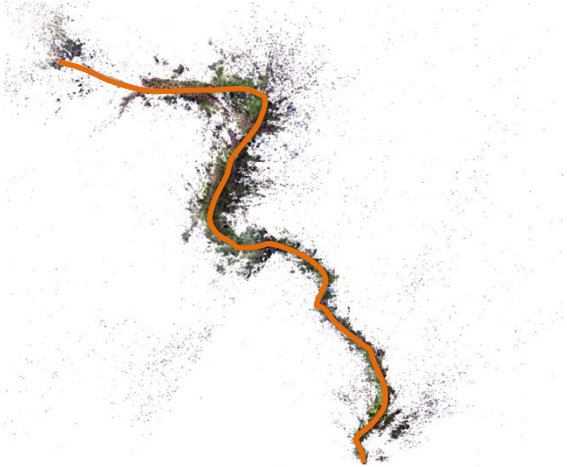




$$(c, q) = \mathrm{ODE}(F_{\text{passive}}, F_{\text{active}}, T_{\text{passive}}, T_{\text{active}})$$



where $P = K[R \quad t]$

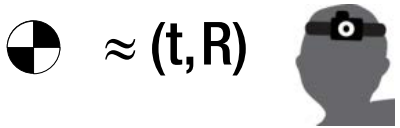


Inverse control:

$$\underset{F,T,X}{\text{minimize}}\ \underbrace{E_{\text{SfM}}}_{\text{Reprojection error}}$$

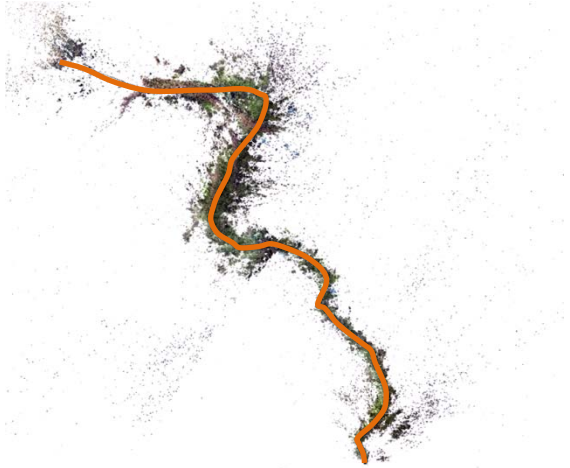
subject to $(\mathrm{t},\mathrm{R}) = \mathrm{ODE}(F,T)$

$$(c,q) = \mathrm{ODE}(F_{\text{passive}}, F_{\text{active}}, T_{\text{passive}}, T_{\text{active}})$$



$\approx (\mathrm{t},\mathrm{R})$

where $\mathrm{P} = \mathrm{K}\begin{bmatrix}\mathrm{R} & \mathrm{t}\end{bmatrix}$

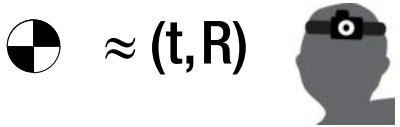


Inverse control:

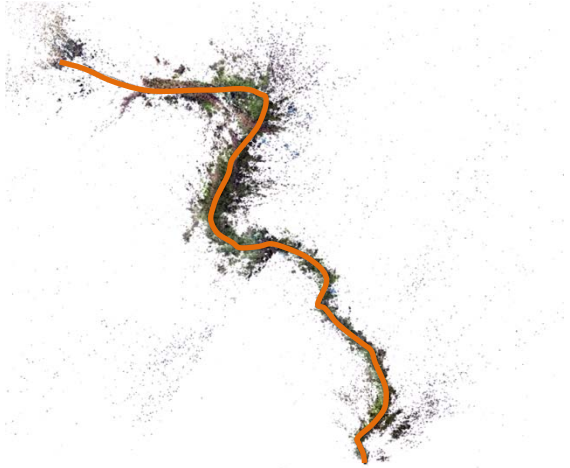
$$\underset{F,T,X}{\text{minimize}}\; E_{\text{SfM}} + \lambda \underbrace{E_{\text{reg}}(F,T)}_{\text{Temporal regularization}}$$

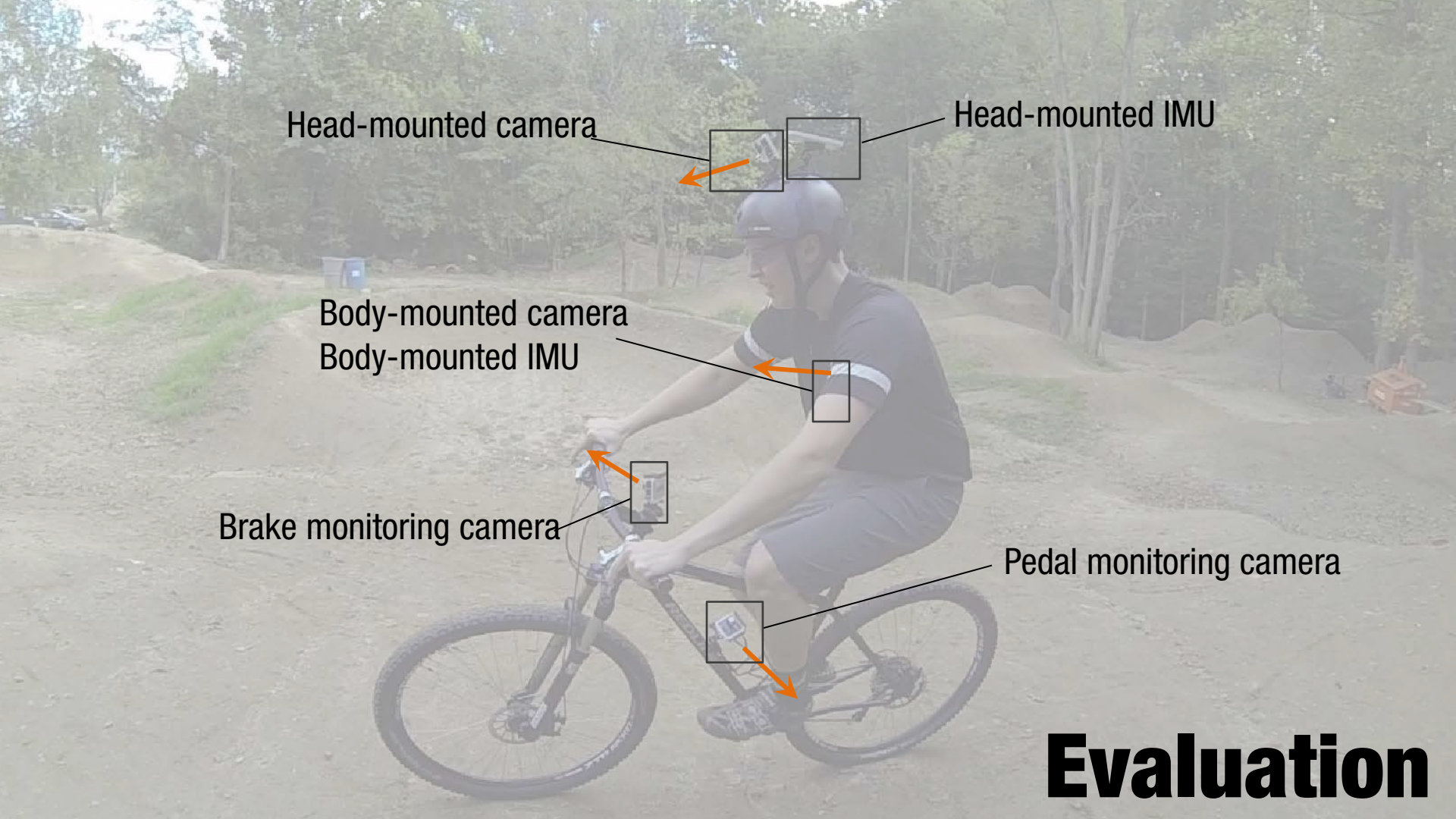
subject to $(\mathrm{t},\mathrm{R}) = \mathrm{ODE}(F,T)$

$$(c,q) = \mathrm{ODE}(F_{\text{passive}}, F_{\text{active}}, T_{\text{passive}}, T_{\text{active}})$$

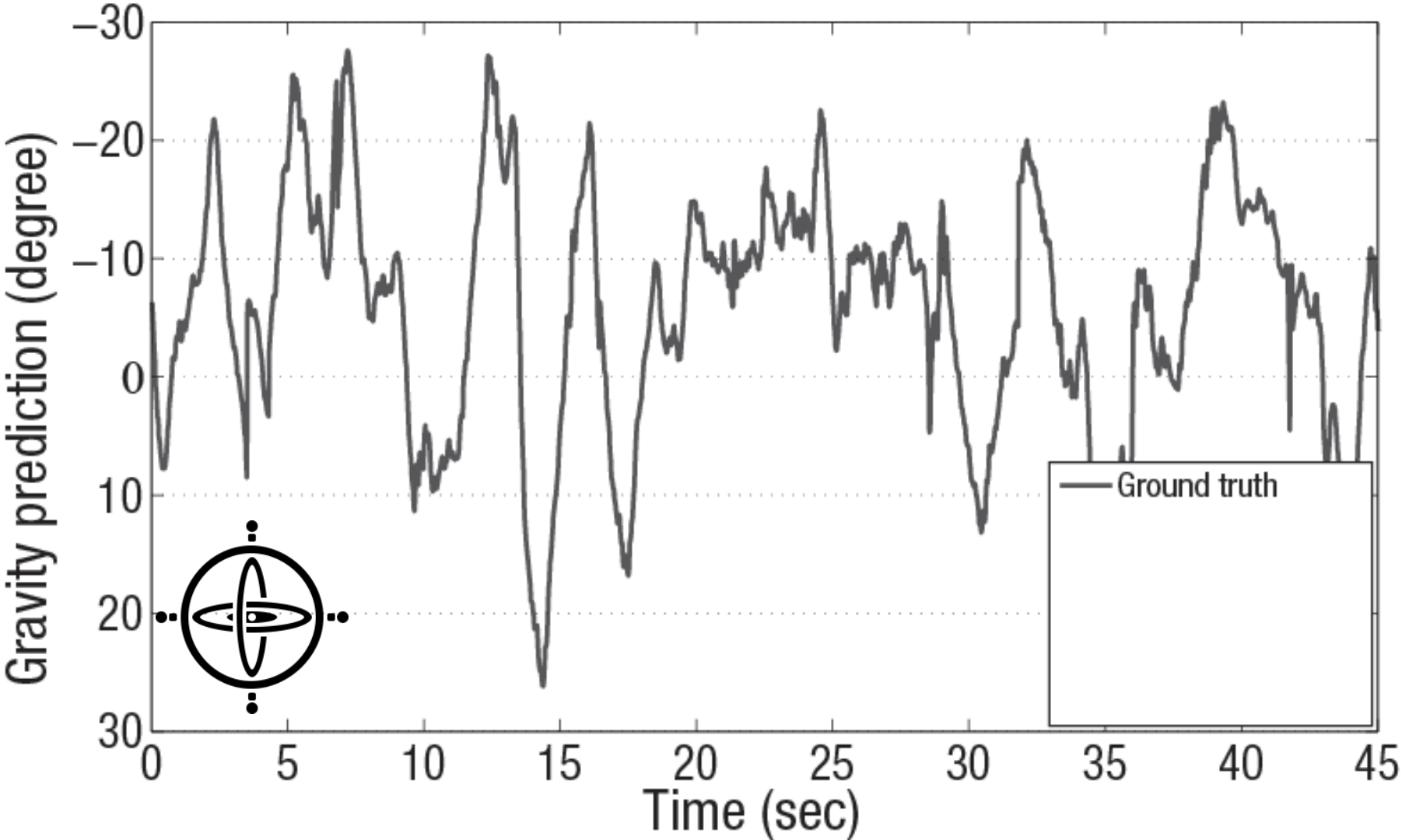


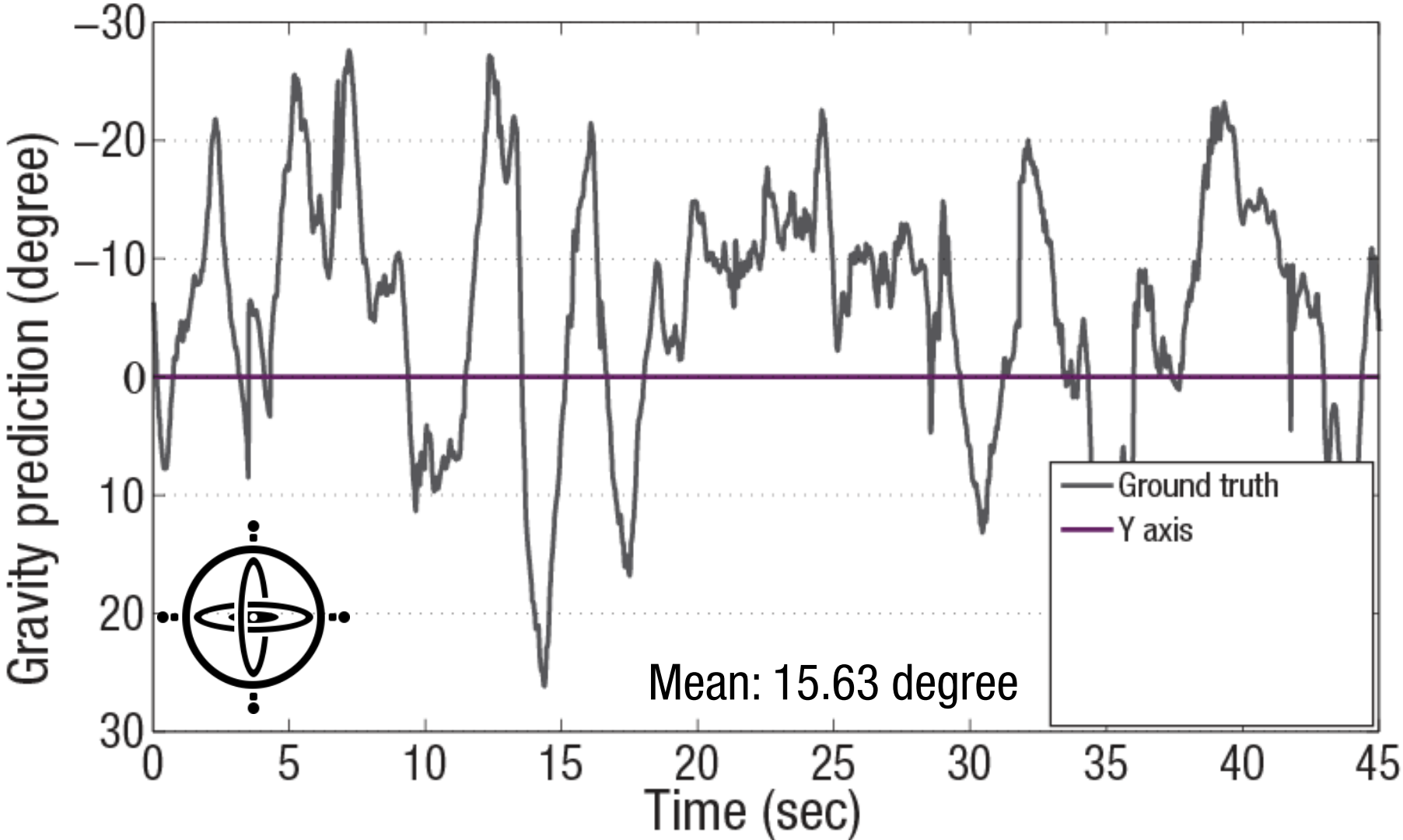
where $\mathrm{P} = \mathrm{K}\begin{bmatrix}\mathrm{R} & \mathrm{t}\end{bmatrix}$

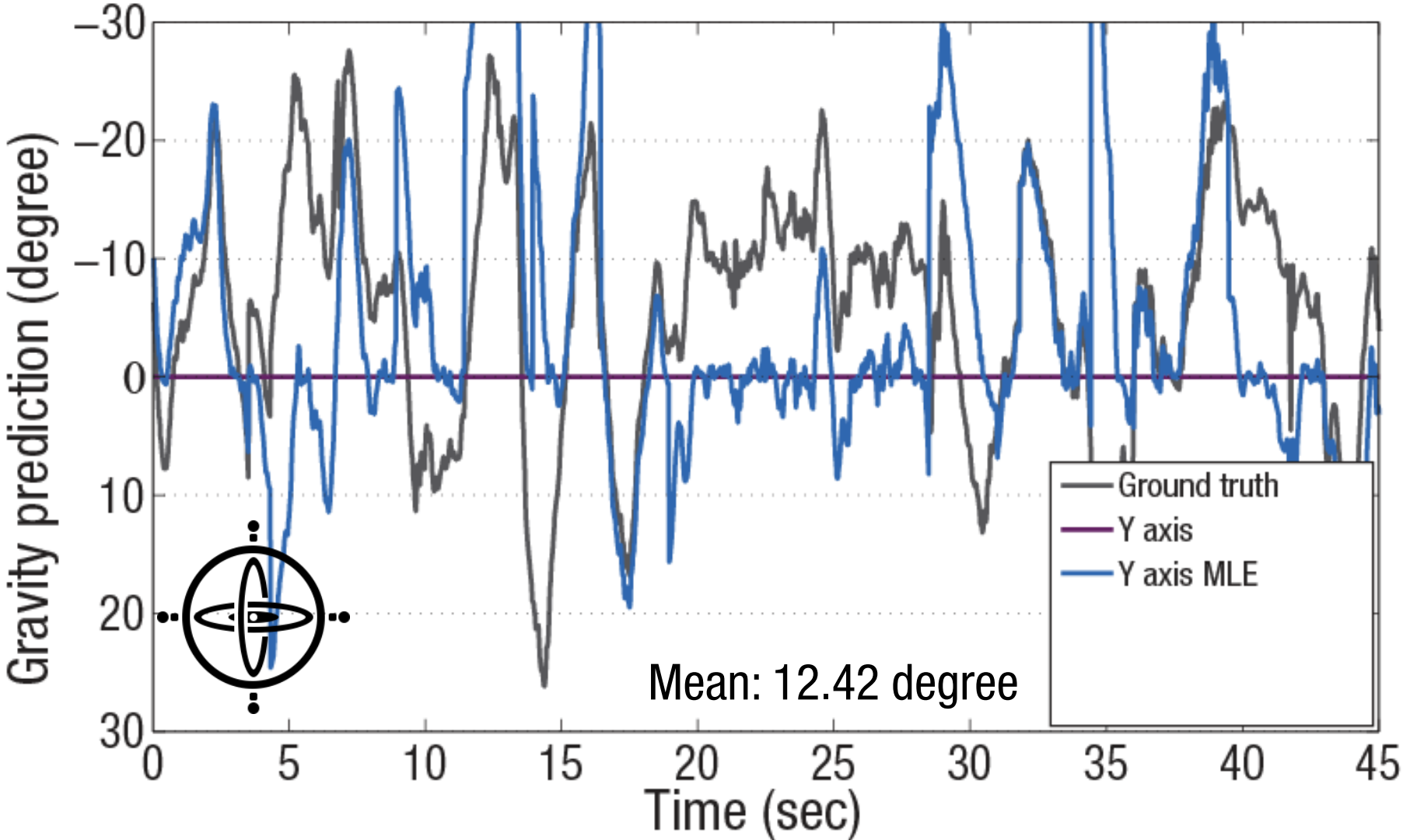


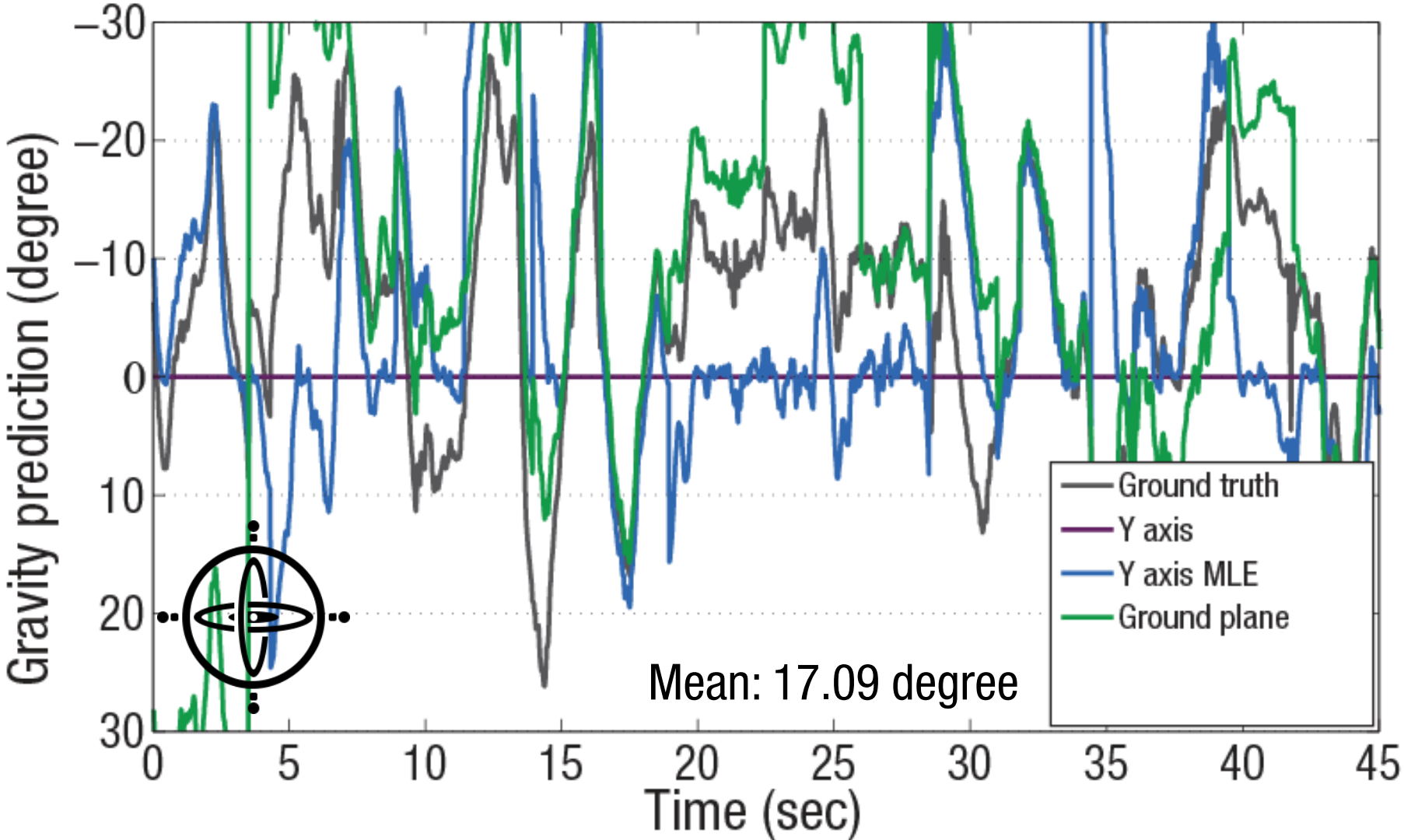

Head-mounted camera
Head-mounted IMU
Body-mounted camera
Body-mounted IMU
Brake monitoring camera
Pedal monitoring camera

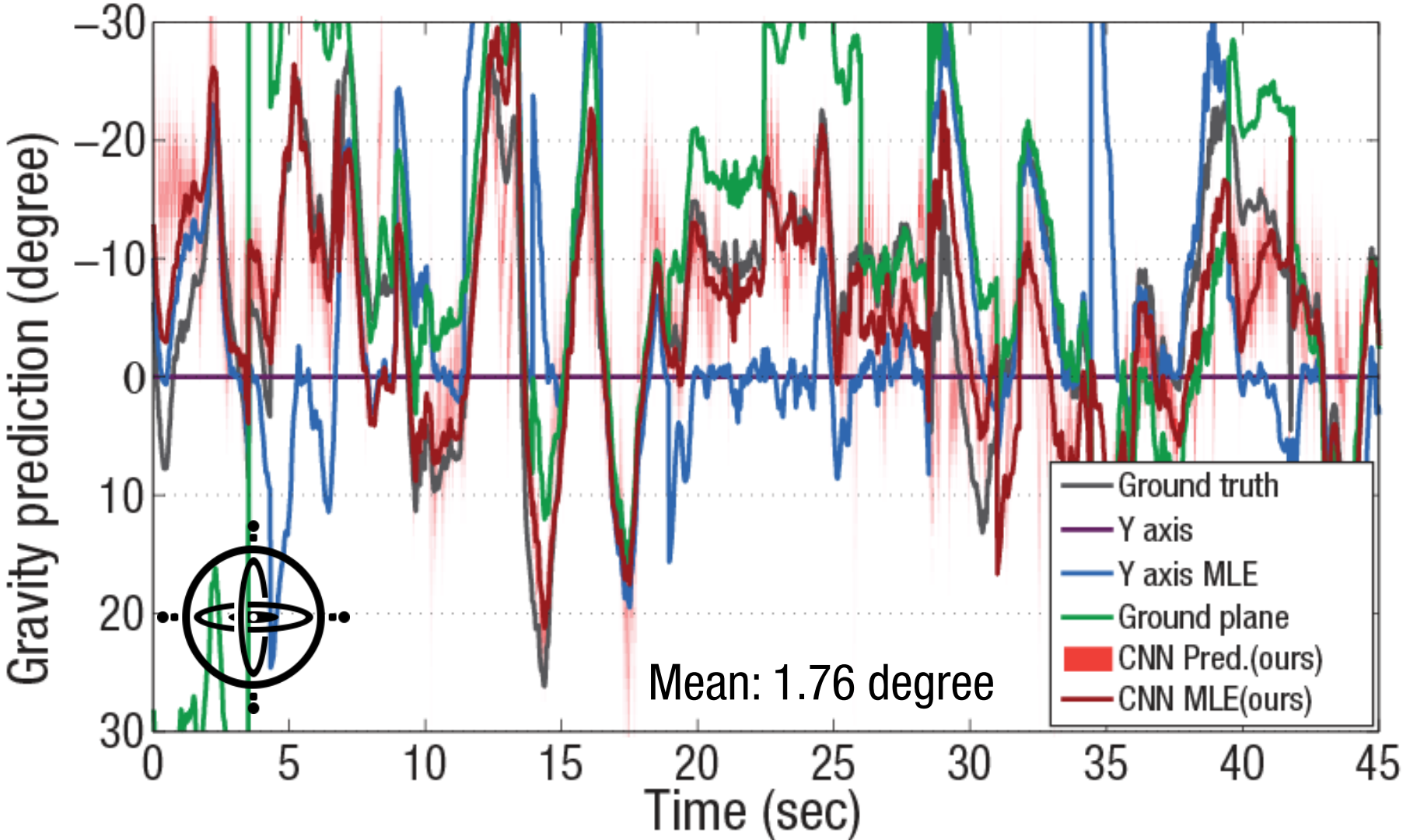
Evaluation

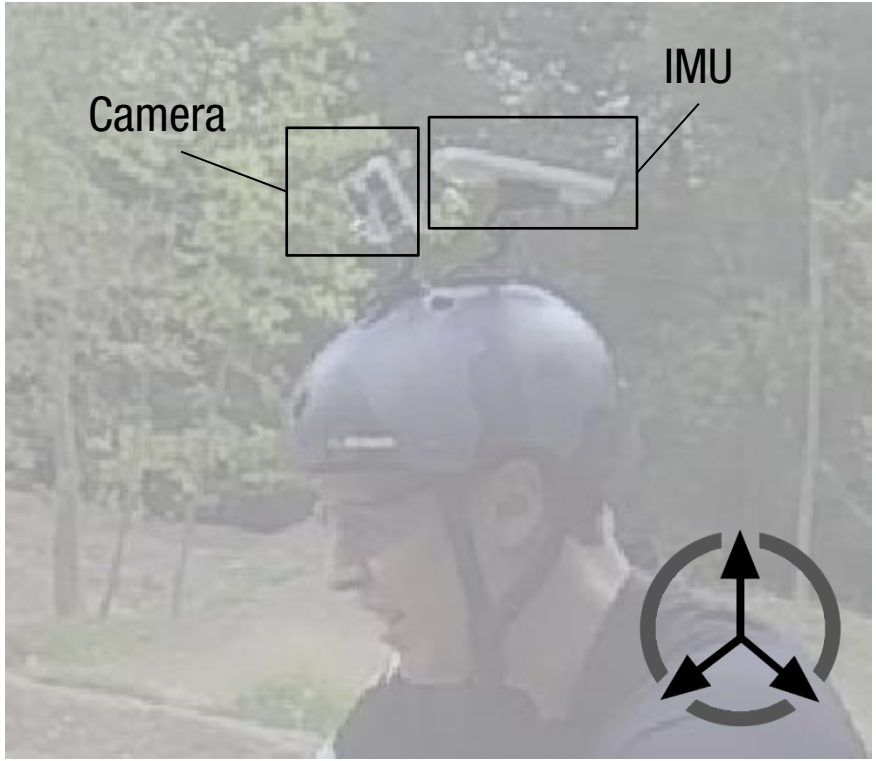

Gravity prediction (degree)
−30
−20
−10
0
10
20
30
0
5
10
15
20
25
30
35
40
45
Time (sec)
Ground truth

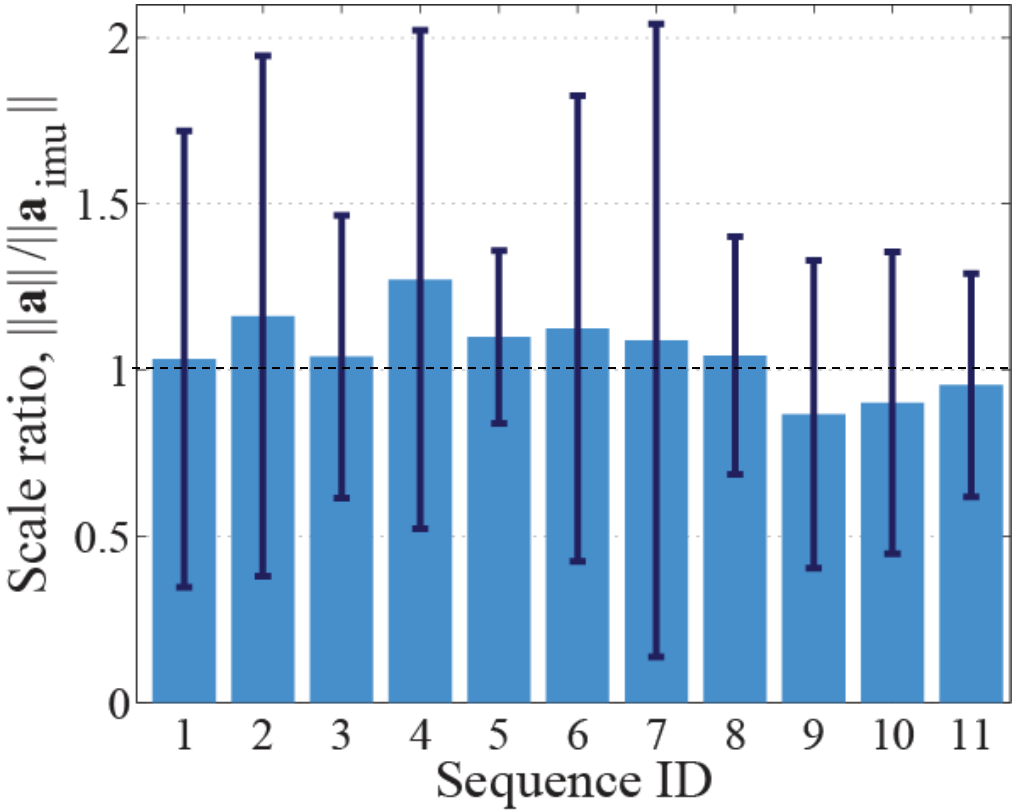

Gravity prediction (degree)
−30
−20
−10
0
10
20
30
0
5
10
15
20
25
30
35
40
45
Time (sec)
Ground truth
Y axis
Mean: 15.63 degree


Gravity prediction (degree)
−30
−20
−10
0
10
20
30
0
5
10
15
20
25
30
35
40
45
Time (sec)
Ground truth
Y axis
Y axis MLE
Mean: 12.42 degree


Gravity prediction (degree)
−30
−20
−10
0
10
20
30
0
5
10
15
20
25
30
35
40
45
Time (sec)
Ground truth
Y axis
Y axis MLE
Ground plane
Mean: 17.09 degree

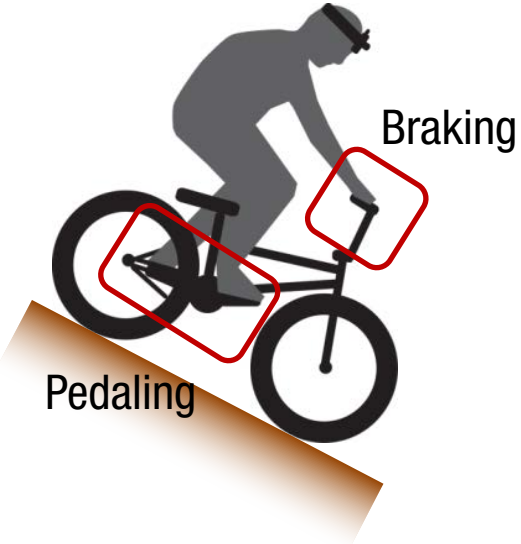

Gravity prediction (degree)
−30
−20
−10
0
10
20
30
0
5
10
15
20
25
30
35
40
45
Time (sec)
Mean: 1.76 degree
Ground truth
Y axis
Y axis MLE
Ground plane
CNN Pred.(ours)
CNN MLE(ours)


Camera
IMU


Scale ratio, $\|\mathbf{a}\|/\|\mathbf{a}_{imu}\|$
0
0.5
1
1.5
2
1
2
3
4
5
6
7
8
9
10
11
Sequence ID

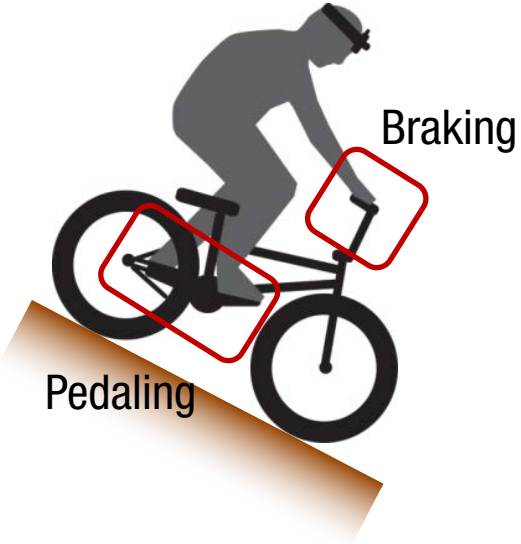
Pedaling activity (acceleration)

Braking activity (deceleration)

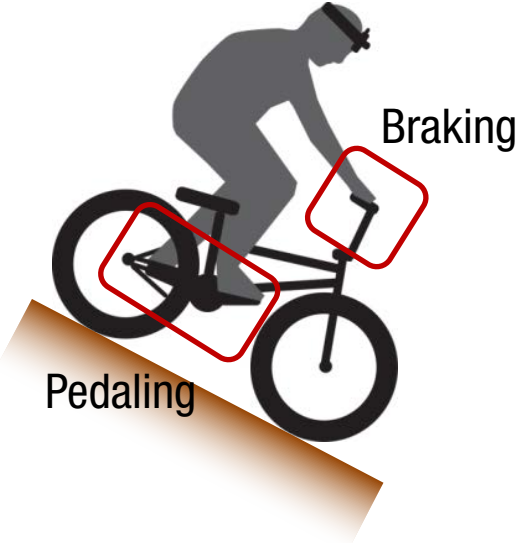


Pedaling activity (acceleration)

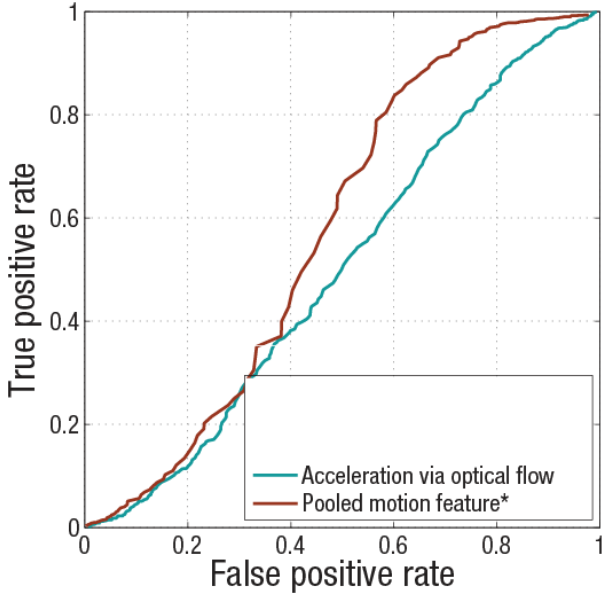
Braking activity (deceleration)



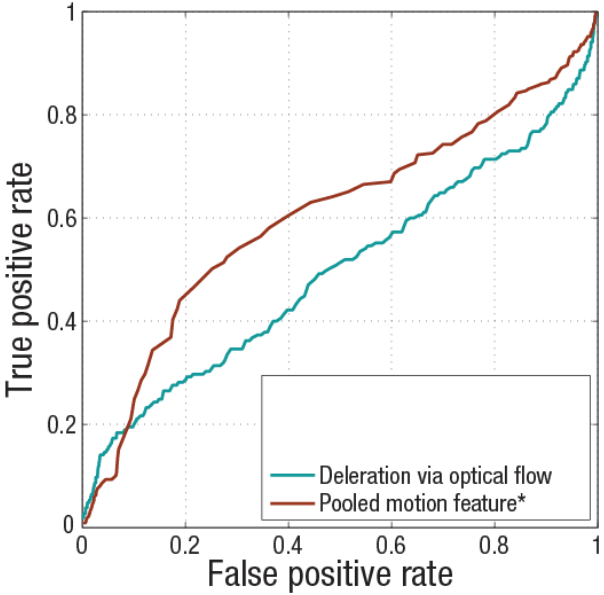
$$m\frac{\mathrm{d}^2 c}{\mathrm{d}t^2} = F = \sum F_{\text{passive}} + \underline{\sum F_{\text{active}}}$$

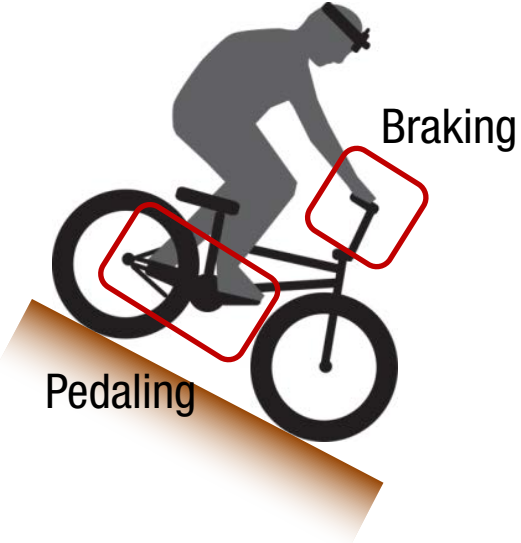


Pedaling activity (acceleration)

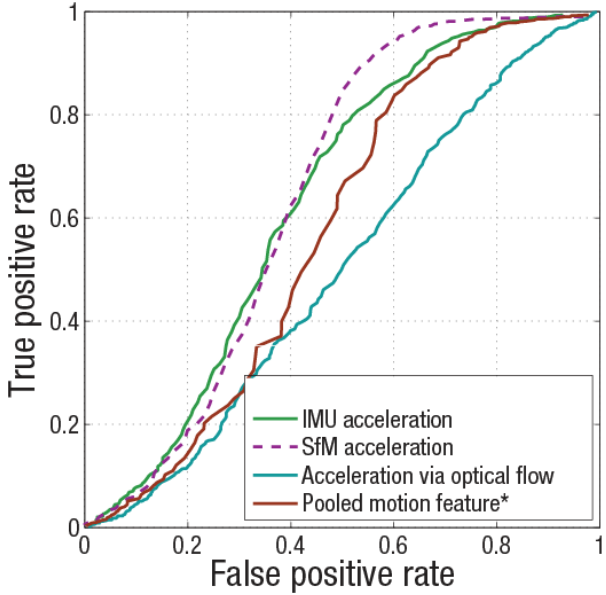


Braking activity (deceleration)

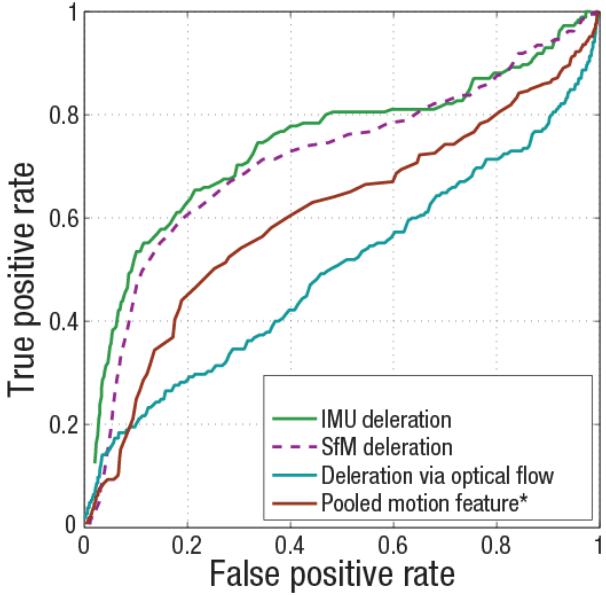


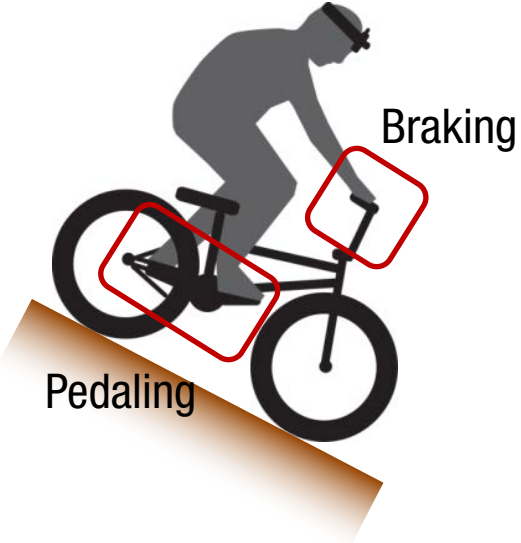


Pedaling activity (acceleration)

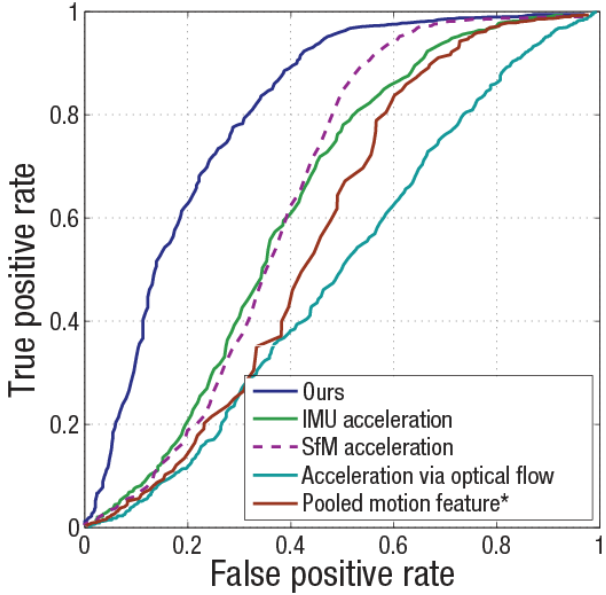


Braking activity (deceleration)

