Apparent Display Resolution Enhancement for Moving Images

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MPI Informatik

Hans-Peter Seidel
MPI Informatik

Motivation

Motivation

Motivation

Motivation

Motivation

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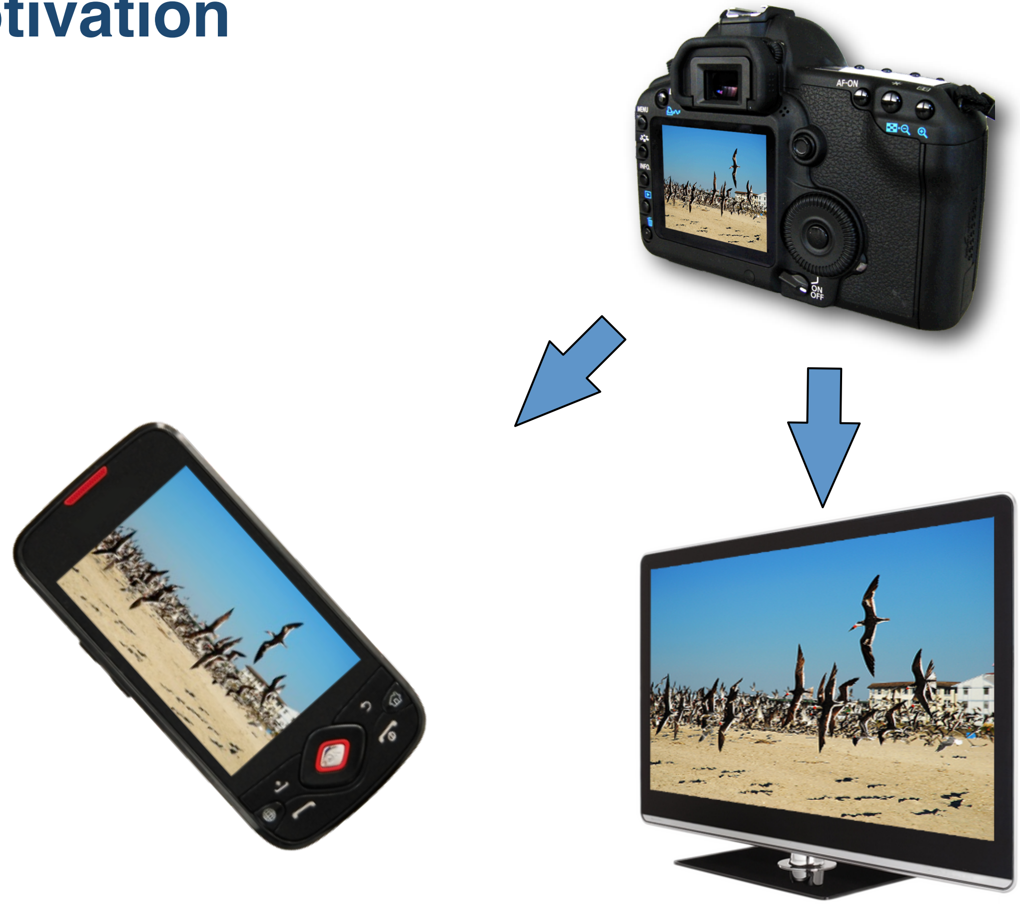

Motivation

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Motivation

source

display devices

Motivation

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more than 10 MPix

source

display devices

Motivation

more than 10 MPix

source

usually 2 MPix

up to 8MPix

display devices

Motivation

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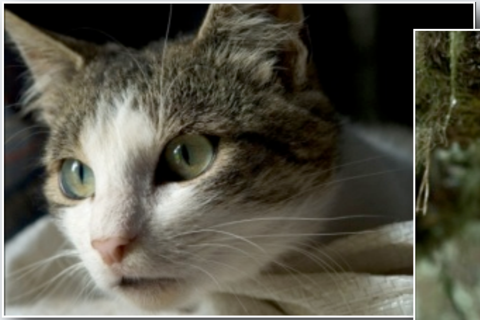
Motivation

Photographs: > 10MPix



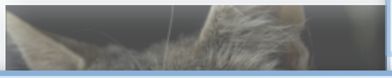
Motivation

Photographs: > 10MPix

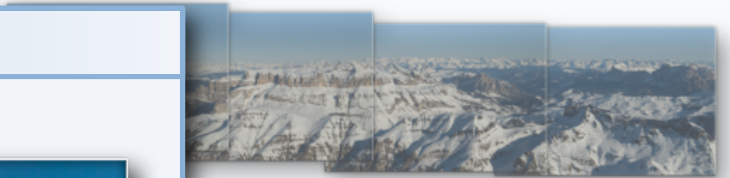
Panoramas: > 50MPix

Motivation

Photographs: > 10MPix



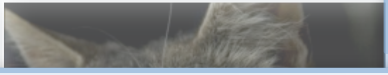
Panoramas: > 50MPix



Gigapixel Photography:

Motivation

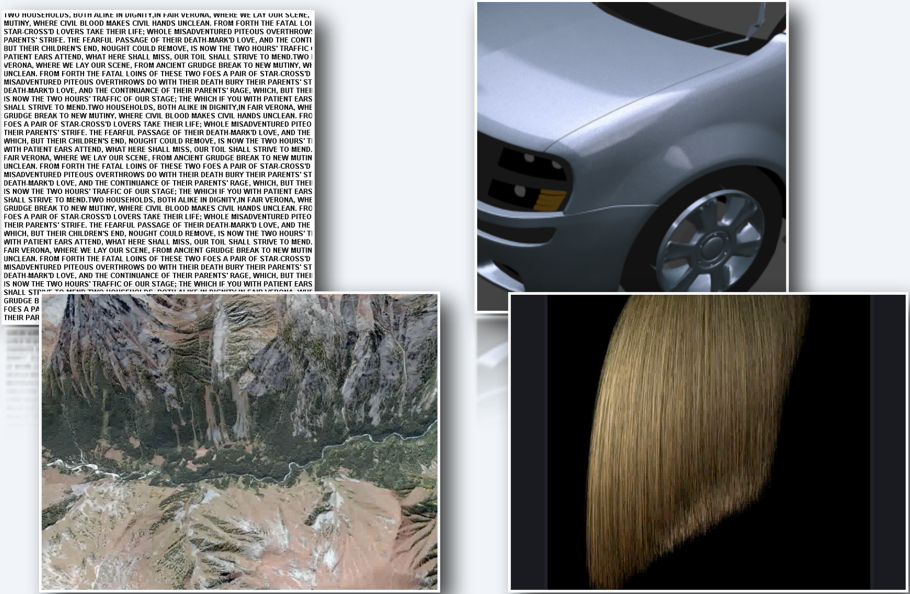
Photographs: > 10MPix



Panoramas: > 50MPix

Gigapixel Photography:

Computer generated: Unlimited



Previous work
Image resampling

high resolution image

Previous work

Image resampling

high resolution image

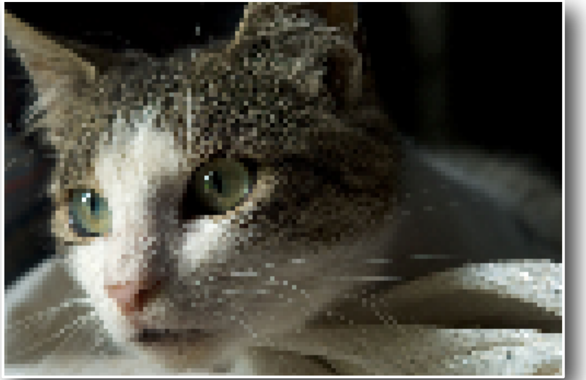
take every n-th pixel

Previous work

Image resampling

high resolution image

take every n-th pixel



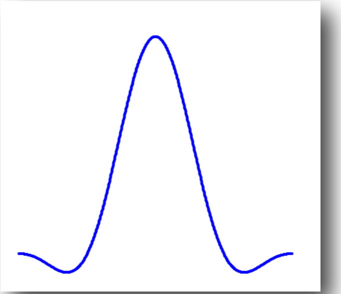
aliasing problem

Previous work
Image resampling

high resolution image

Previous work
Image resampling

high resolution image



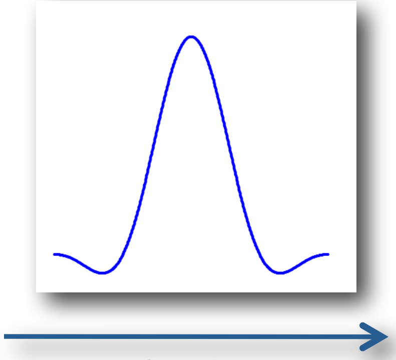
filtering

"Lanczos Filtering in One and Two Dimensions"
[Duchon 1979]

"Reconstruction Filters in Computer Graphics"
[Mitchell et al. 1988]