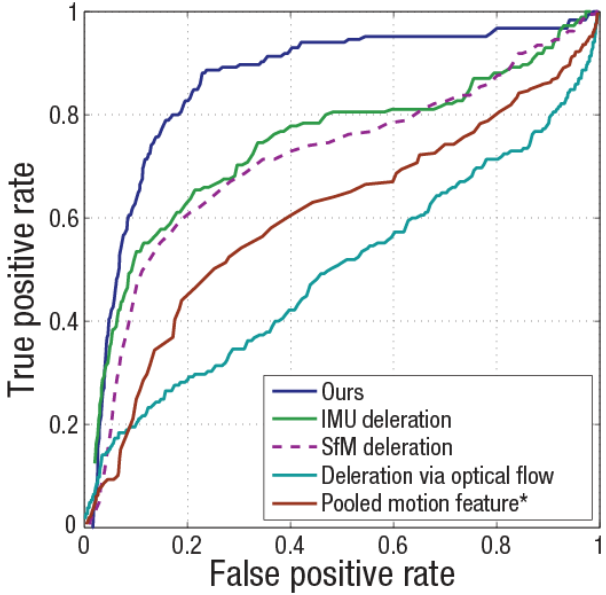


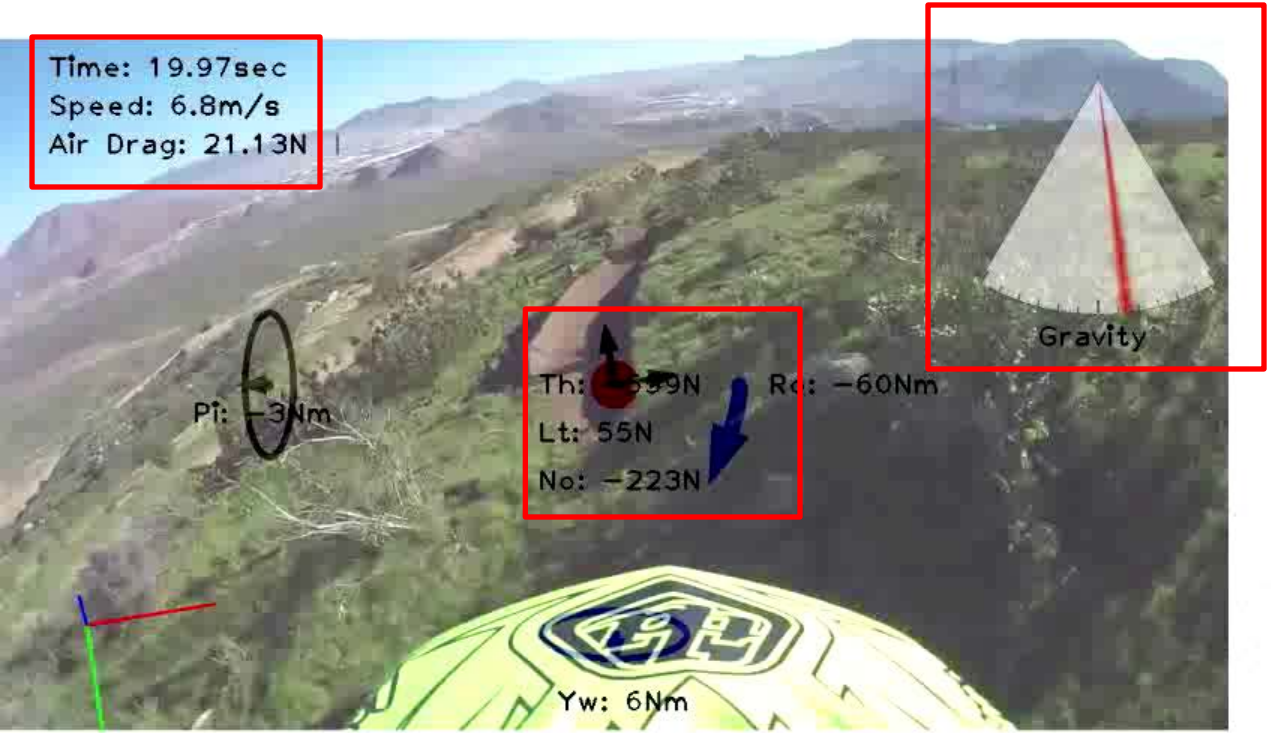


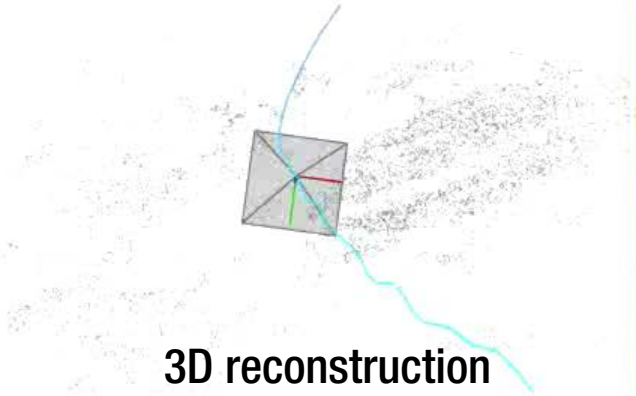
Pedaling activity (acceleration)



Braking activity (deceleration)

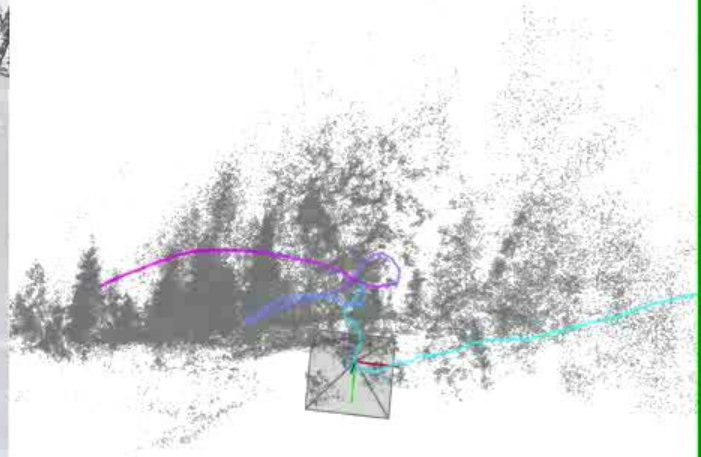






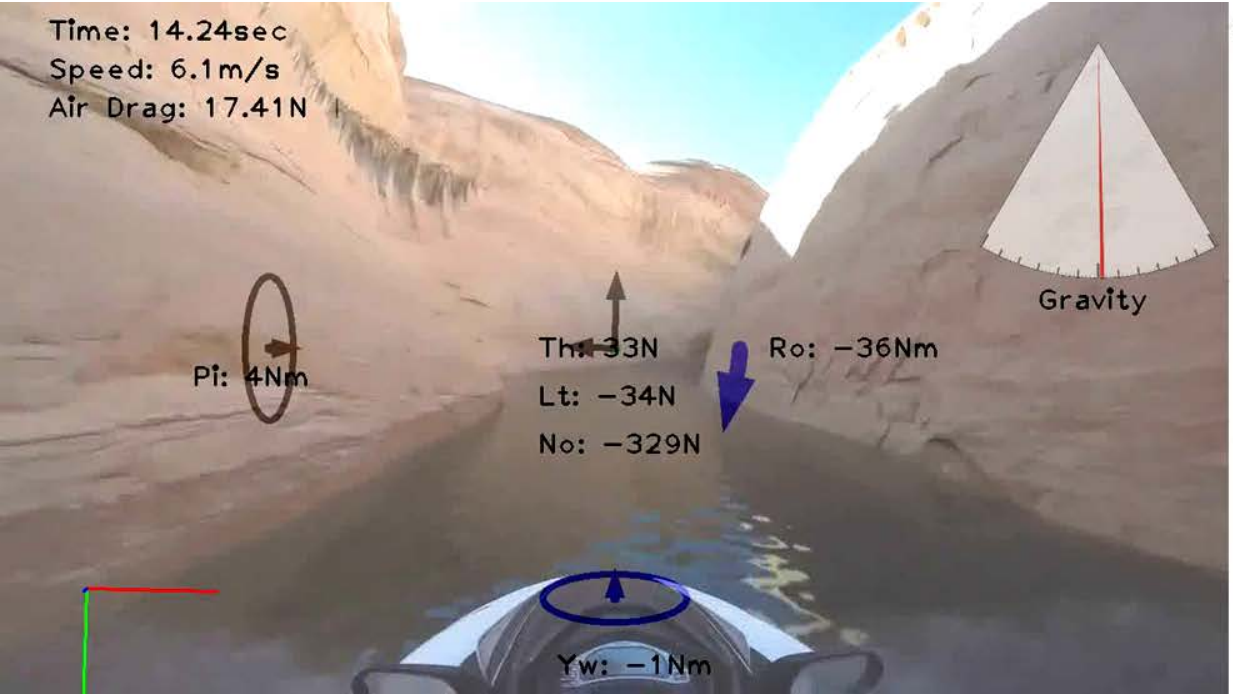
3D reconstruction

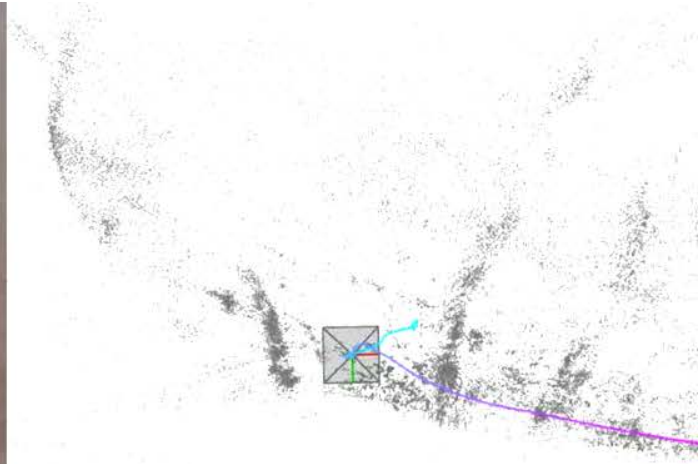
https://www.youtube.com/watch?v=aVJ45wlUE88

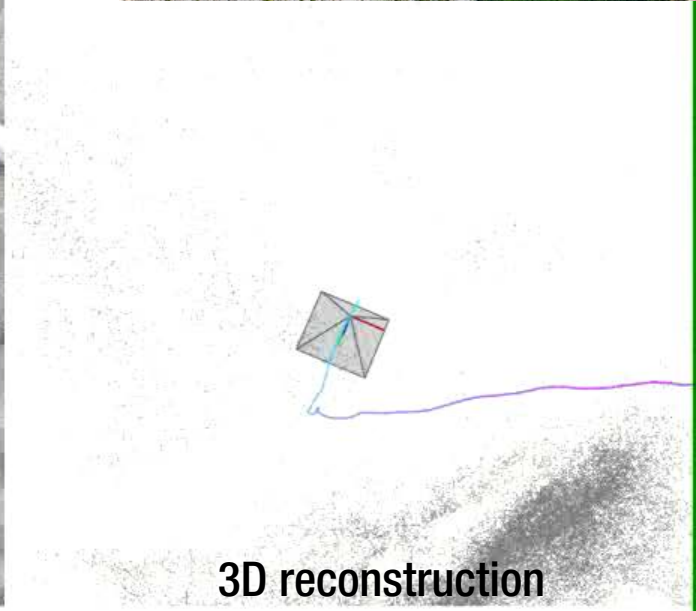


3D reconstruction

https://www.youtube.com/watch?v=pCcuKClUpLs


Time: 14.24sec
Speed: 6.1m/s
Air Drag: 17.41N
Gravity
Pi: 4Nm
Th: 33N
Lt: −34N
No: −329N
Ro: −36Nm
Yw: −1Nm





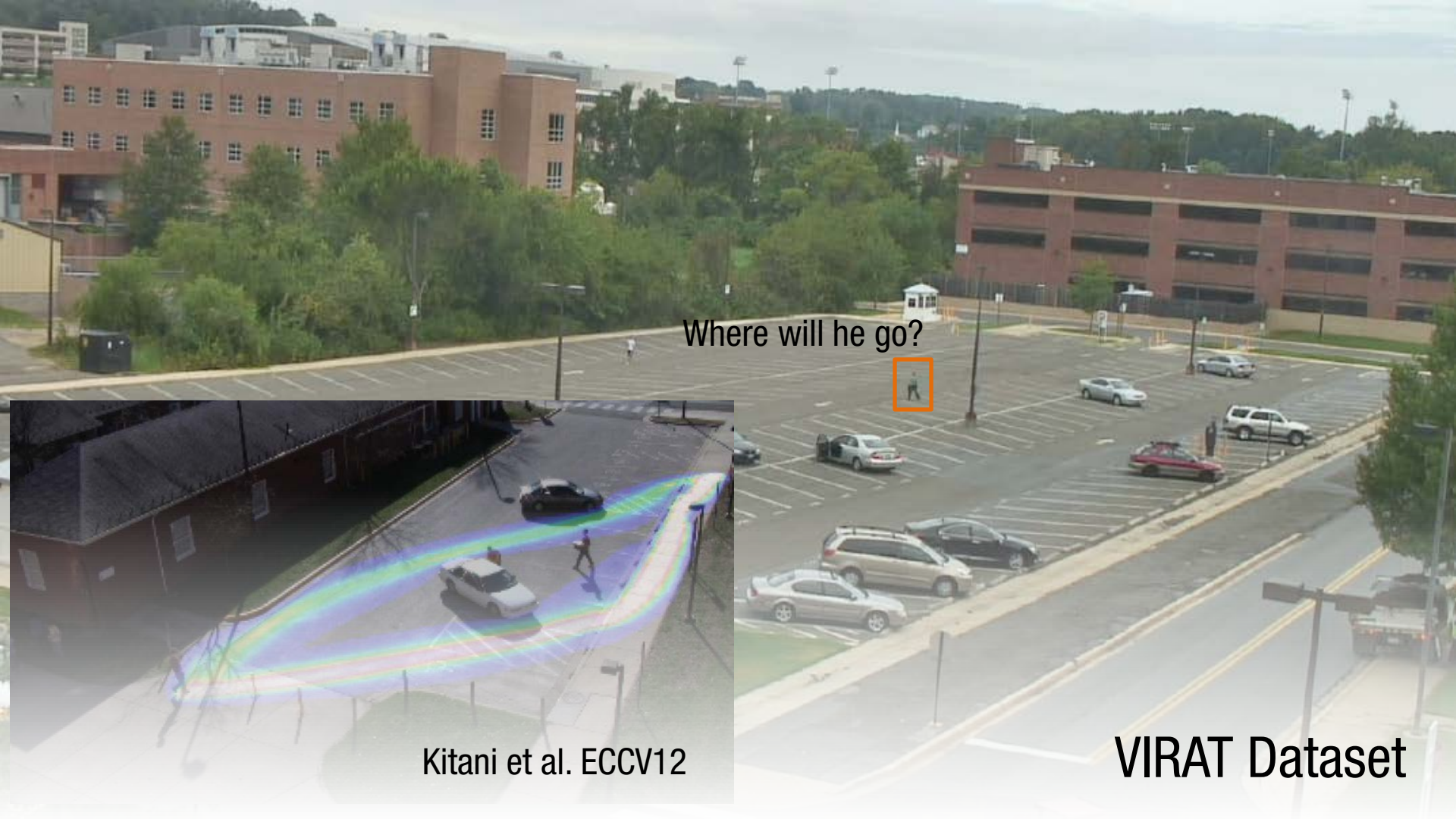
3D reconstruction

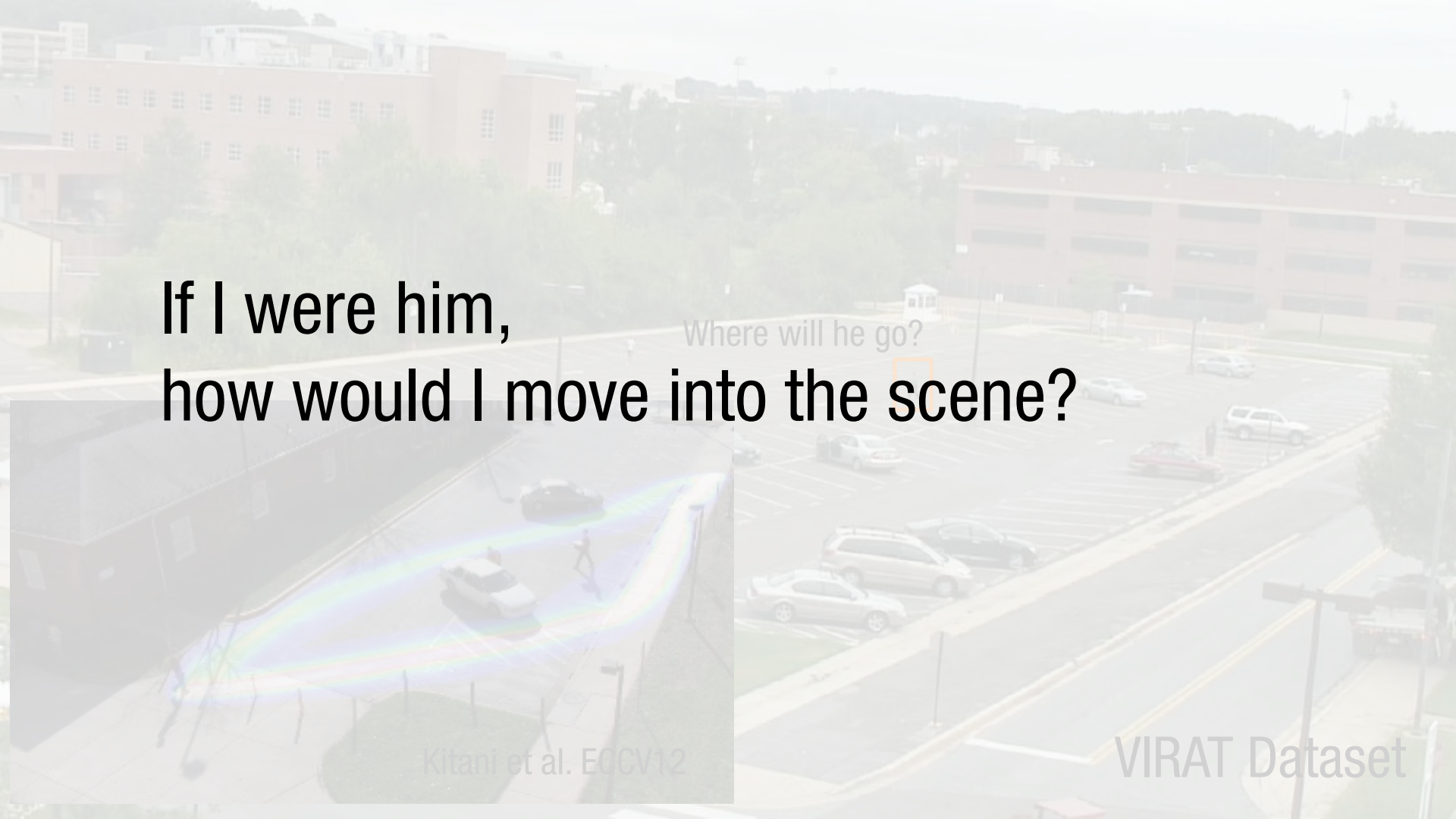
https://www.youtube.com/watch?v=rnvvsjstveM

What can first person vision tell us about my <u>future motion</u>?


VIRAT Dataset


Where will he go?
VIRAT Dataset

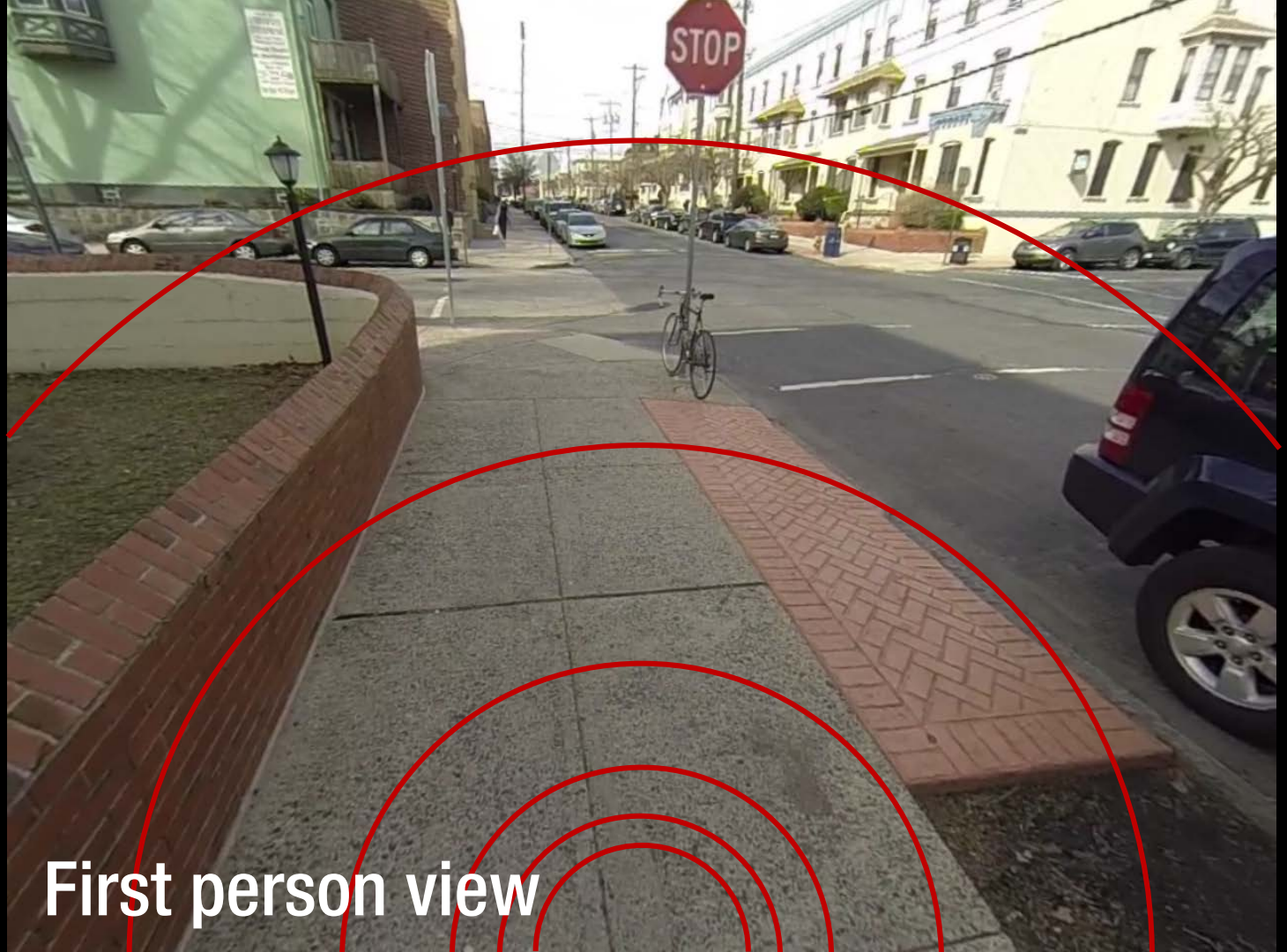

Where will he go?
Kitani et al. ECCV12
VIRAT Dataset

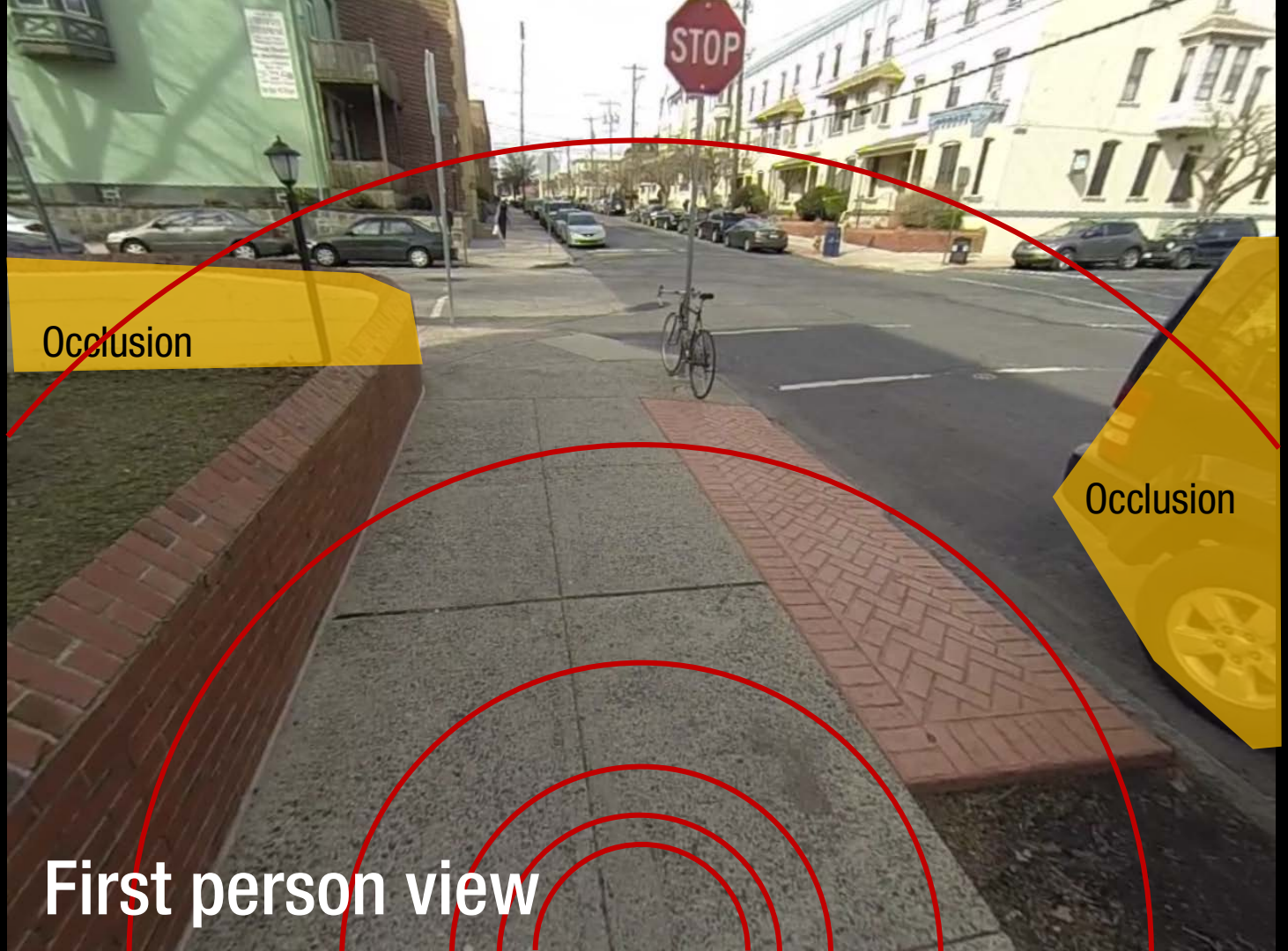

If I were him,
how would I move into the scene?
Where will he go?
Kitani et al. ECCV12
VIRAT Dataset

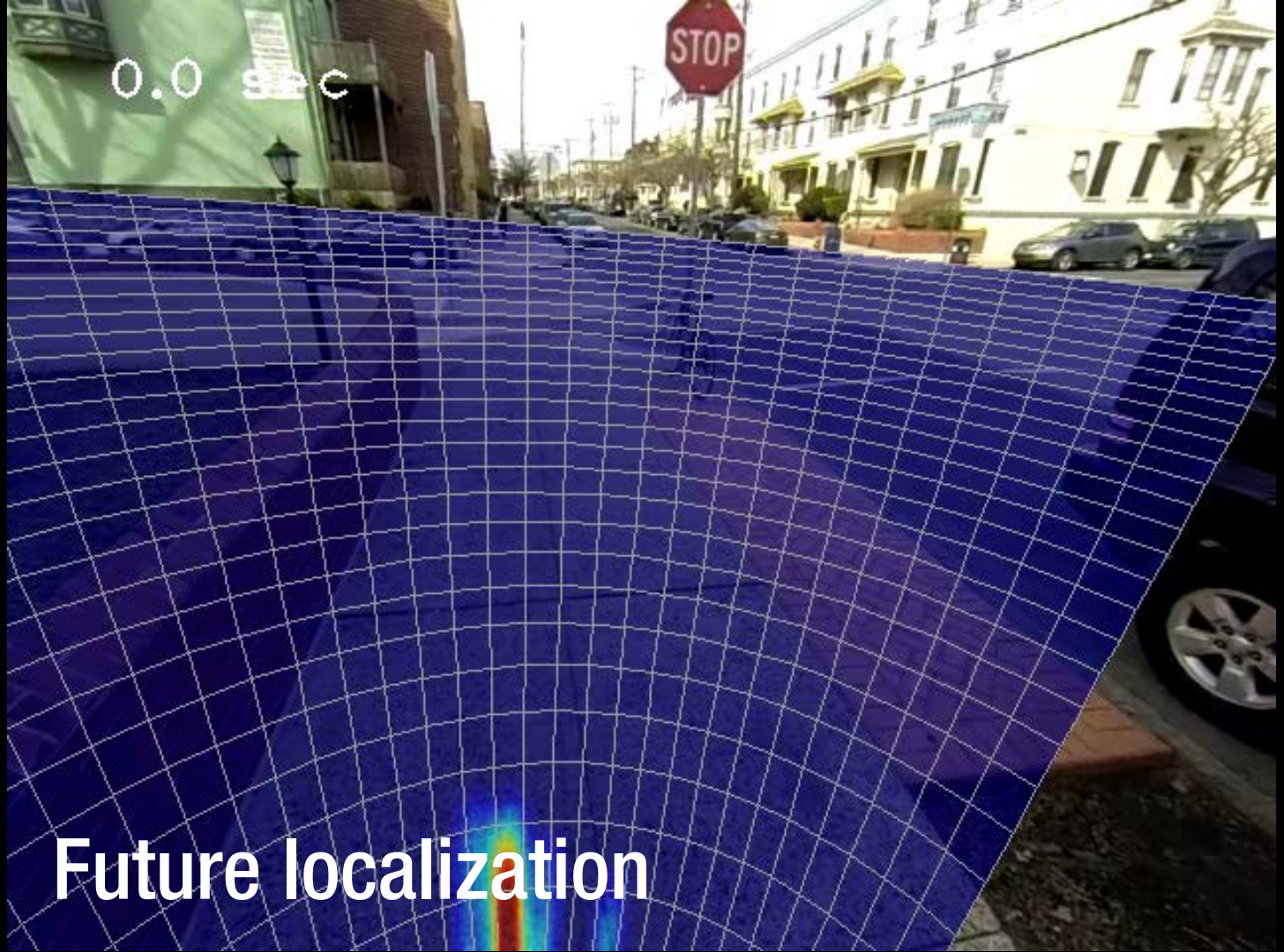
What is he experiencing visually?

First person view

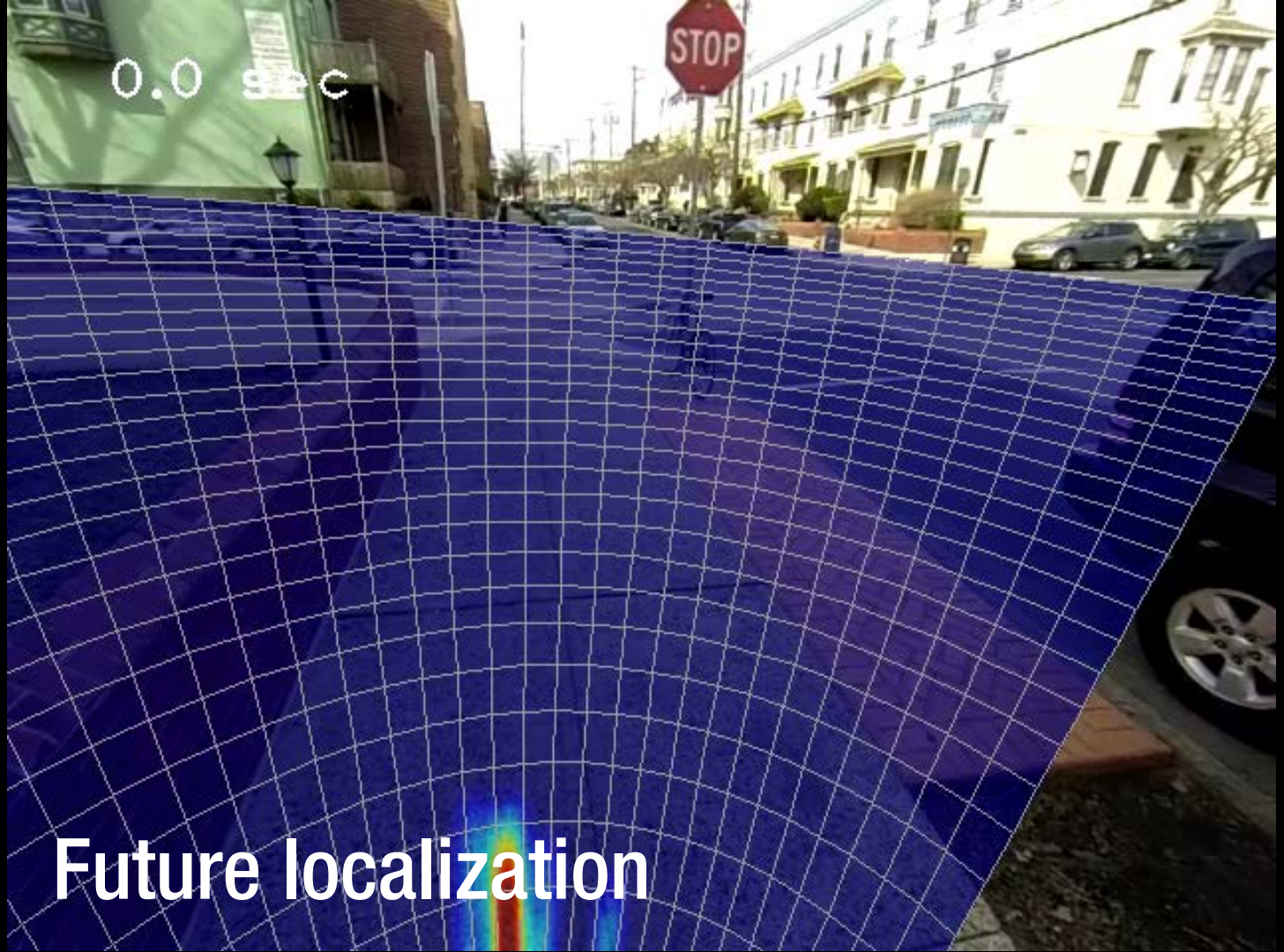

STOP
First person view
RGBD


STOP
First person view

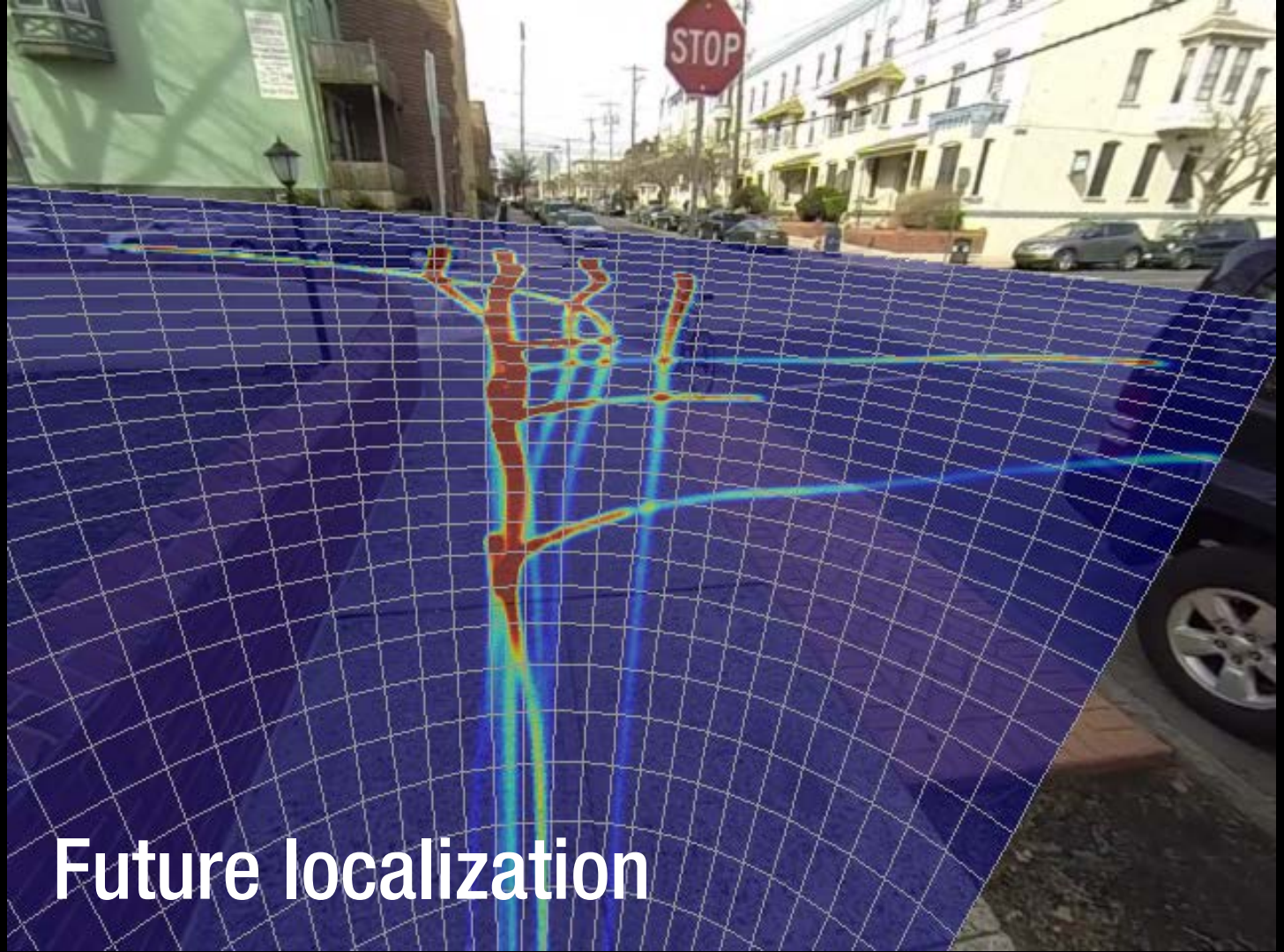

STOP
Occlusion
Occlusion
First person view



Future localization

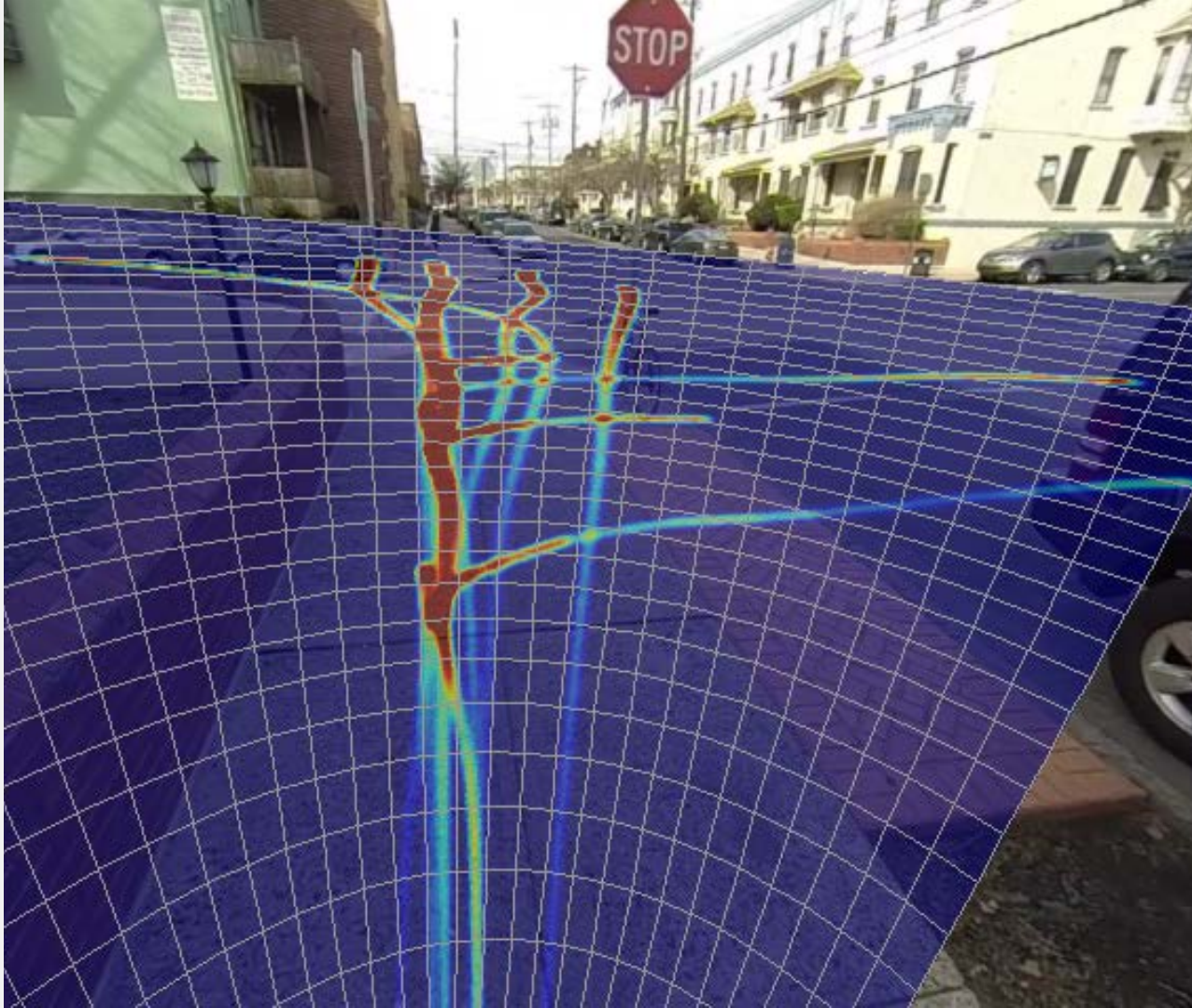


Future localization



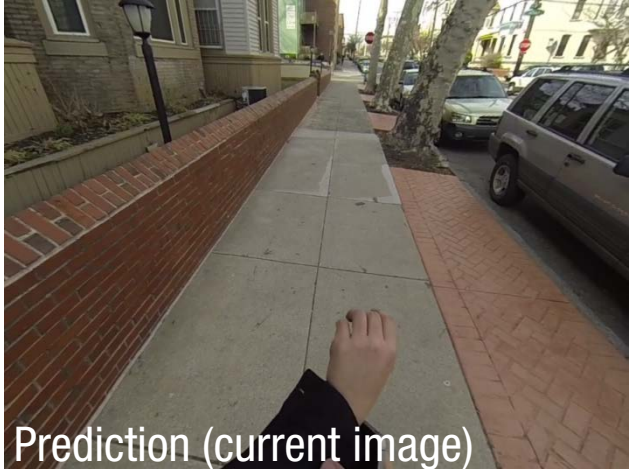
Future localization

Why challenging?

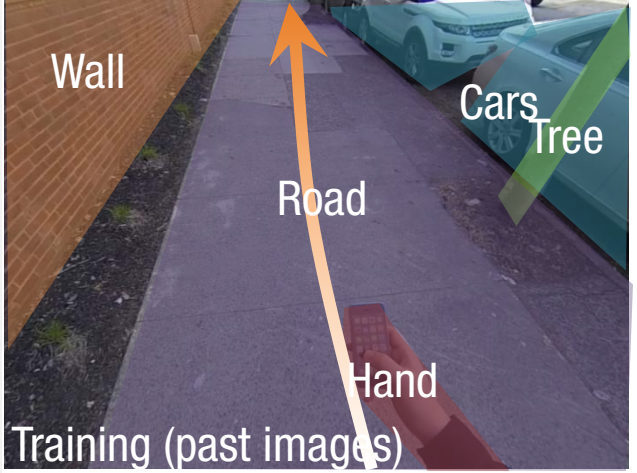


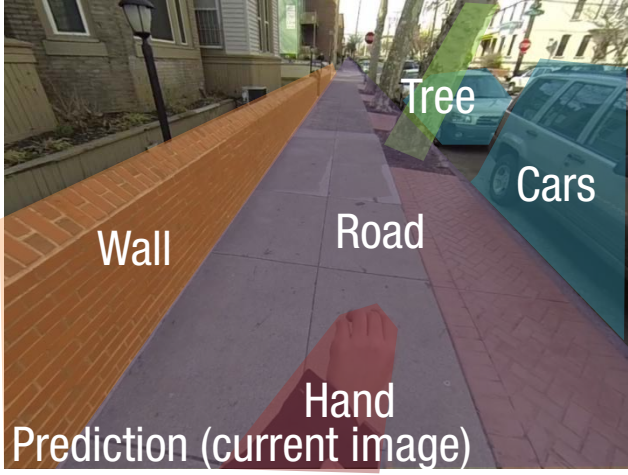
Why challenging?

Why challenging?



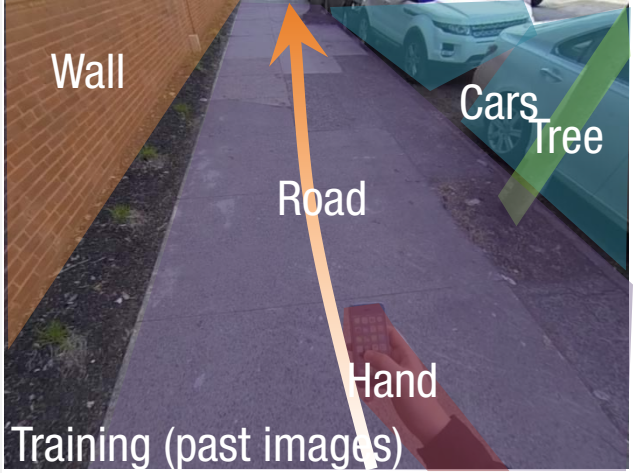
Why challenging?

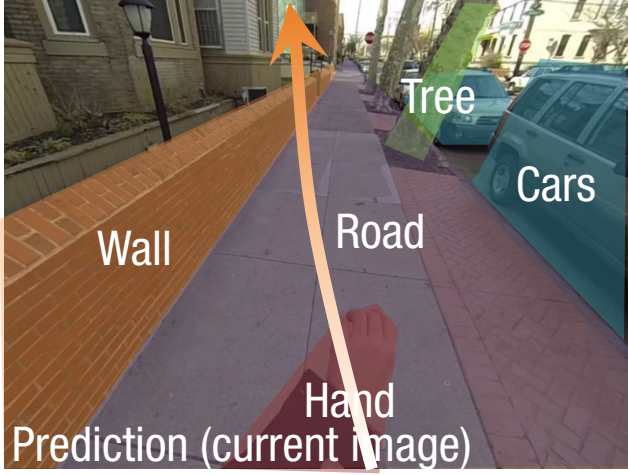




Why challenging?

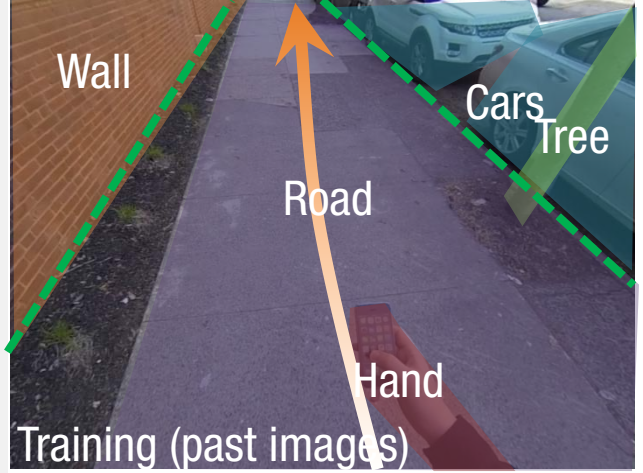
1. Geometric inconsistency

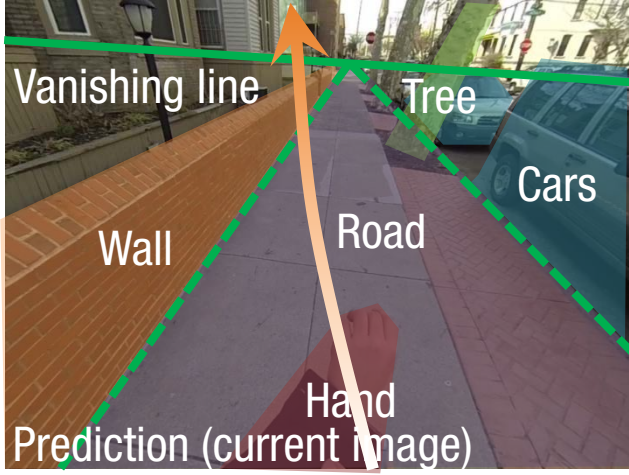


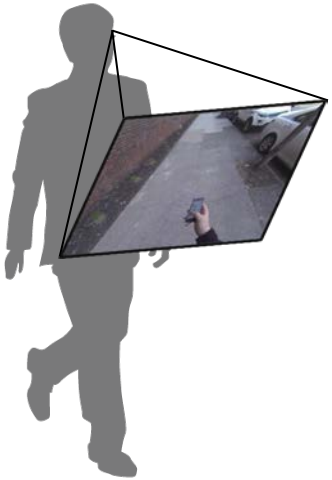


Why challenging?