Previous work
Image resampling

high resolution image



filtering

"Lanczos Filtering in One and Two Dimensions"
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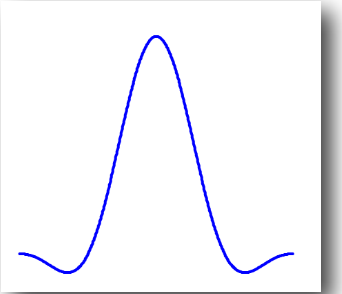
[Mitchell et al. 1988]

Previous work
Image resampling

high resolution image



filtering

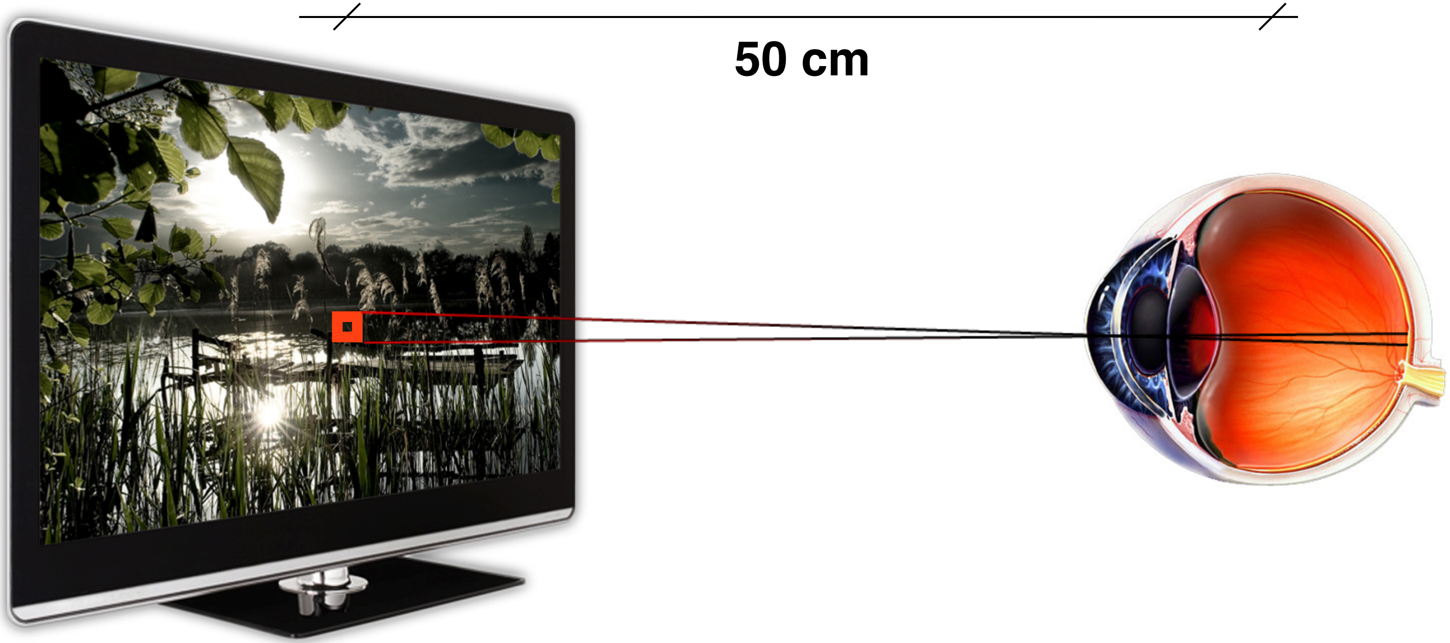
downsampling

“Lanczos Filtering in One and Two Dimensions”
[Duchon 1979]

“Reconstruction Filters in Computer Graphics”
[Mitchell et al. 1988]

Motivation

Motivation

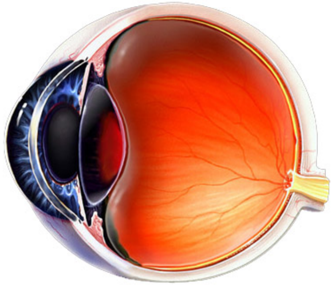


1px → more than 9 receptors

(in the fovea region)

Motivation

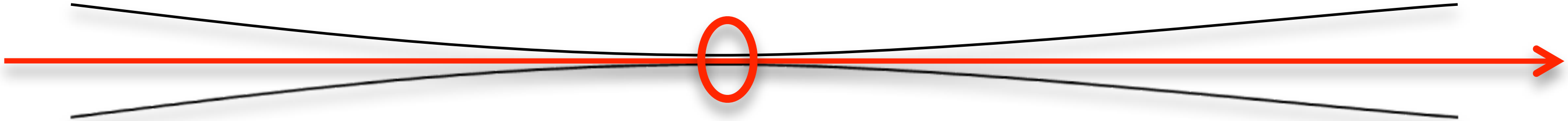
Summary



easily ~50 MPix

~ 2-8 MPix

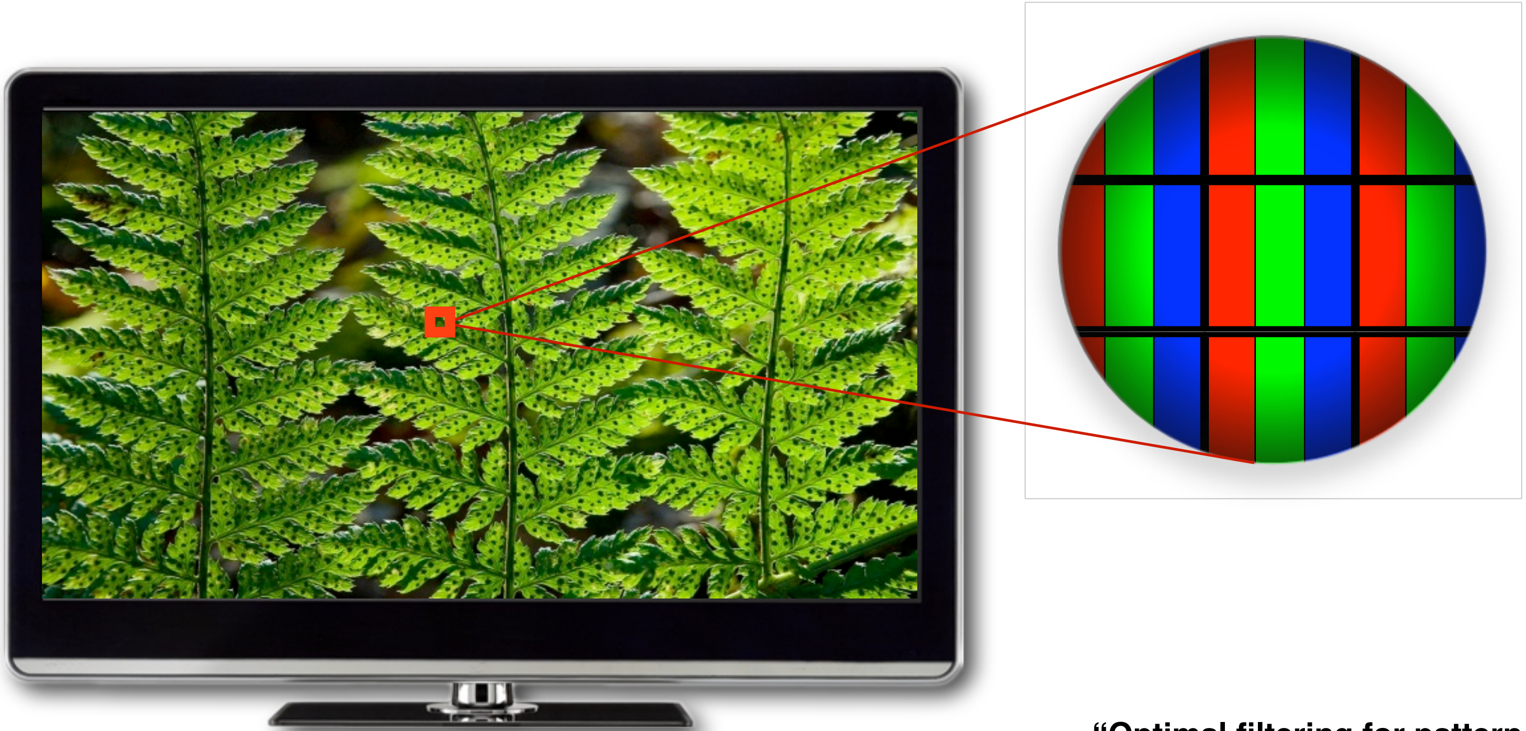
1px → > 9 receptors



Previous work
Color Matrix Displays

“Optimal filtering for pattern displays”
[Platt 2000]

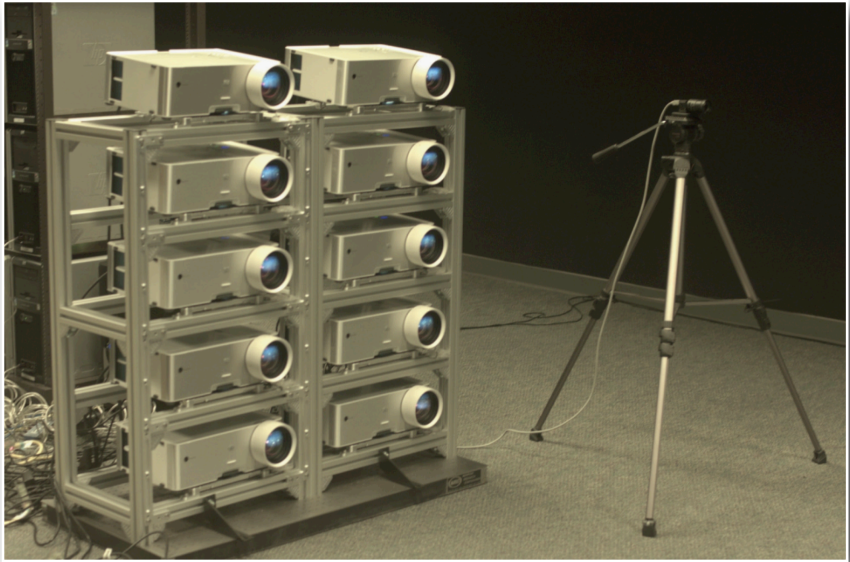
Previous work
Color Matrix Displays

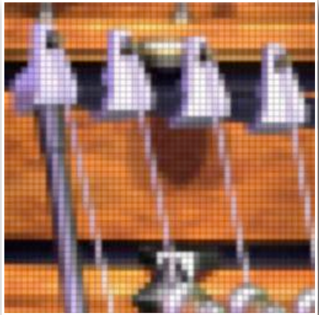


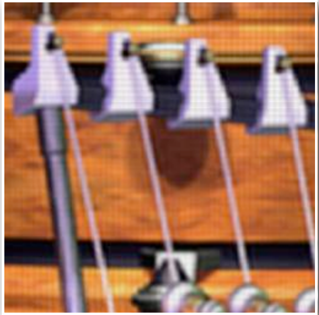
“Optimal filtering for pattern displays”
[Platt 2000]

Previous work

Display Supersampling and Wobulation



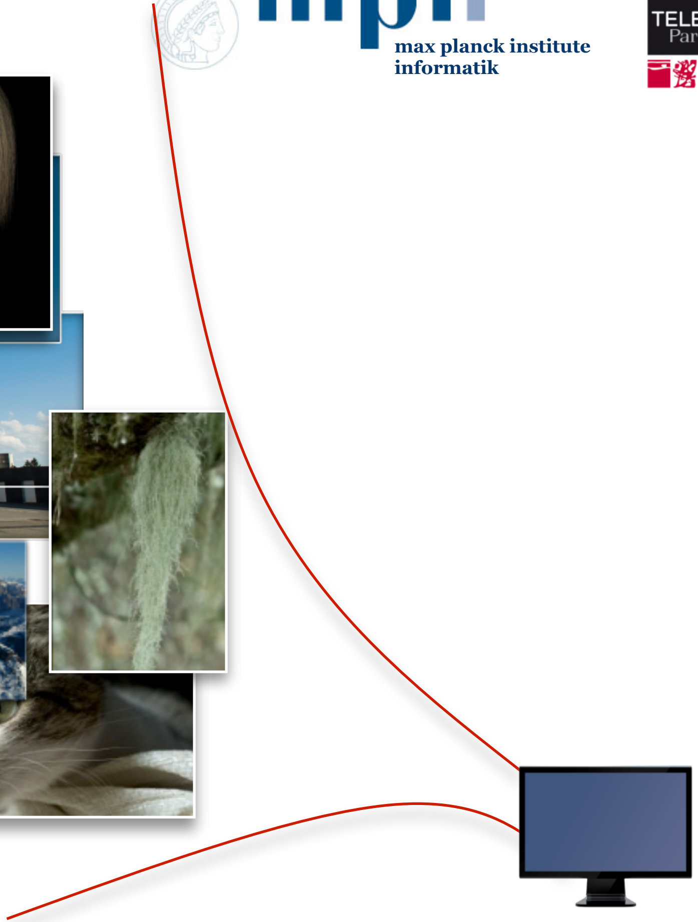




“Display Supersampling”
[Damera-Venkata et al. 2009]

“Wobulation: Doubling the Addressed Resolution of Projection Displays”
[Allen et al. 2005]

Motivation



Motivation

Our goal

high resolution image

Our goal

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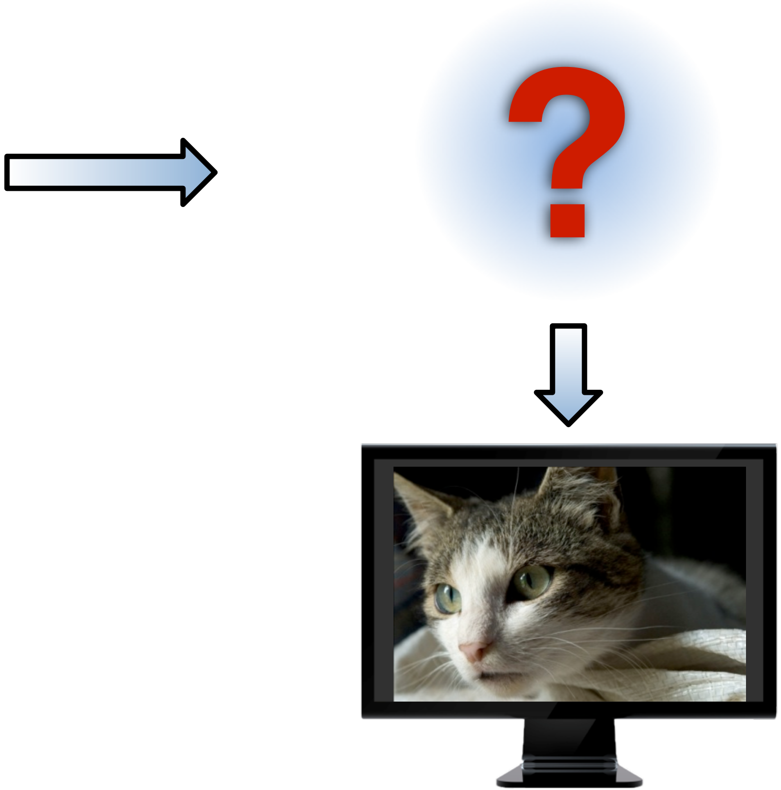
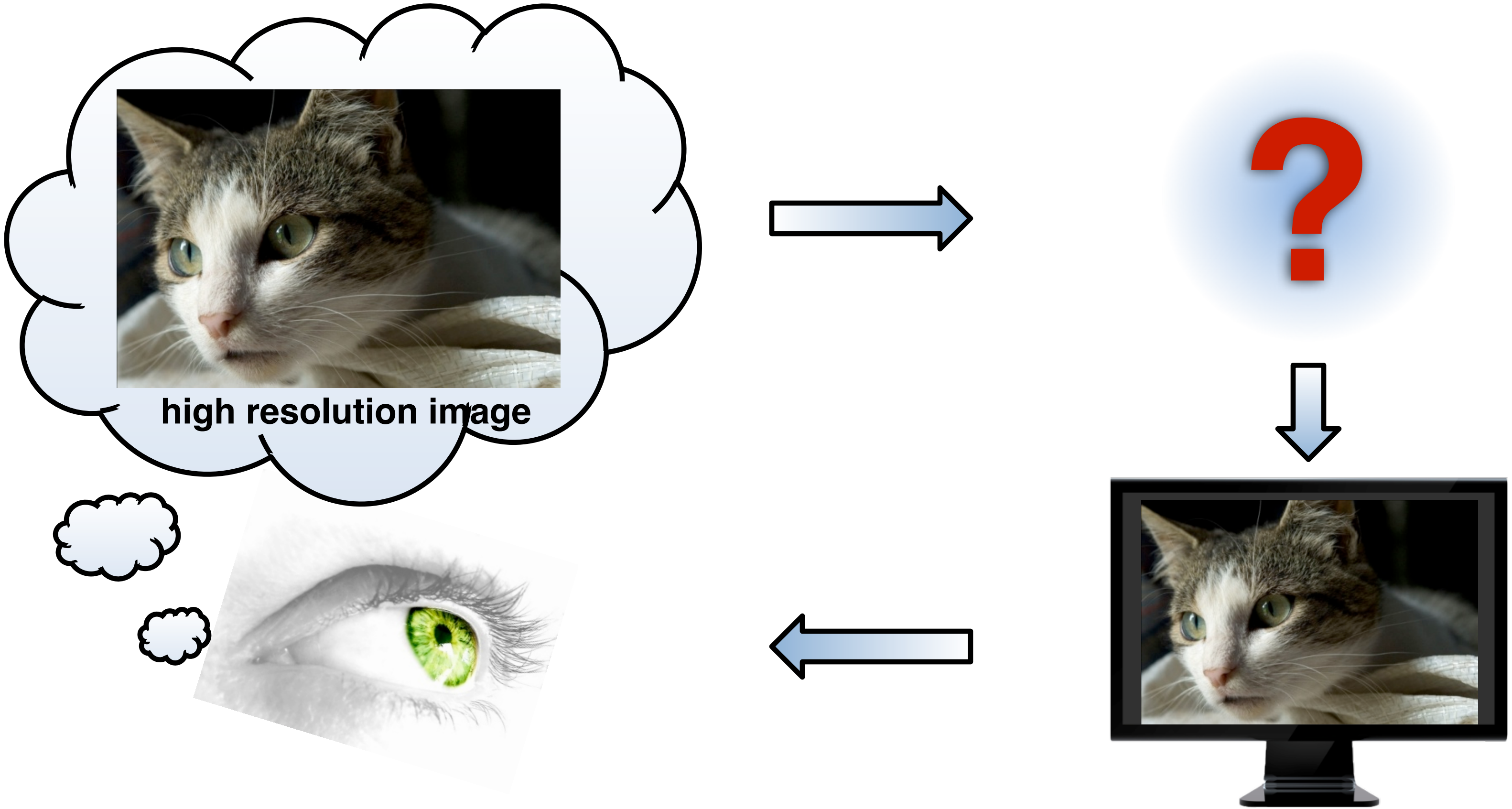
high resolution image