1. Geometric inconsistency







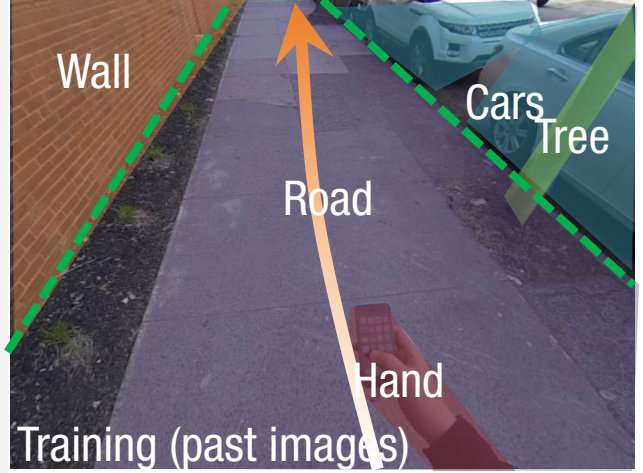
Looking down

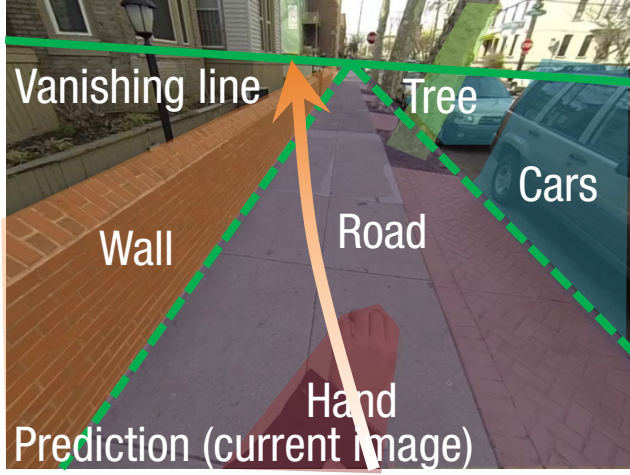
Looking forward

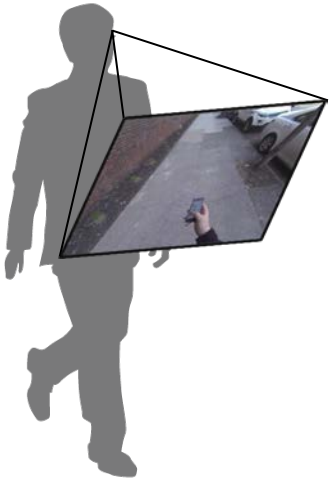
Why challenging?

1. Geometric inconsistency

2. Semantic inconsistency





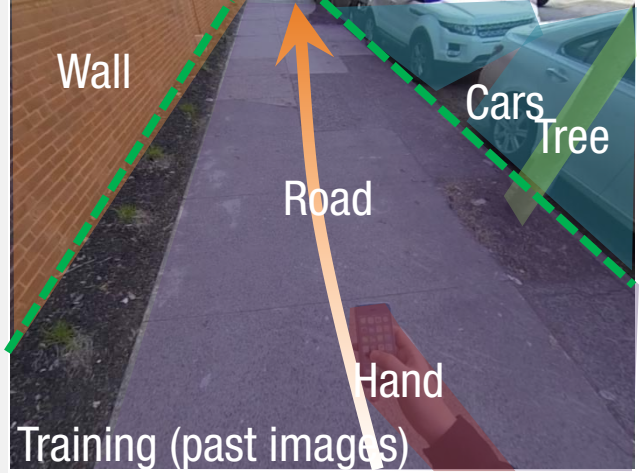


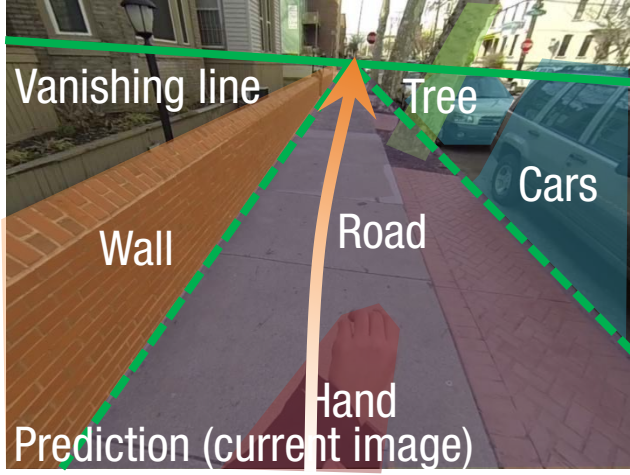
Looking down

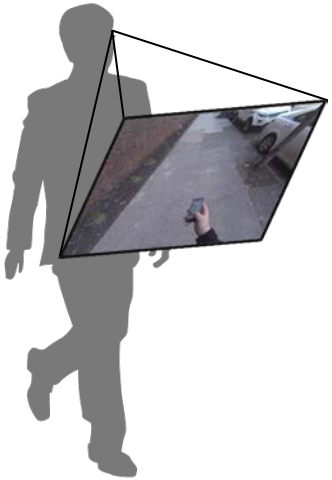
Looking forward

Why challenging?

1. Geometric inconsistency
   → EgoRetinal representation
2. Semantic inconsistency
   → Preference learning







Looking down

Looking forward

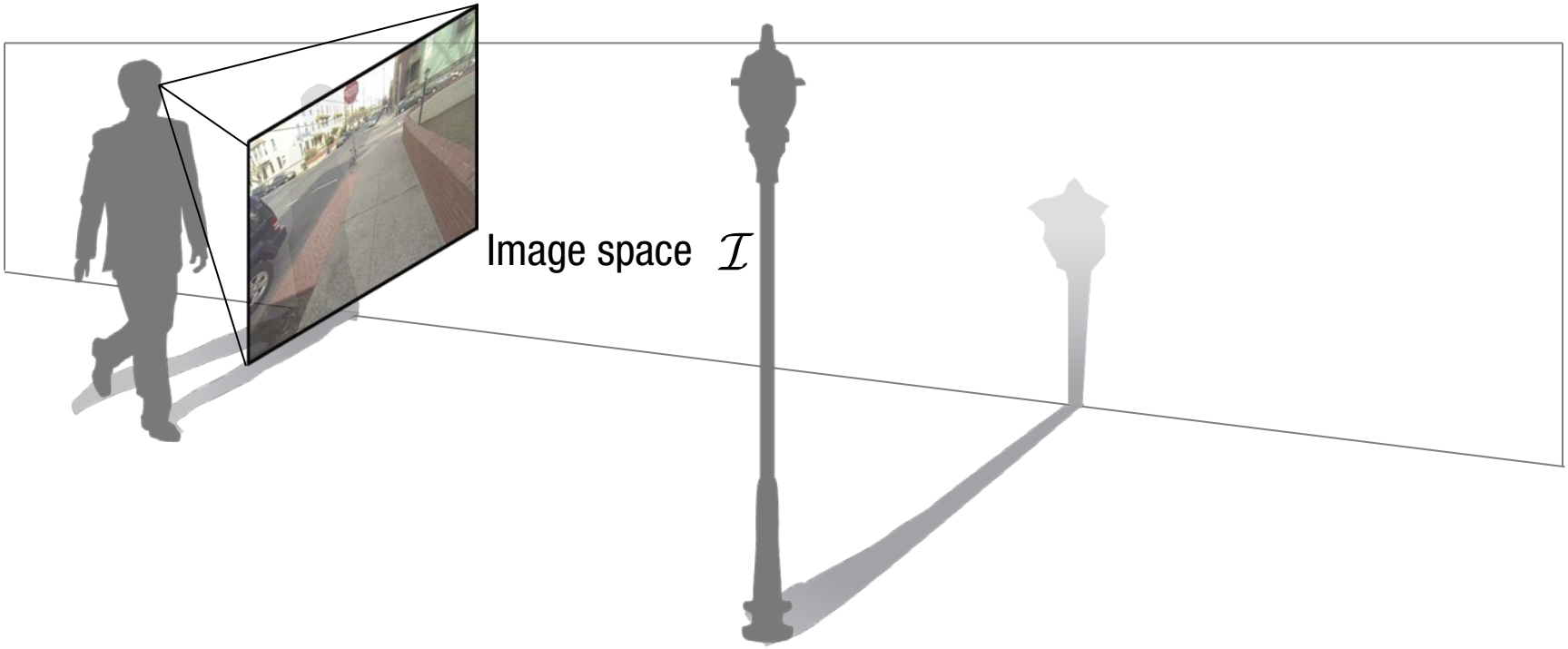


Image space $\mathcal{I}$

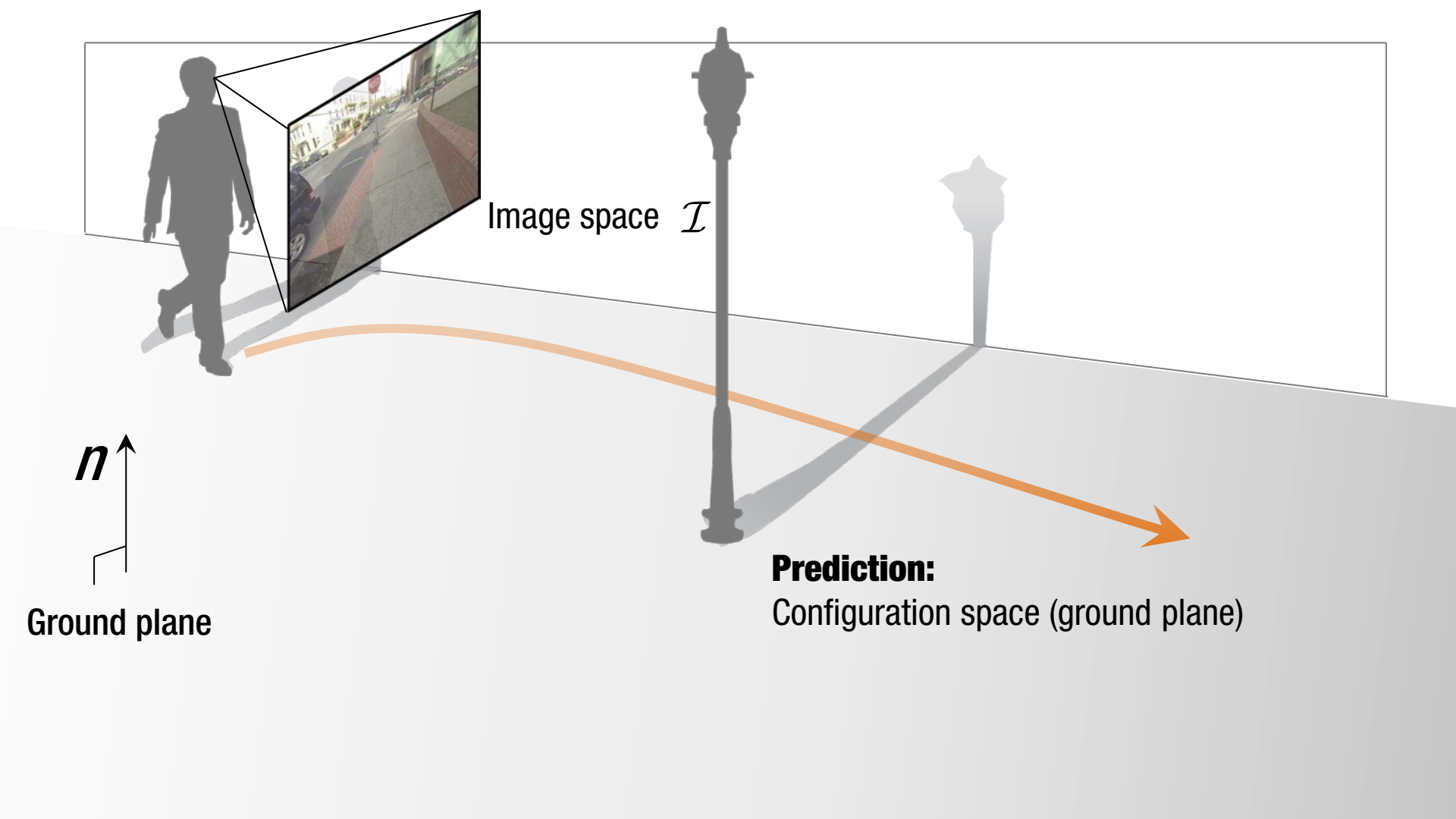
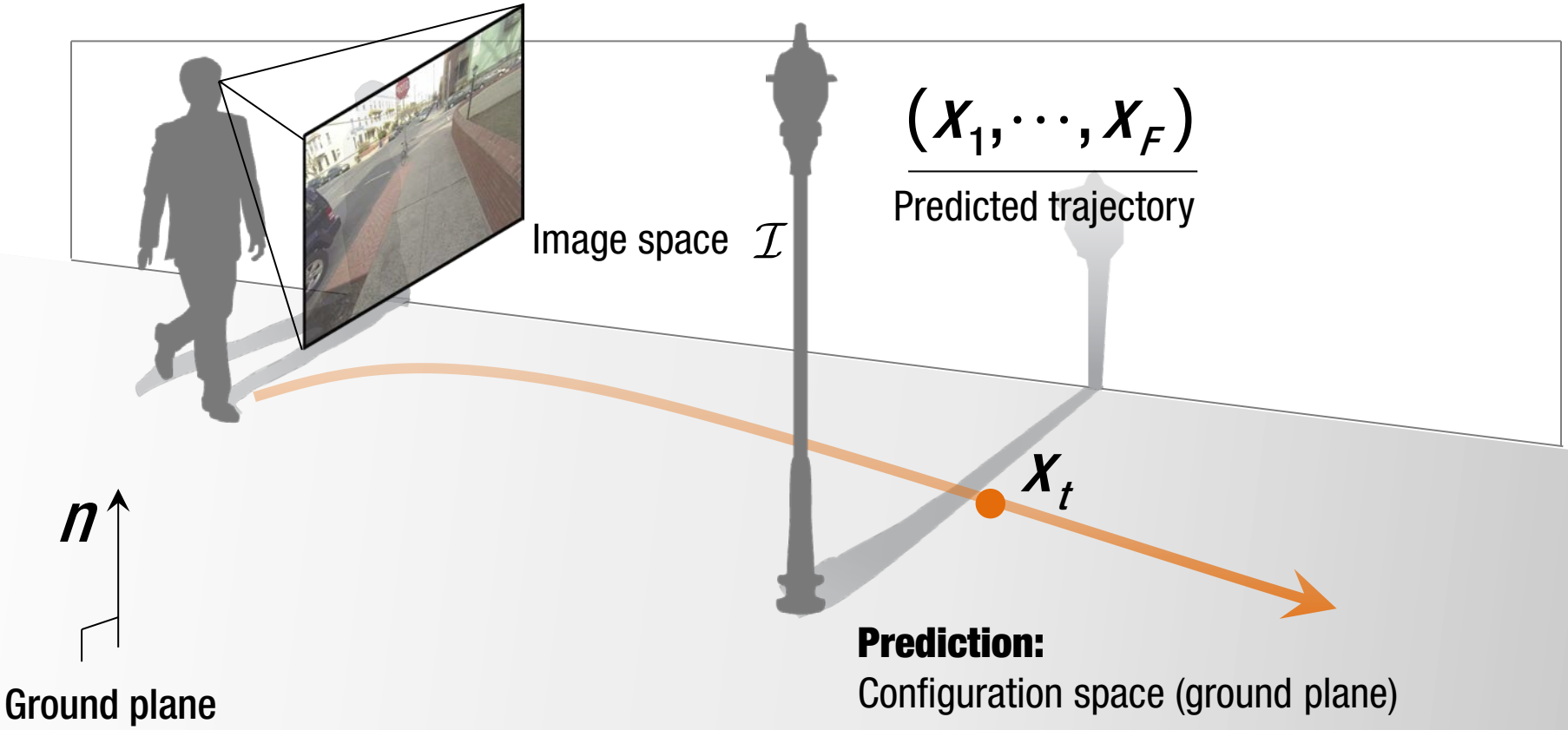
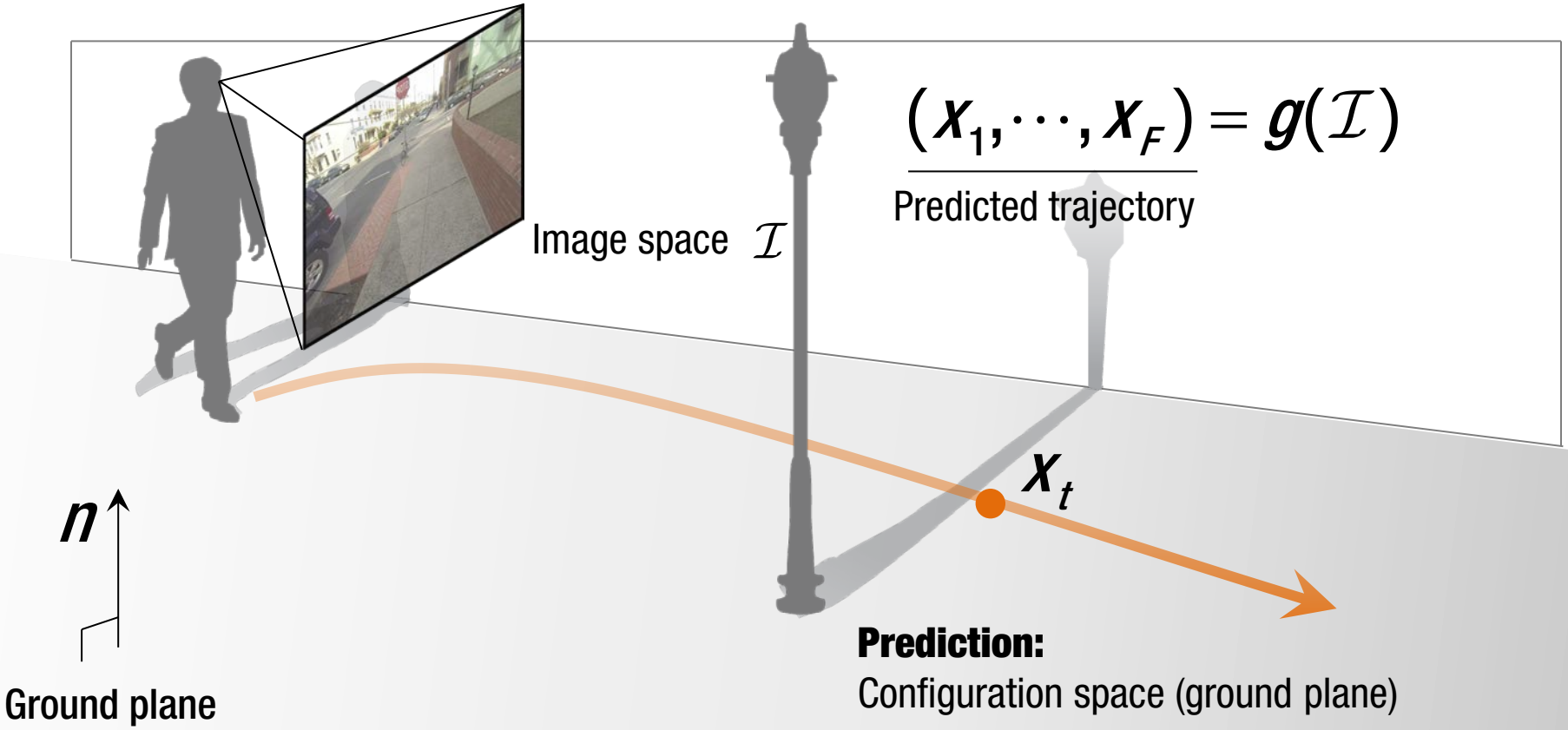
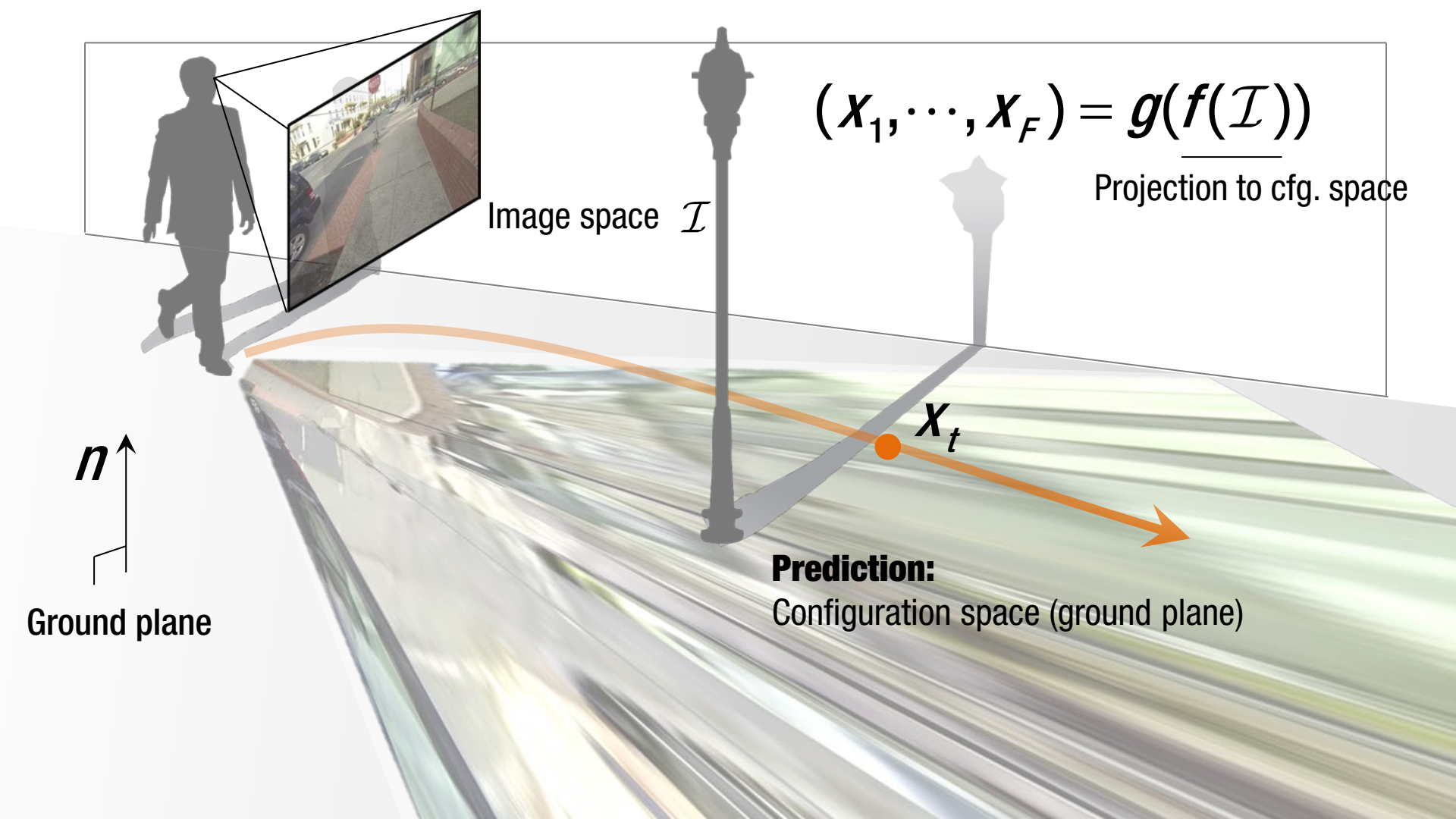
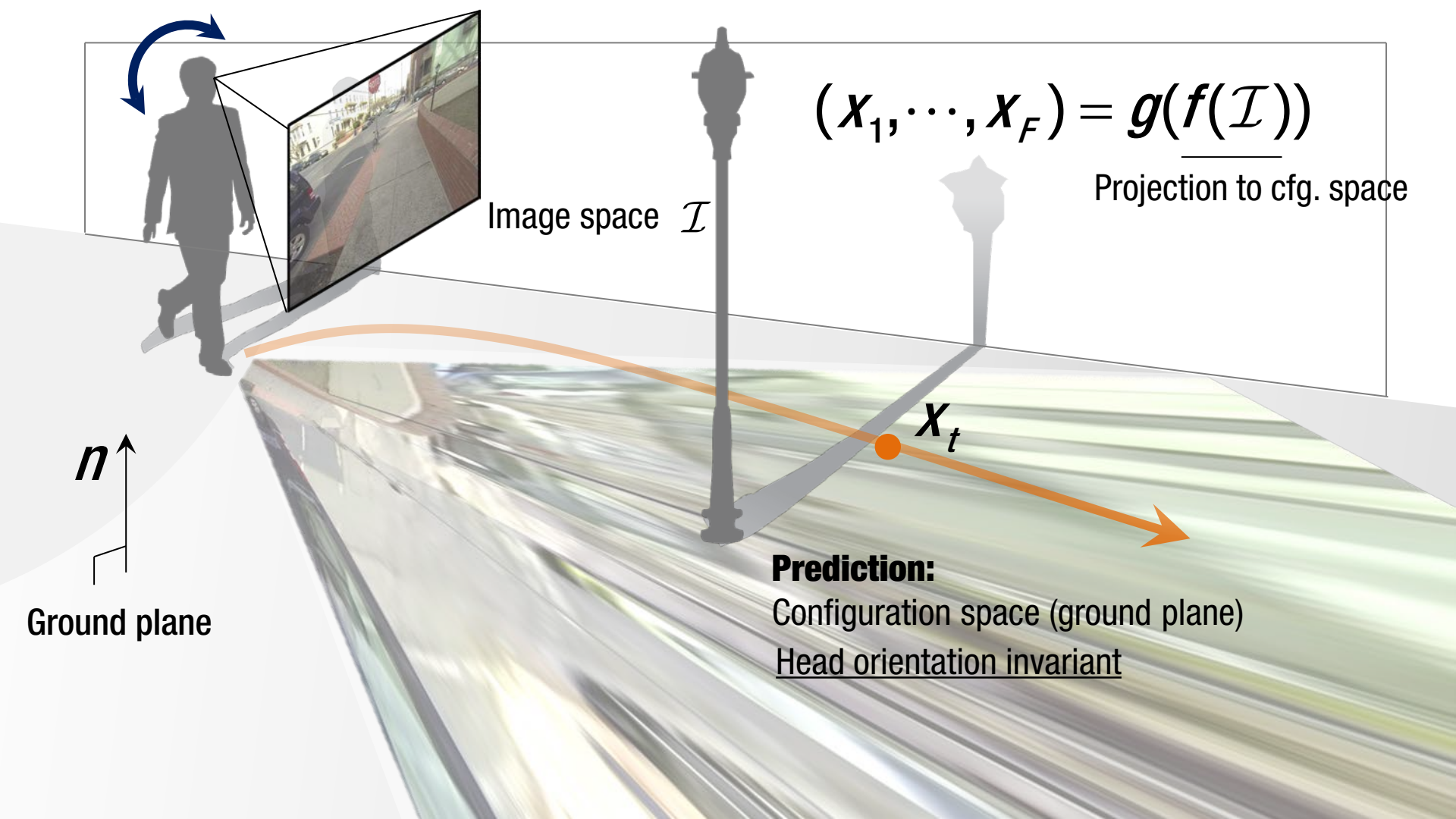


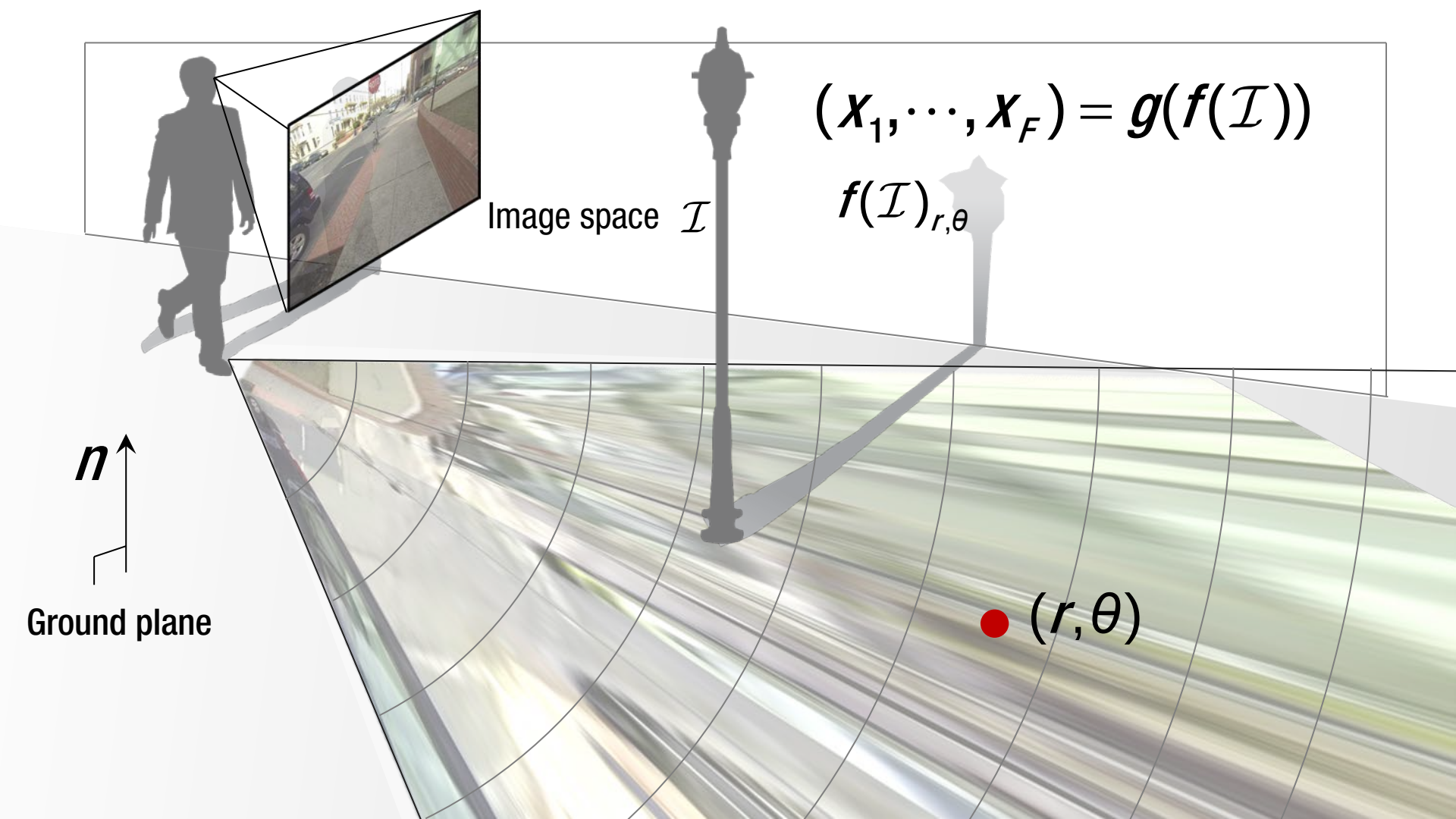
Image space $\mathcal{I}$
n
Ground plane
Prediction:
Configuration space (ground plane)

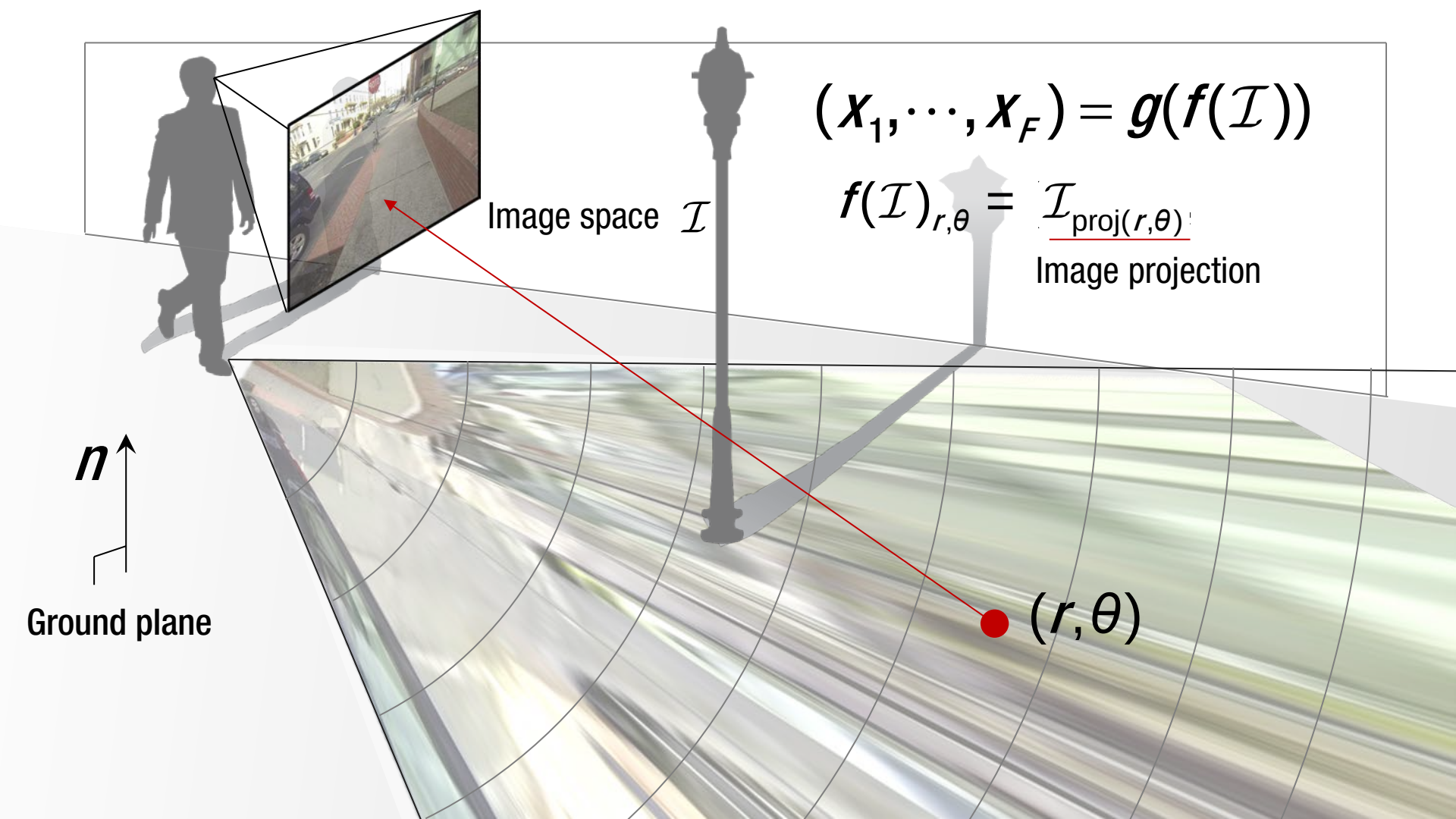

$(x_1, \cdots, x_F)$
Predicted trajectory
Image space $\mathcal{I}$
x_t
n
Ground plane
Prediction:
Configuration space (ground plane)

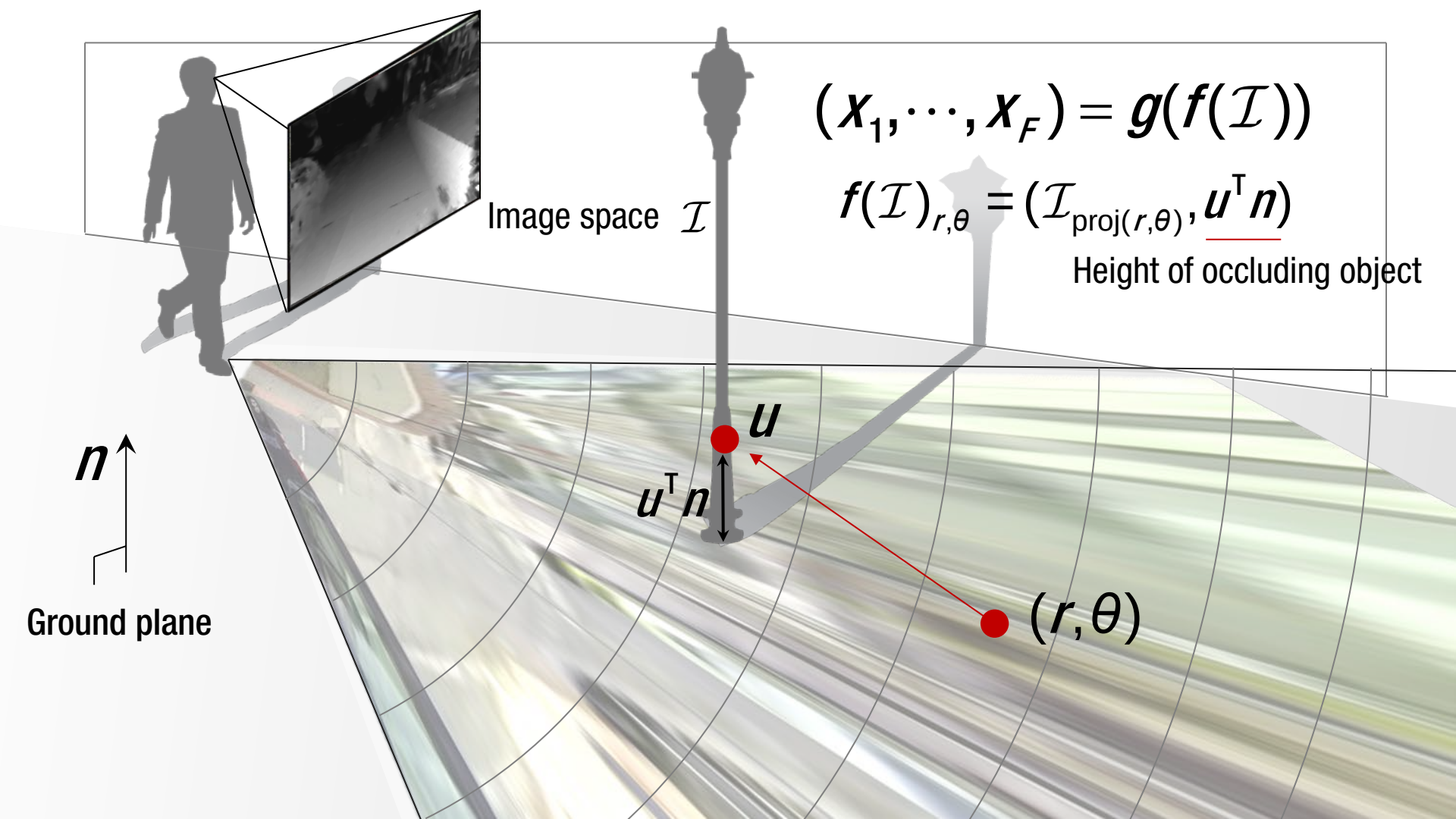

$(x_1, \cdots, x_F) = g(\mathcal{I})$
Predicted trajectory
Image space $\mathcal{I}$
x_t
n
Ground plane
Prediction:
Configuration space (ground plane)

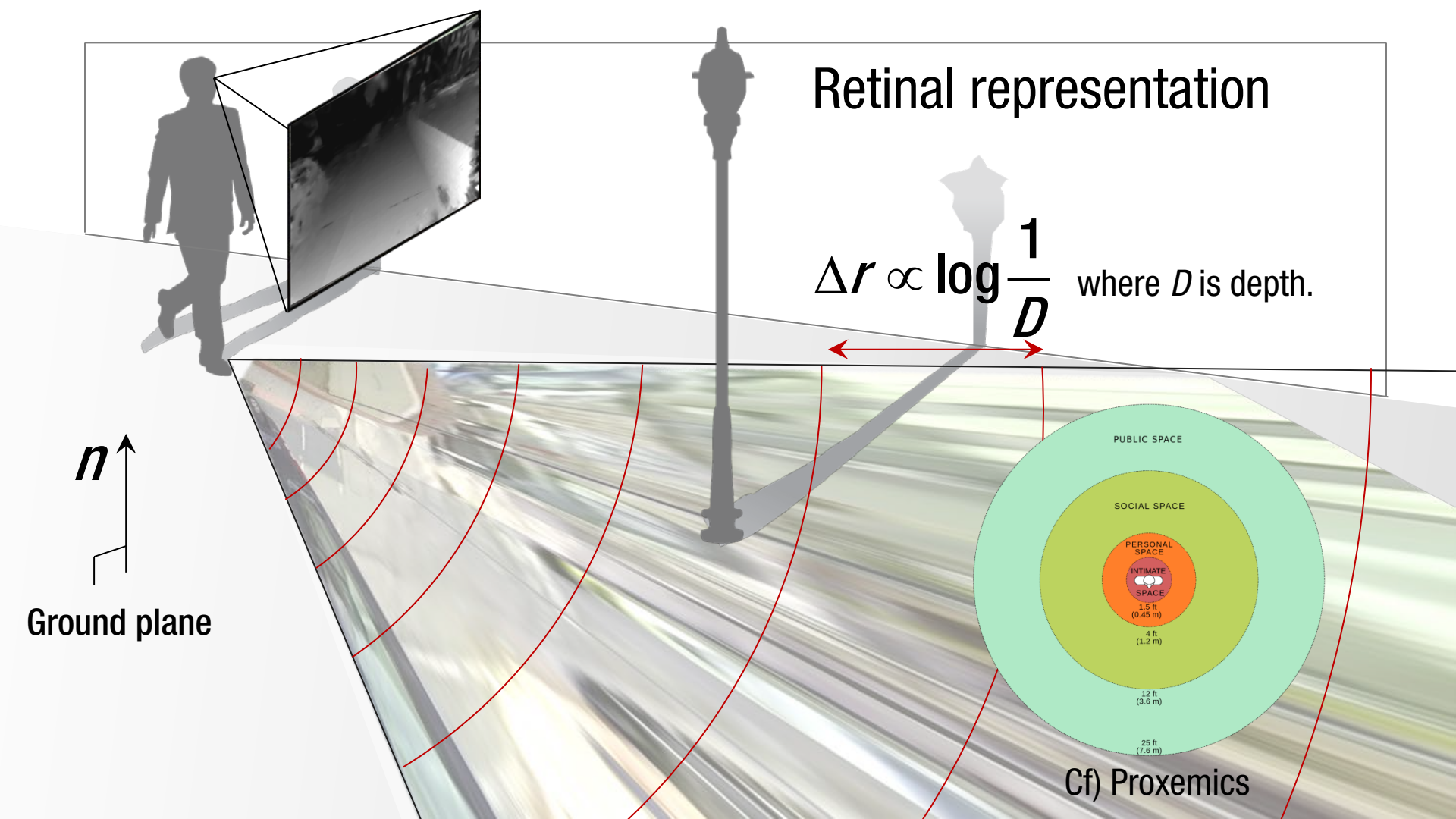

$(x_1, \cdots, x_F) = g(f(\mathcal{I}))$
Projection to cfg. space
Image space $\mathcal{I}$
x_t
n
Ground plane
Prediction:
Configuration space (ground plane)


$(x_1, \cdots, x_F) = g(f(\mathcal{I}))$
Projection to cfg. space
Image space $\mathcal{I}$
x_t
n
Ground plane
Prediction:
Configuration space (ground plane)
Head orientation invariant


$(x_1, \cdots, x_F) = g(f(\mathcal{I}))$
Image space $\mathcal{I}$
$f(\mathcal{I})_{r,\theta}$
n
Ground plane
(r, θ)


$(x_1, \cdots, x_F) = g(f(\mathcal{I}))$
$f(\mathcal{I})_{r,\theta} = \mathcal{I}_{\mathrm{proj}(r,\theta)}$
Image projection
Image space $\mathcal{I}$
n
Ground plane
(r, θ)