Our goal

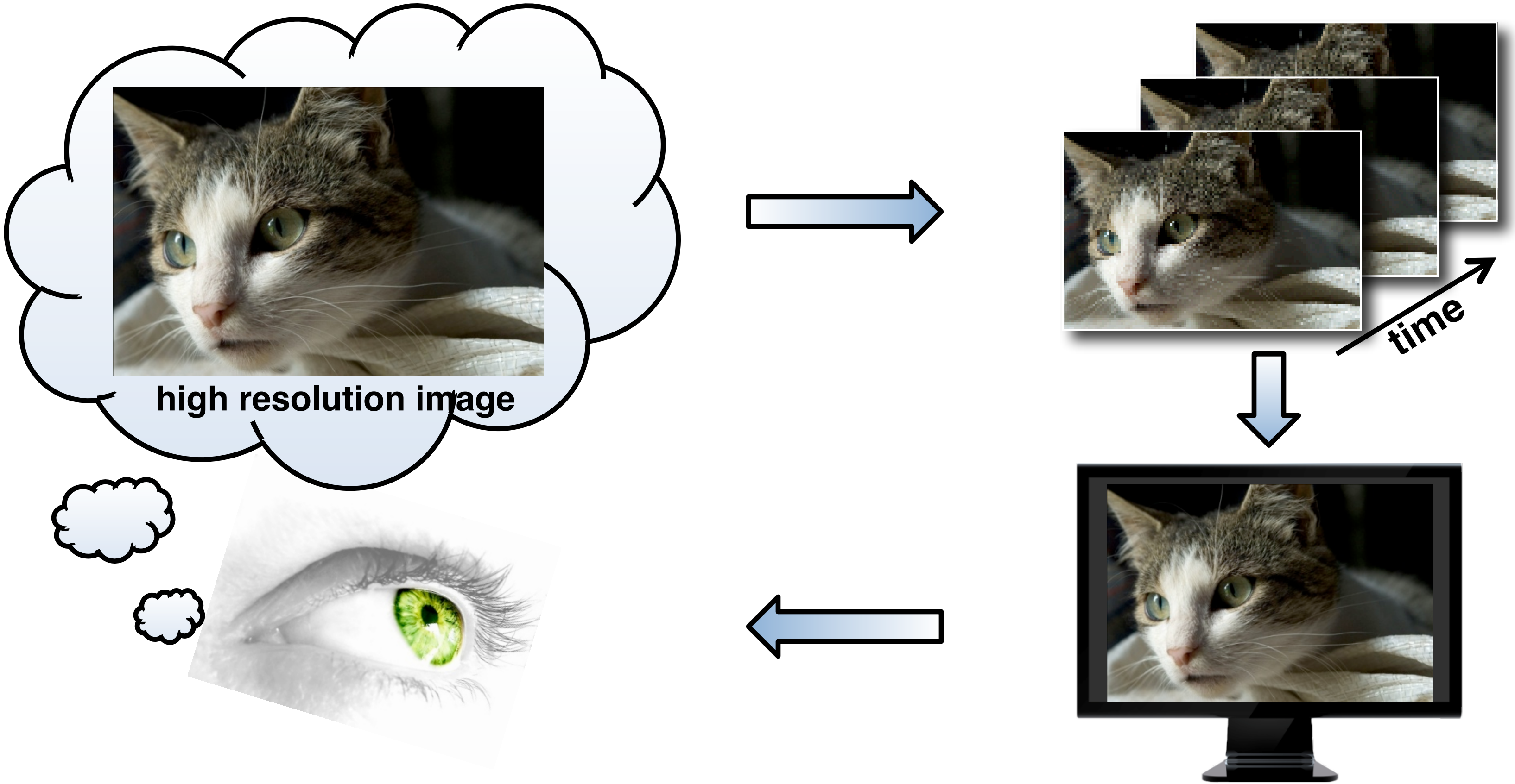
high resolution image



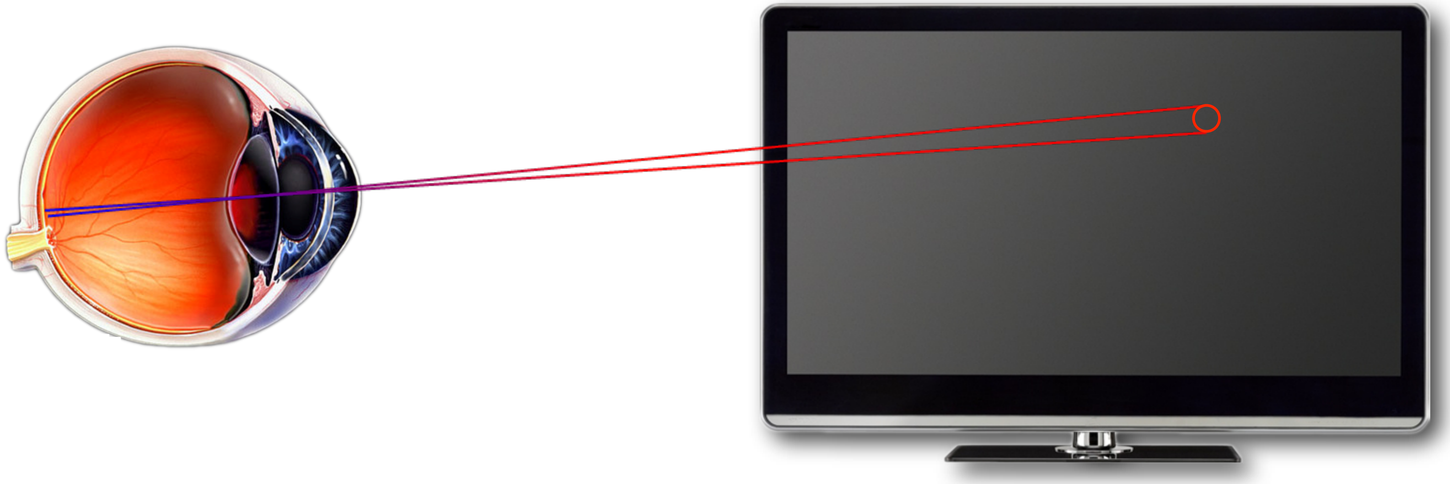
Our goal



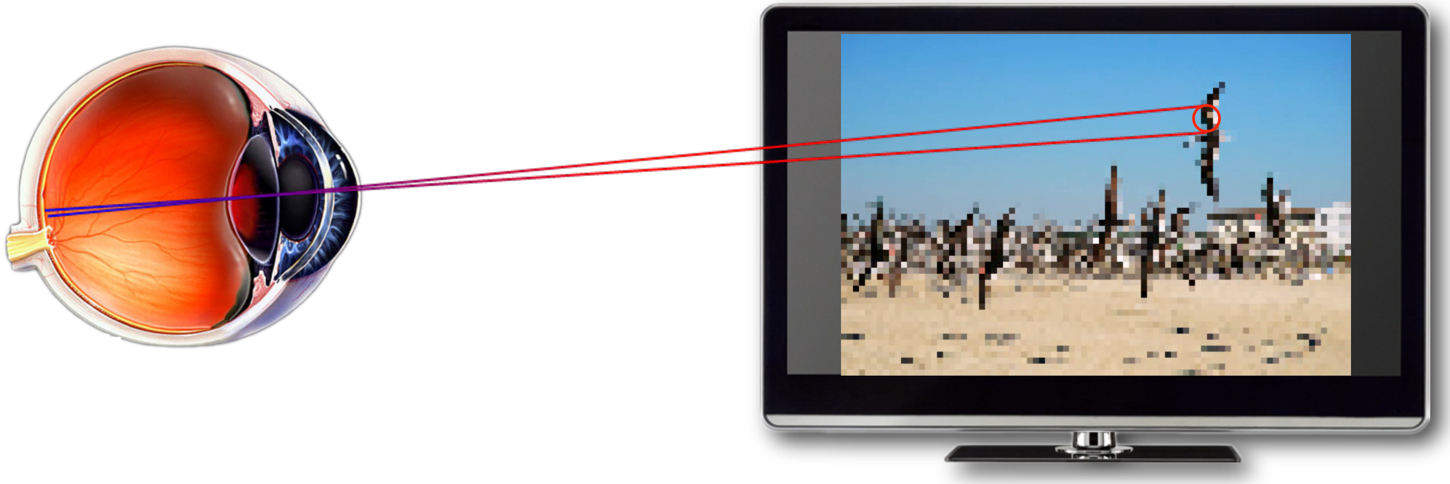
Our goal



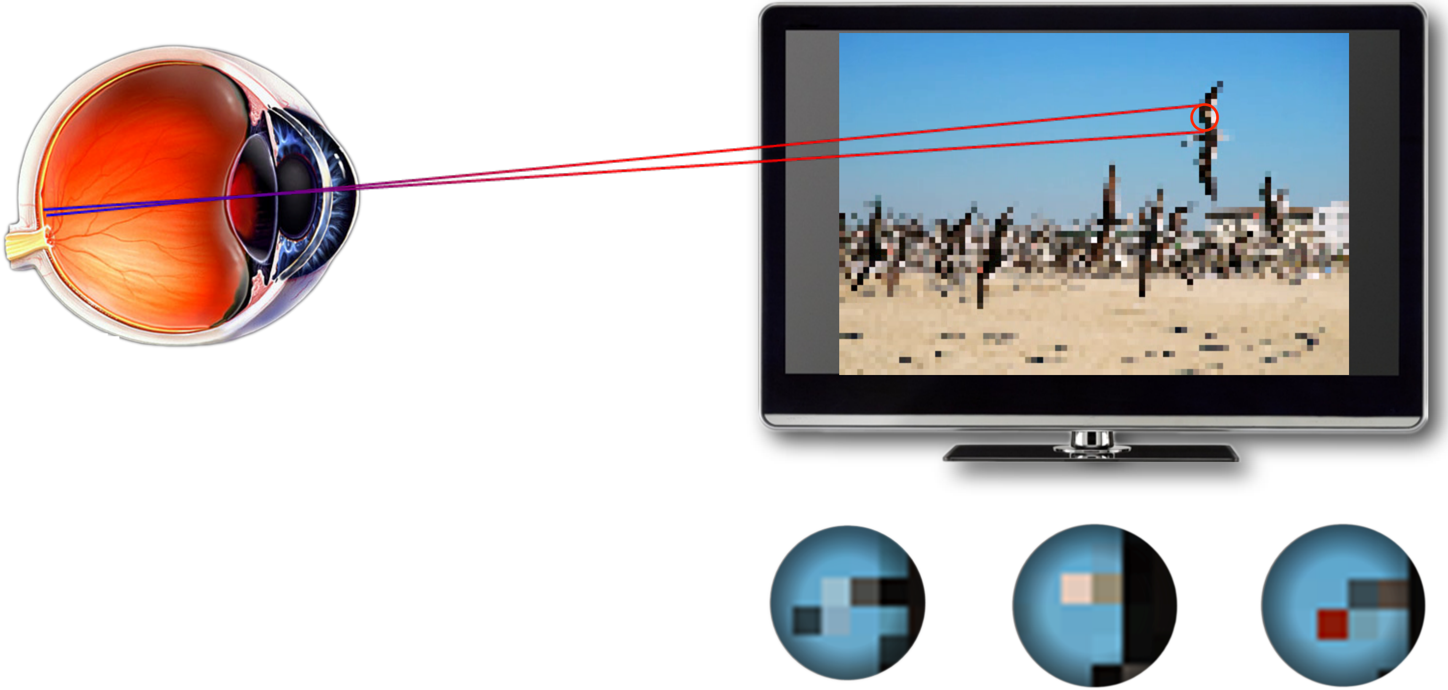
Temporal domain - static case



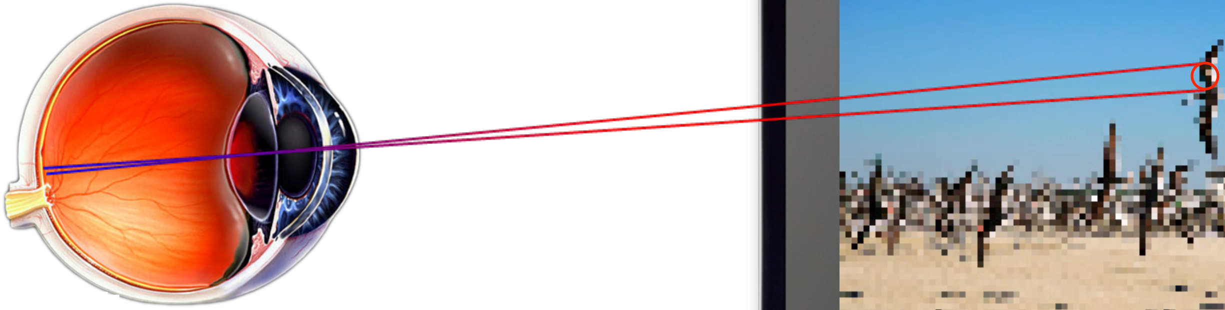
Temporal domain - static case



Temporal domain - static case



Temporal domain - static case



result on retina

Temporal domain - temporal case

Temporal domain - temporal case

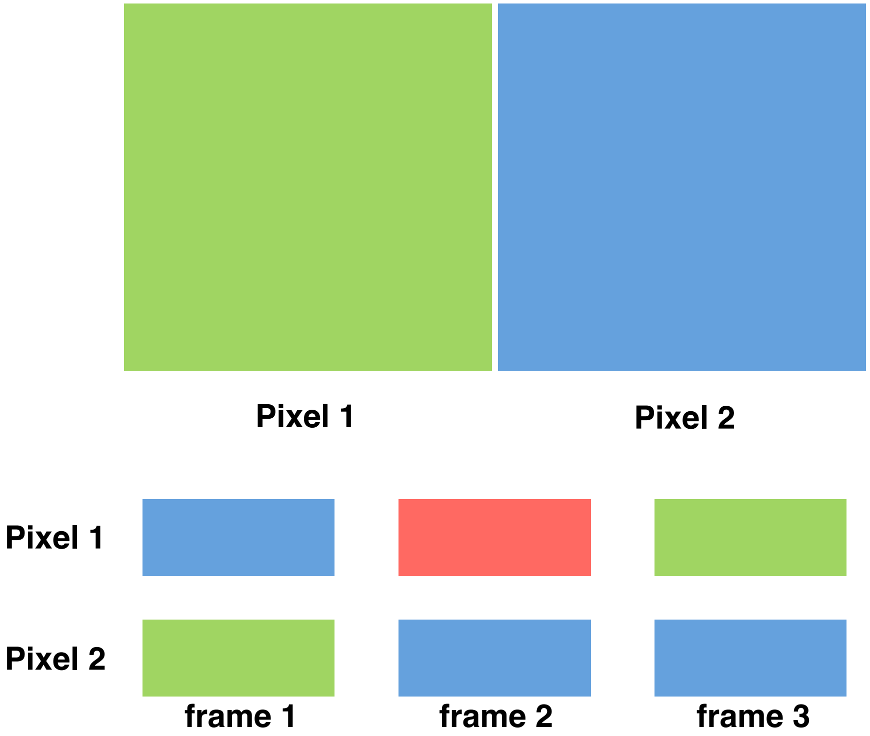
Temporal domain

Pixel 1 Pixel 2

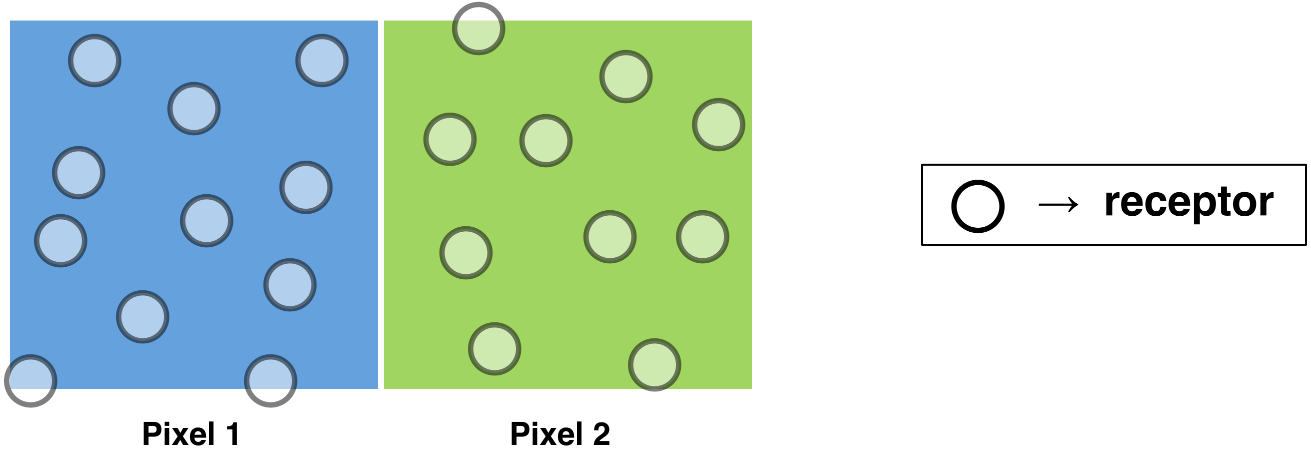
Pixel 1

Pixel 2

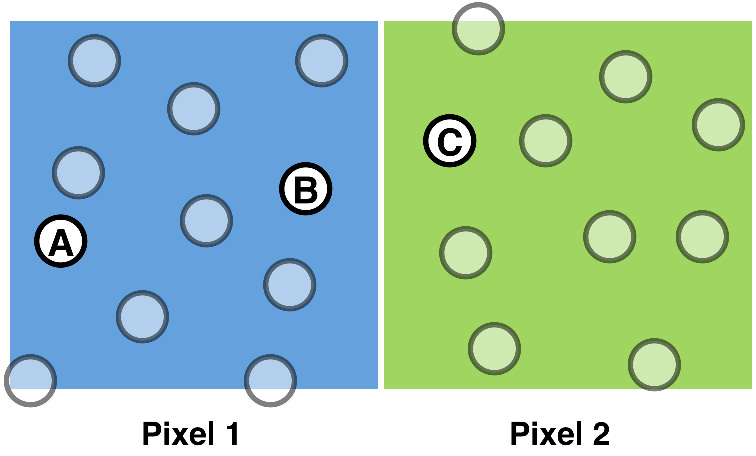
Temporal domain

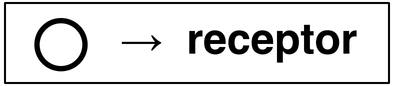


Temporal domain – static case



Temporal domain – static case