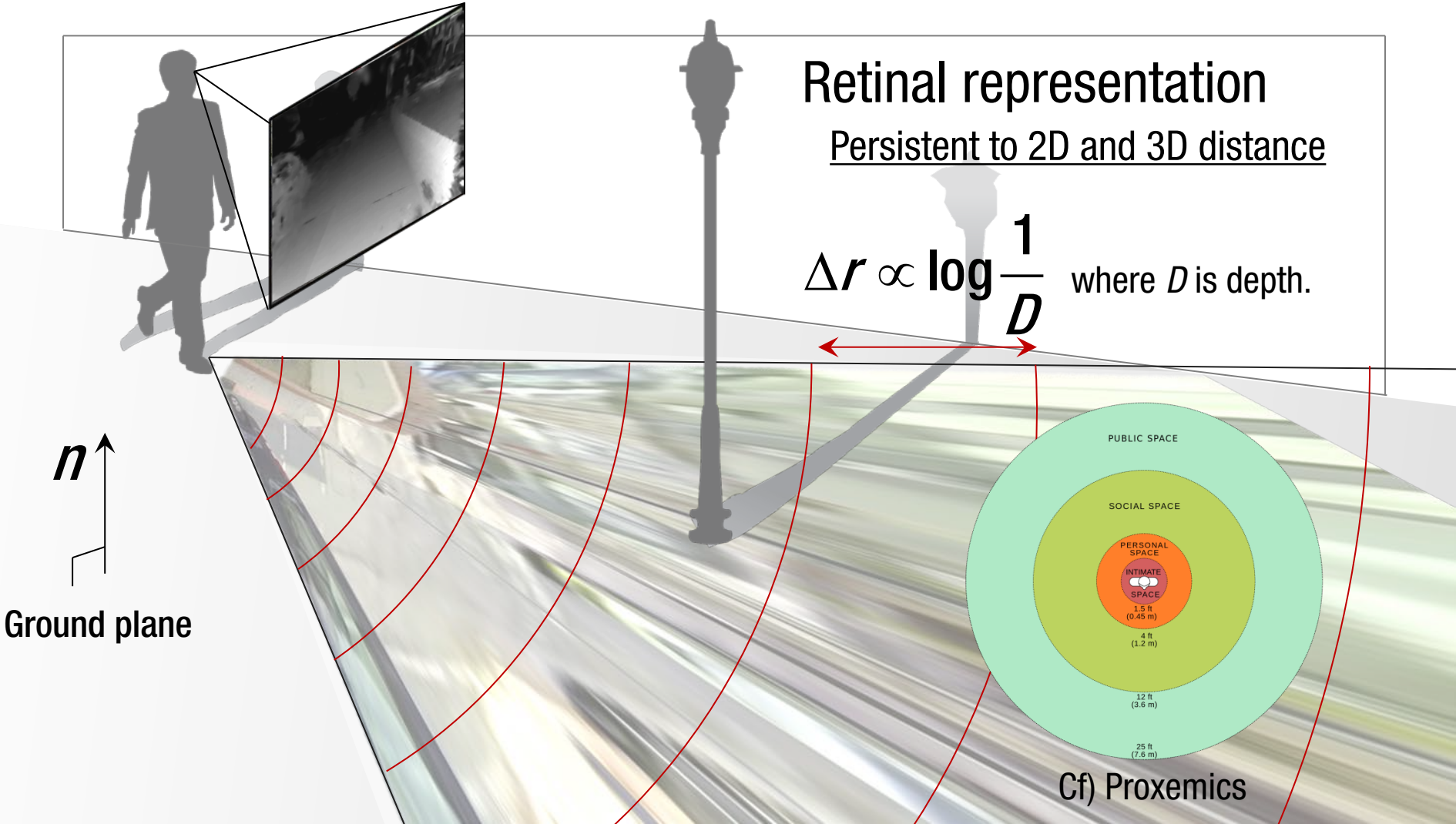

$(x_1, \cdots, x_F) = g(f(\mathcal{I}))$
$f(\mathcal{I})_{r,\theta} = (\mathcal{I}_{\mathrm{proj}(r,\theta)}, u^{\mathsf{T}} n)$
Height of occluding object
Image space $\mathcal{I}$
u
$u^{\mathsf{T}} n$
(r, θ)
n
Ground plane

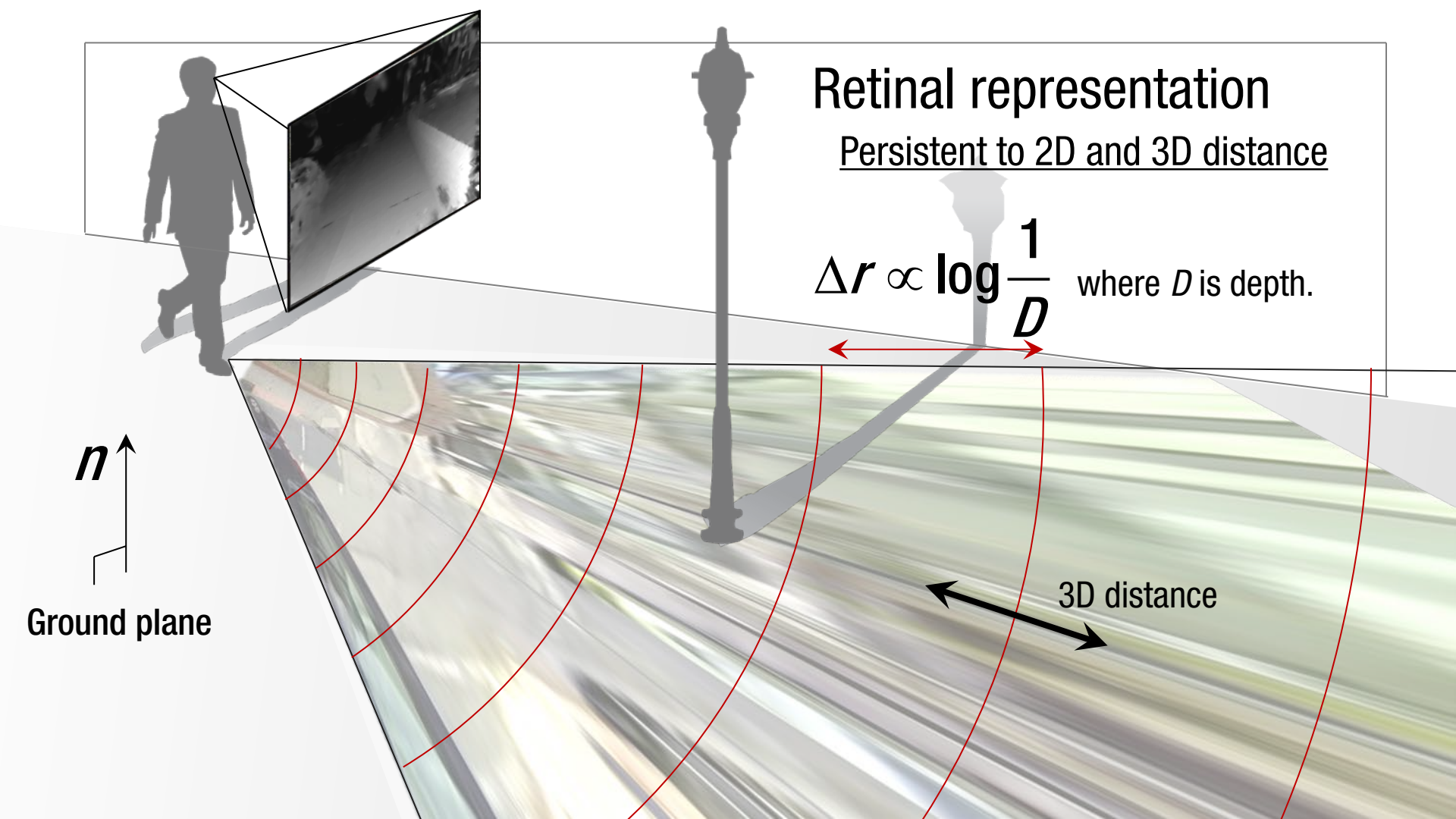

Retinal representation
$\Delta r \propto \log \frac{1}{D}$ where D is depth.
n
Ground plane
PUBLIC SPACE
SOCIAL SPACE
PERSONAL SPACE
INTIMATE SPACE
1.5 ft (0.45 m)
4 ft (1.2 m)
12 ft (3.6 m)
25 ft (7.6 m)
Cf) Proxemics

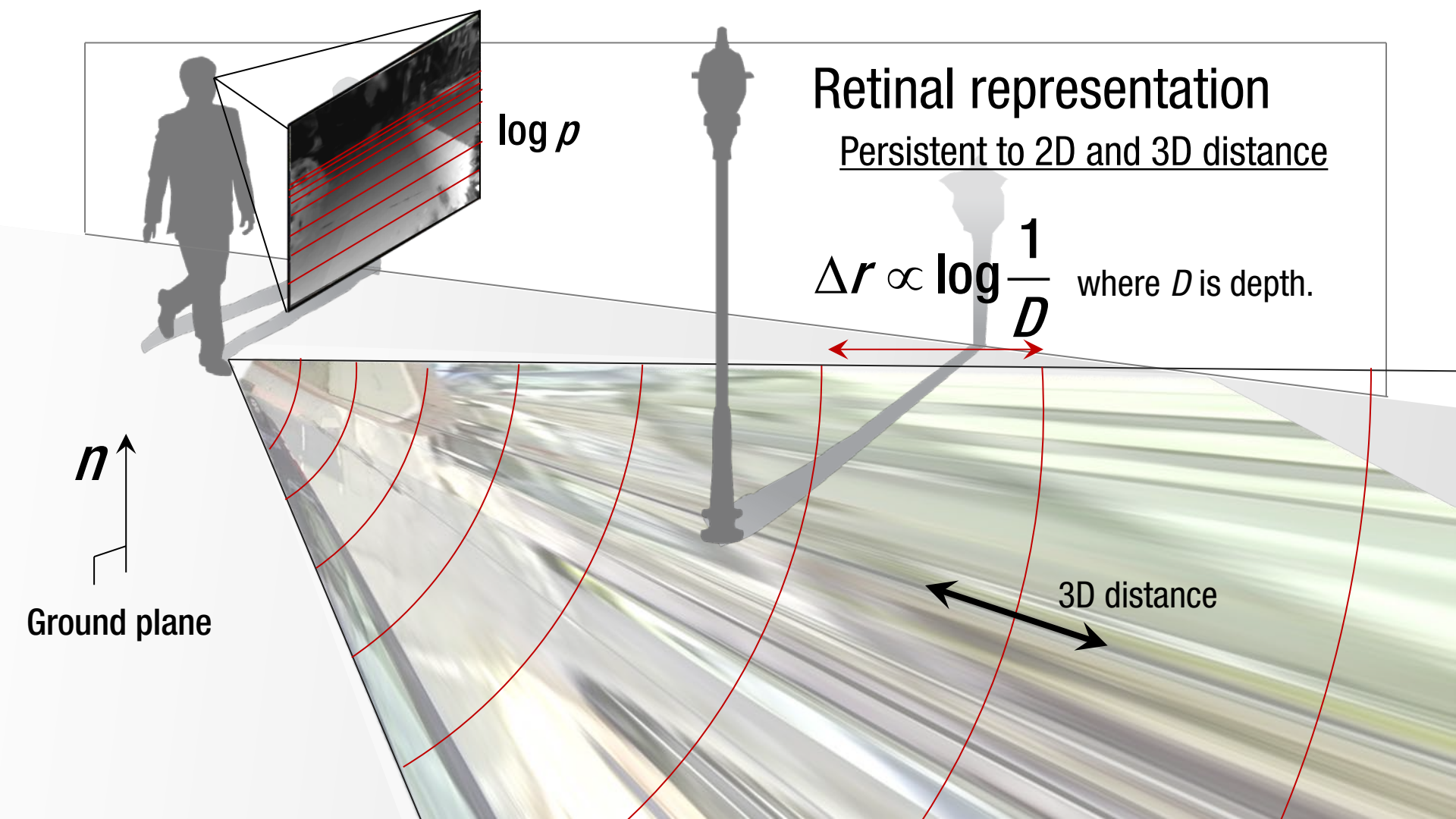
Retinal representation

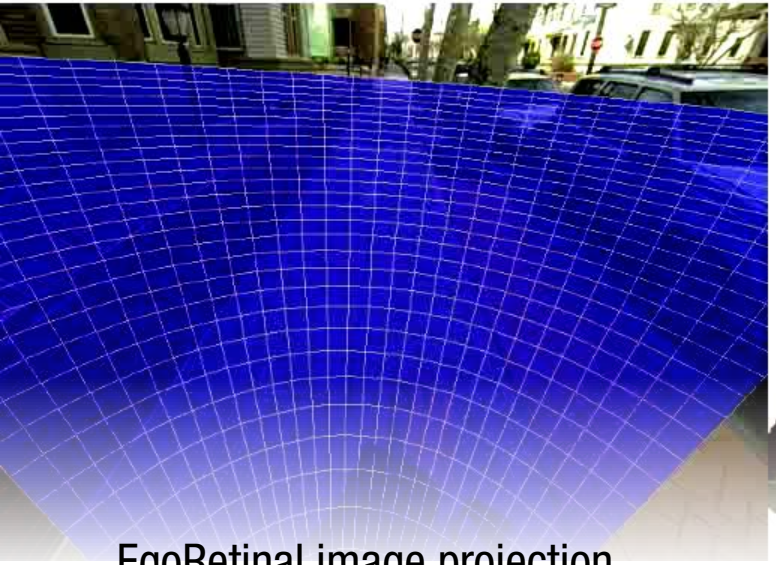
Persistent to 2D and 3D distance

$$\Delta r \propto \log \frac{1}{D}$$ where D is depth.



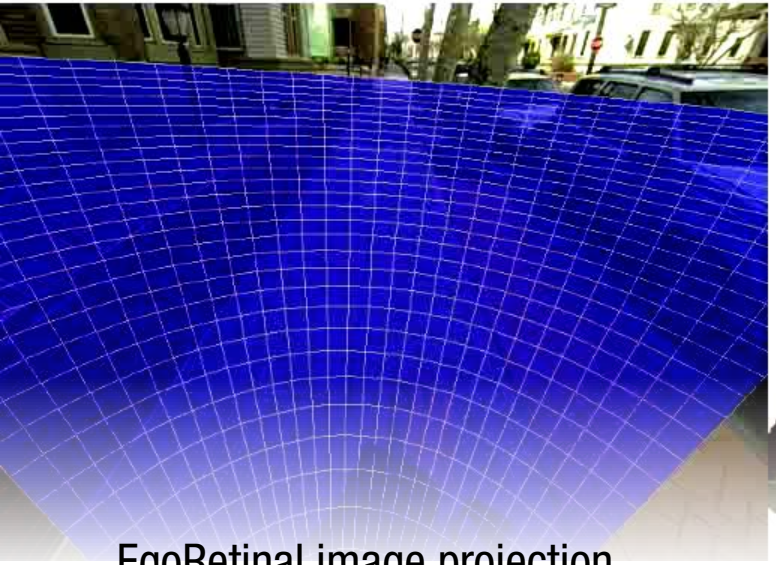

Retinal representation
Persistent to 2D and 3D distance
$\Delta r \propto \log \frac{1}{D}$ where D is depth.
n
Ground plane
3D distance


Retinal representation
Persistent to 2D and 3D distance
$\Delta r \propto \log \frac{1}{D}$ where D is depth.
log p
n
Ground plane
3D distance



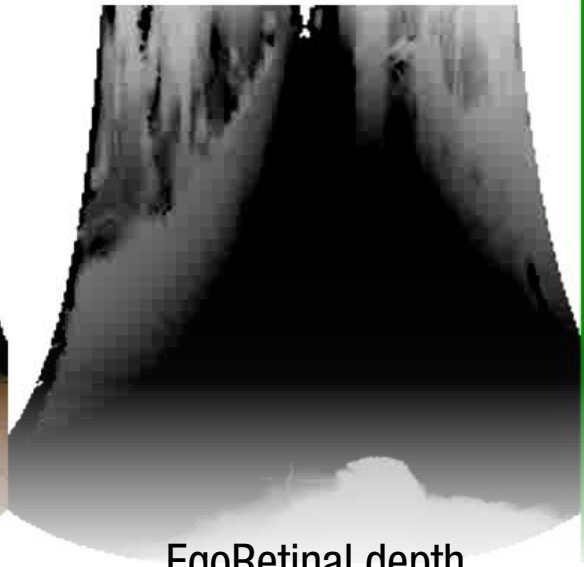
EgoRetinal image projection

EgoRetinal RGB

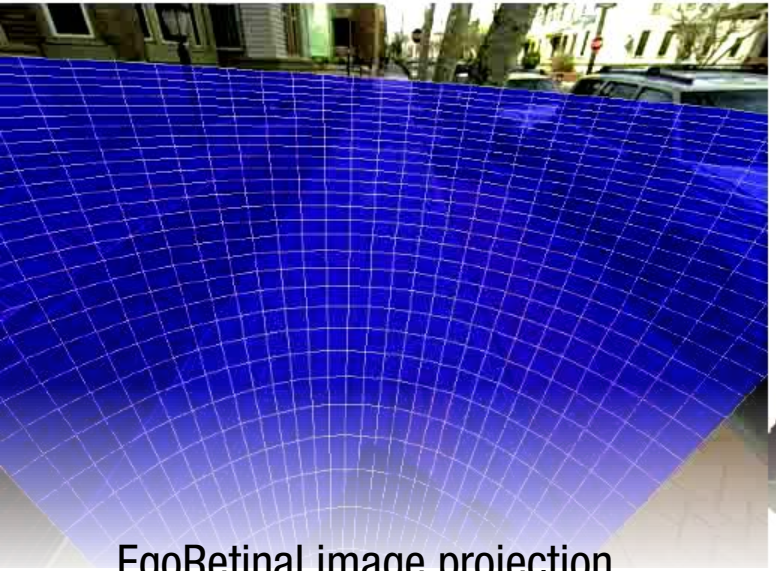


EgoRetinal image projection

EgoRetinal RGB

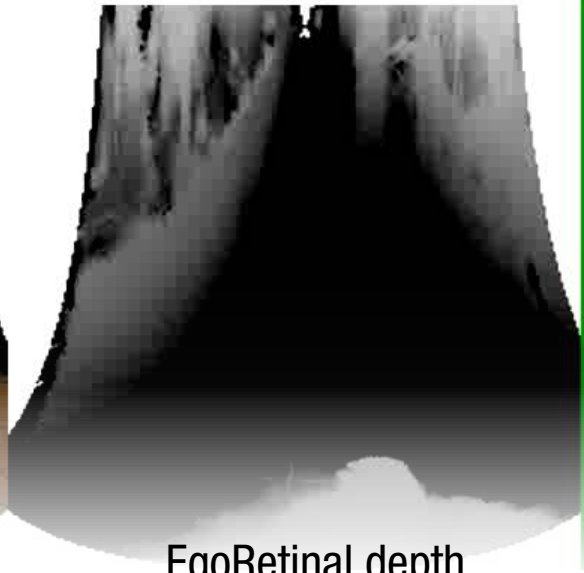


EgoRetinal depth



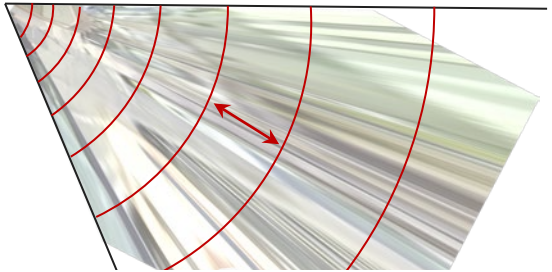
EgoRetinal image projection

EgoRetinal RGB

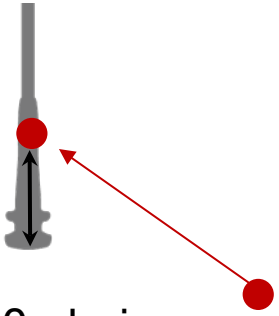


EgoRetinal depth

P1: Head orientation invariant

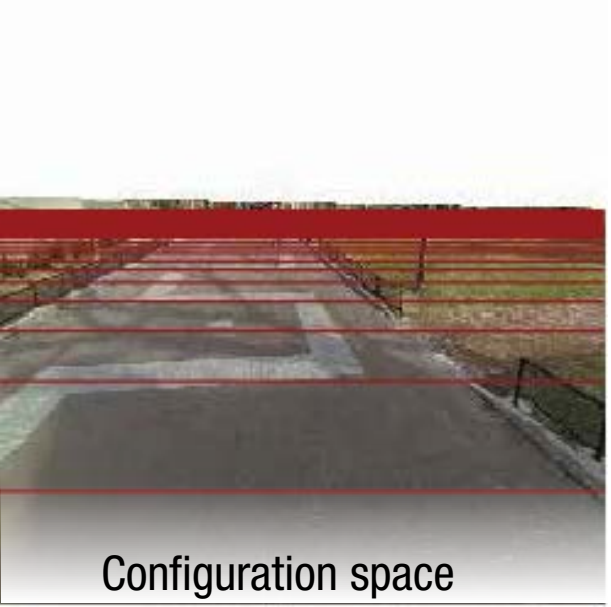


P2: 2D and 3D persistent



P3: Occlusion reasoning


Cartesian in image (LeCun et al.)


Configuration space

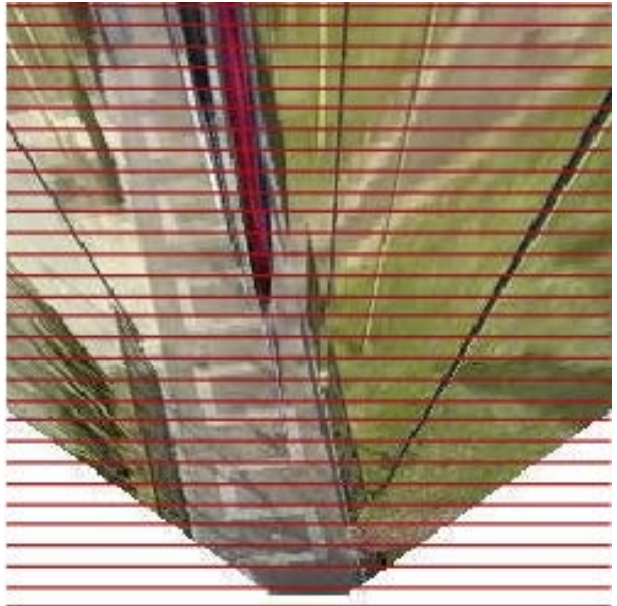

Cartesian in image (LeCun et al.)


Configuration space


Cartesian in image (LeCun et al.)


Cartesian in ground plane

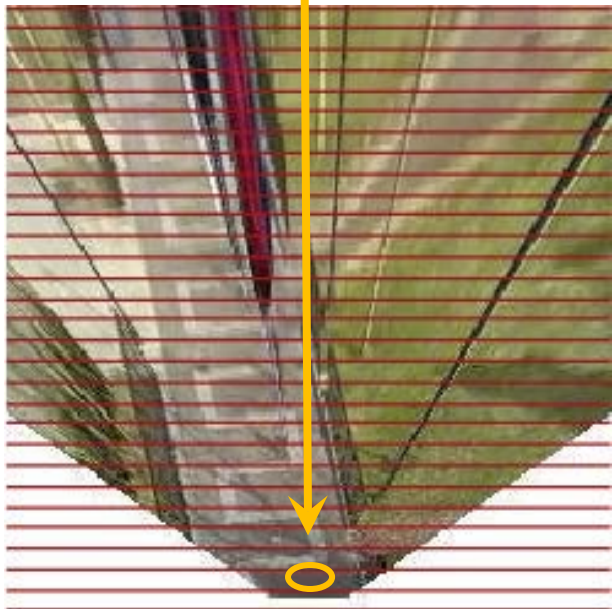

Configuration space




Cartesian in image (LeCun et al.)


Cartesian in ground plane

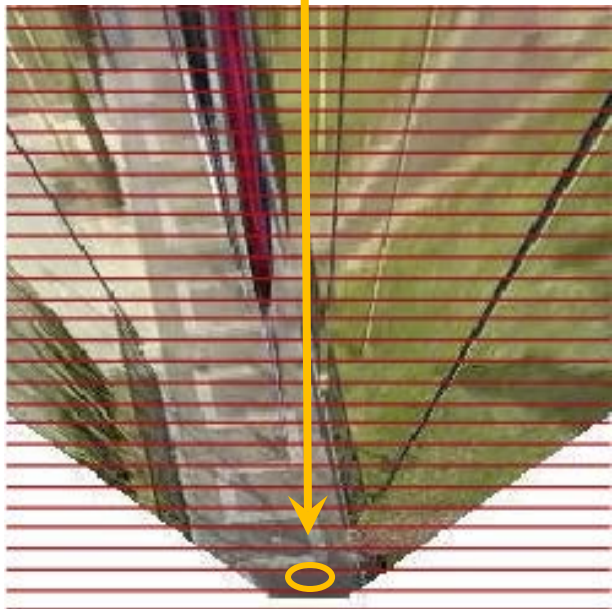

Configuration space

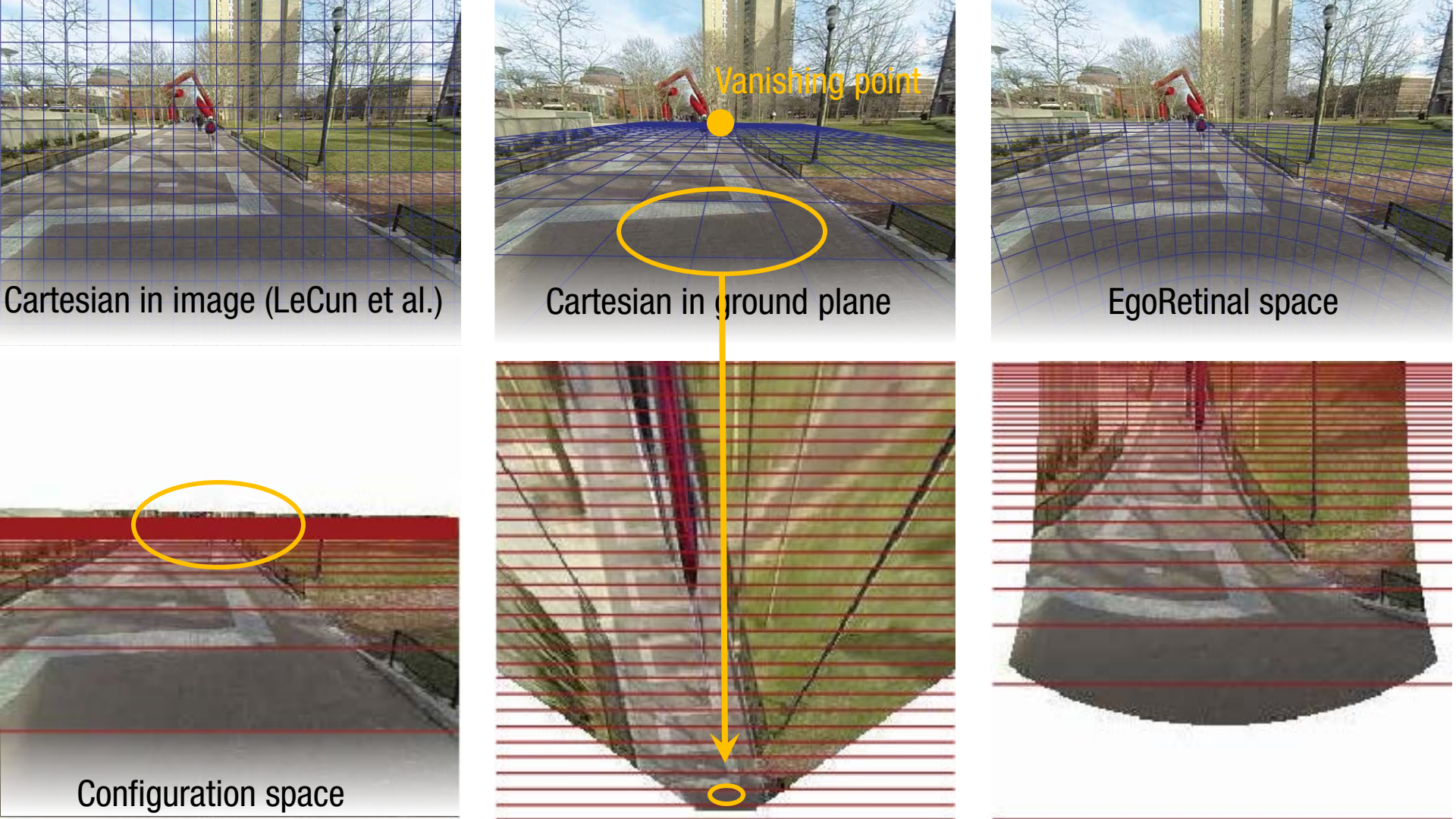



Cartesian in image (LeCun et al.)

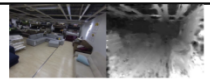
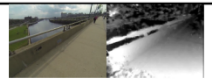
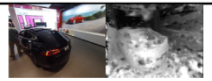

Vanishing point
Cartesian in ground plane


Configuration space



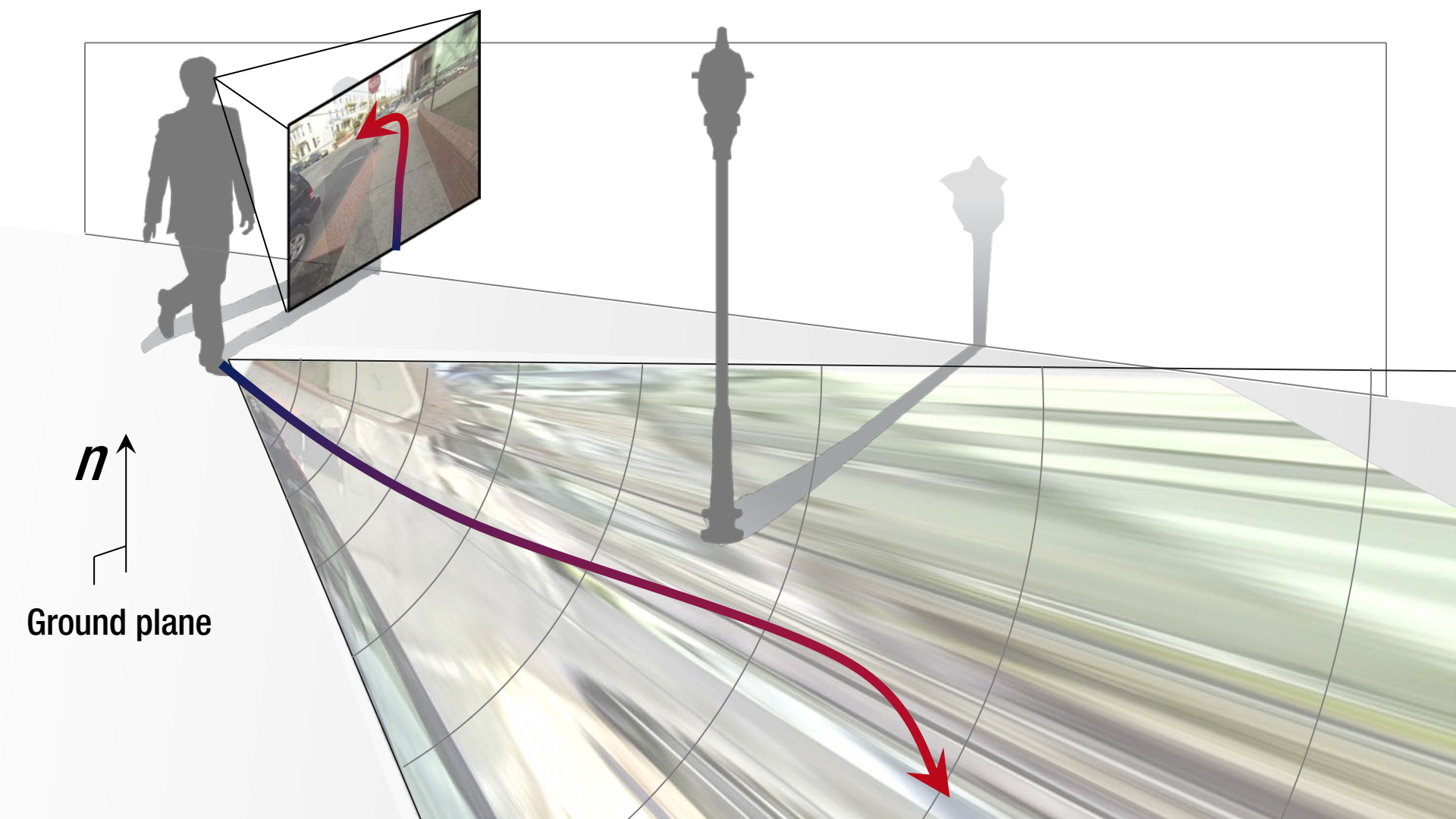

Cartesian in image (LeCun et al.)
Vanishing point
Cartesian in ground plane
EgoRetinal space
Configuration space

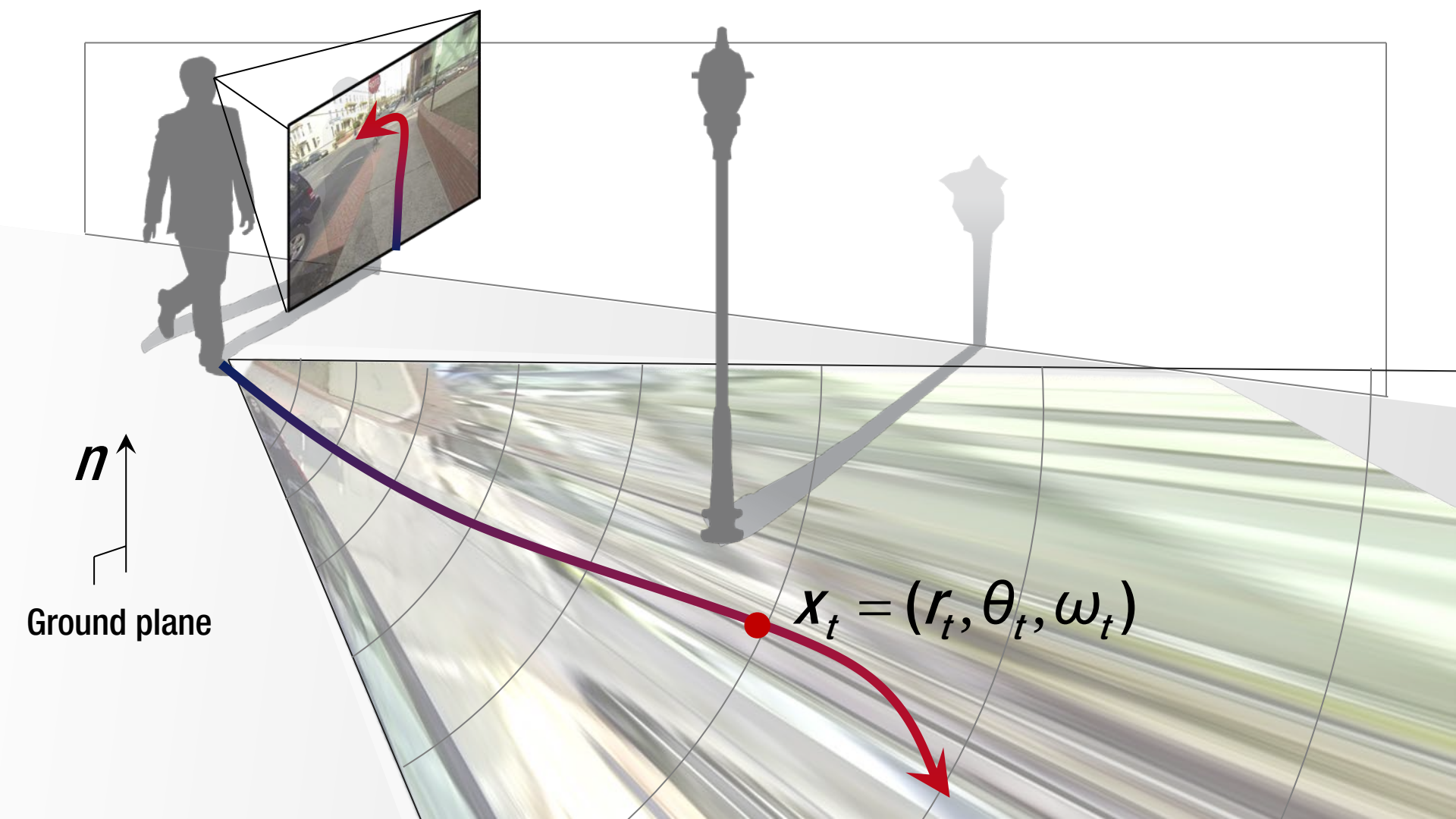

EgoMotion Dataset (outdoor)

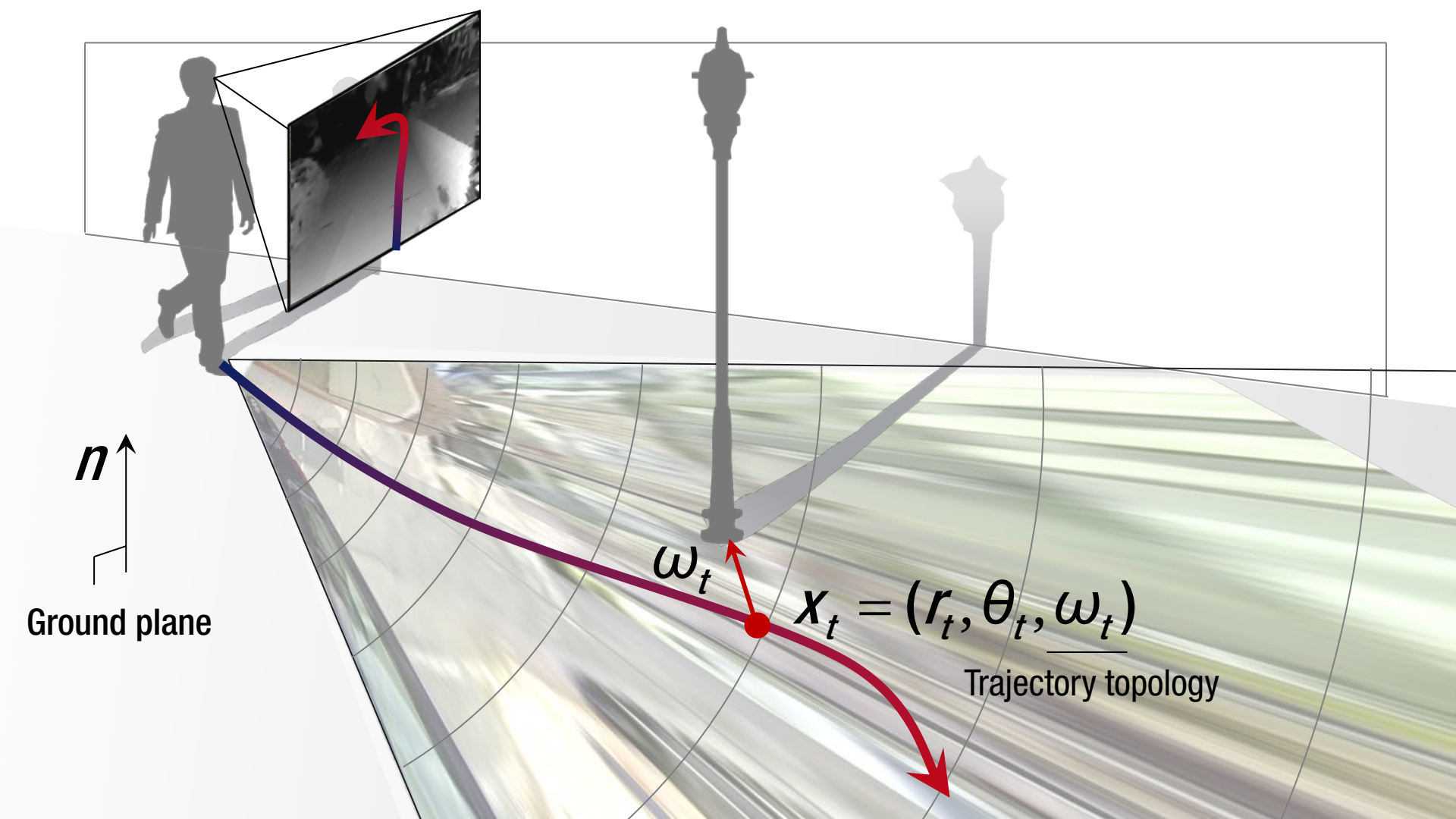
Image Disparity								
Scene	IKEA	Costco	Mall	Park	School1/2	Downtown1/2	Grocery1/2/3	Bus1/2
Frames	966	577	2683	3088	3754/3736	2856/3405	2858/2892/2834	2292/1850
Duration	08:03	04:49	22:22	25:44	31:17/31:08	23:48/28:23	23:49/24:06/23:37	19:06/15:25
Image Disparity								
Scene	Campus1/2/3	CVS1/2	Train Sta.1/2	River1/2	Dep. store	Library	Apartment	Caffe
Frames	2607/1884/1975	2359/3337	4034/2568	3378/2250	2250	1255	2050	1550
Duration	21:44/15:42/16:28	19:40/27:49	33:37/21:24	28:09/18:45	13:20	10:30	17:05	13:00

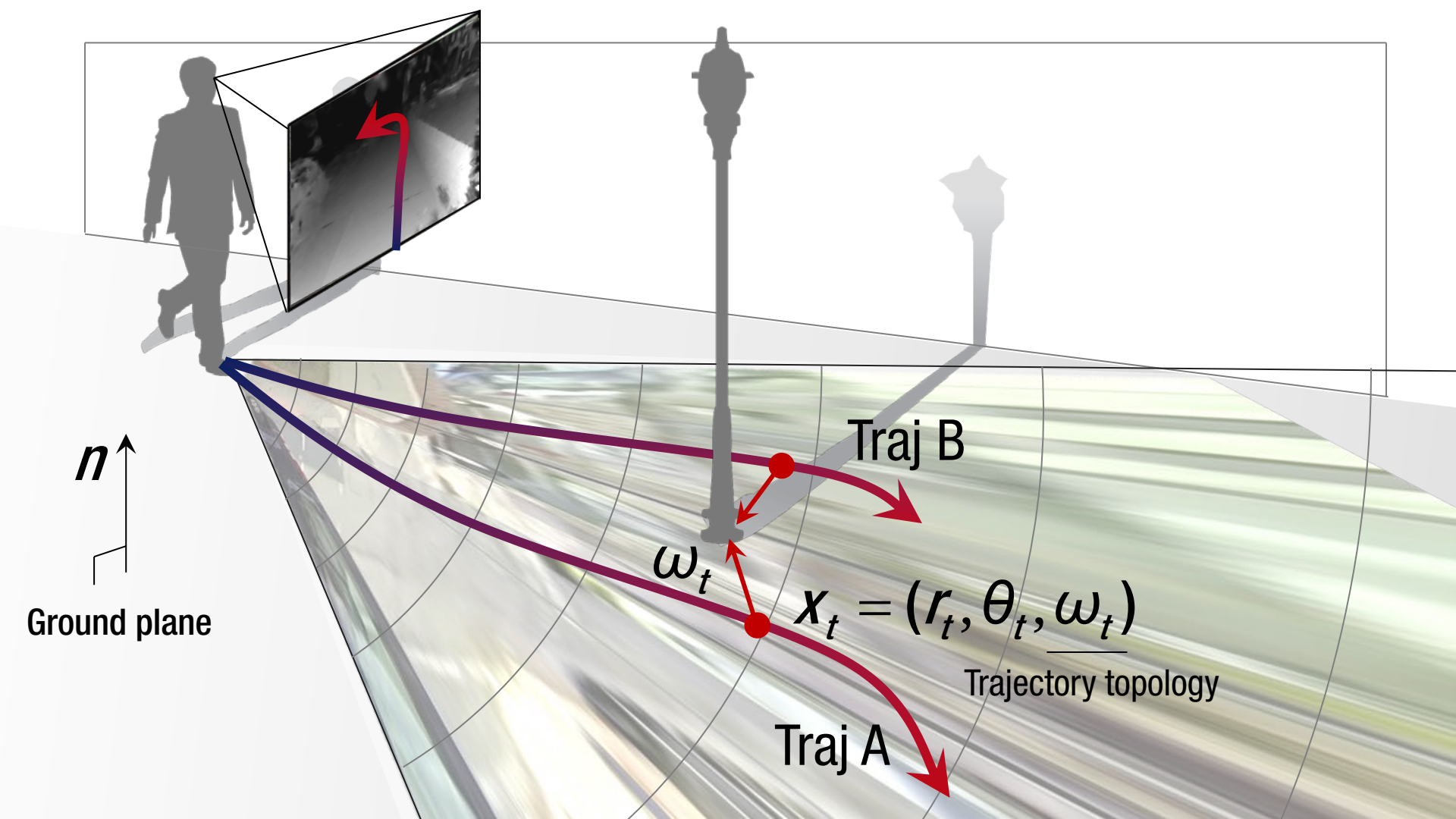
Dataset summary

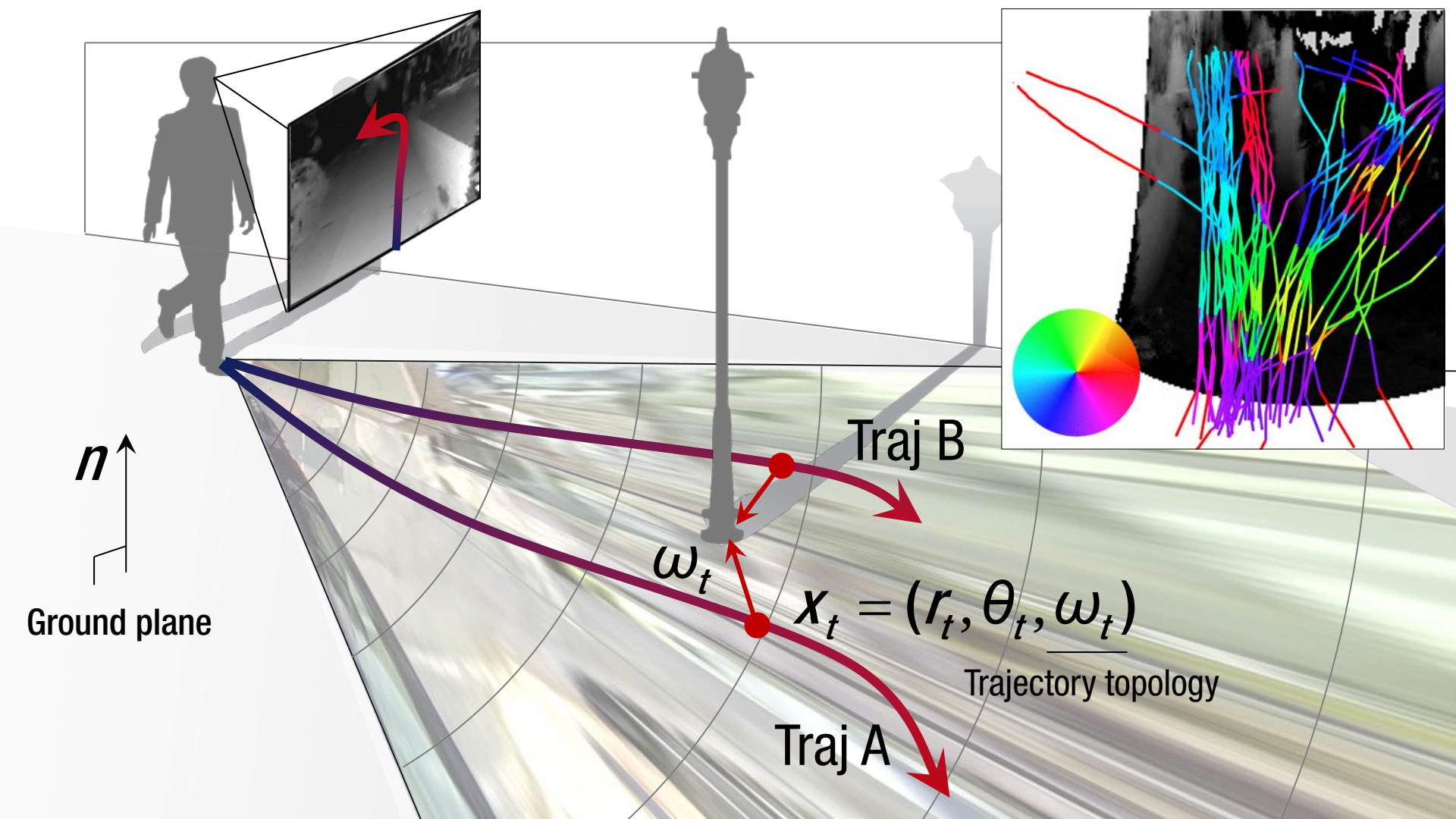
- 1280x960 stereo (100mm baseline, ~15m depth resolution)
- 26 scenes (13 indoor, 13 outdoor)
- 65.5k frames (9.1 hours)

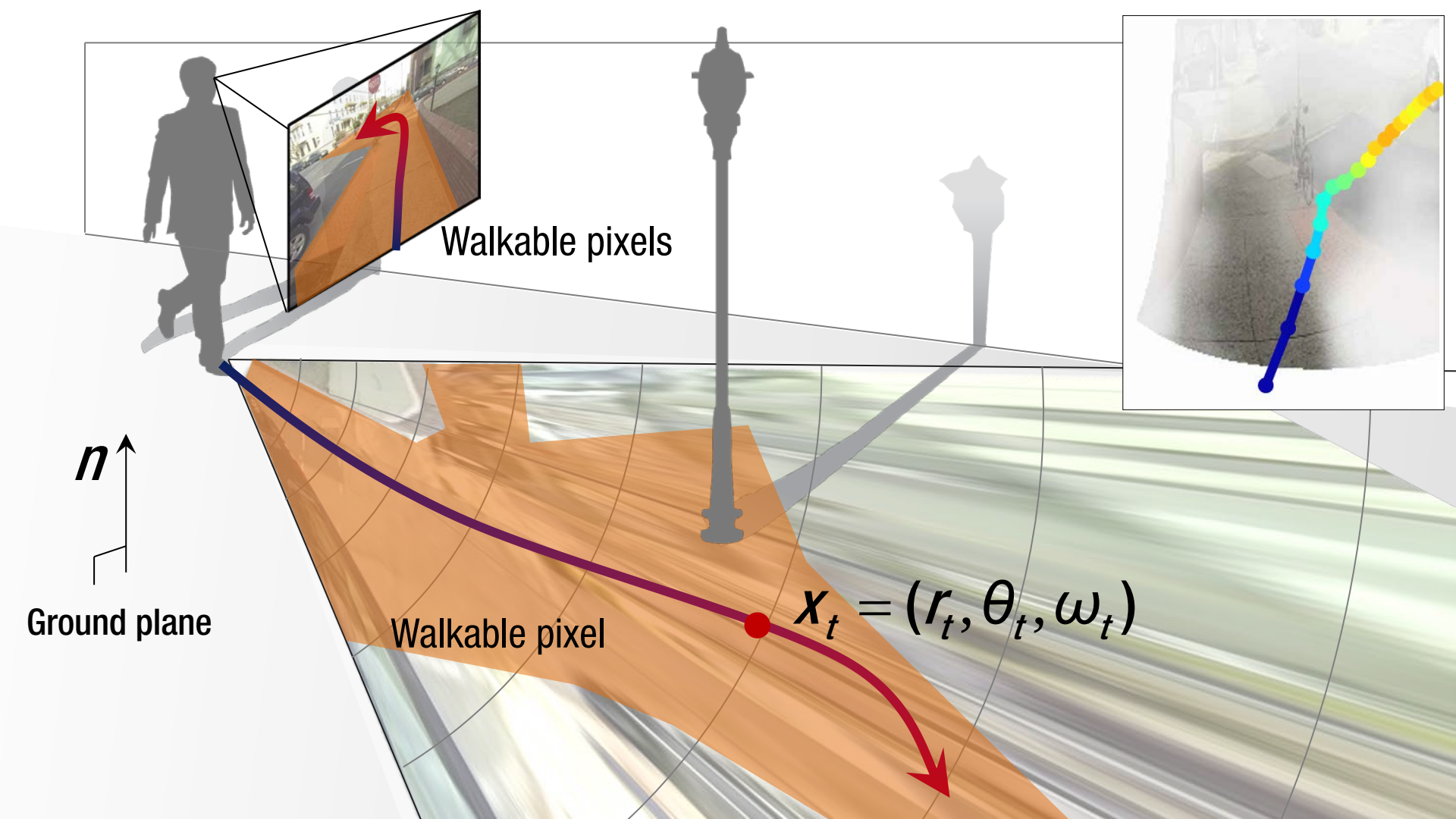

n
Ground plane

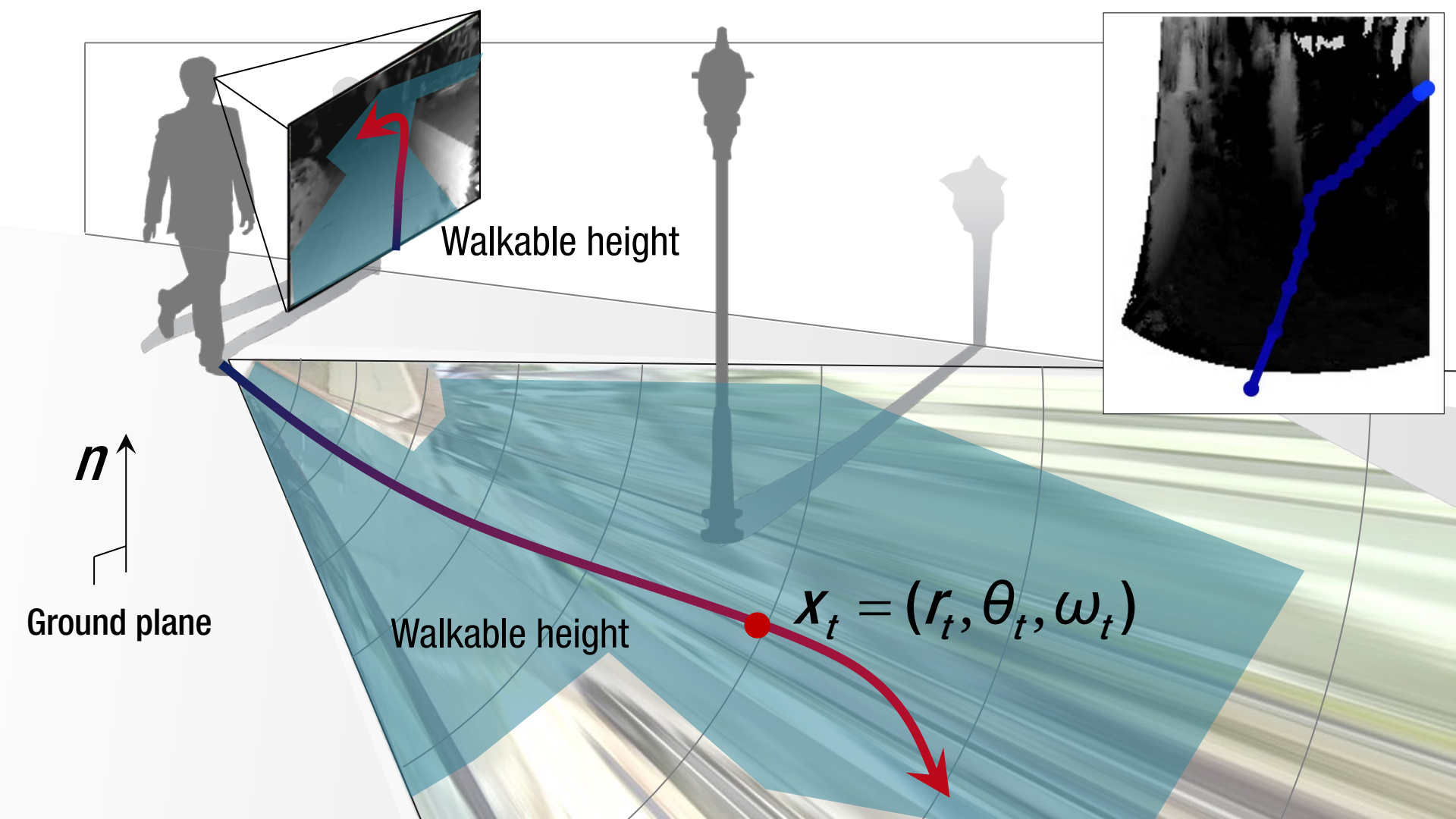

n
Ground plane
$x_t = (r_t, \theta_t, \omega_t)$


n
Ground plane
ω_t
$x_t = (r_t, \theta_t, \omega_t)$
Trajectory topology


n
Ground plane
Traj B
ω_t
$x_t = (r_t, \theta_t, \underline{\omega_t})$
Trajectory topology
Traj A

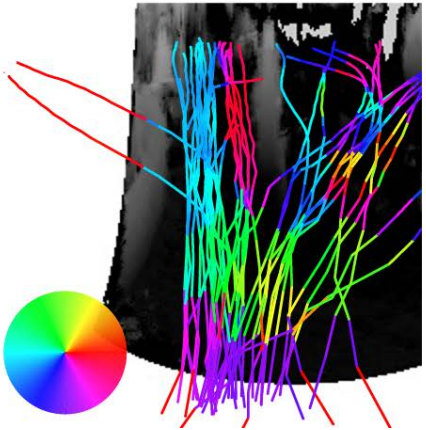

Traj B
ω_t
$x_t = (r_t, \theta_t, \underline{\omega_t})$
Trajectory topology
Traj A
n
Ground plane


Walkable pixels
n
Ground plane
Walkable pixel
$x_t = (r_t, \theta_t, \omega_t)$


Walkable height
n
Ground plane
Walkable height
$x_t = (r_t, \theta_t, \omega_t)$

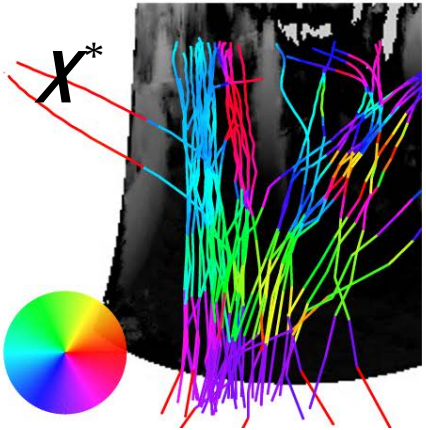
Testing image

Testing image



Trajectory retrieval

Testing image

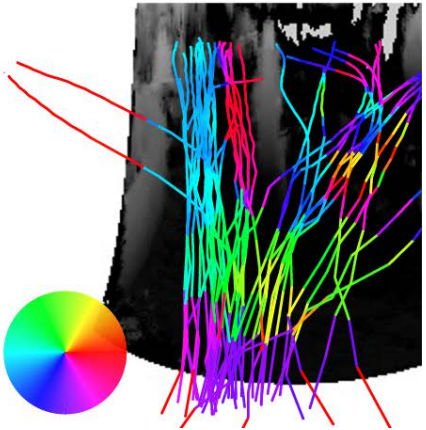


Trajectory retrieval

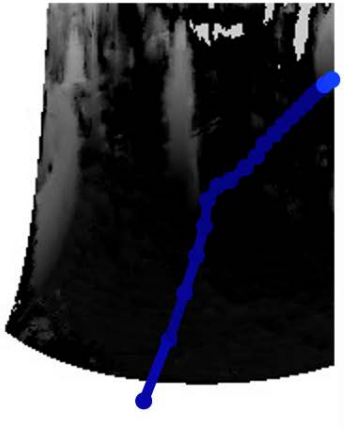
$$\underset{X}{\text{minimize}}\; E_{\text{D}} + E_{\text{RGB}} + \underbrace{\lambda \left\| X - X^* \right\|^2}_{\text{Data cost}}$$

X^* : retrieved trajectory

Testing image



Trajectory retrieval

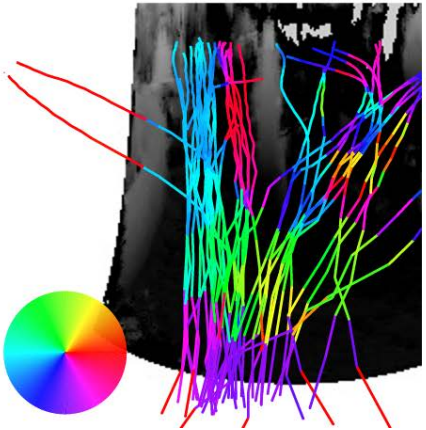


Depth cost

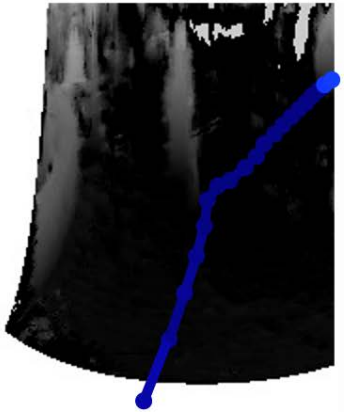
$$\underset{X}{\text{minimize}}\ \underbrace{E_{\text{D}}}_{\text{Depth walking preference}} + E_{\text{RGB}} + \lambda \left\| X - X^{*} \right\|^{2}$$

X^{*} : retrieved trajectory

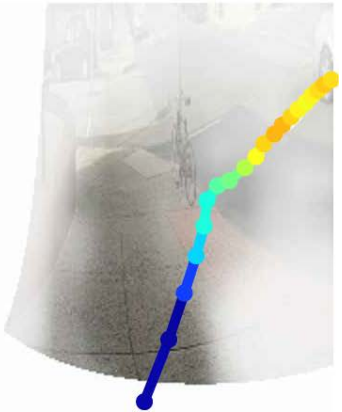
Testing image



Trajectory retrieval



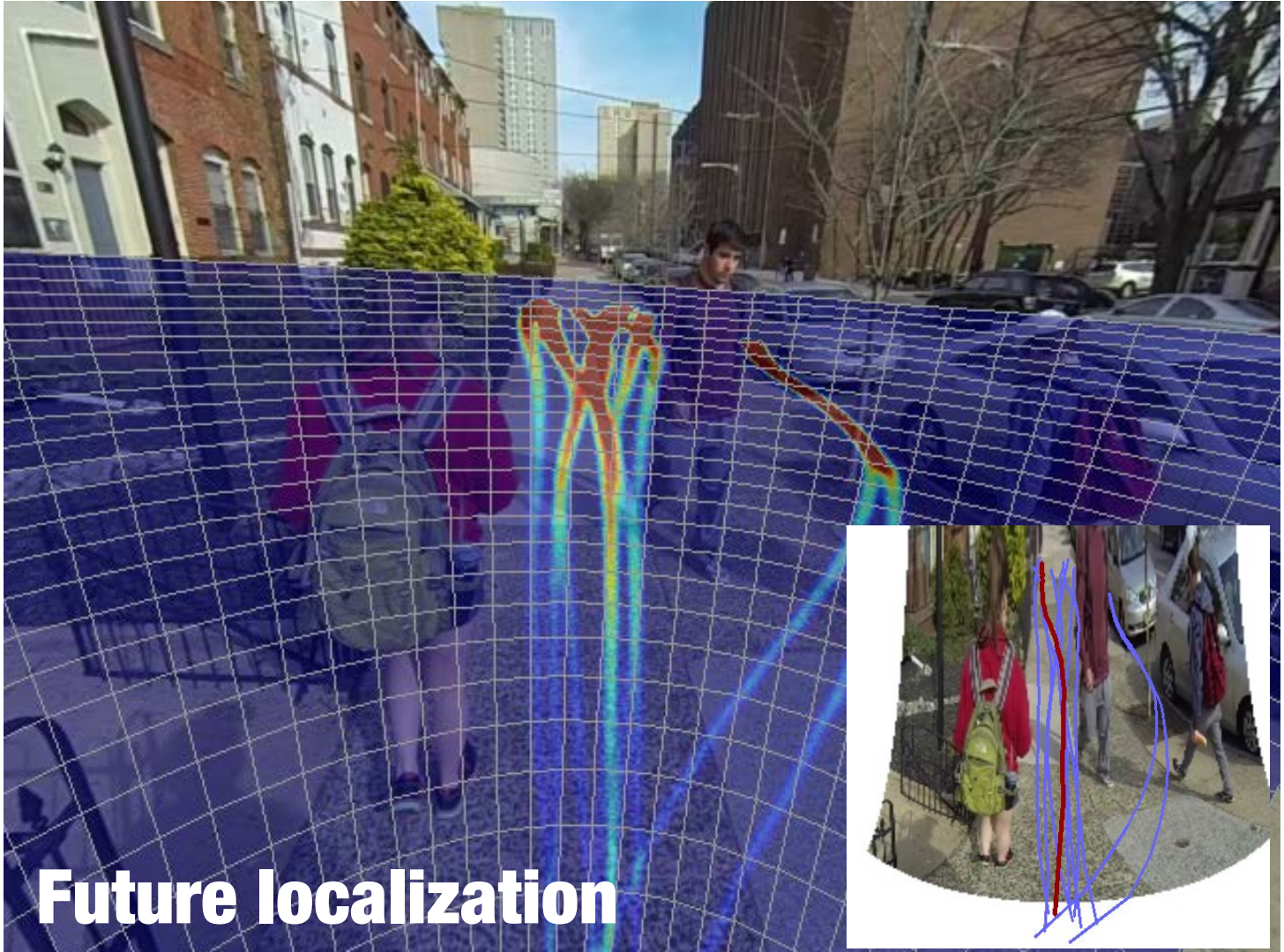
Depth cost

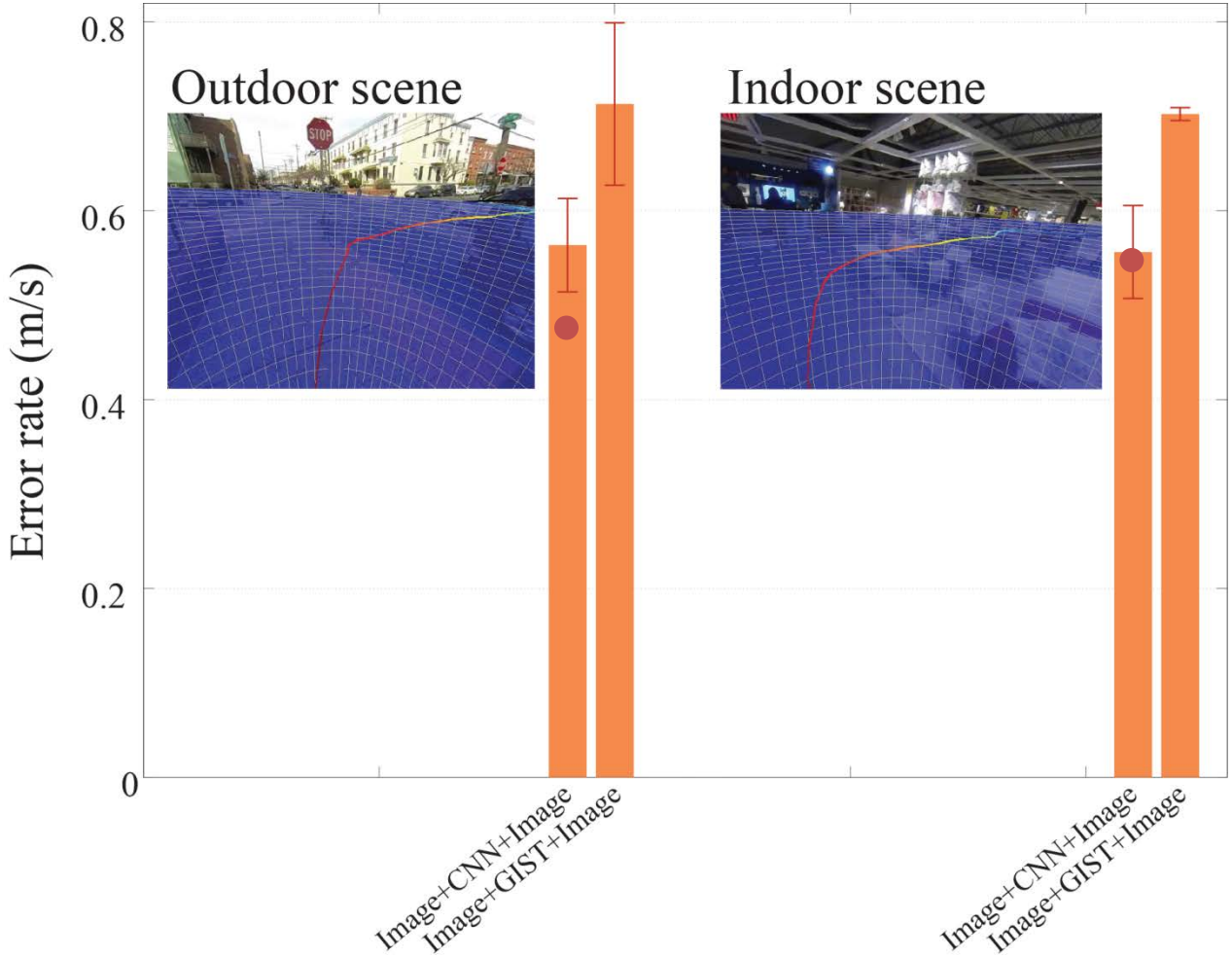


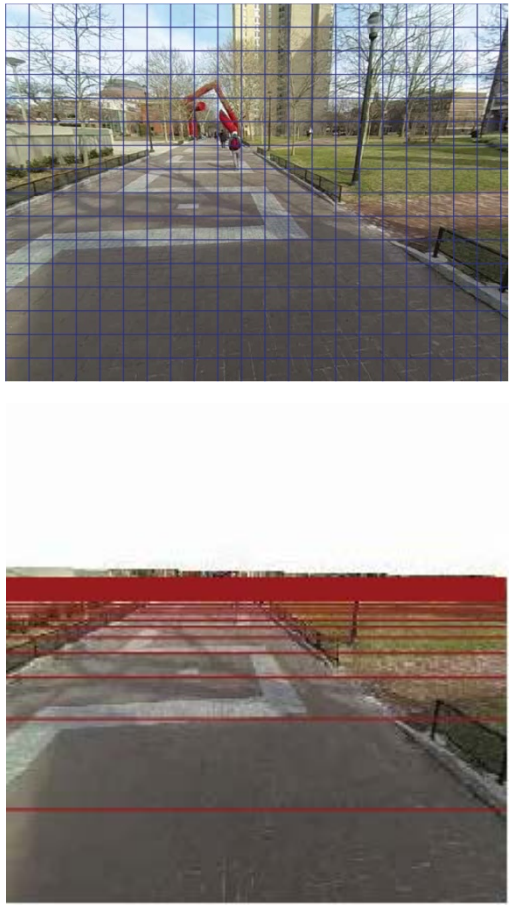
RGB cost

$$\underset{X}{\text{minimize}}\; E_{\text{D}} + \underbrace{E_{\text{RGB}}}_{\text{Walking preference}} + \lambda \left\| X - X^{*} \right\|^{2}$$

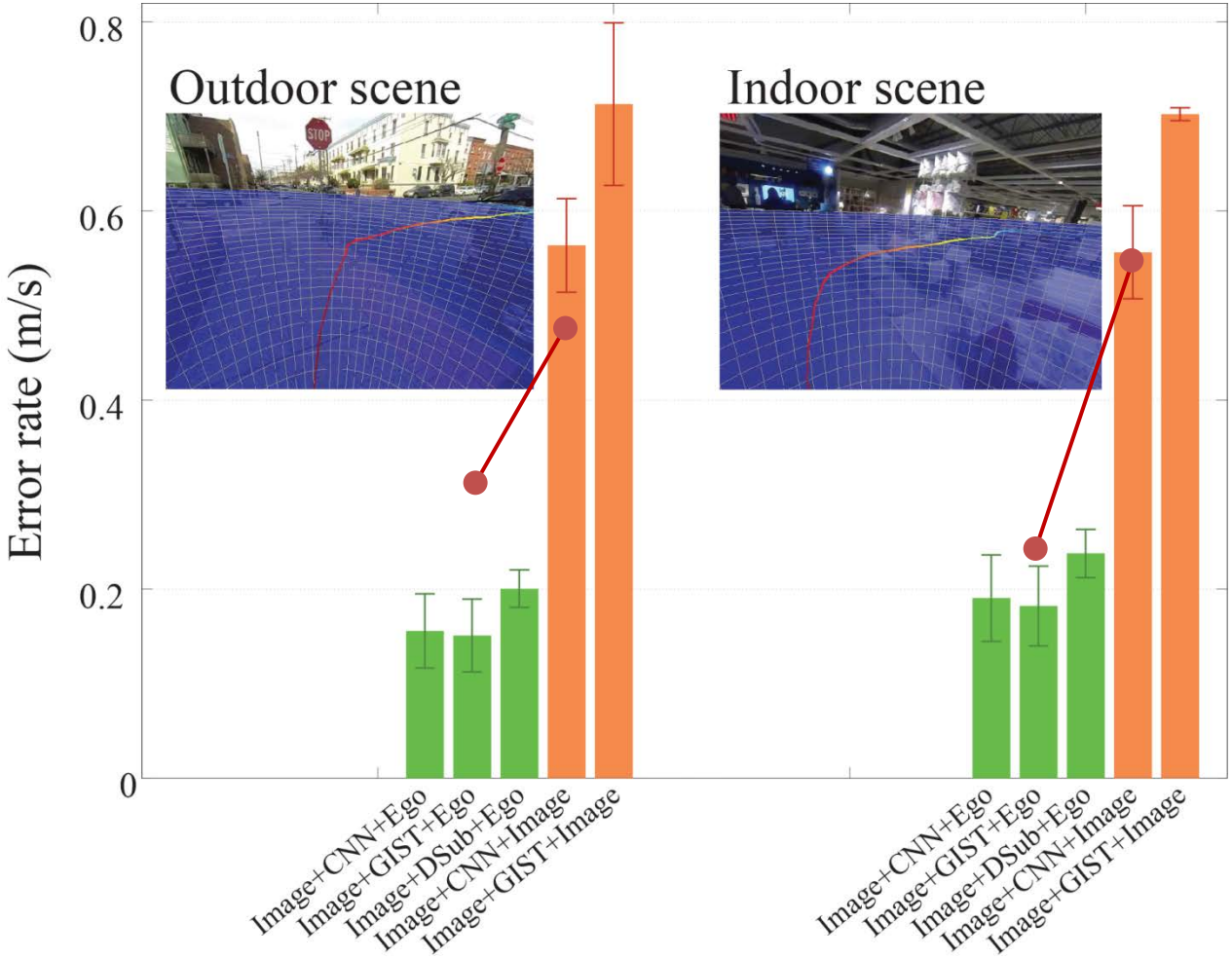
X^{*} : retrieved trajectory

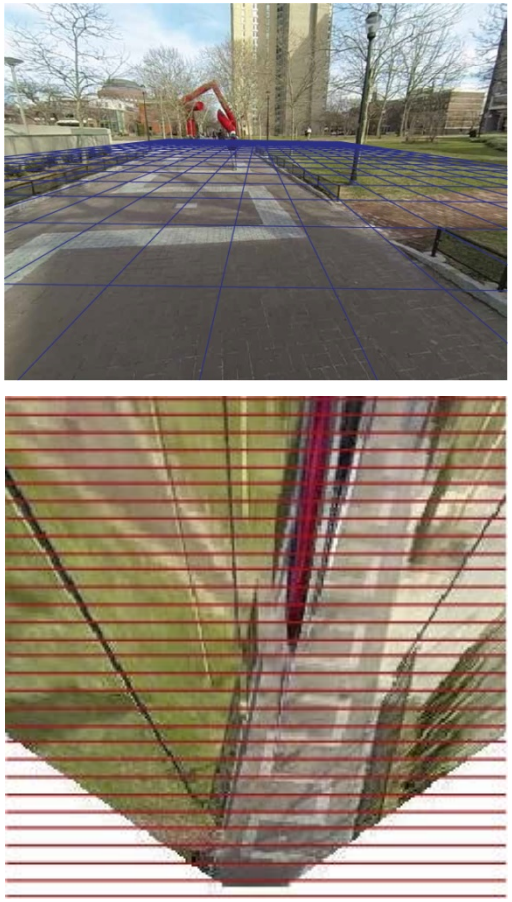

Future localization



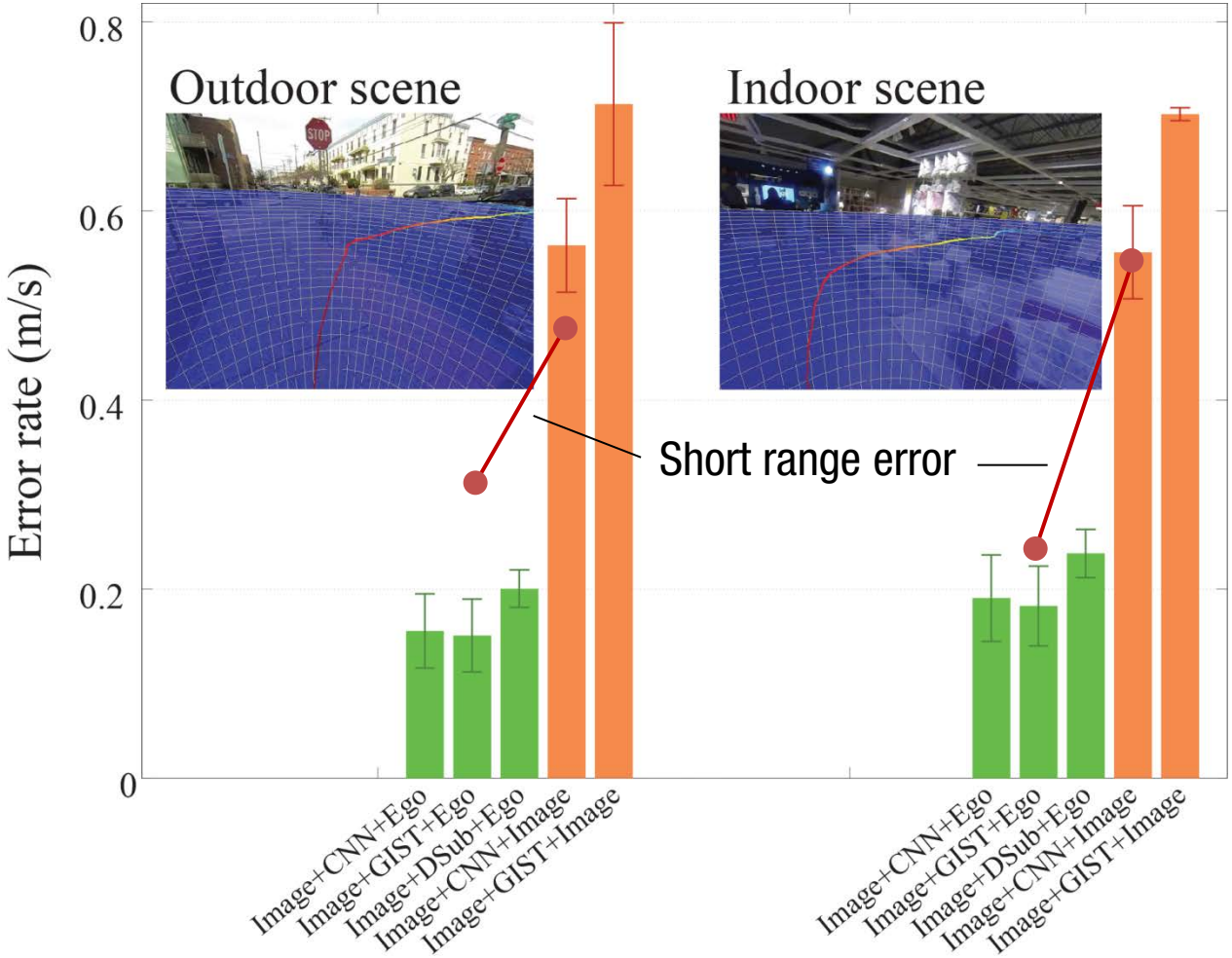


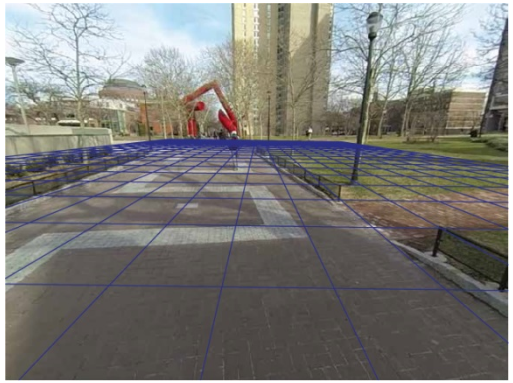
Cartesian in image (LeCun et al.)

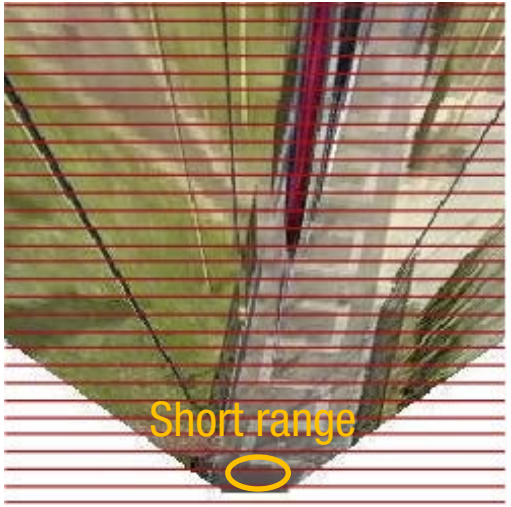




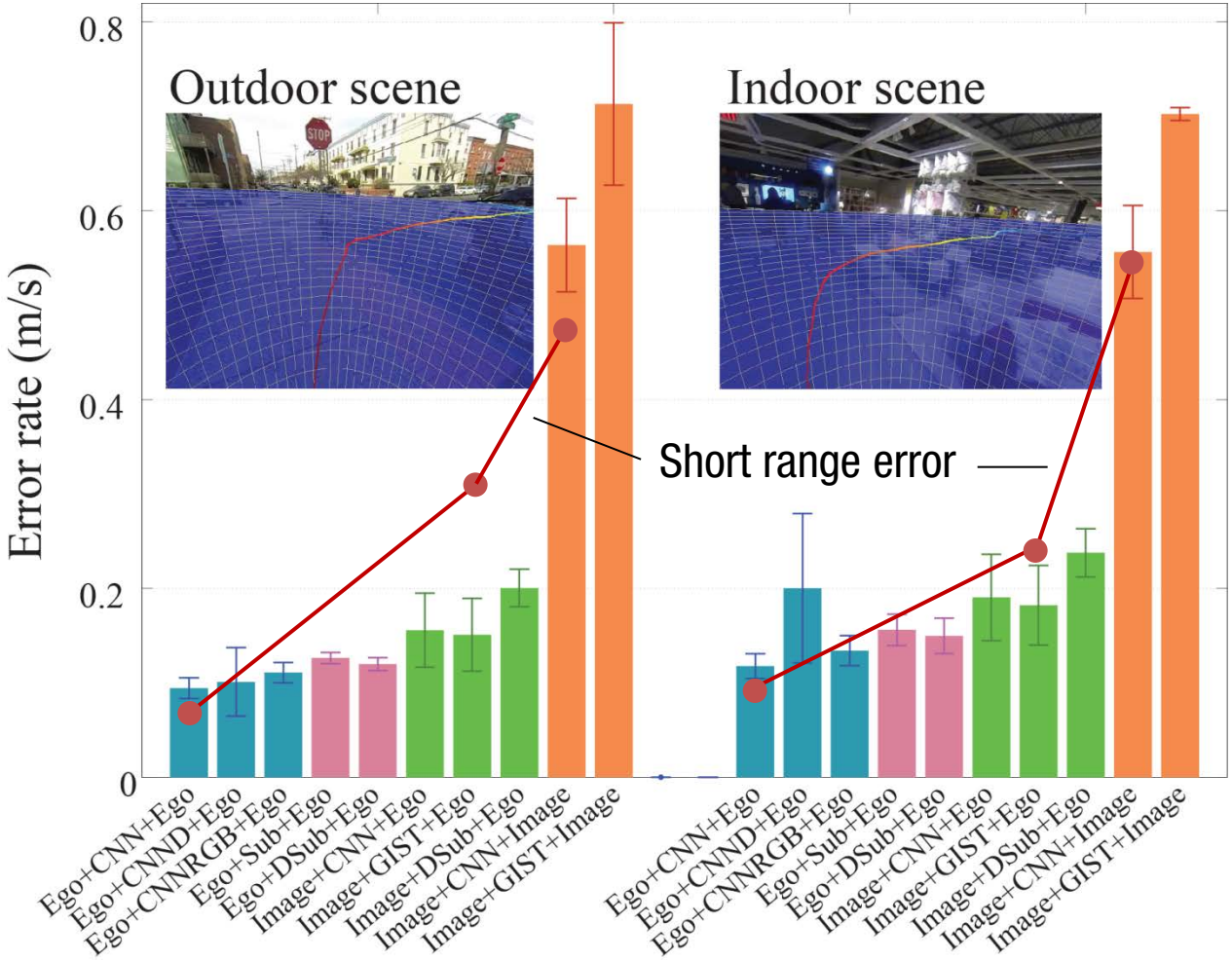
Cartesian on ground plane

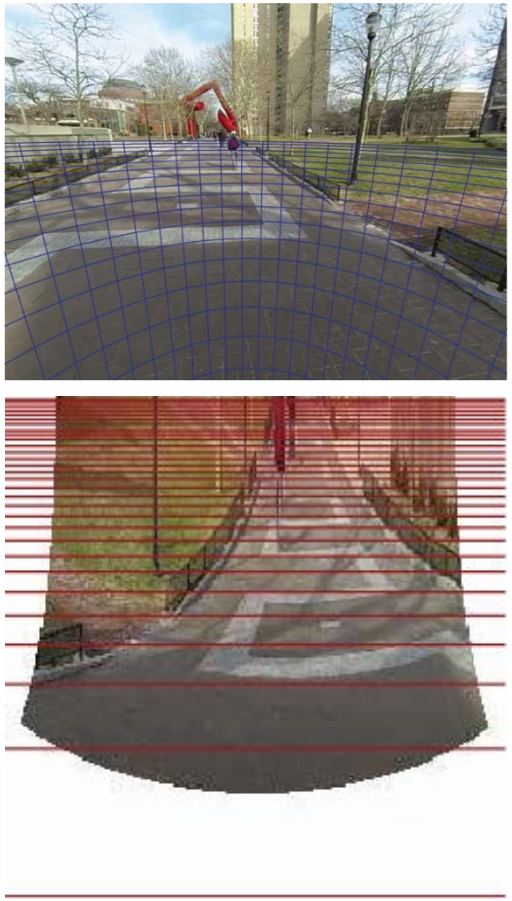




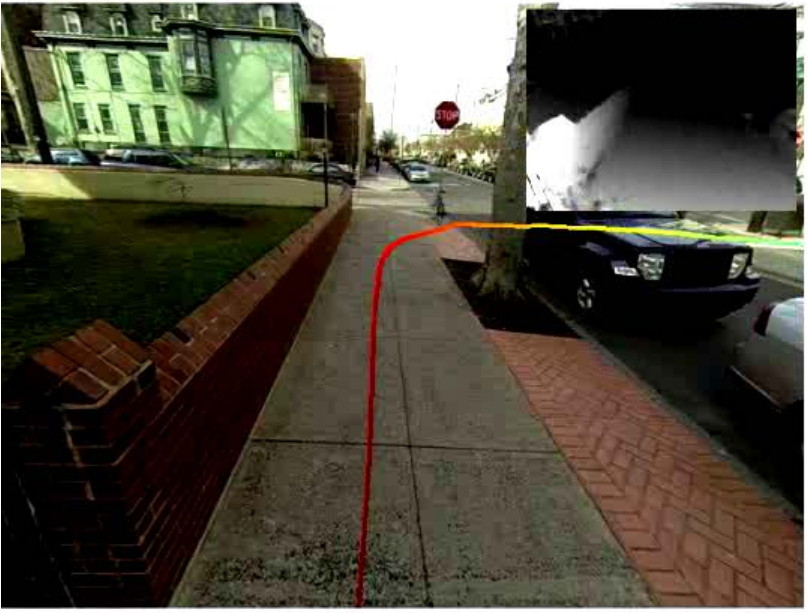


Cartesian on ground plane

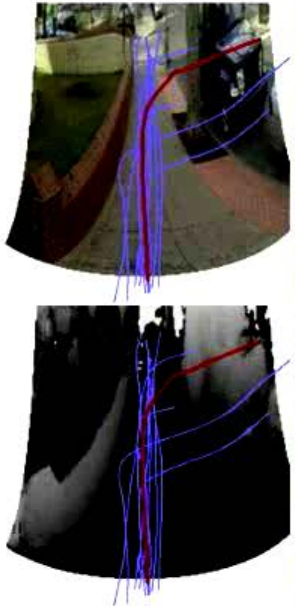

Outdoor scene
Indoor scene
Short range error
Error rate (m/s)
0.8
0.6
0.4
0.2
0
Ego+CNN+Ego
Ego+CNND+Ego
Ego+CNNRGB+Ego
Ego+Sub+Ego
Ego+DSub+Ego
Image+CNN+Ego
Image+GIST+Ego
Image+DSub+Ego
Image+CNN+Image
Image+GIST+Image