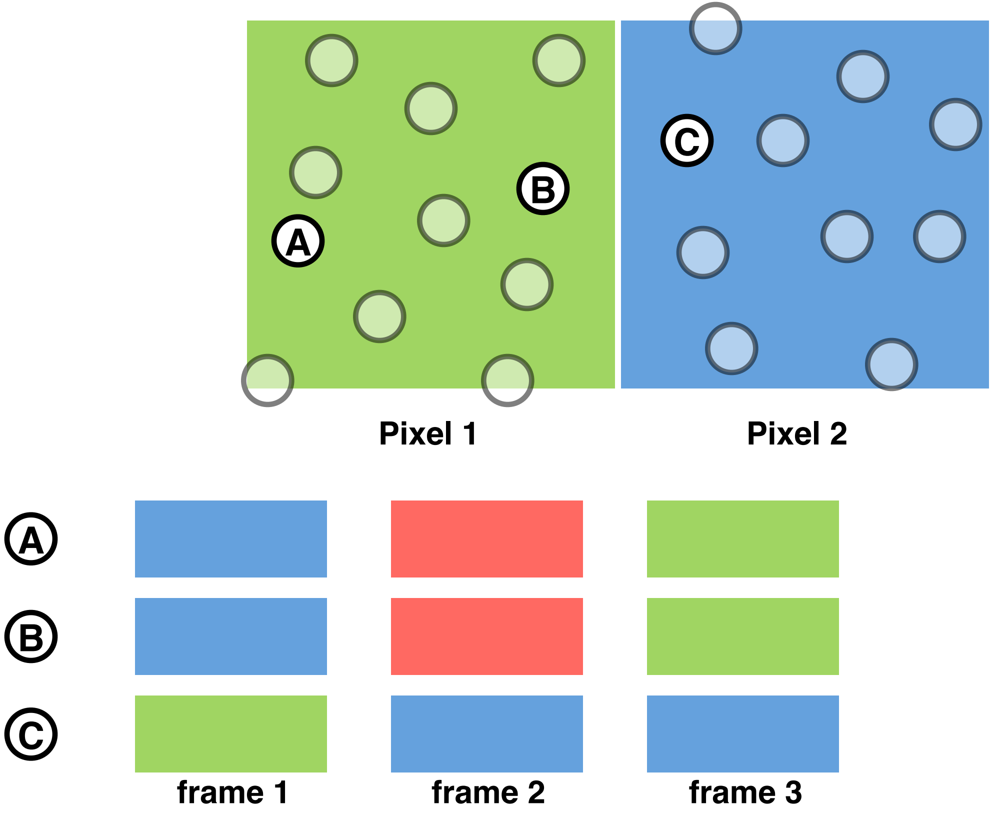


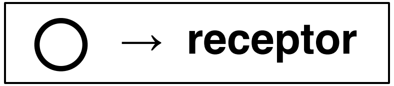
Ⓐ

Ⓑ

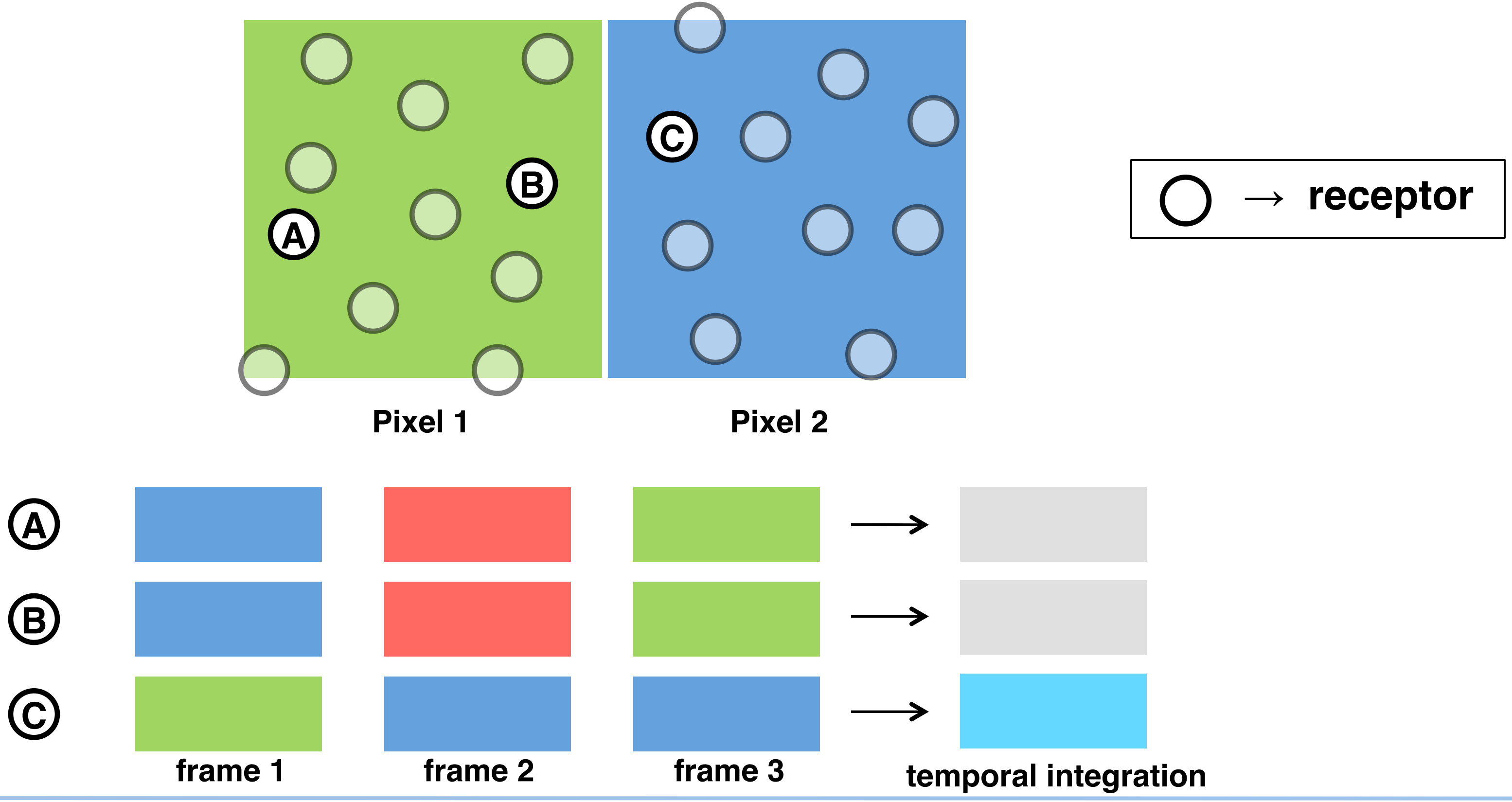
Ⓒ

Temporal domain – static case





Temporal domain – static case



Temporal domain - temporal case

Temporal domain - temporal case

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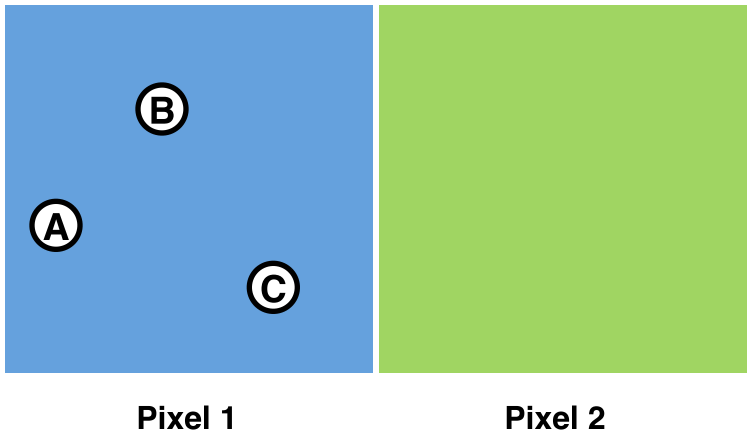
Temporal domain - dynamic case



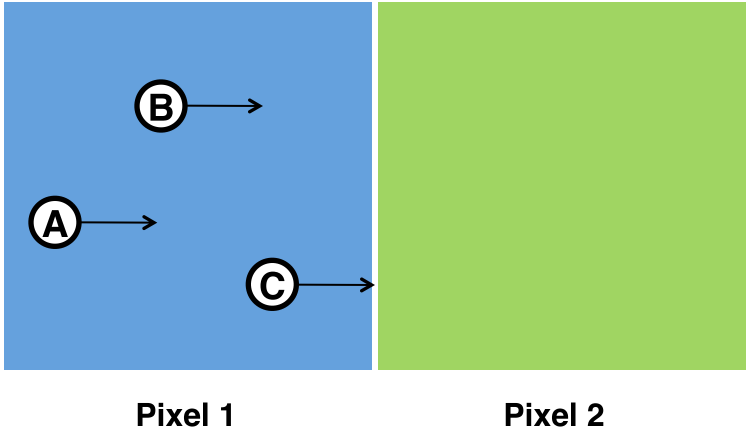
○ → receptor

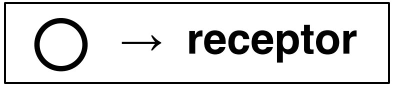
Ⓐ

Ⓑ

Ⓒ

Temporal domain - dynamic case



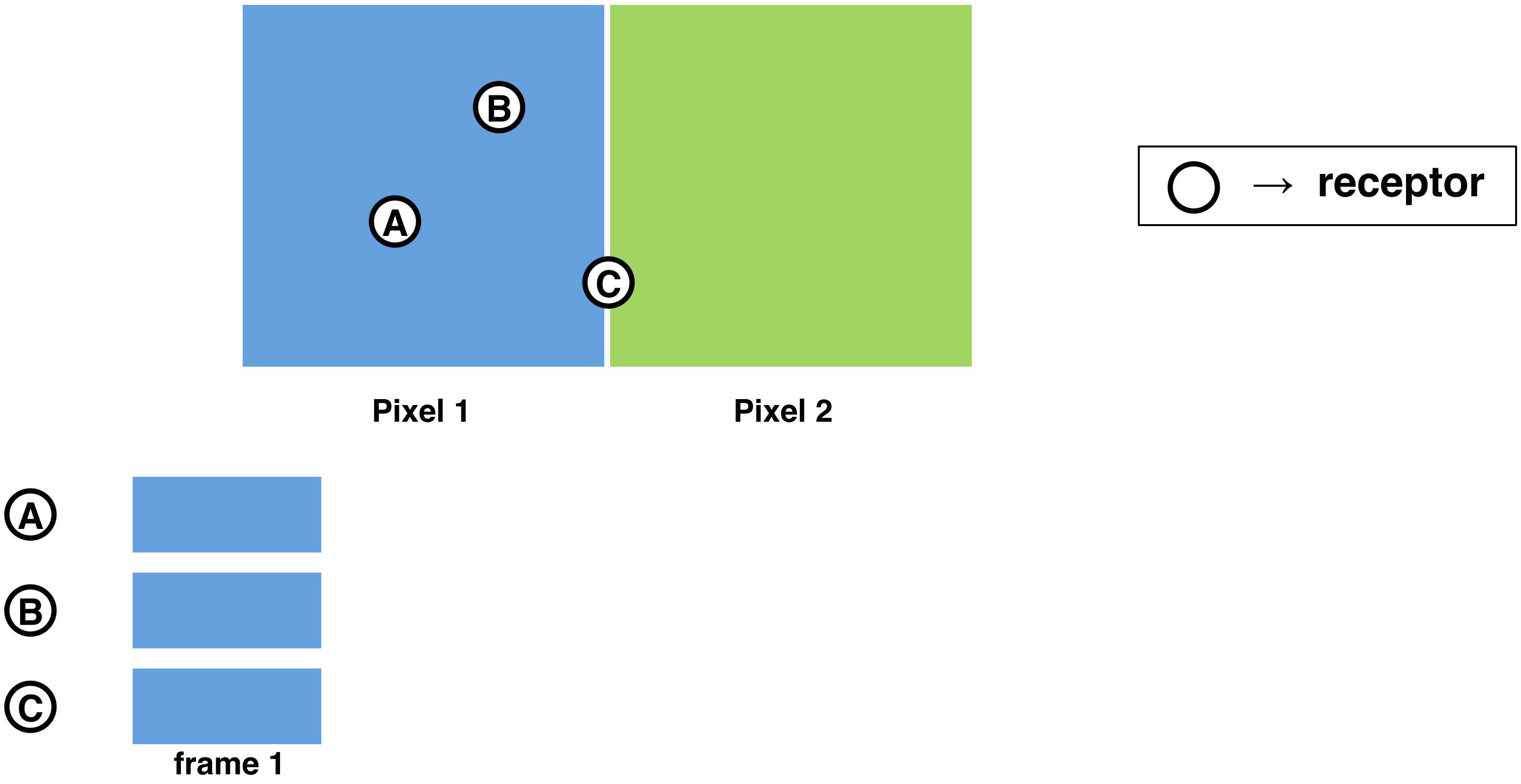


A

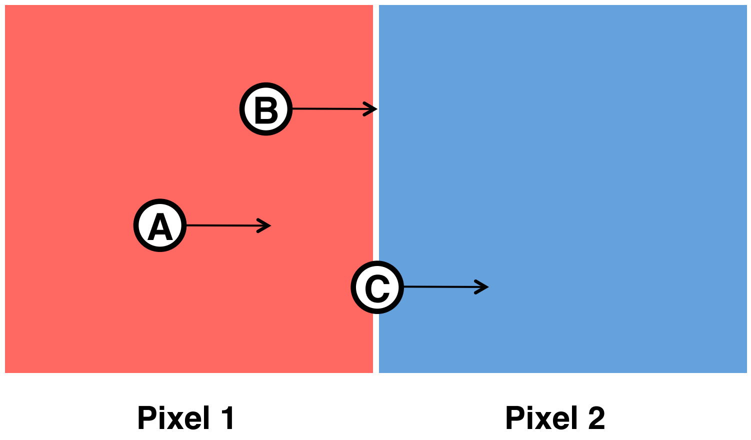
B

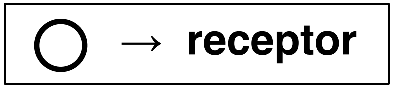
C

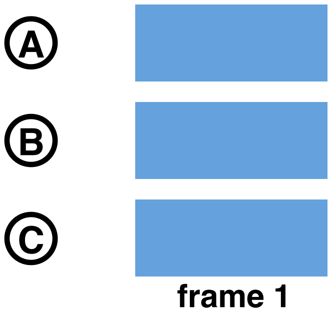