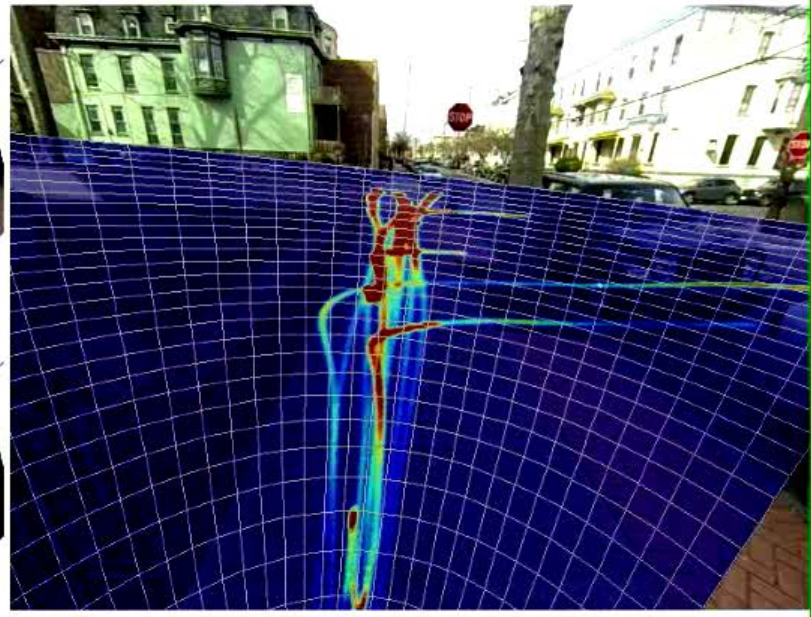
Ours



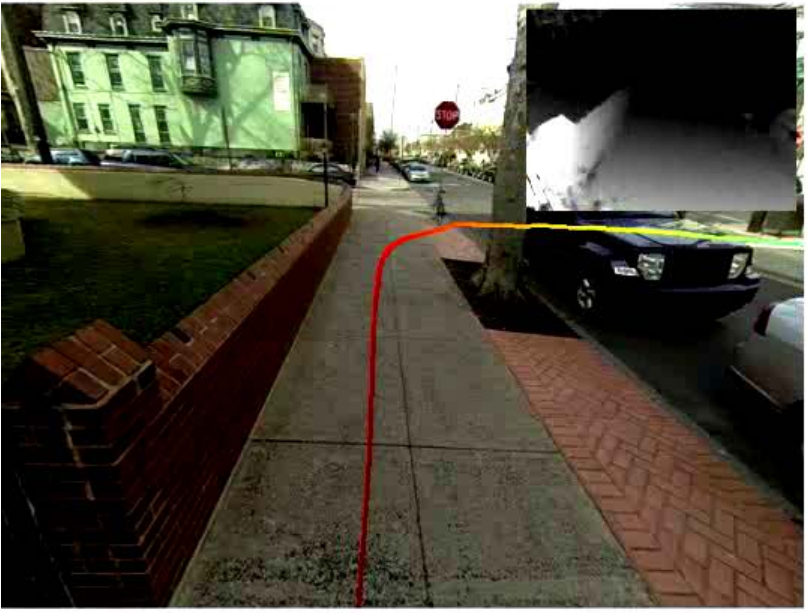
Ground truth



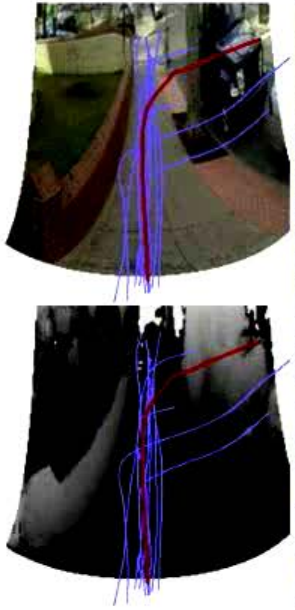
EgoRetinal map



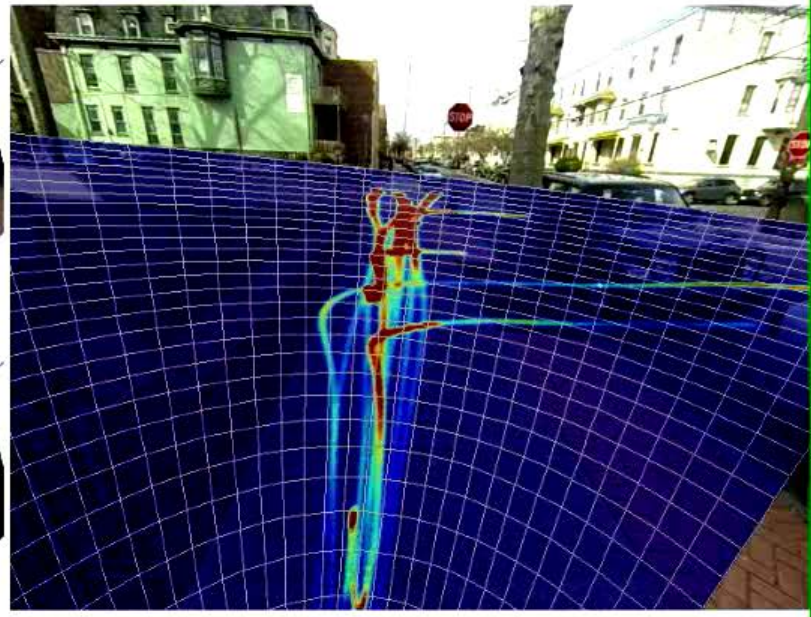
Predicted trajectories



Ground truth

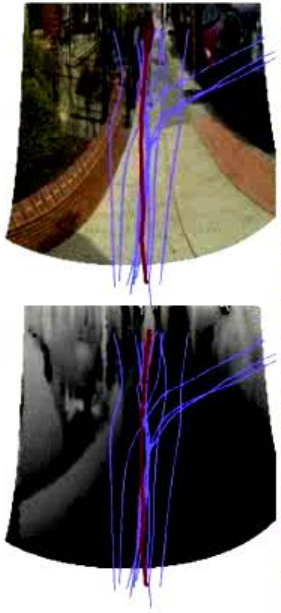


EgoRetinal map

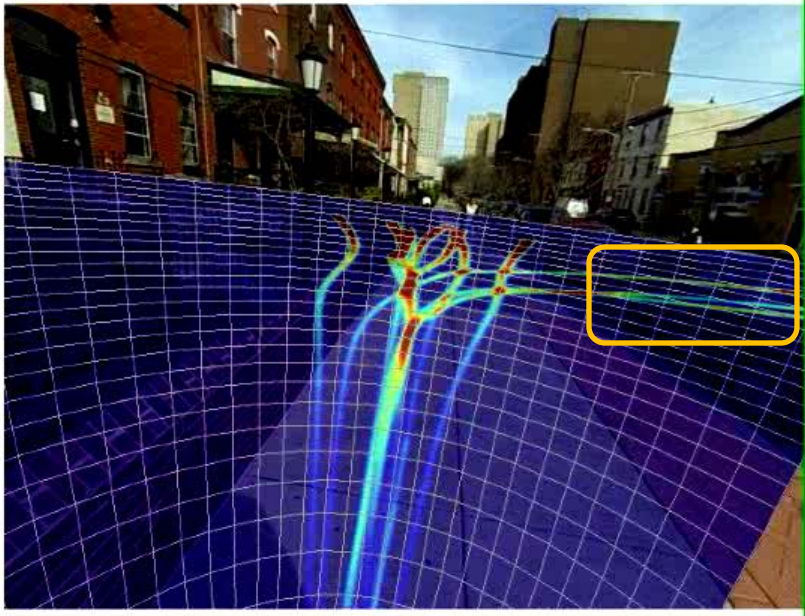


Predicted trajectories

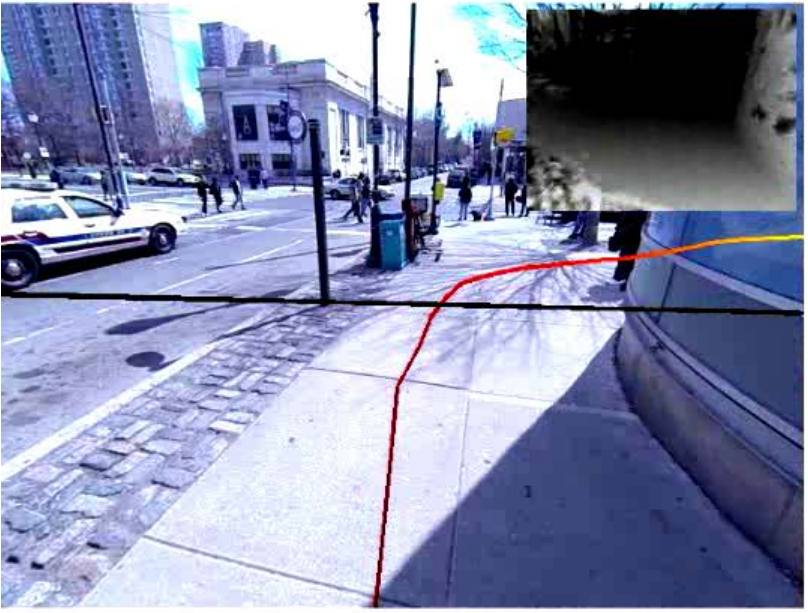
Ground truth



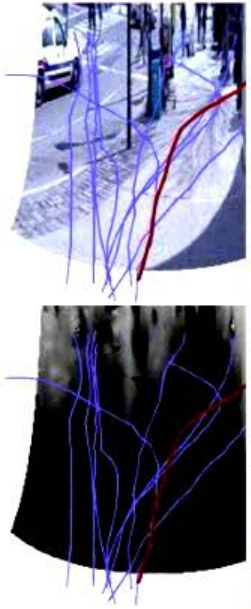
EgoRetinal map



Predicted trajectories



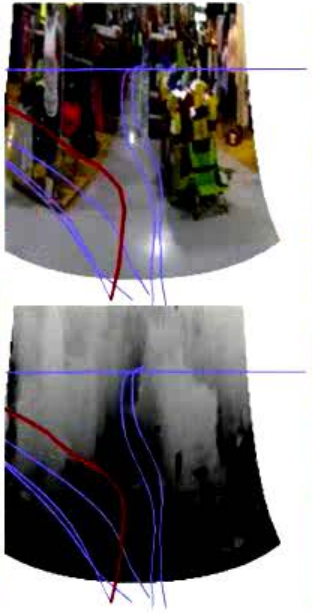
Ground truth



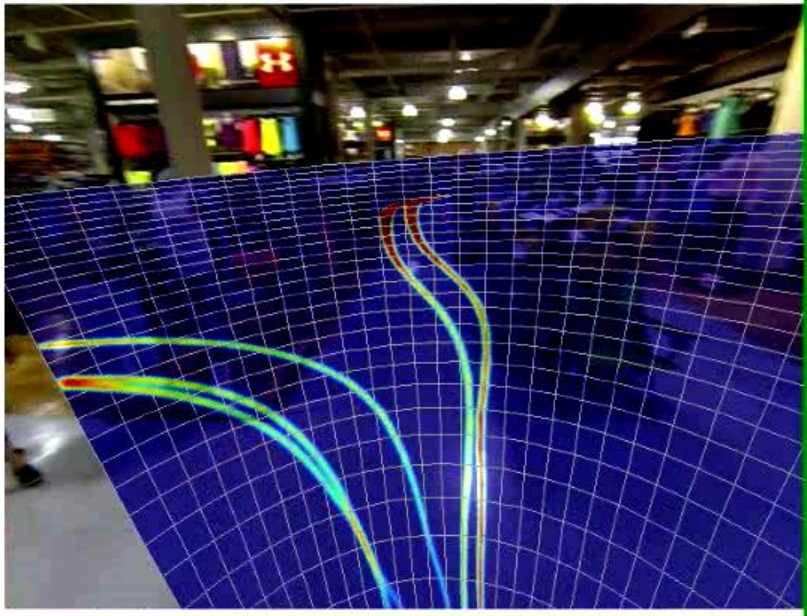
EgoRetinal map

Predicted trajectories

Ground truth

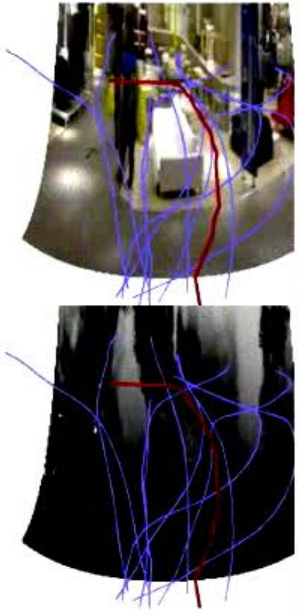


EgoRetinal map

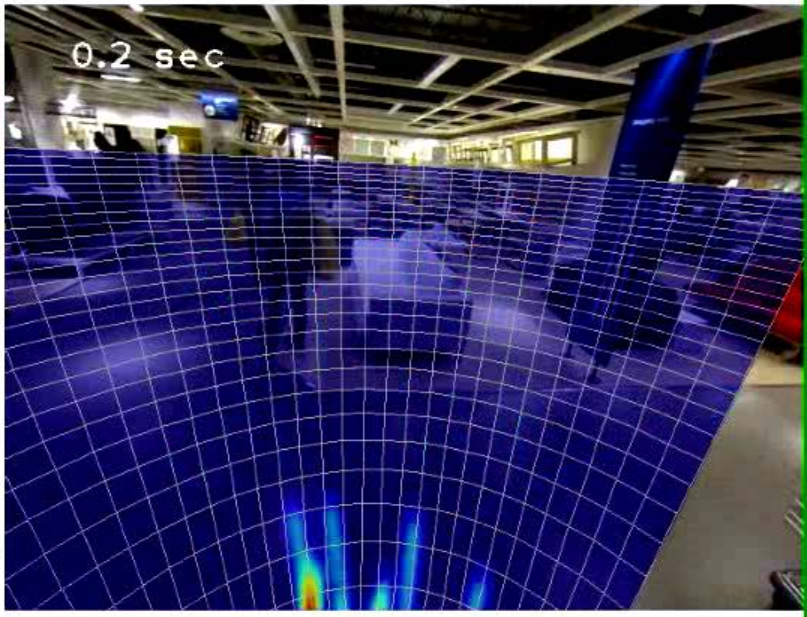


Predicted trajectories

Ground truth

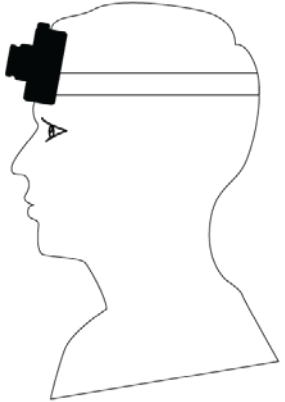


EgoRetinal map

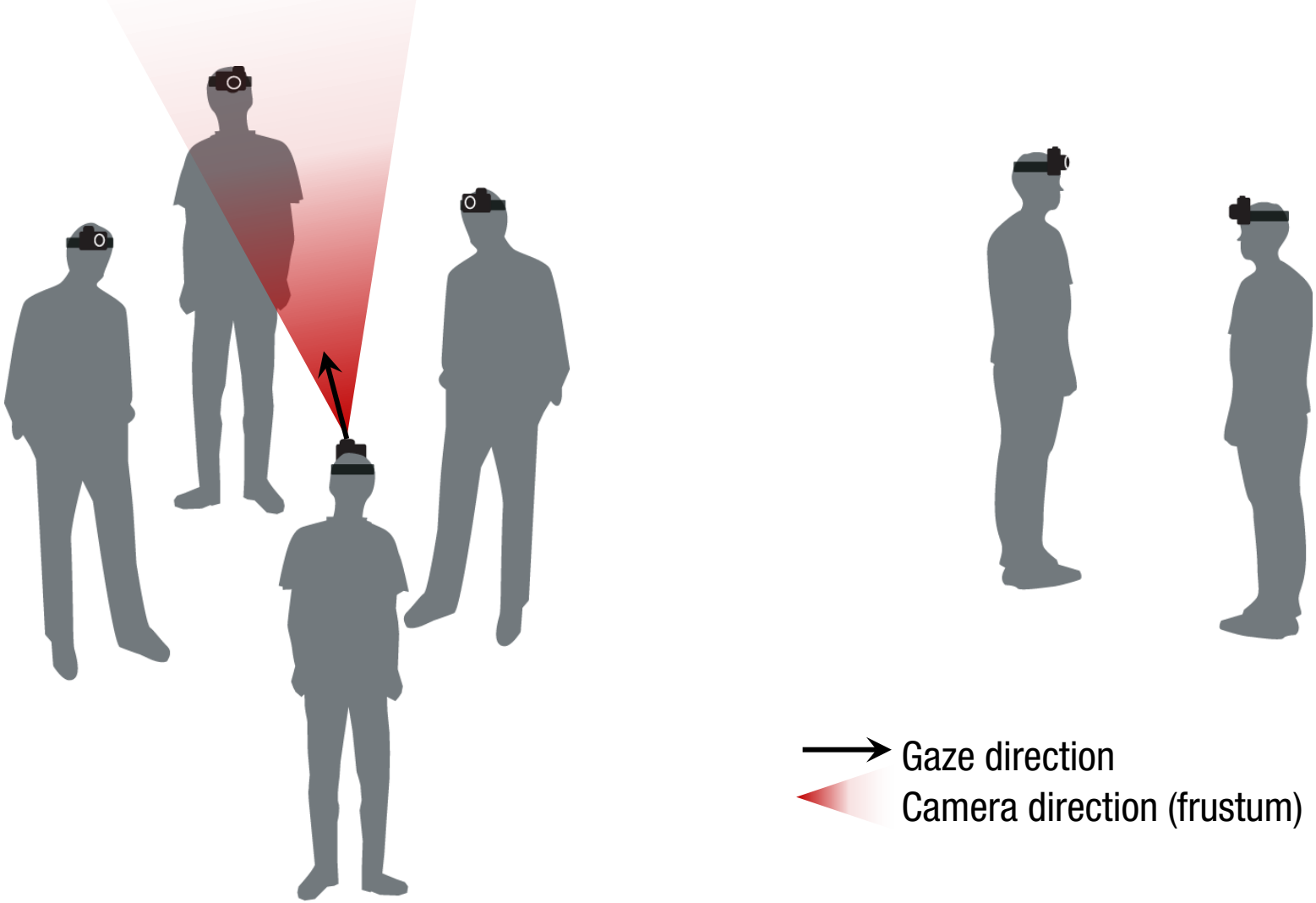


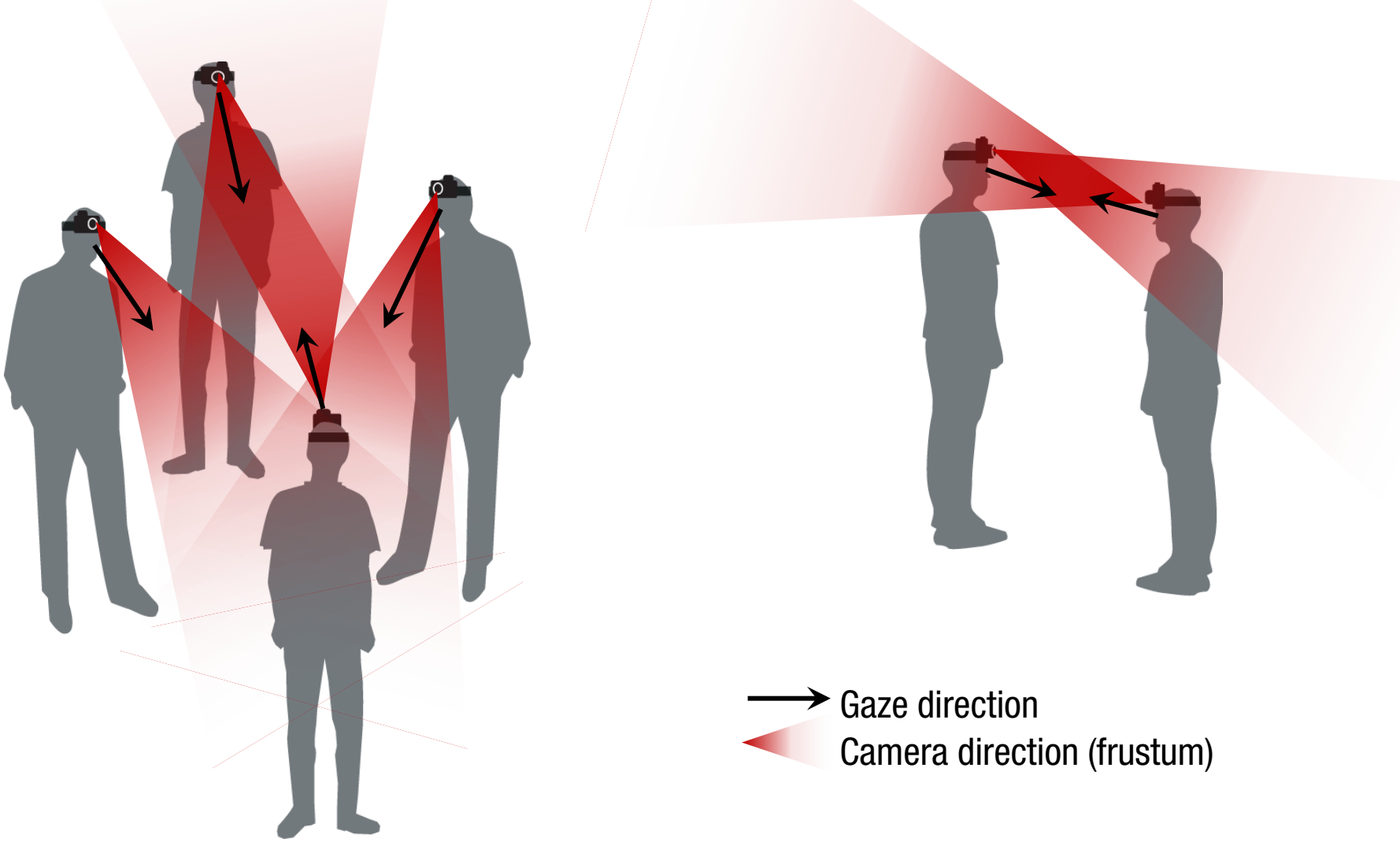
Predicted trajectories

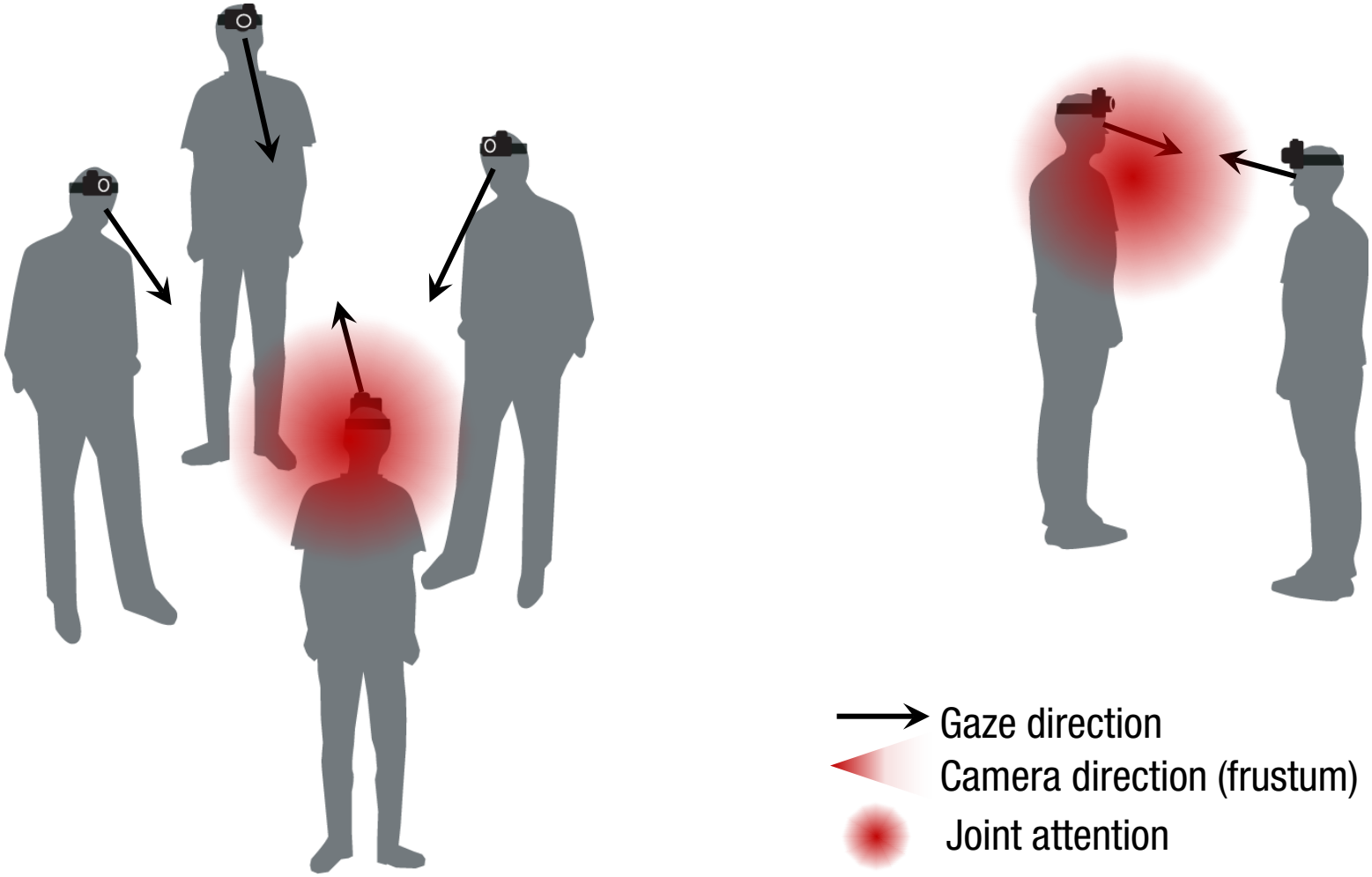
What can first person vision tell us?



What can first person vision tell us about our social interactions?

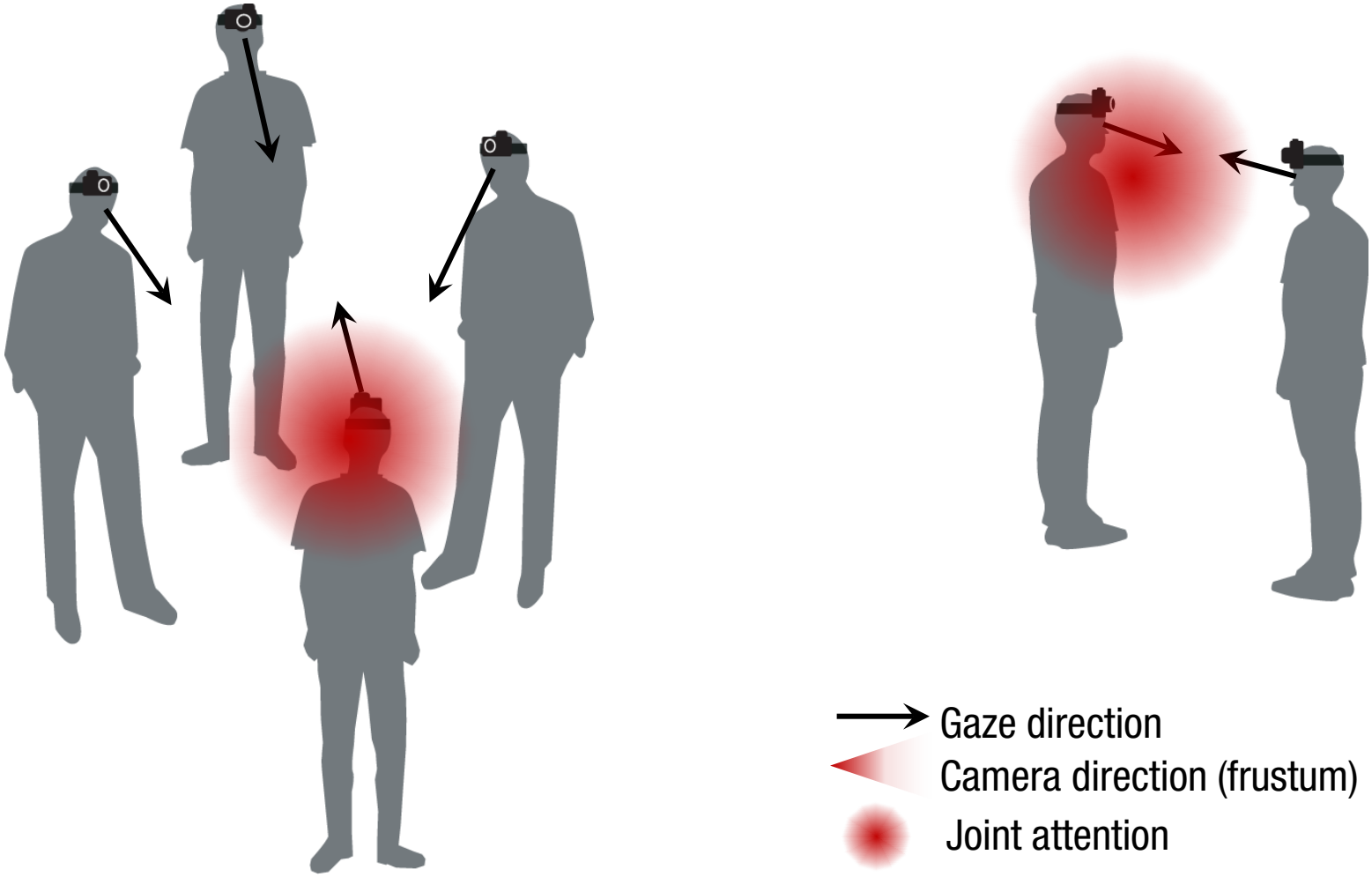

Gaze direction
Camera direction (frustum)


Gaze direction
Camera direction (frustum)


Gaze direction
Camera direction (frustum)
Joint attention

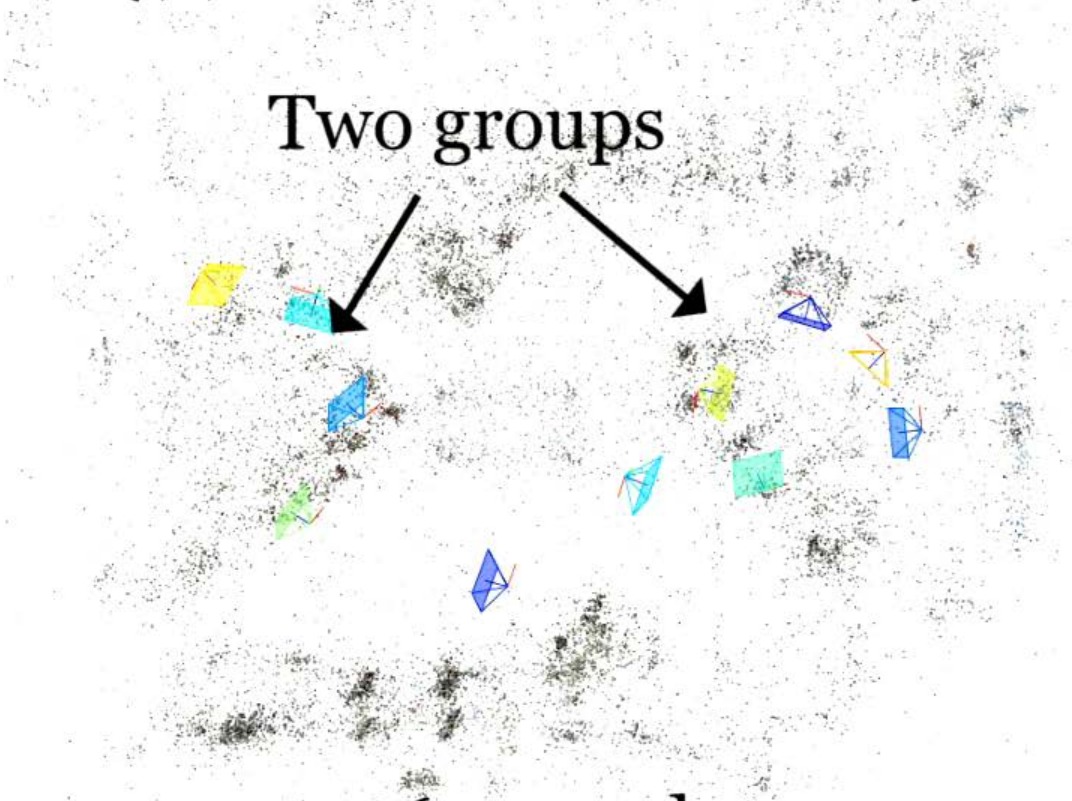
Joint Attention

Autism spectrum disorder (ASD)
Attention deficit hyperactivity disorder (ADHD)

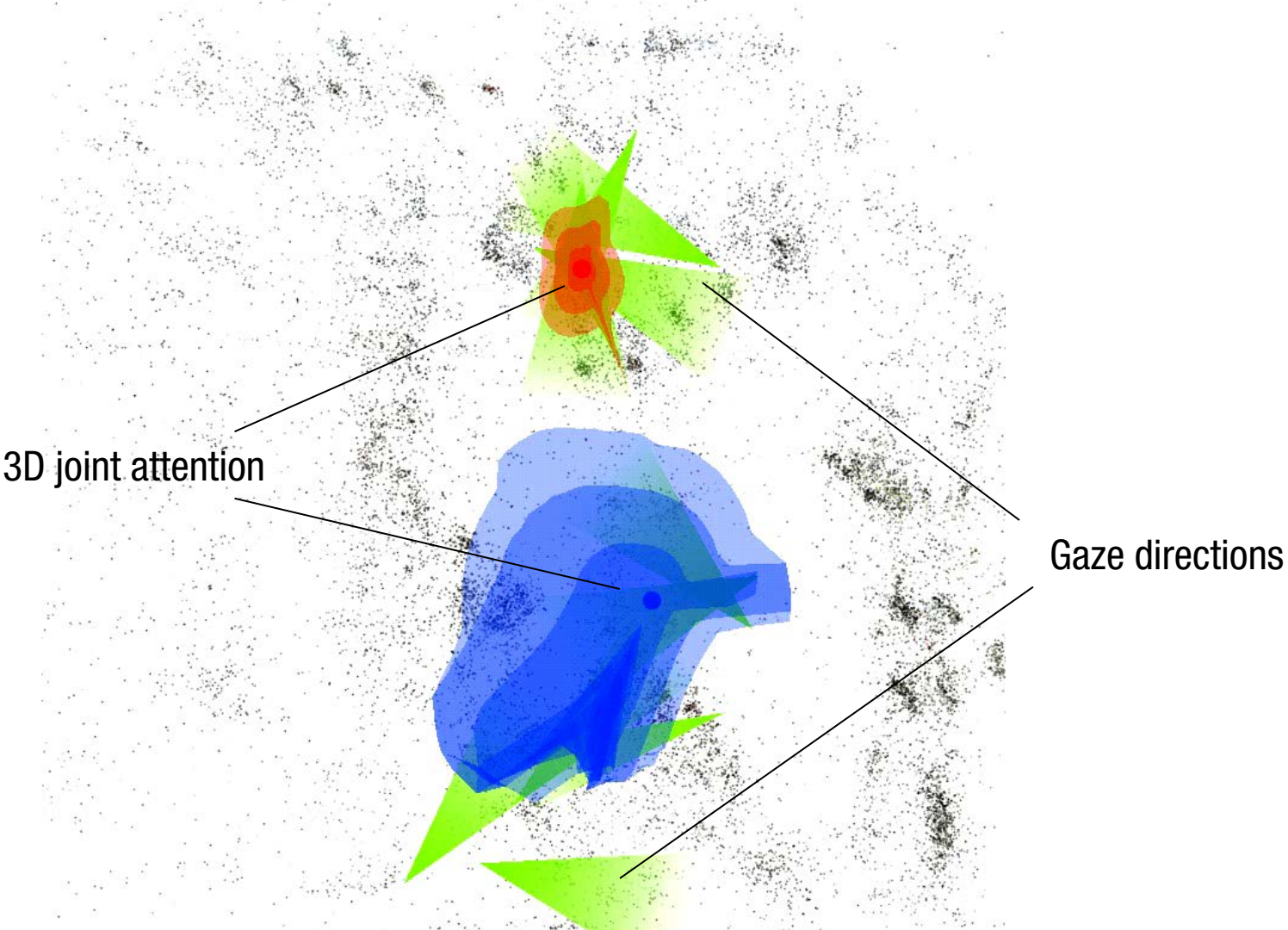

Gaze direction
Camera direction (frustum)
Joint attention

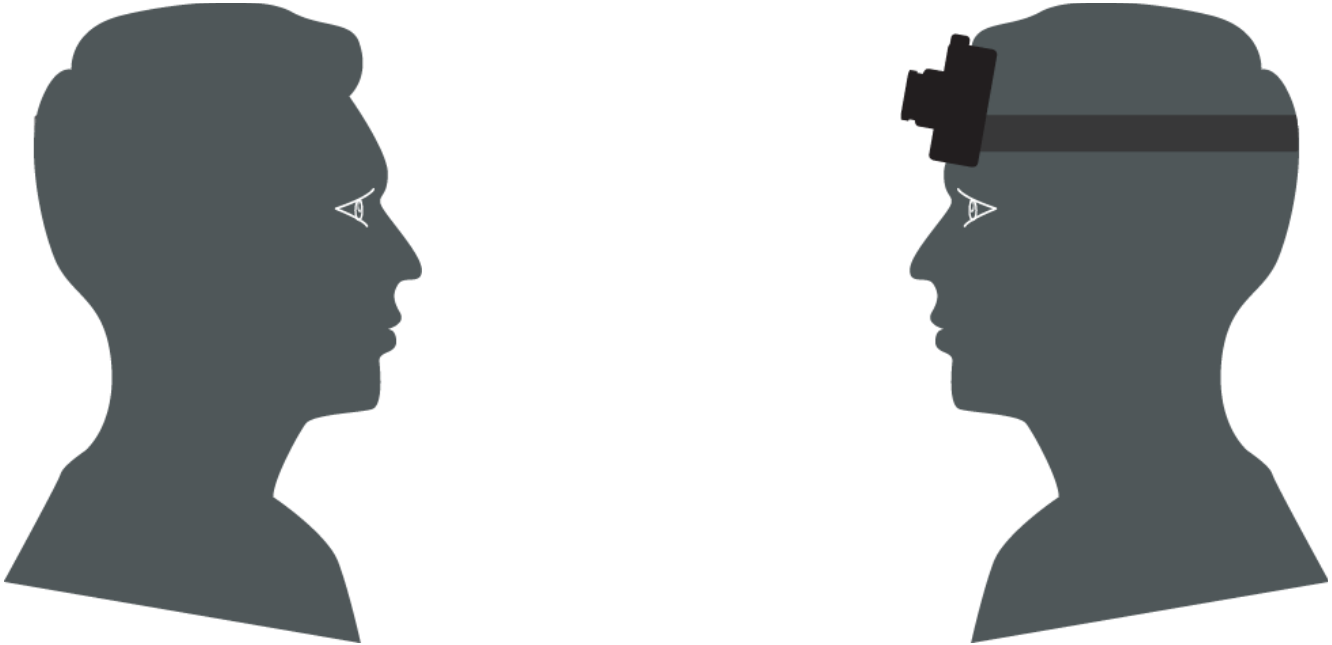

Input Video: Meeting Scene
1x speed

3D Camera Pose Estimation
(Structure from motion)



6x speed


3D joint attention
Gaze directions

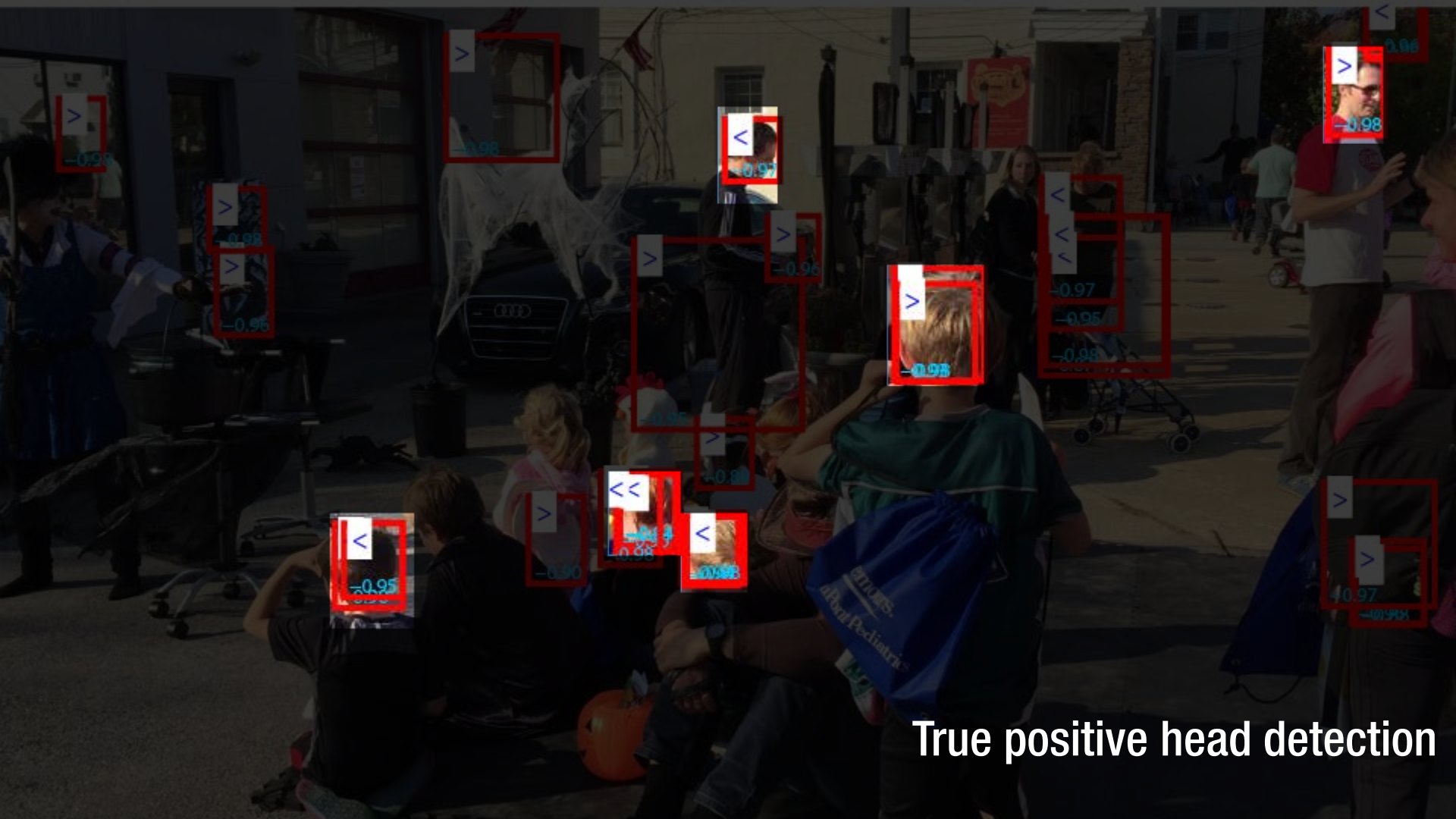


Can we predict <u>without</u> first person cameras?


dPont Pediatrics


Pediatrics


Gaze detection

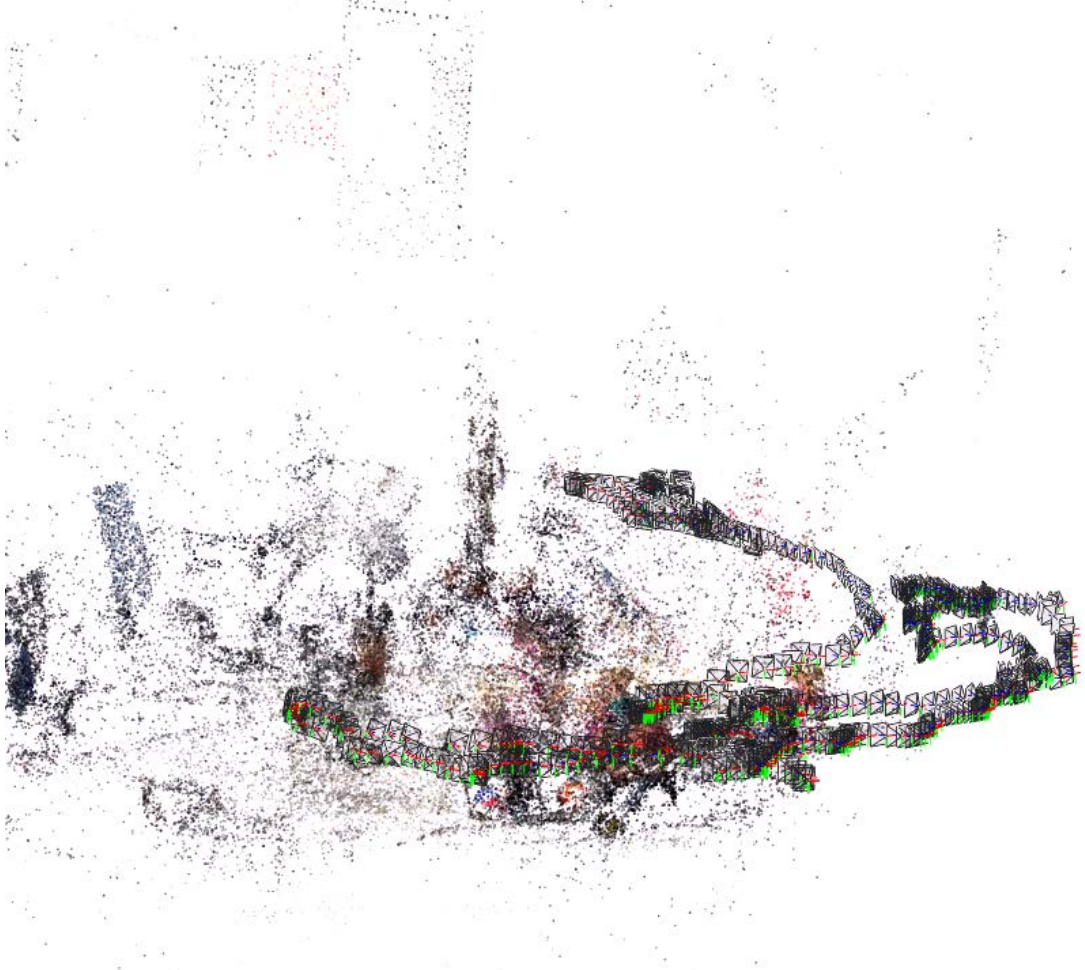


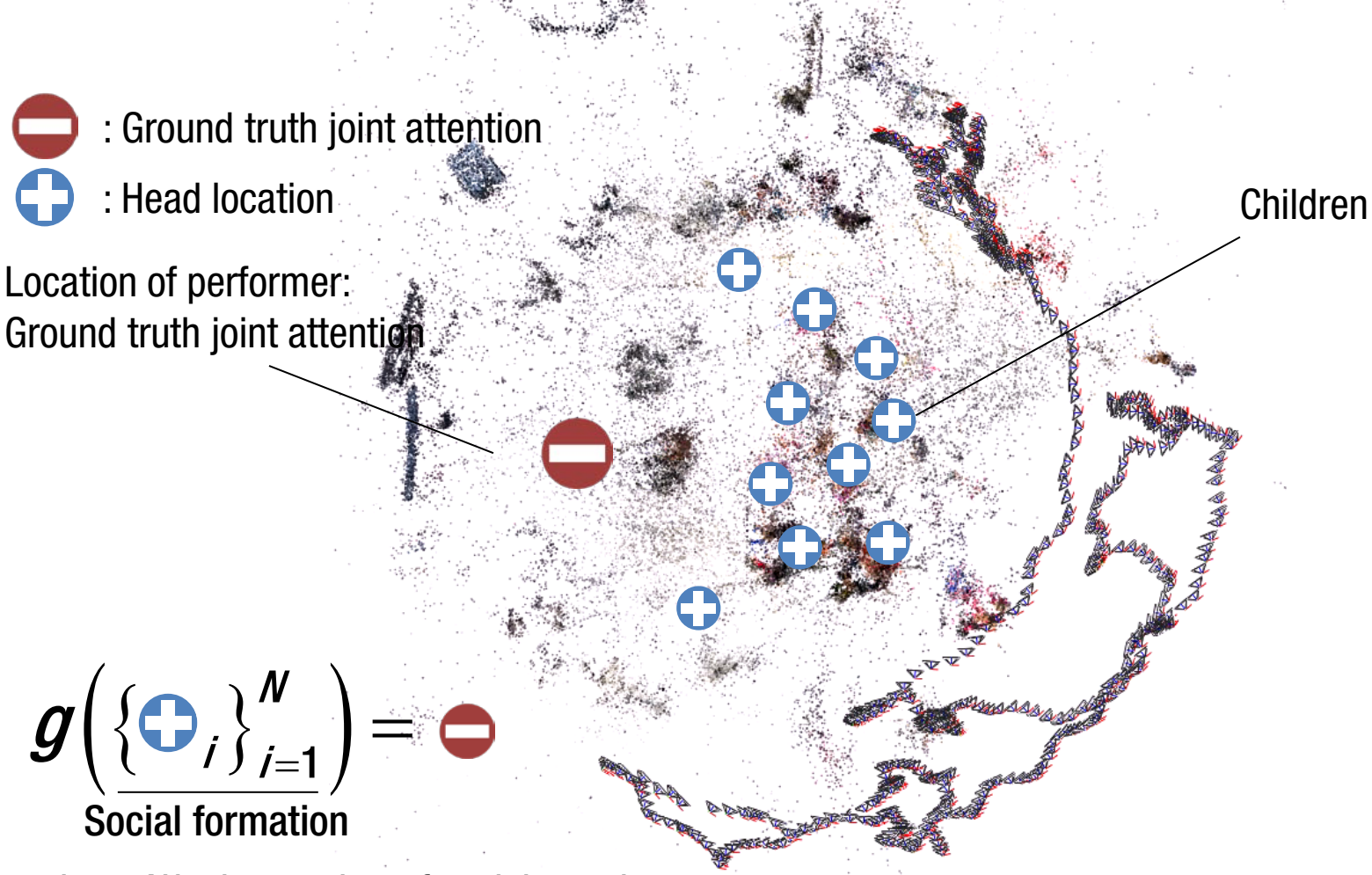
True positive head detection


True positive gaze detection


Halloween show
Children
Social saliency
Top view
Social saliency: likelihood of joint attention


Halloween show
Children
Social saliency
Top view



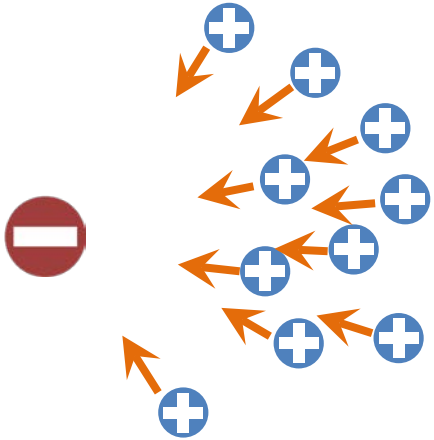


$$g\left(\underbrace{\left\{ \oplus_i \right\}_{i=1}^{N}}_{\text{Social formation}}\right) = \ominus$$

where N is the number of social members.

: Ground truth joint attention

: Head location



$$g\left(\underbrace{\left\{ \oplus_i \right\}_{i=1}^{N}}_{\textbf{Social formation}}\right) = \ominus$$

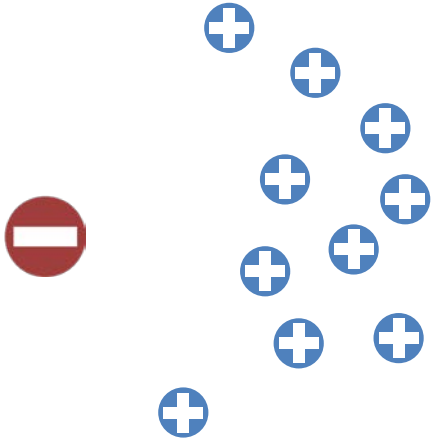
where N is the number of social members.

cf. $$g\left(\left\{ \oplus \rightarrow_i \right\}_{i=1}^{N}\right) = \ominus$$

Geometric localization: deterministic

: Ground truth joint attention

: Head location

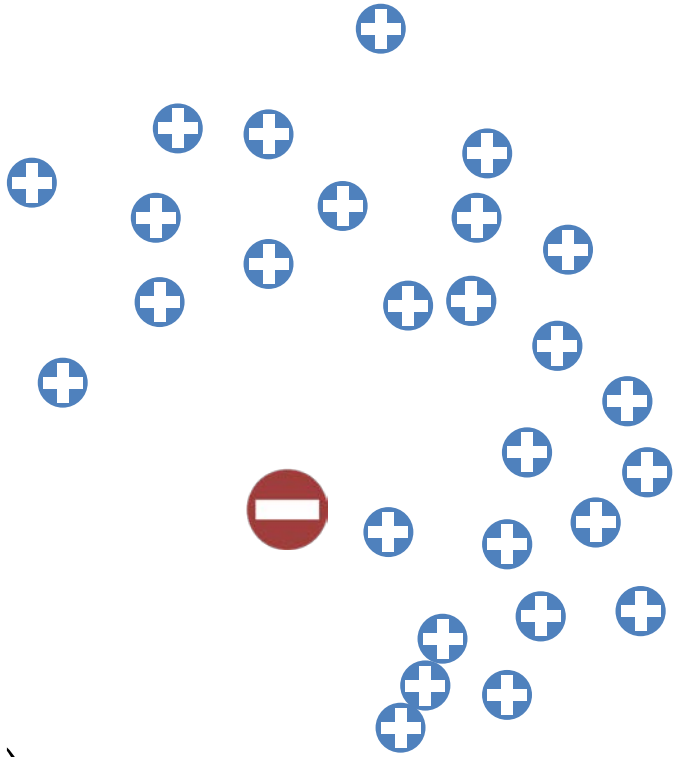


$$g\left(\underbrace{\left\{ \oplus_i \right\}_{i=1}^{N}}_{\text{Social formation}}\right) = \ominus$$

where N is the number of social members.

cf. $g\left(\left\{ \oplus \rightarrow_i \right\}_{i=1}^{N}\right) = \ominus$

Geometric localization: deterministic



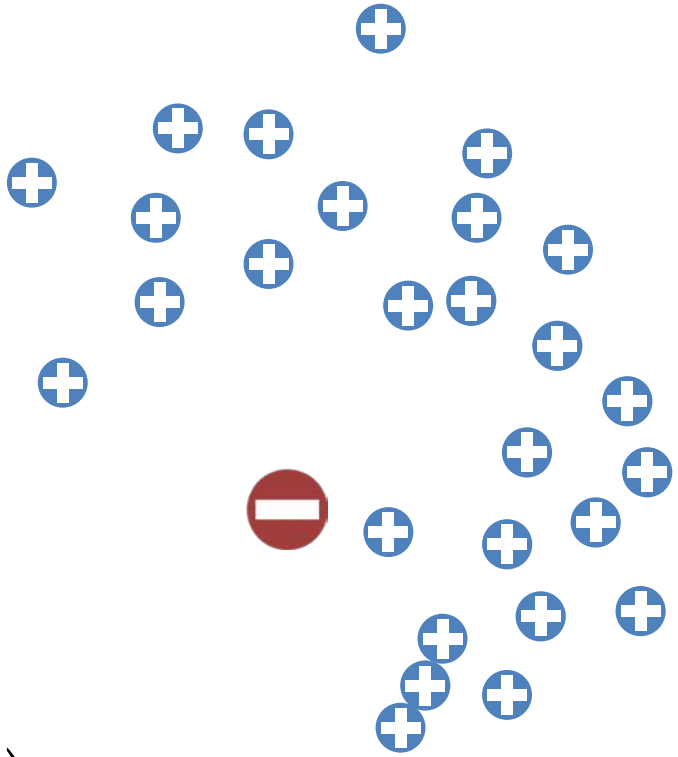
Scale variation

$$g\left(\underbrace{\left\{ \oplus_i \right\}_{i=1}^{N}}_{\text{Social formation}}\right) = \ominus$$

where N is the number of social members.

$\ominus$: Ground truth joint attention

$\oplus$: Head location



Scale variation
Orientation variation

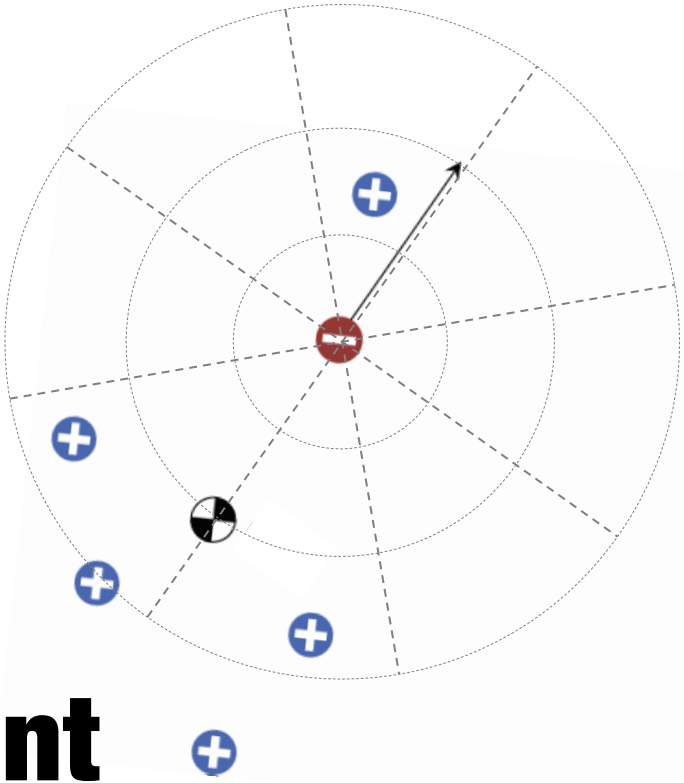
$$g\left(\underbrace{\left\{ \oplus_i \right\}_{i=1}^{N}}_{\text{Social formation}}\right) = \ominus$$

where N is the number of social members.

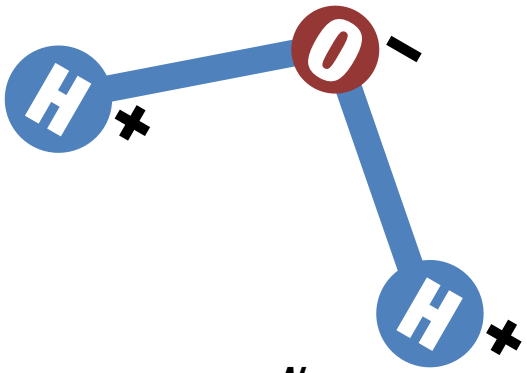
$\ominus$: Ground truth joint attention

$\oplus$: Head location

Representation: Social Dipole Moment



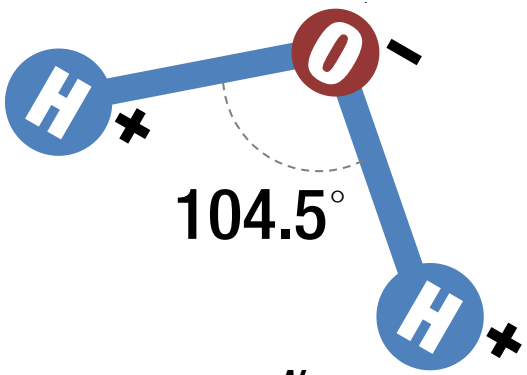
Water molecule, H_2O



$$\mathbf{q}_e = \sum_i^N (\mathbf{e} - \mathbf{p}_i)$$

Electric dipole moment

Water molecule, H_2O



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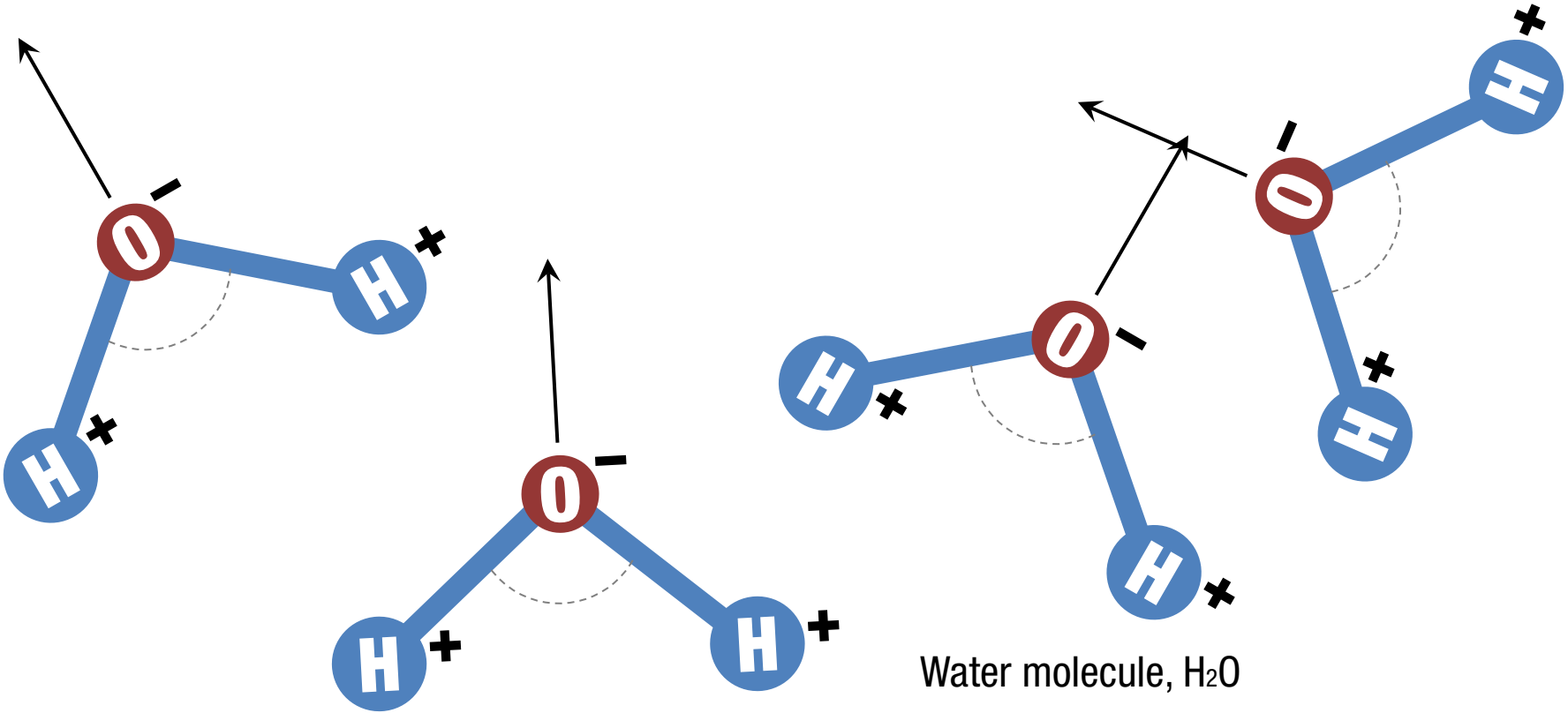
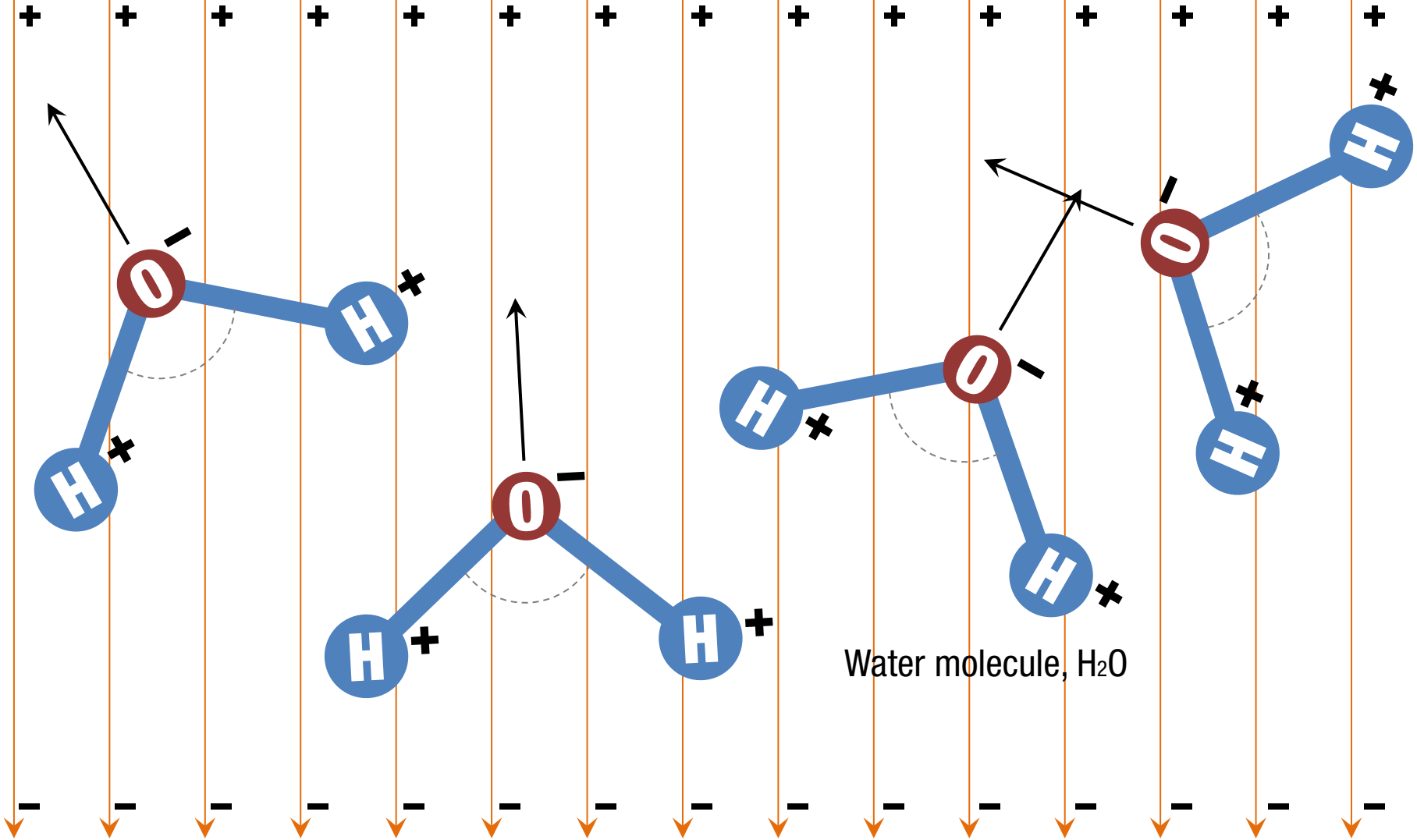
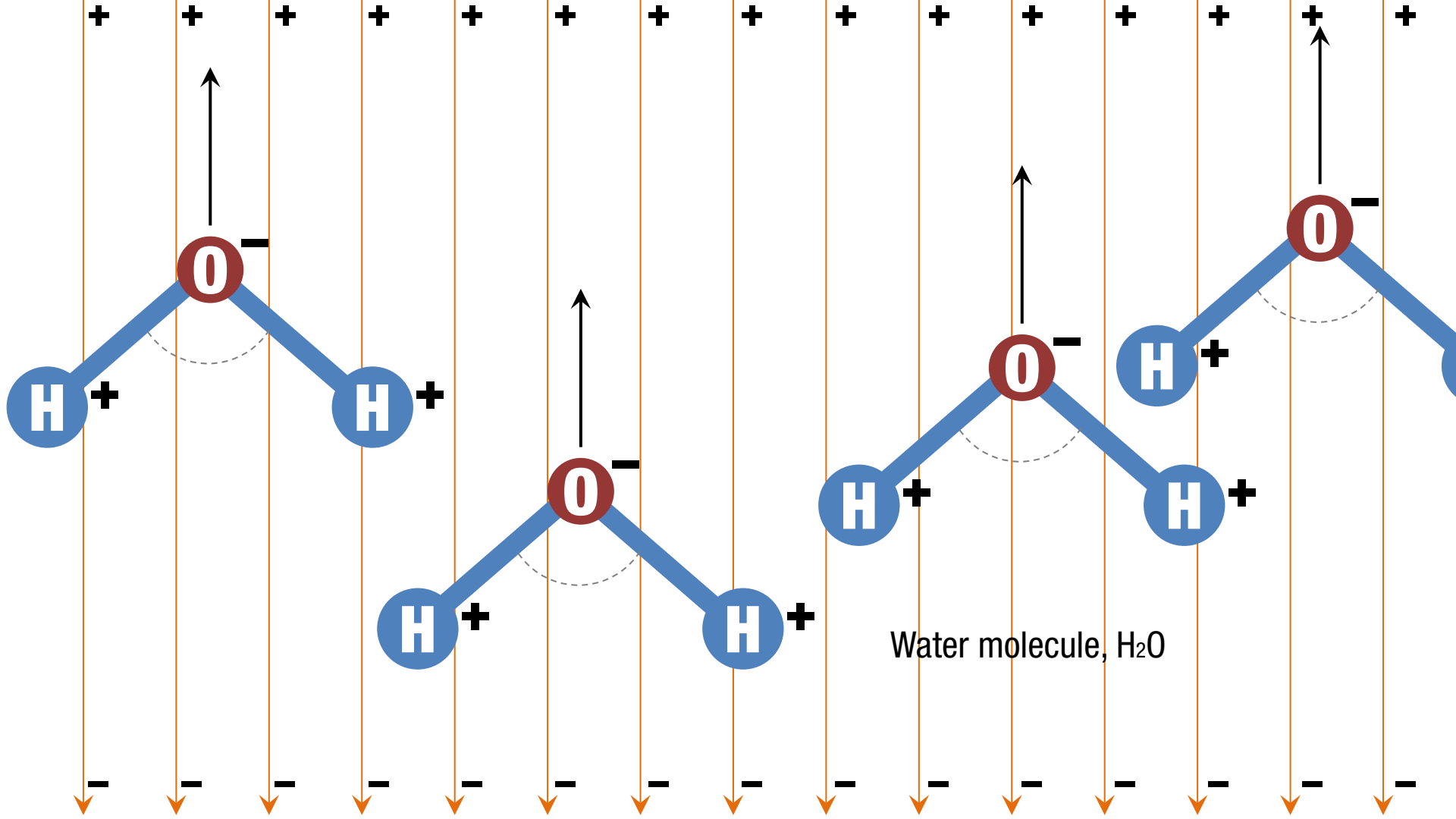
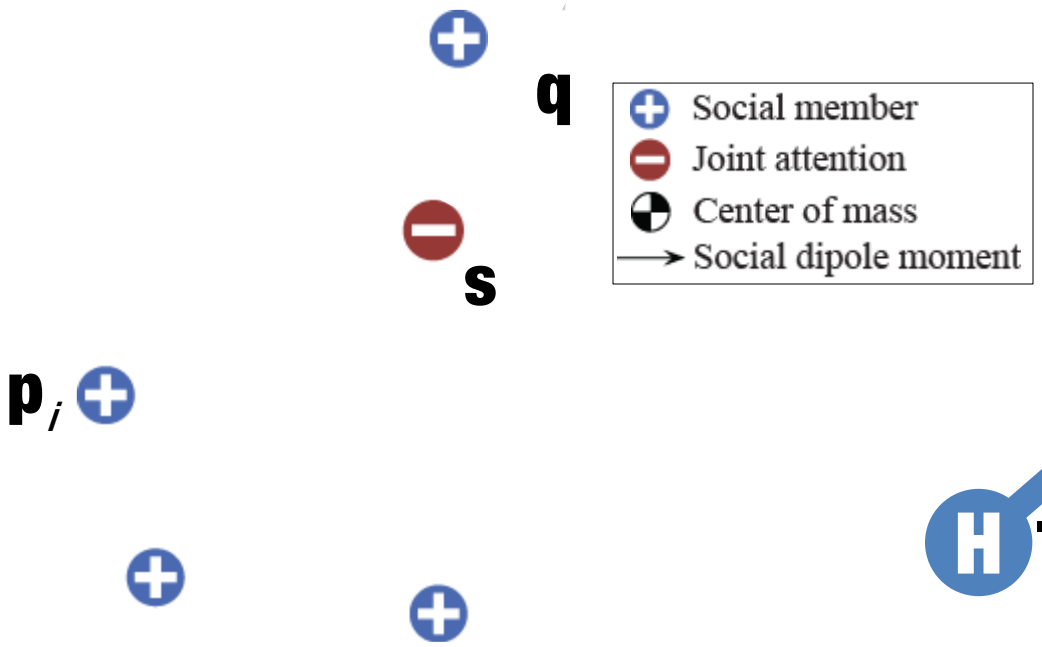
Electric dipole moment

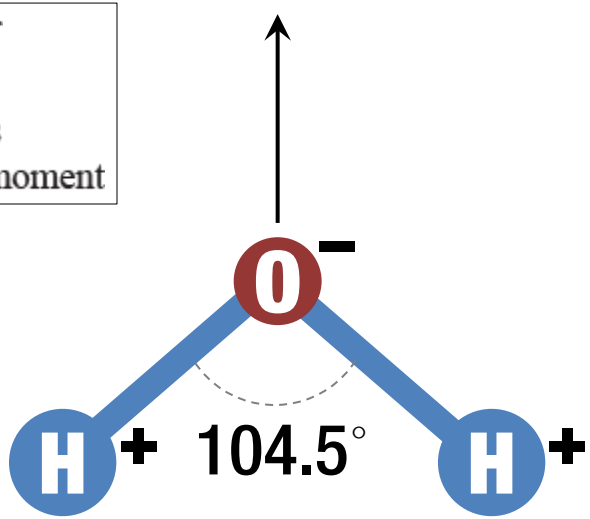


Water molecule, H_2O


Water molecule, H_2O


Water molecule, H_2O



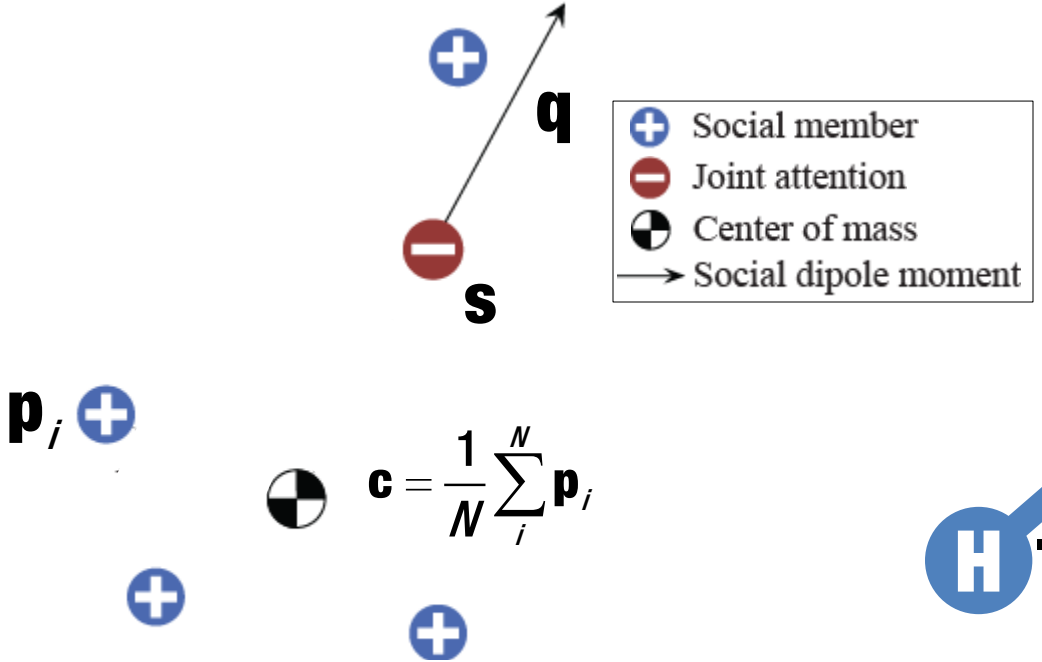


Social dipole moment

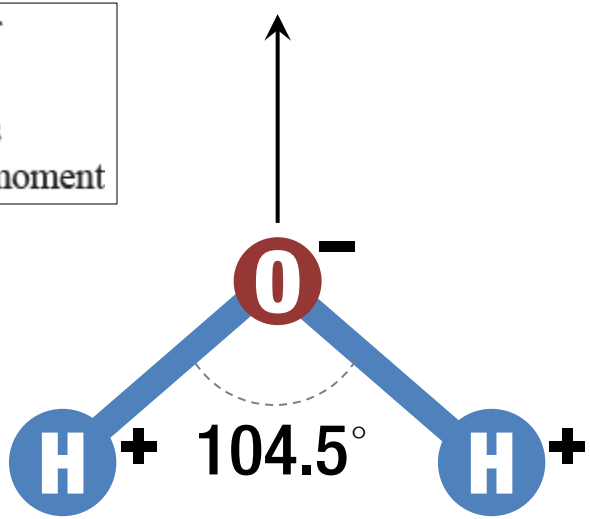
$$\mathbf{q} = \mathbf{s} - \frac{1}{N}\sum_{i}^{N}\mathbf{p}_i = \mathbf{s} - \mathbf{c}$$

Electric dipole moment

$$\mathbf{q}_e = \sum_{i}^{N}(\mathbf{e} - \mathbf{p}_i)$$



$$\mathbf{c} = \frac{1}{N}\sum_i^N \mathbf{p}_i$$



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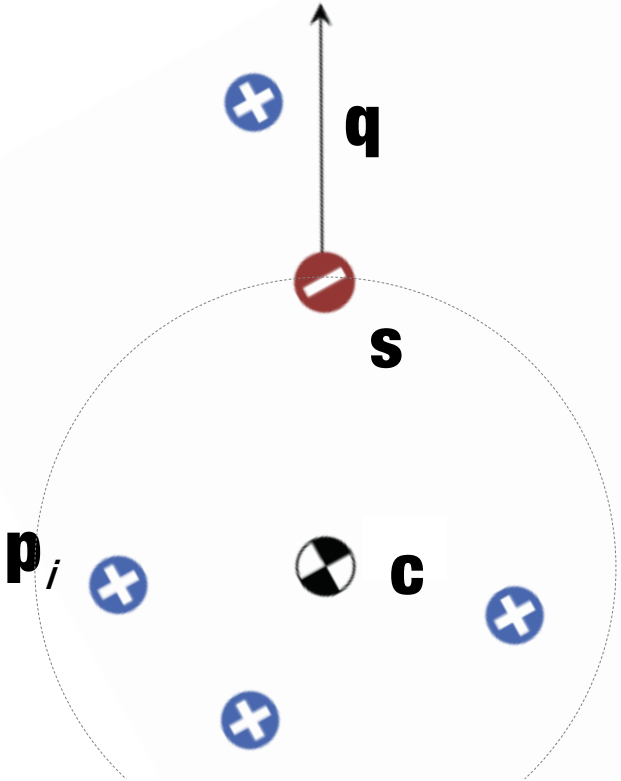
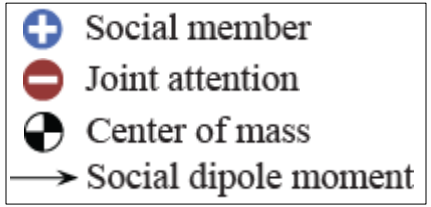
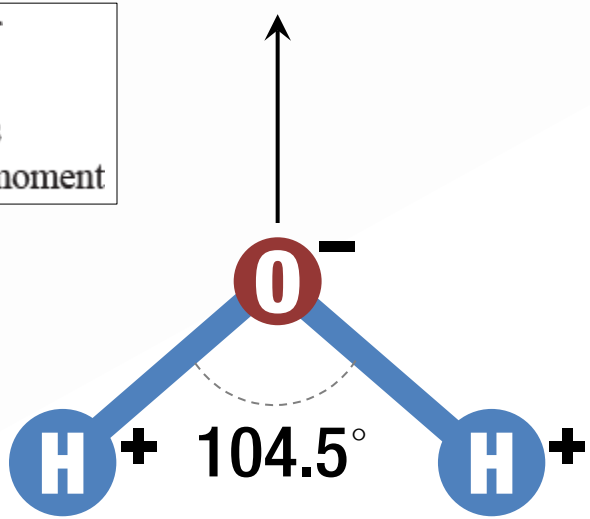
Electric dipole moment

$$\mathbf{q}_e = \sum_i^N (\mathbf{e} - \mathbf{p}_i)$$







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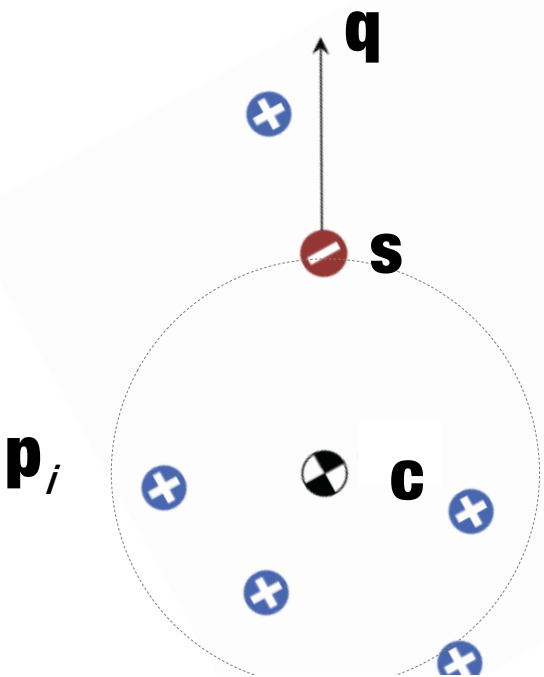
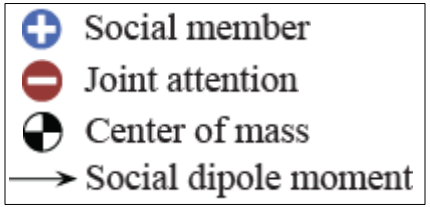
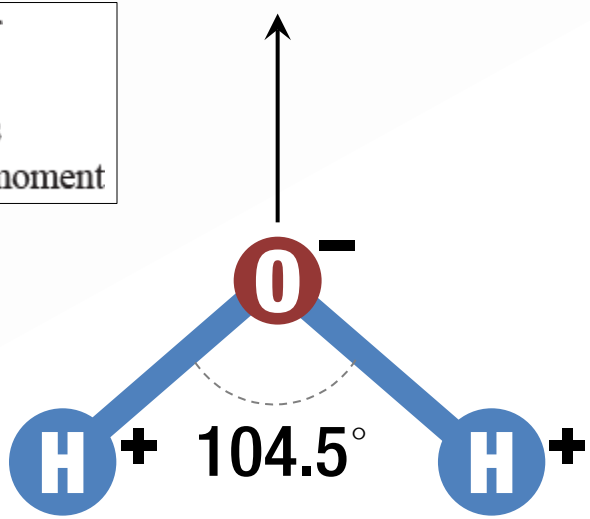
Electric dipole moment

$$\mathbf{q}_e = \sum_{i}^{N}(\mathbf{e} - \mathbf{p}_i)$$







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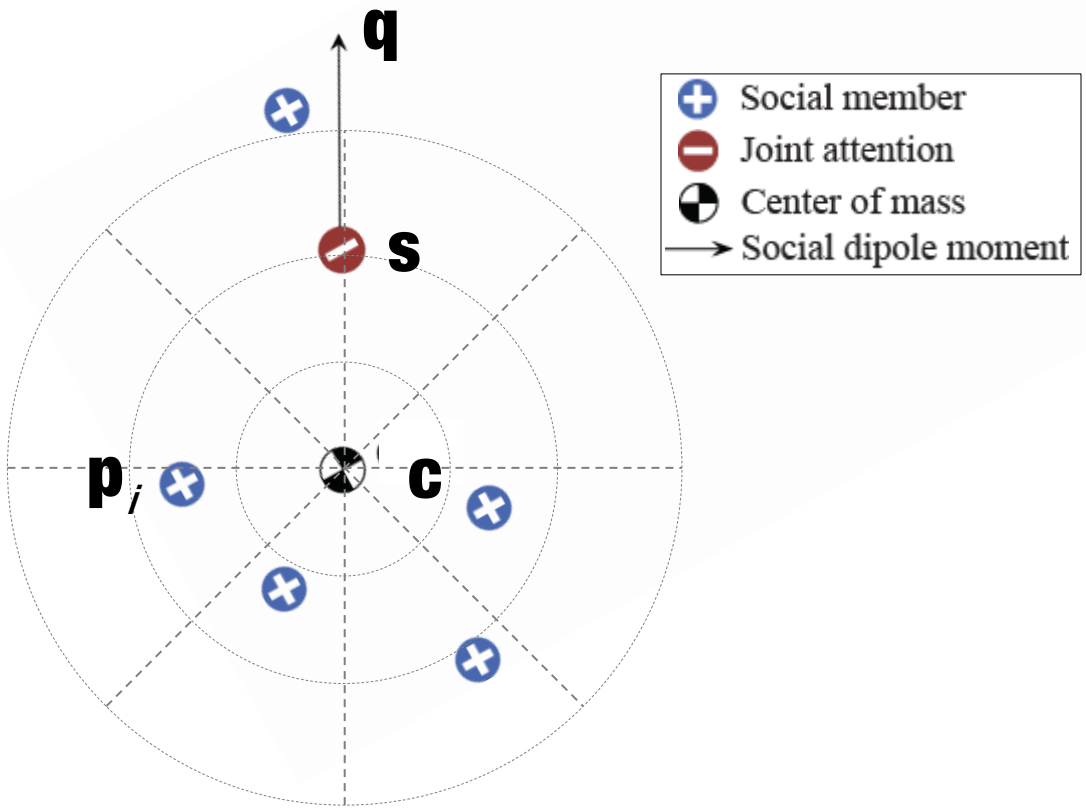
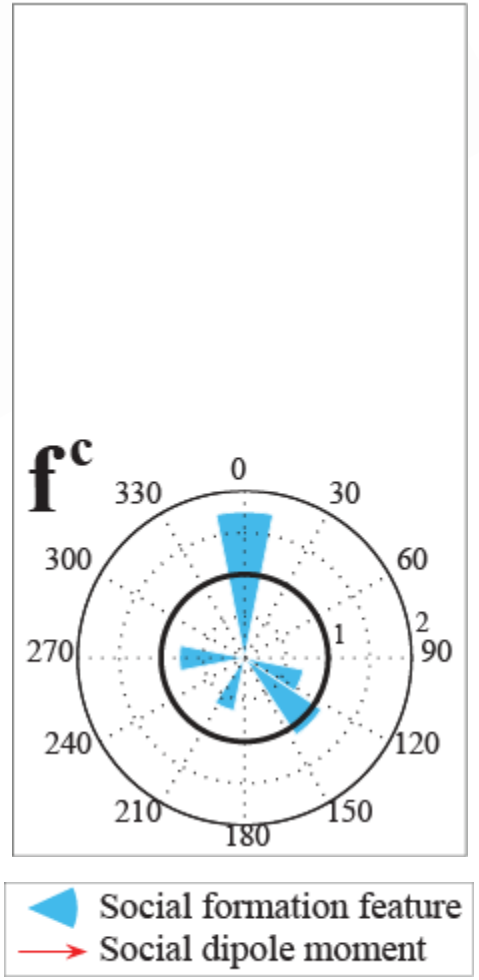
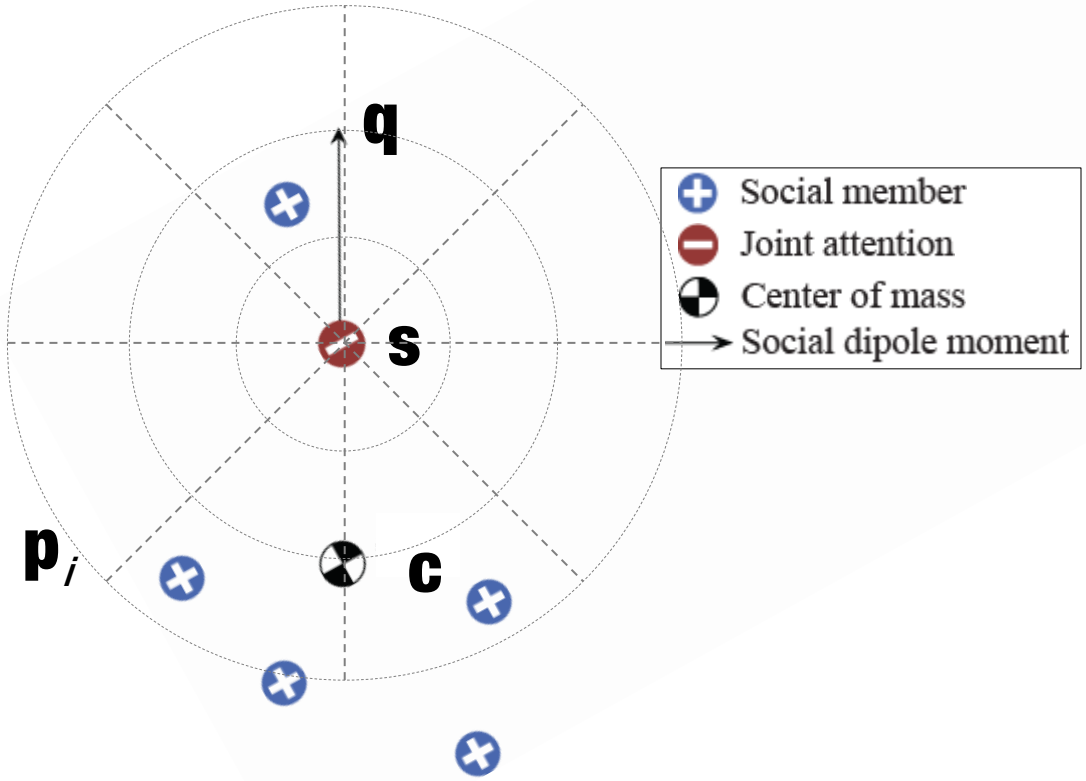
Electric dipole moment

$$\mathbf{q}_e = \sum_{i}^{N}(\mathbf{e} - \mathbf{p}_i)$$


q
s
p_i
c
Social member
Joint attention
Center of mass
Social dipole moment


f^c
0
30
60
90
120
150
180
210
240
270
300
330
1
2
Social formation feature
Social dipole moment


q
s
c
p_i
Social member
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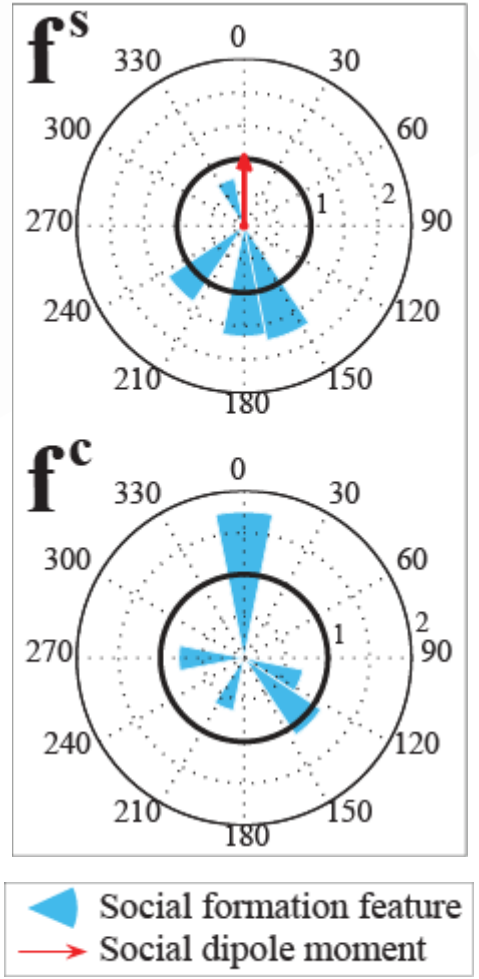
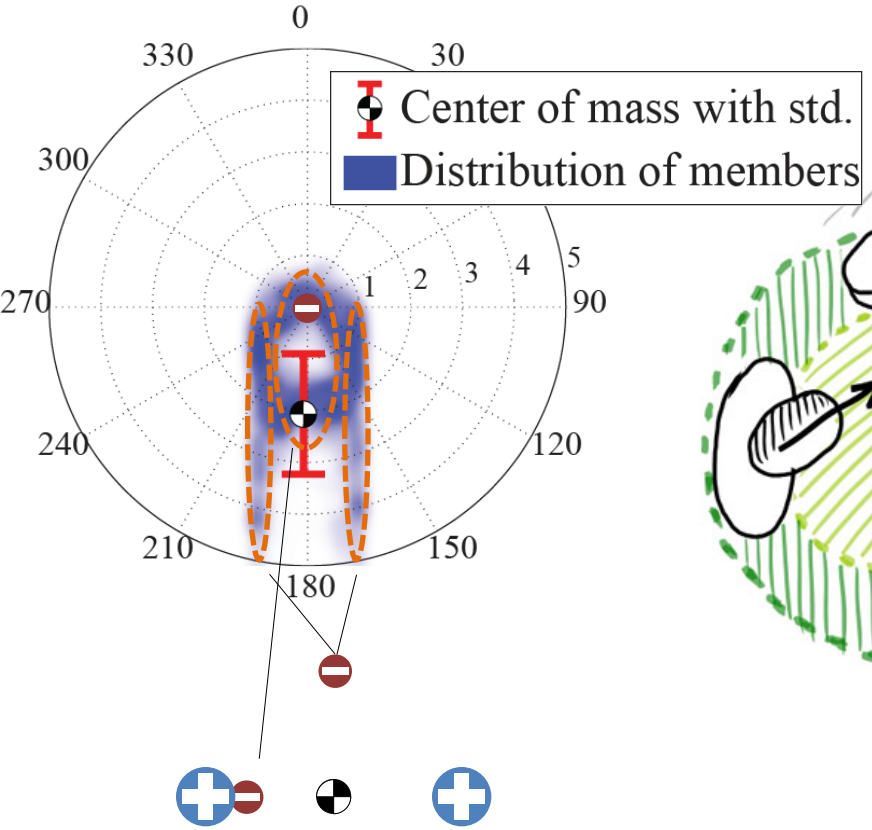
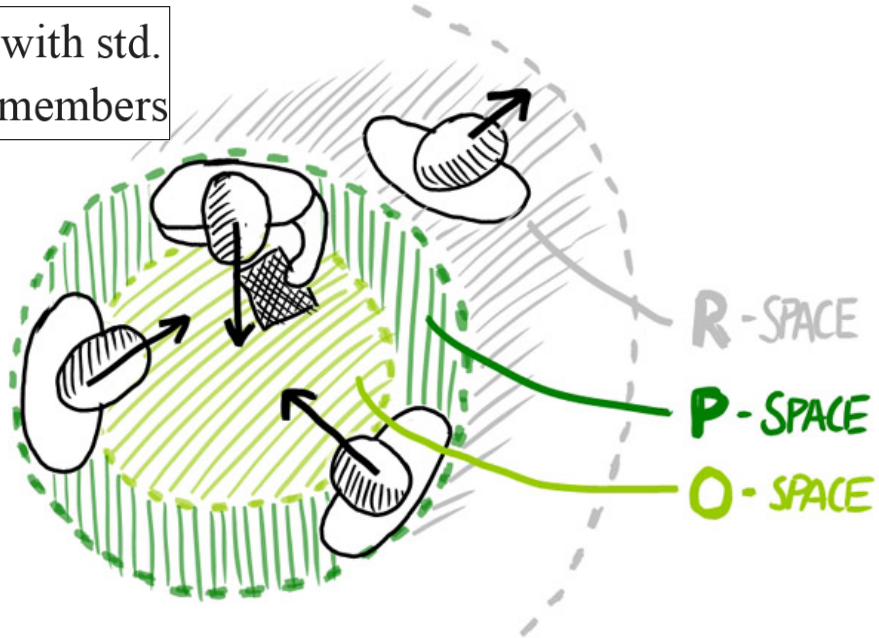

f^s
f^c
0
30
60
90
120
150
180
210
240
270
300
330
1
2
Social formation feature
Social dipole moment

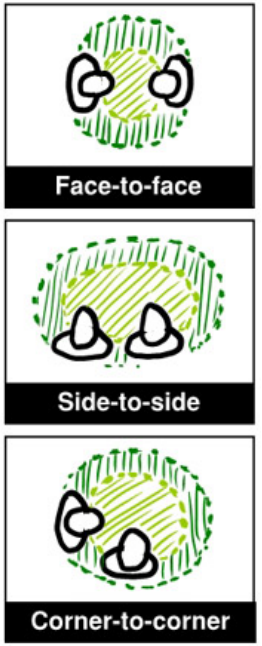
Scene	*N*	*T(sec)*	*F*
B-boy I	18	105	317
B-boy II	18	450	1351
B-boy III	18	160	528
B-boy IV	18	50	180
Surprise party	11	120	2227
Class	11	360	3590
Croquet	6	300	6000
Busker I	6	120	3566
Busker II	6	180	5394
Card game	3	180	768
Hide and seek	3	180	214
Block building	3	700	2702
Social game	8	450	2086
Meeting I	11	120	832
Meeting II	5	440	1120
Picnic	6	60	965
Musical	7	180	2184
Dance	6	180	5301
4 way party	11	180	1909
Snowman	4	753	8256

Total 49,490 social formations

Dyadic interaction



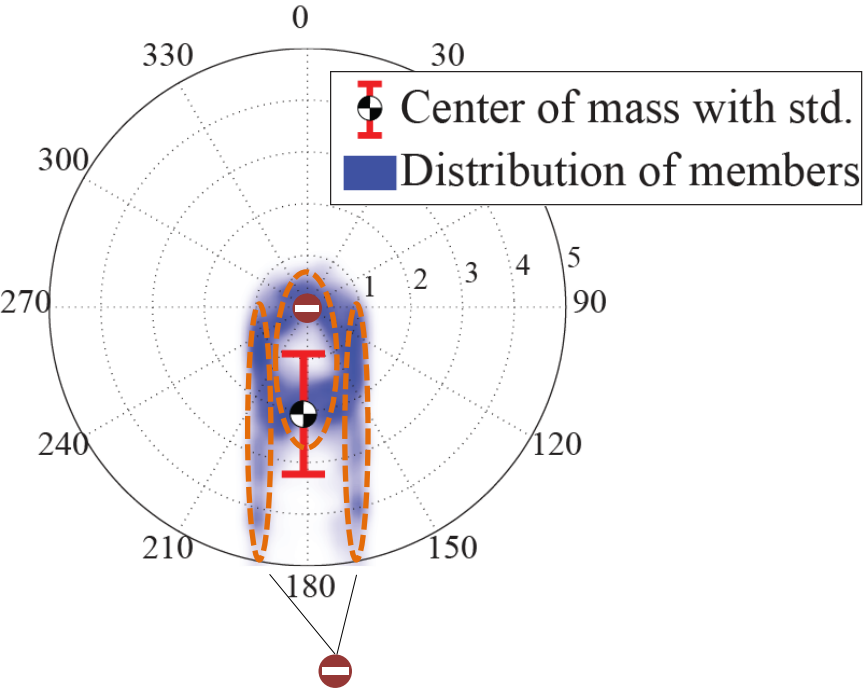


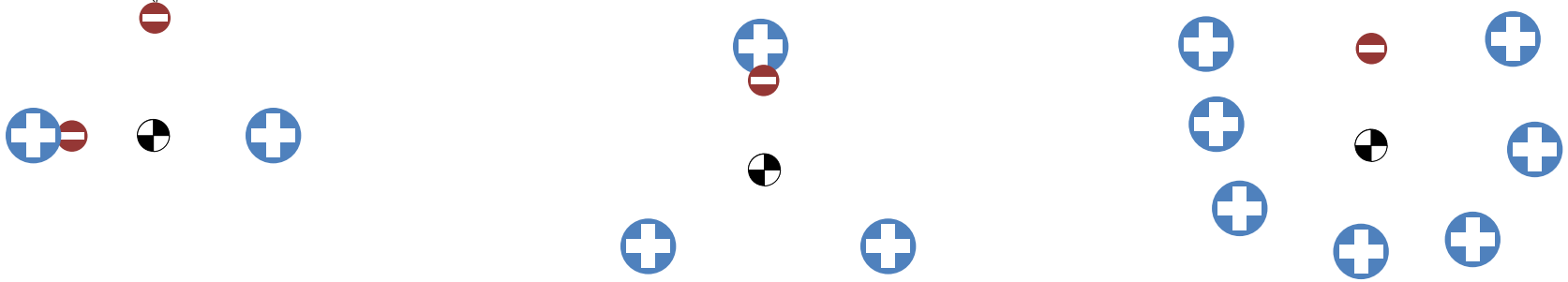


Social formation theory (F-formation)*

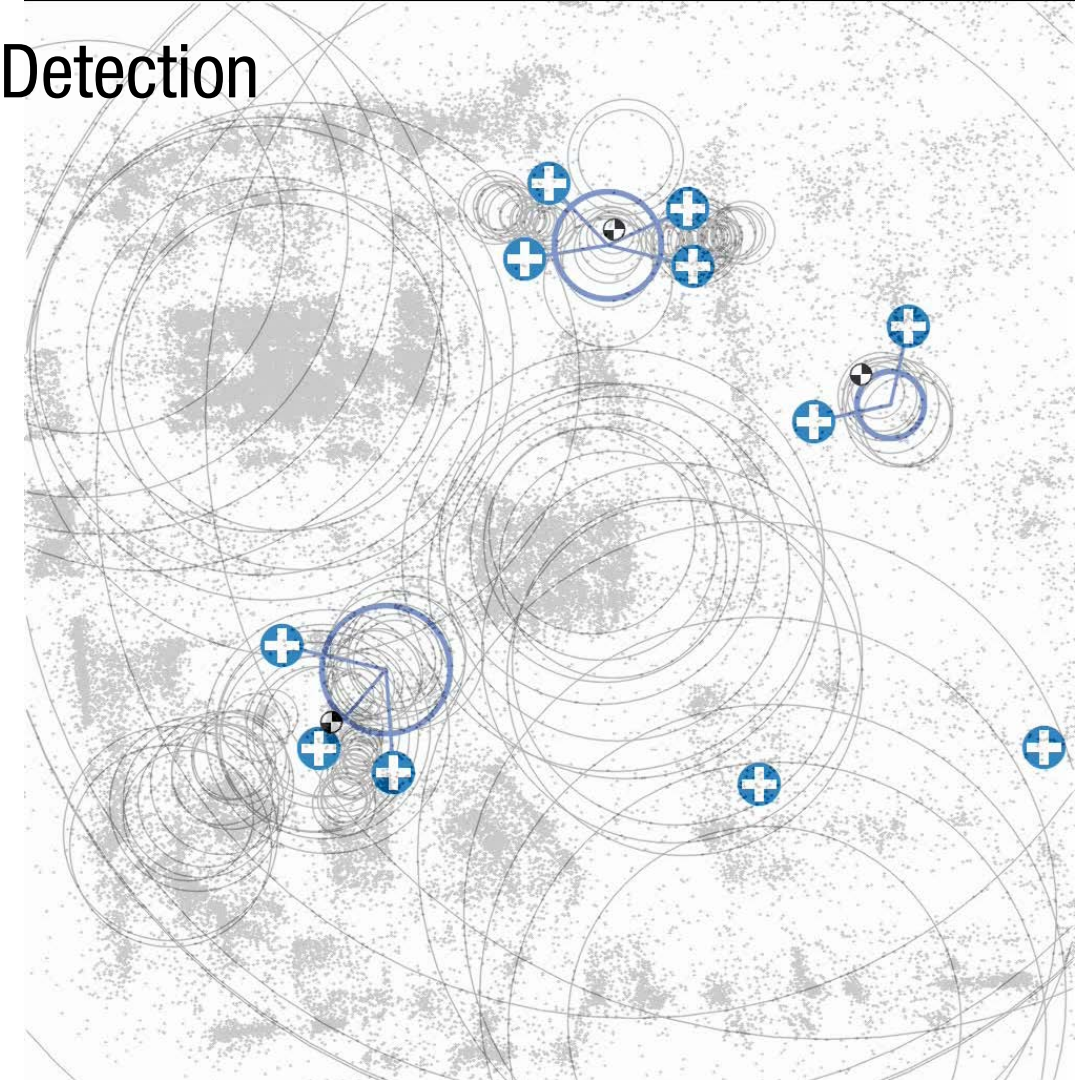
*A. Kendon, “Conducting Interaction: Patterns of Behavior in Focused Encounters”, Cambridge University Press, 1990.

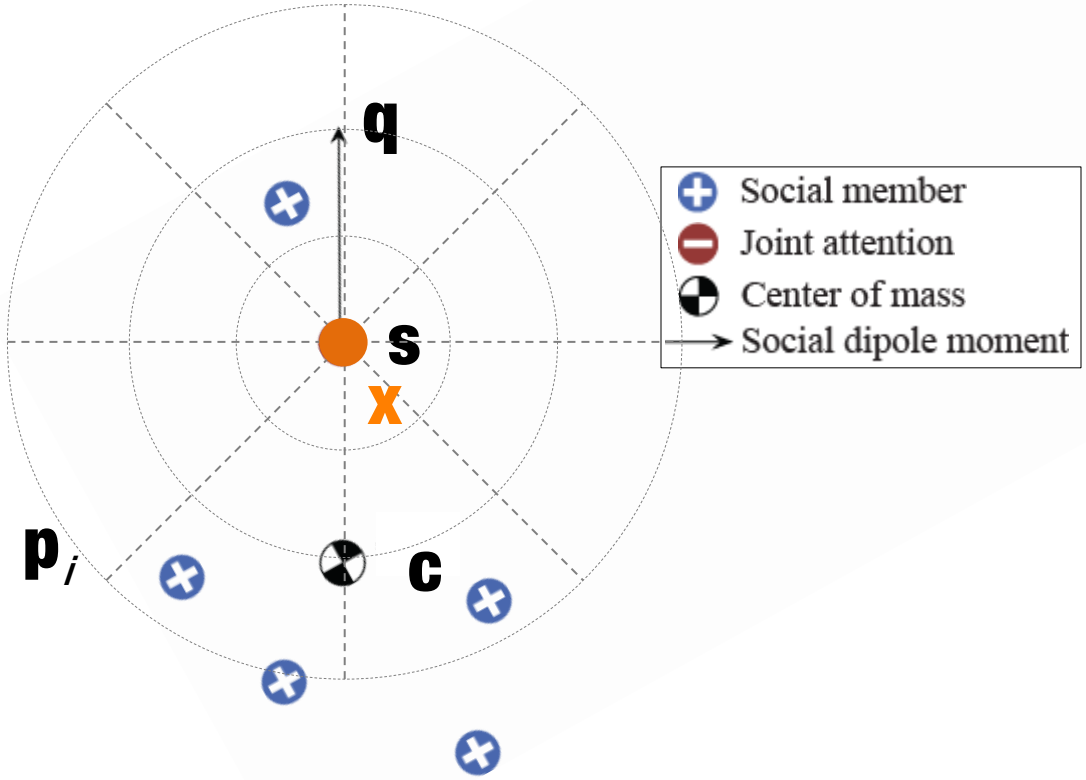
Dyadic interaction



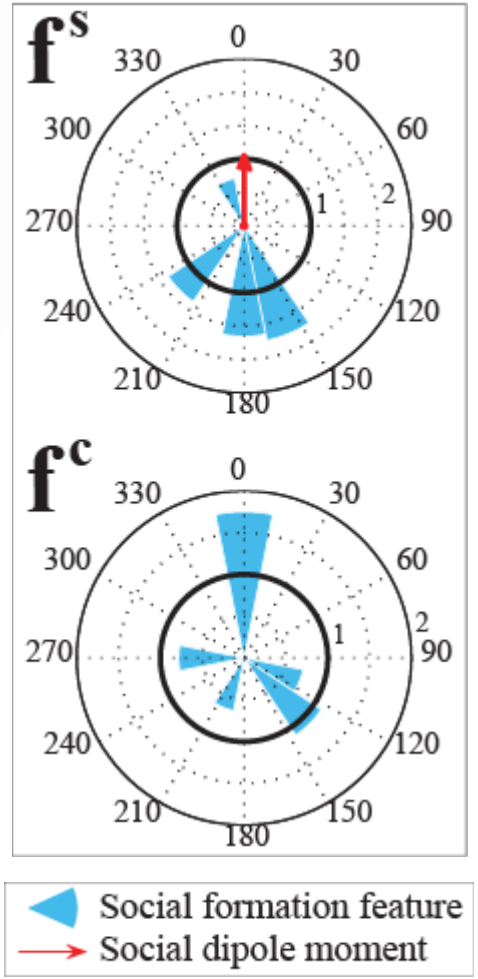


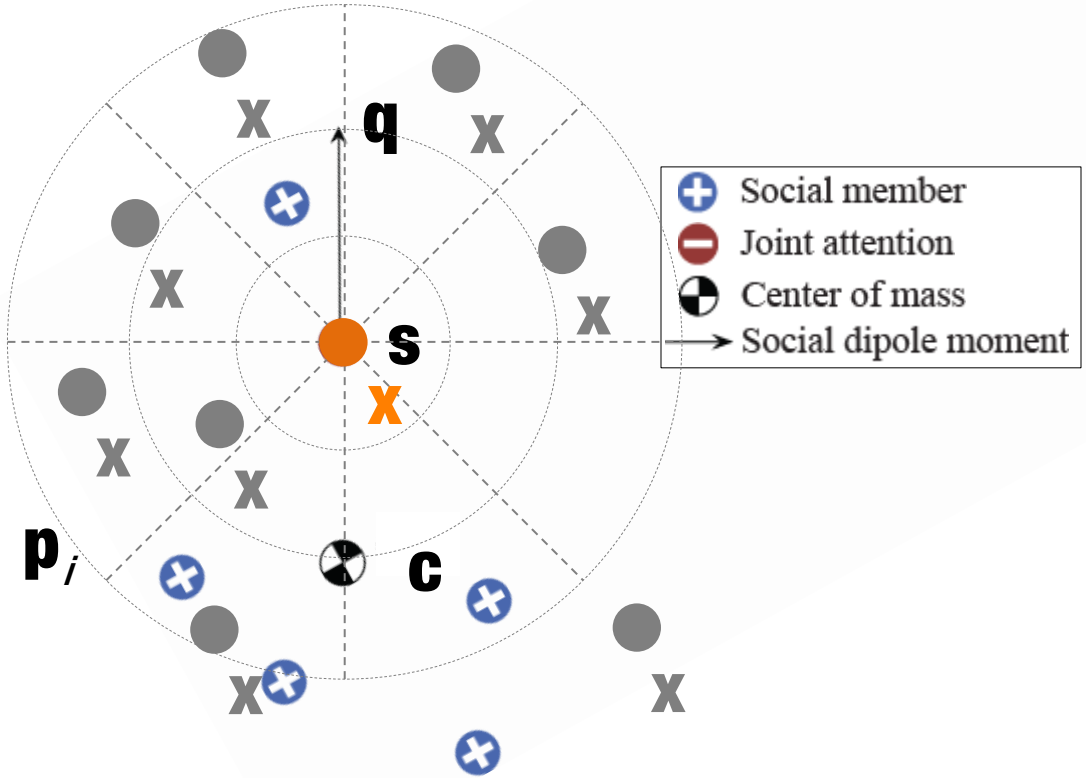
Social Group Detection



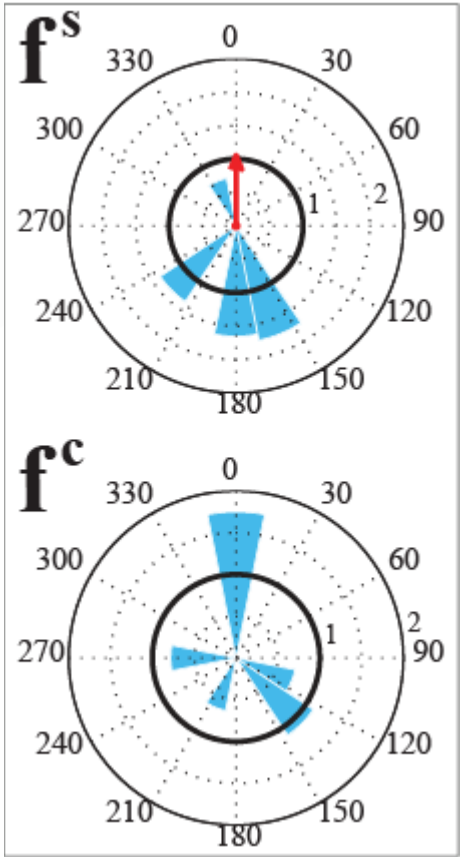


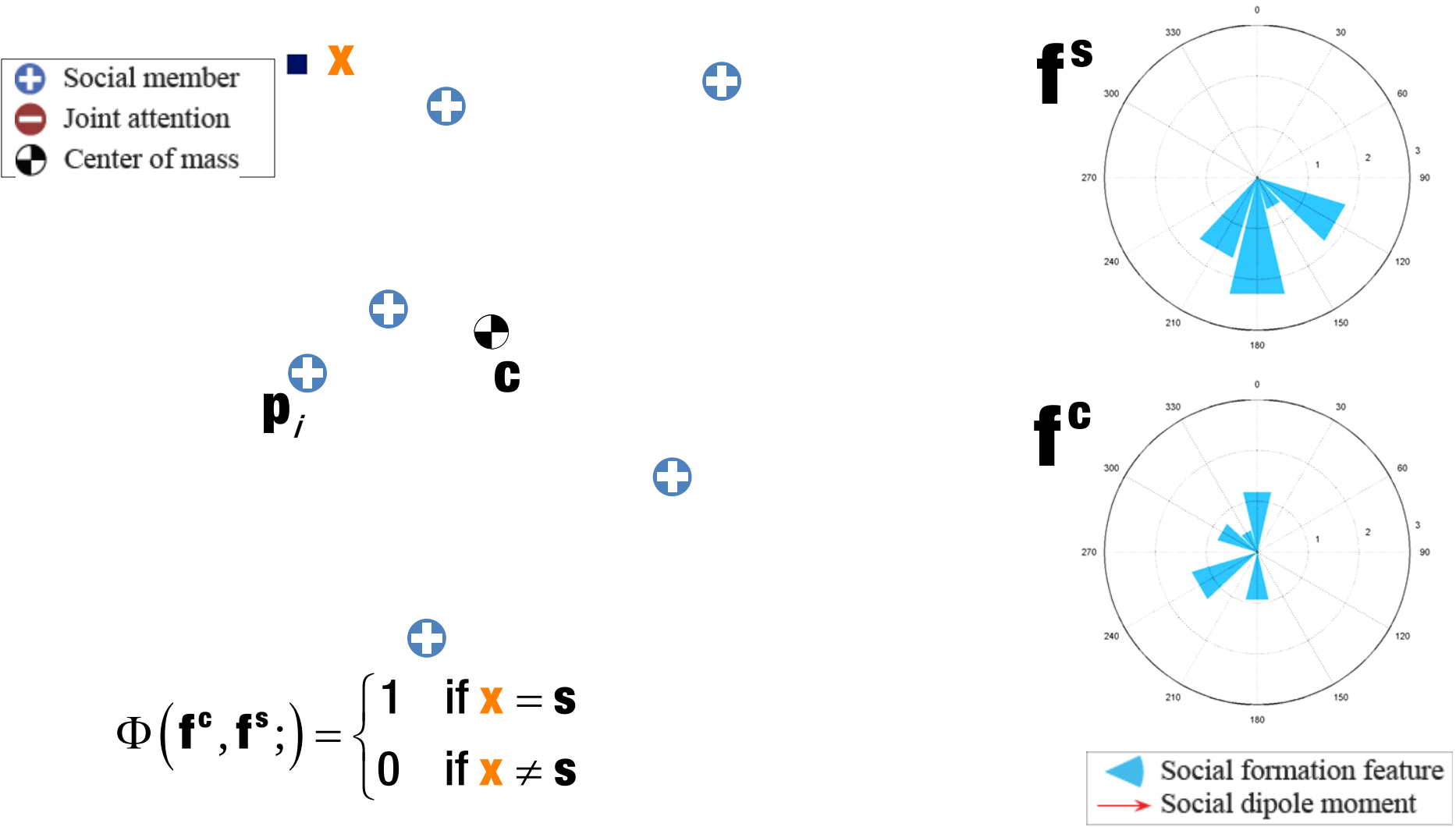
$$\Phi\left(\mathbf{f}^{\mathbf{c}}, \mathbf{f}^{\mathbf{s}};\right) = \begin{cases} 1 & \text{if } \mathbf{x} = \mathbf{s} \\ & \end{cases}$$



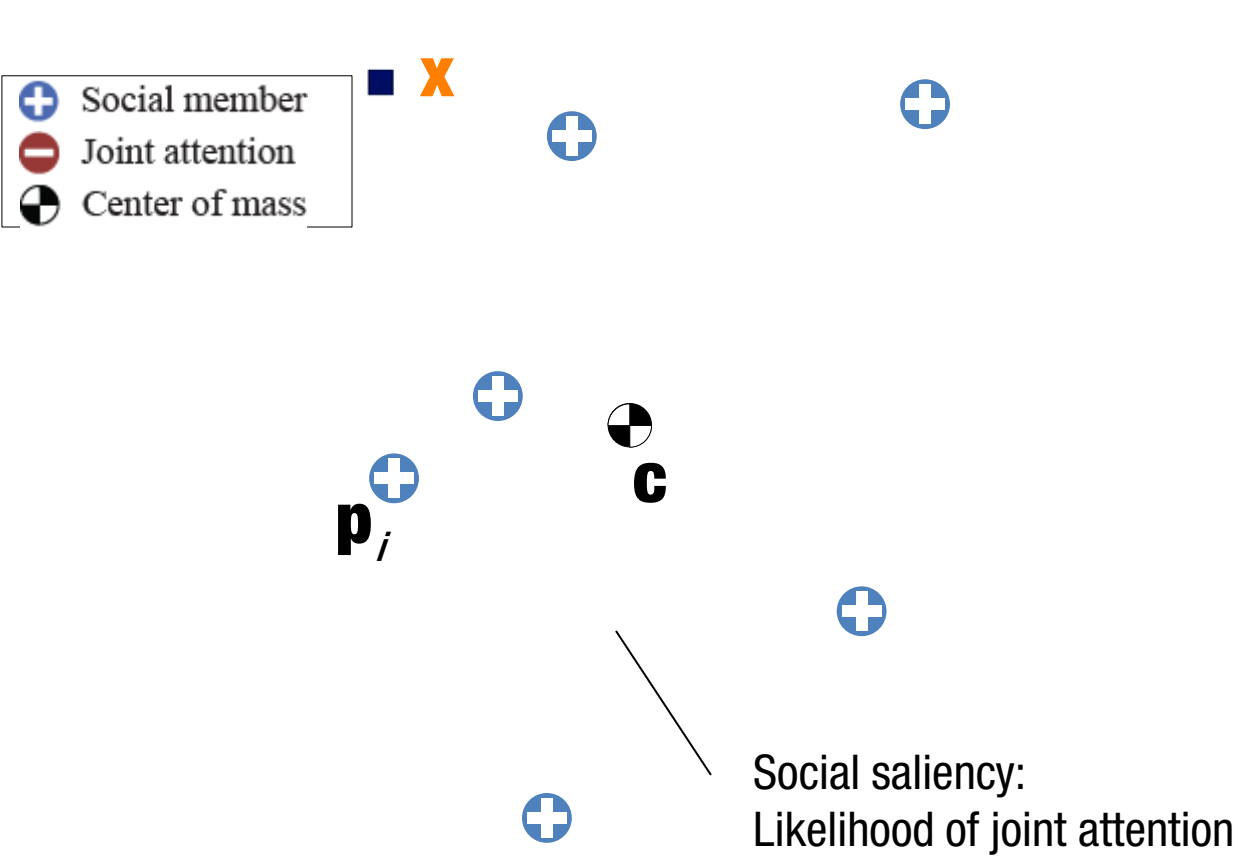


$$\Phi\left(\mathbf{f}^{\mathbf{c}},\mathbf{f}^{\mathbf{s}};\right)=\begin{cases}1 & \text{if } \mathbf{x}=\mathbf{s}\\ 0 & \text{if } \mathbf{x}\neq\mathbf{s}\end{cases}$$



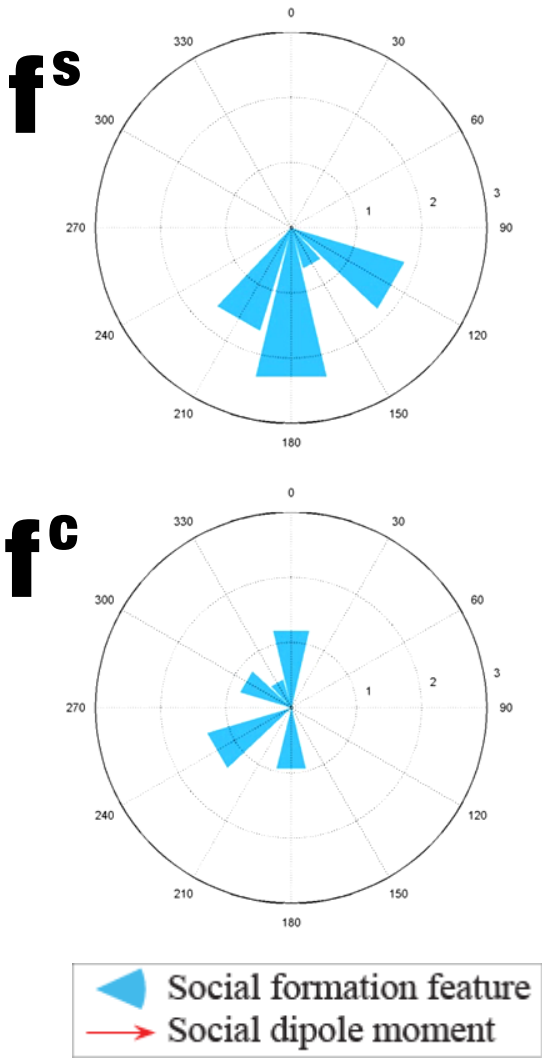


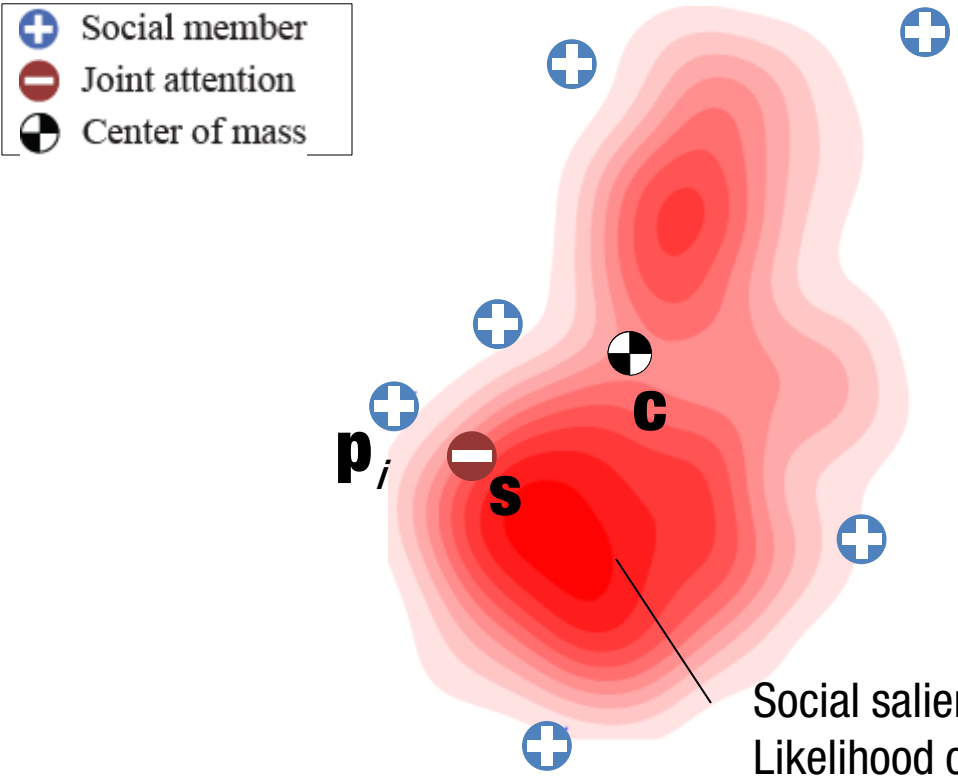
$$\Phi\left(\mathbf{f}^{\mathbf{c}},\mathbf{f}^{\mathbf{s}};\right)=\begin{cases}1 & \text{if } \mathbf{x}=\mathbf{s}\\ 0 & \text{if } \mathbf{x}\neq\mathbf{s}\end{cases}$$



Social saliency:
Likelihood of joint attention

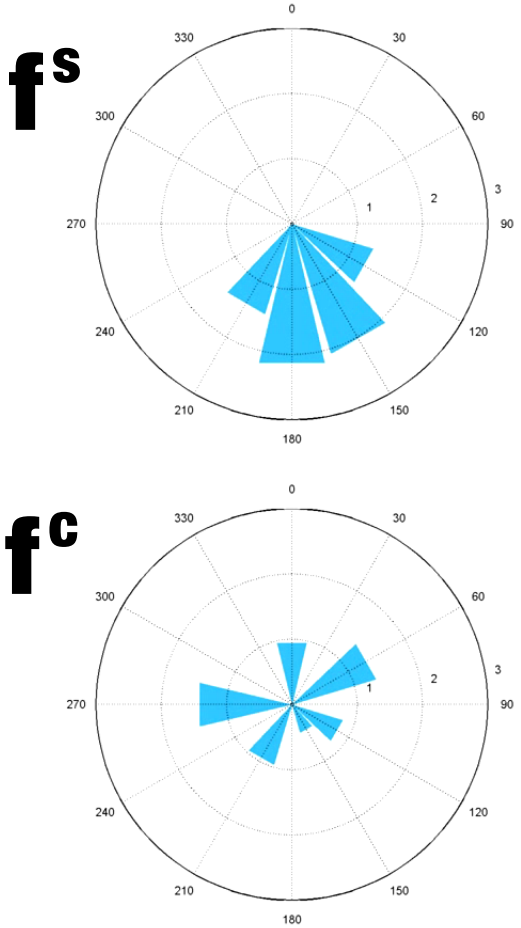
$$\Phi\left(\mathbf{f}^{\mathbf{c}}, \mathbf{f}^{\mathbf{s}};\right) = \begin{cases} 1 & \text{if } \mathbf{x} = \mathbf{s} \\ 0 & \text{if } \mathbf{x} \neq \mathbf{s} \end{cases}$$

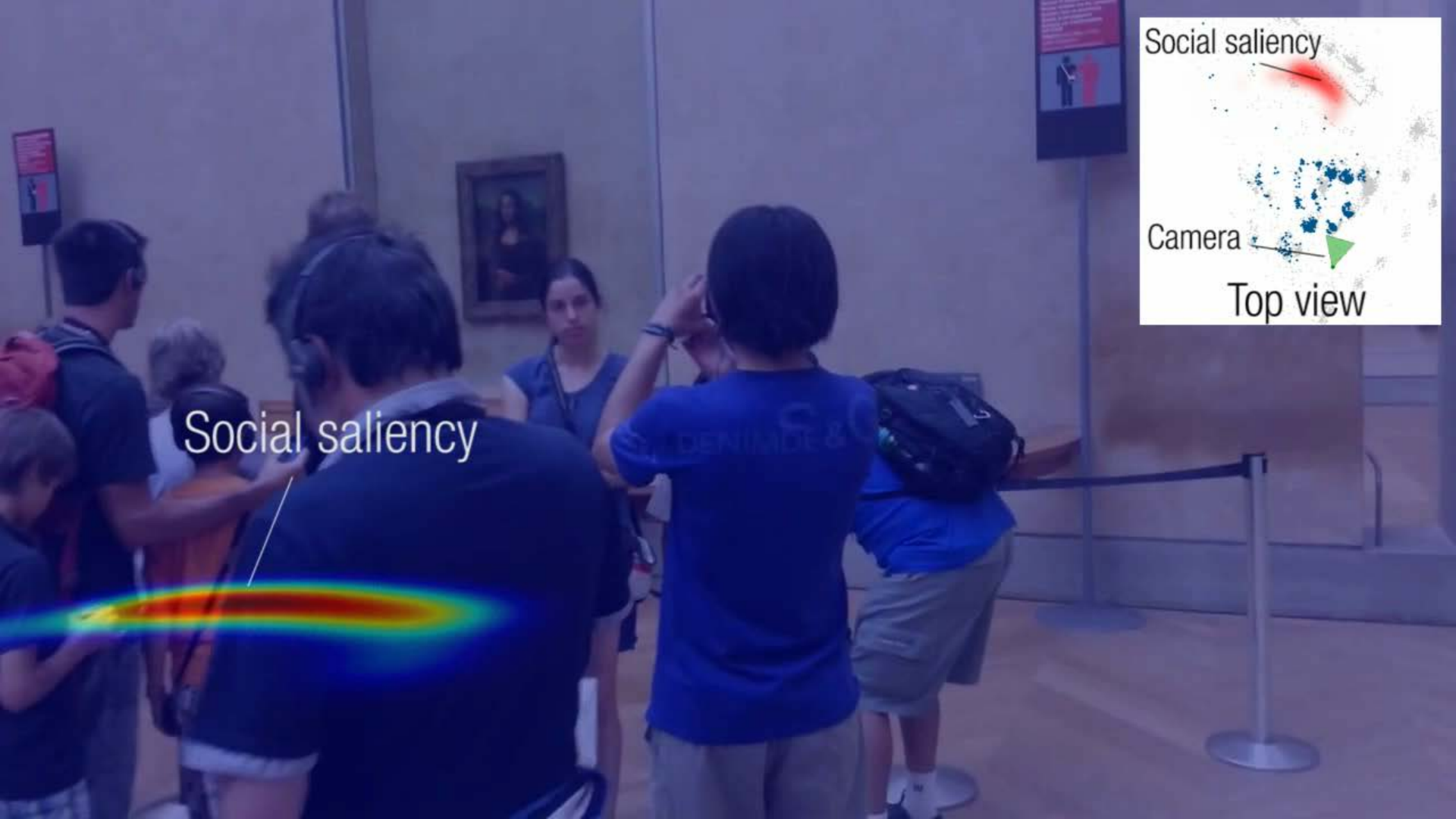




Social saliency:
Likelihood of joint attention

$$\Phi\left(\mathbf{f}^{\mathbf{c}},\mathbf{f}^{\mathbf{s}};\right)=\begin{cases}1 & \text{if } \mathbf{x}=\mathbf{s}\\ 0 & \text{if } \mathbf{x}\neq\mathbf{s}\end{cases}$$



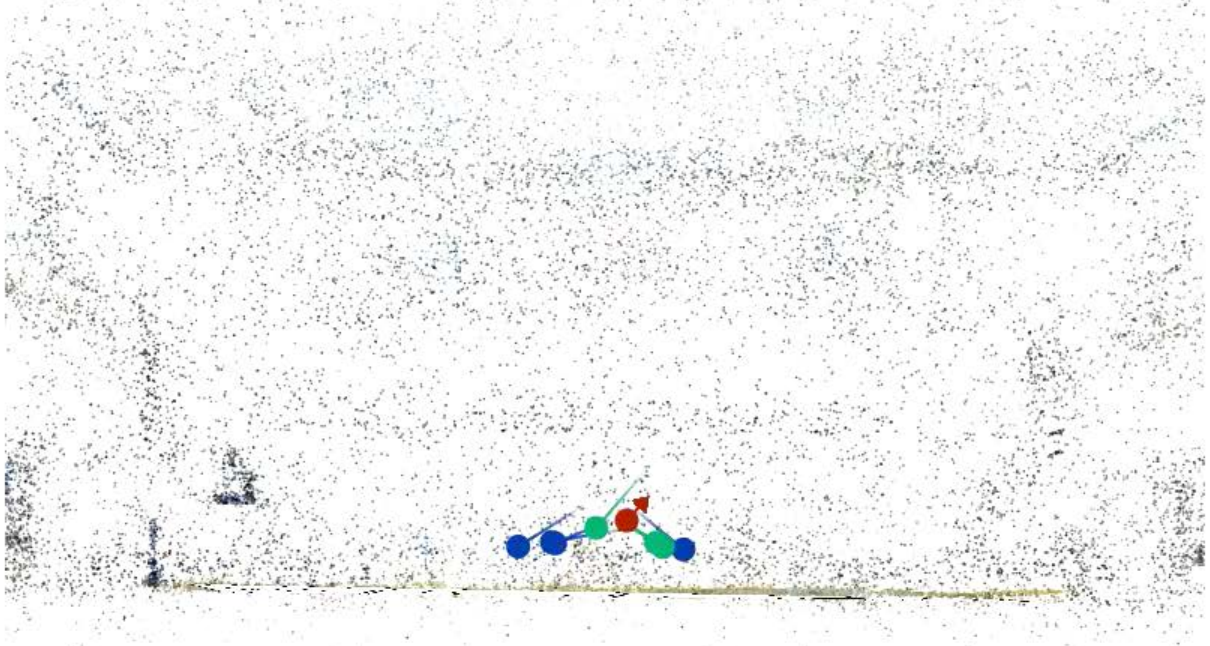

Social saliency
Social saliency
Camera
Top view

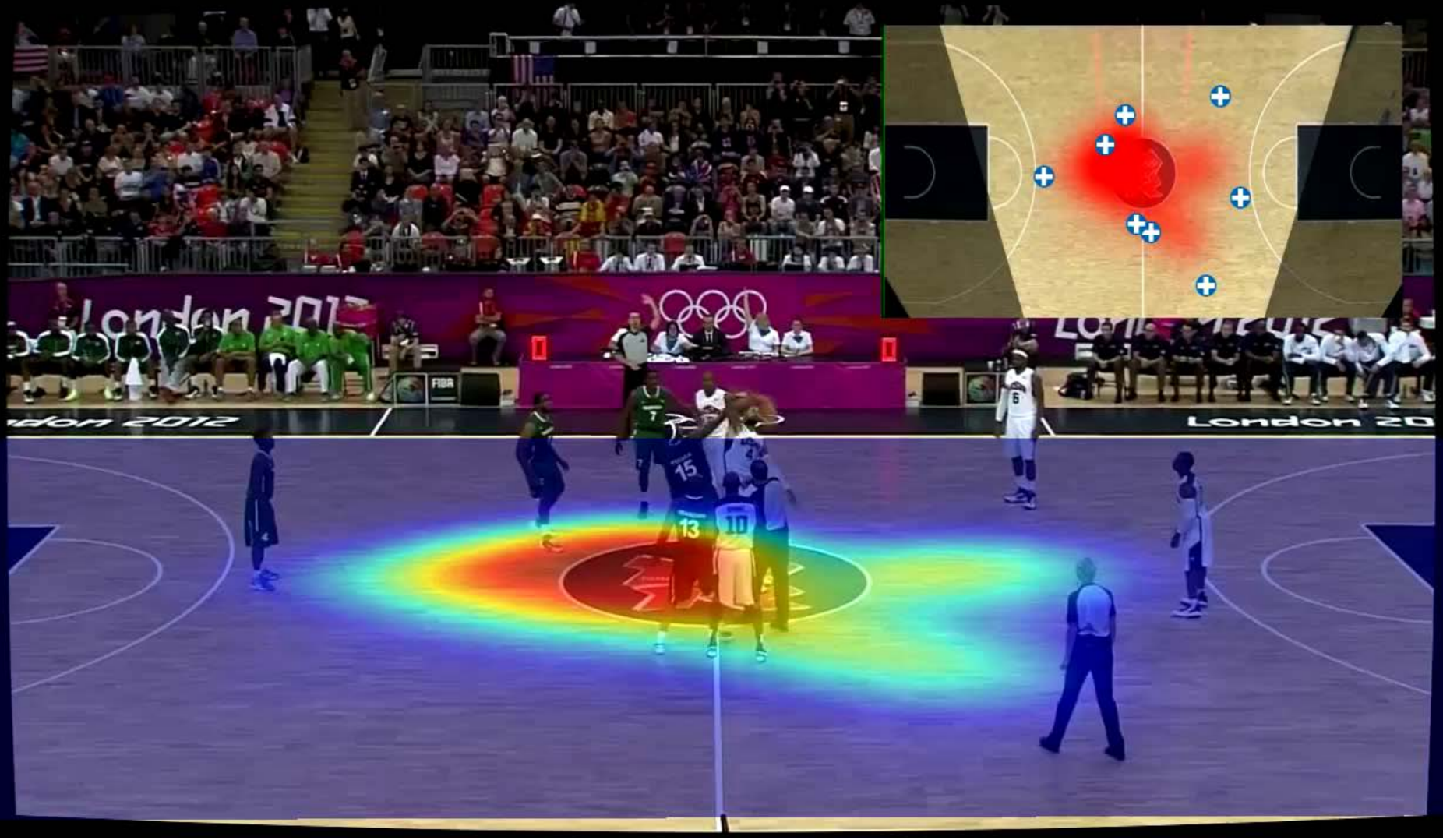
Time Square

Source: https://www.youtube.com/watch?v=ezyrSKgcyJw

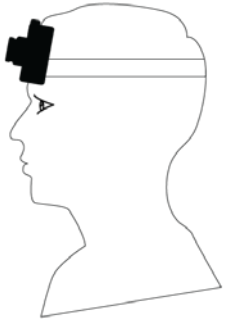

USA 5
NGR 0
9:25 1ST
Input Video

First Person Basketball Data

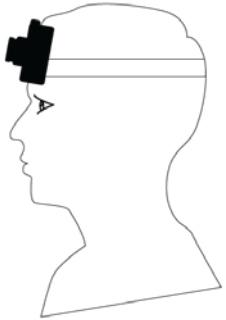


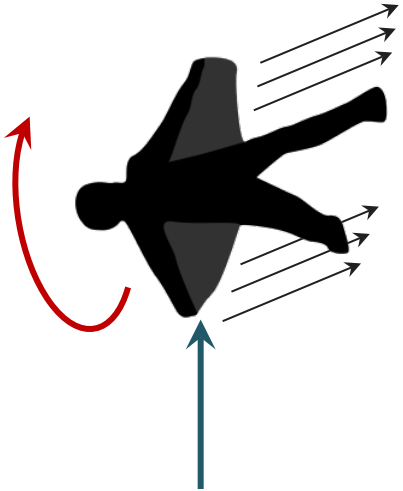

London 2012
FIBA
London 2012
London 20

What can first person vision tell us about?



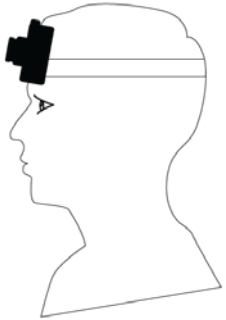
What can first person vision tell us about?

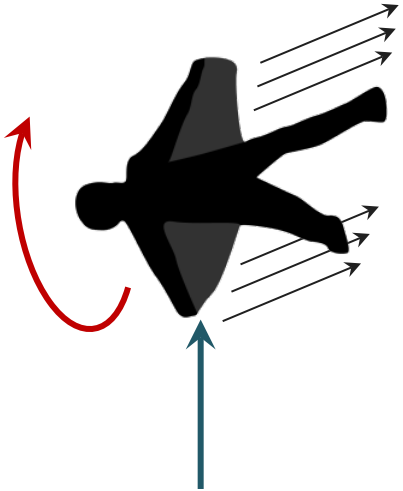




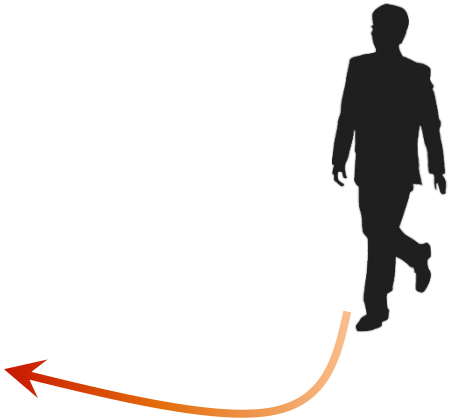
Force from Motion
CVPR 2016

What can first person vision tell us about?



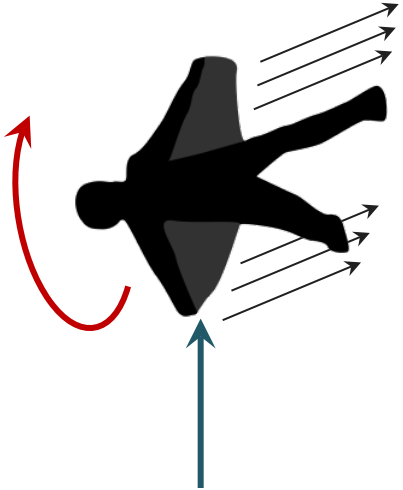


Force from Motion
CVPR 2016

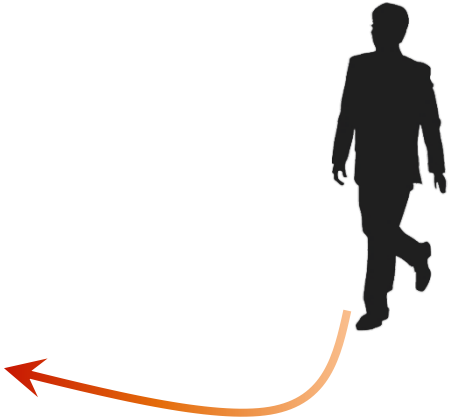


Future Localization
CVPR 2016

What can first person vision tell us about?



Force from Motion
CVPR 2016



Future Localization
CVPR 2016

Social Saliency Prediction
CVPR 2015

What can first person vision tell us about?

First person video tells us about <u>me</u>.

Force from Motion
CVPR 2016 oral

Future Localization
CVPR 2016 oral

Social Saliency Prediction
CVPR 2015 oral


How do we control our vehicle w.r.t. visuals?

How do we control our vehicle w.r.t. visuals?


RPM: 24.56 % ACC: 68.00 % Handle: R 0.54 %
Speed: 1.00 % BRK: 0.00 %