Temporal domain - dynamic case



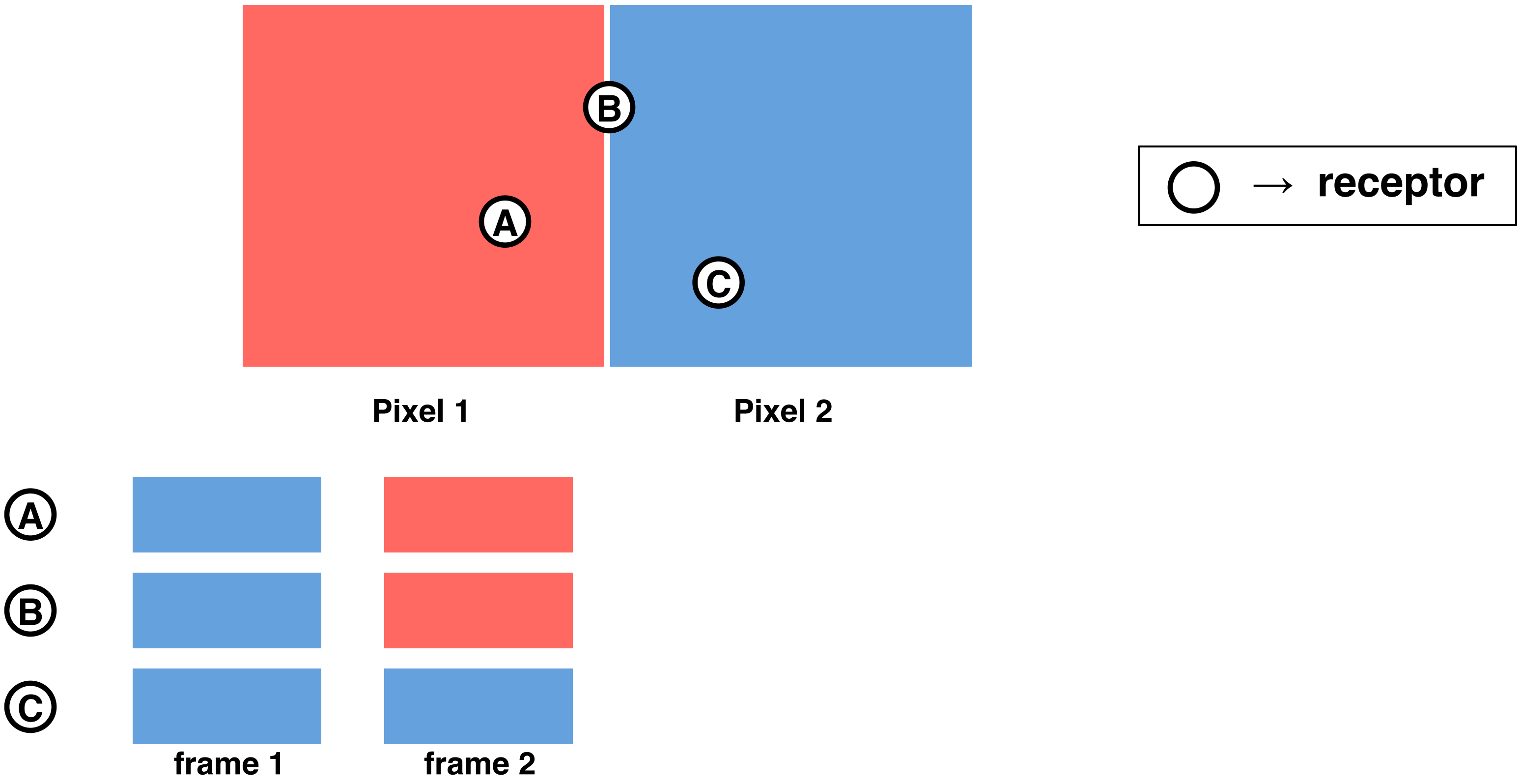
Temporal domain - dynamic case







Temporal domain - dynamic case



Temporal domain - dynamic case

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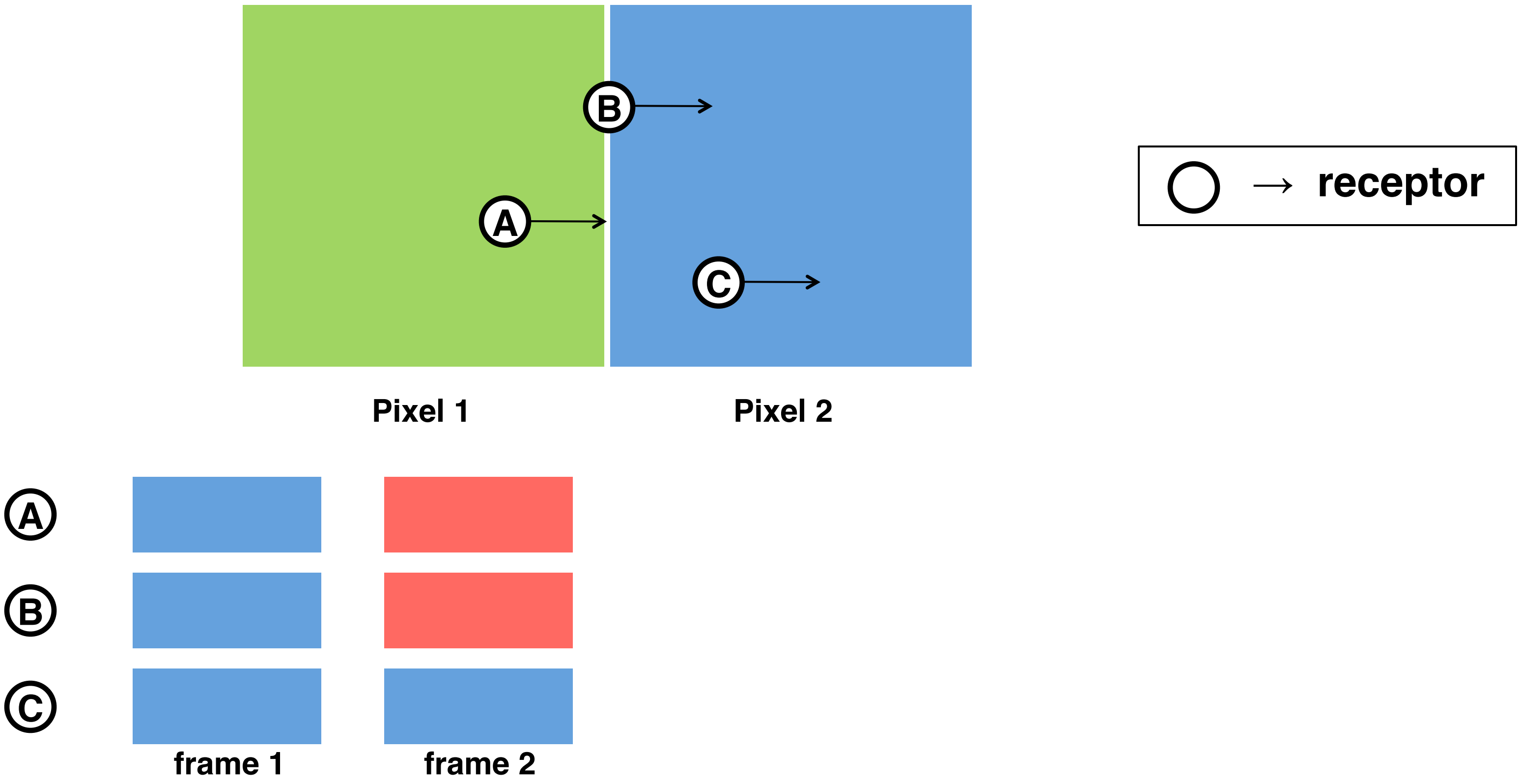
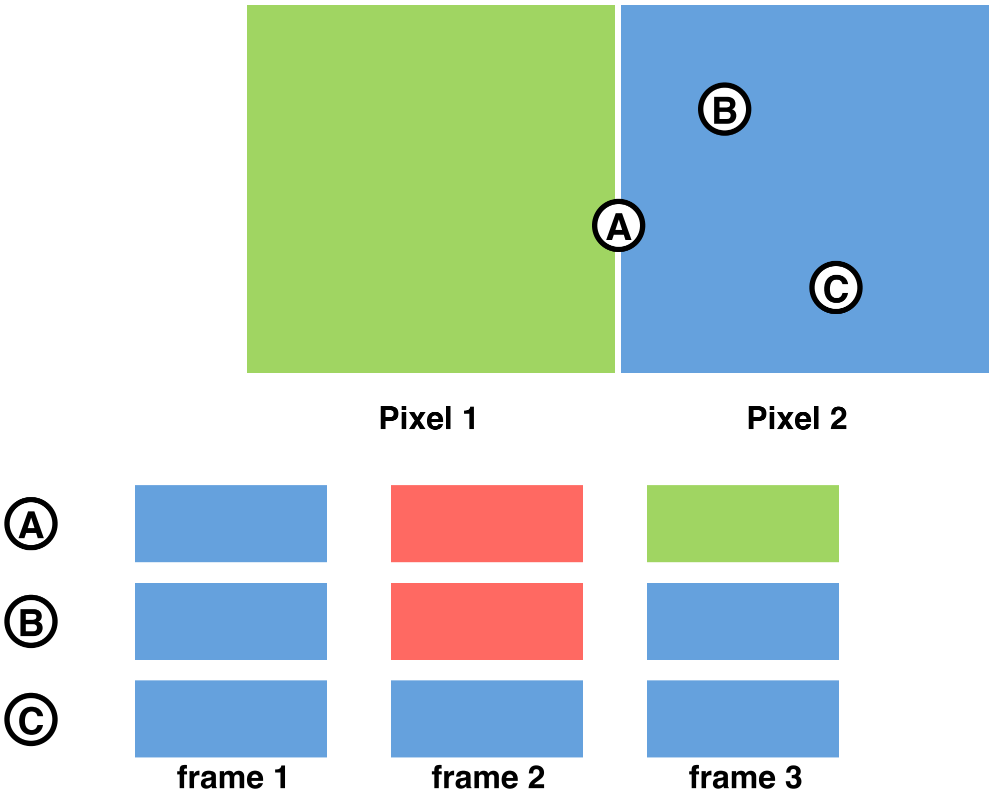
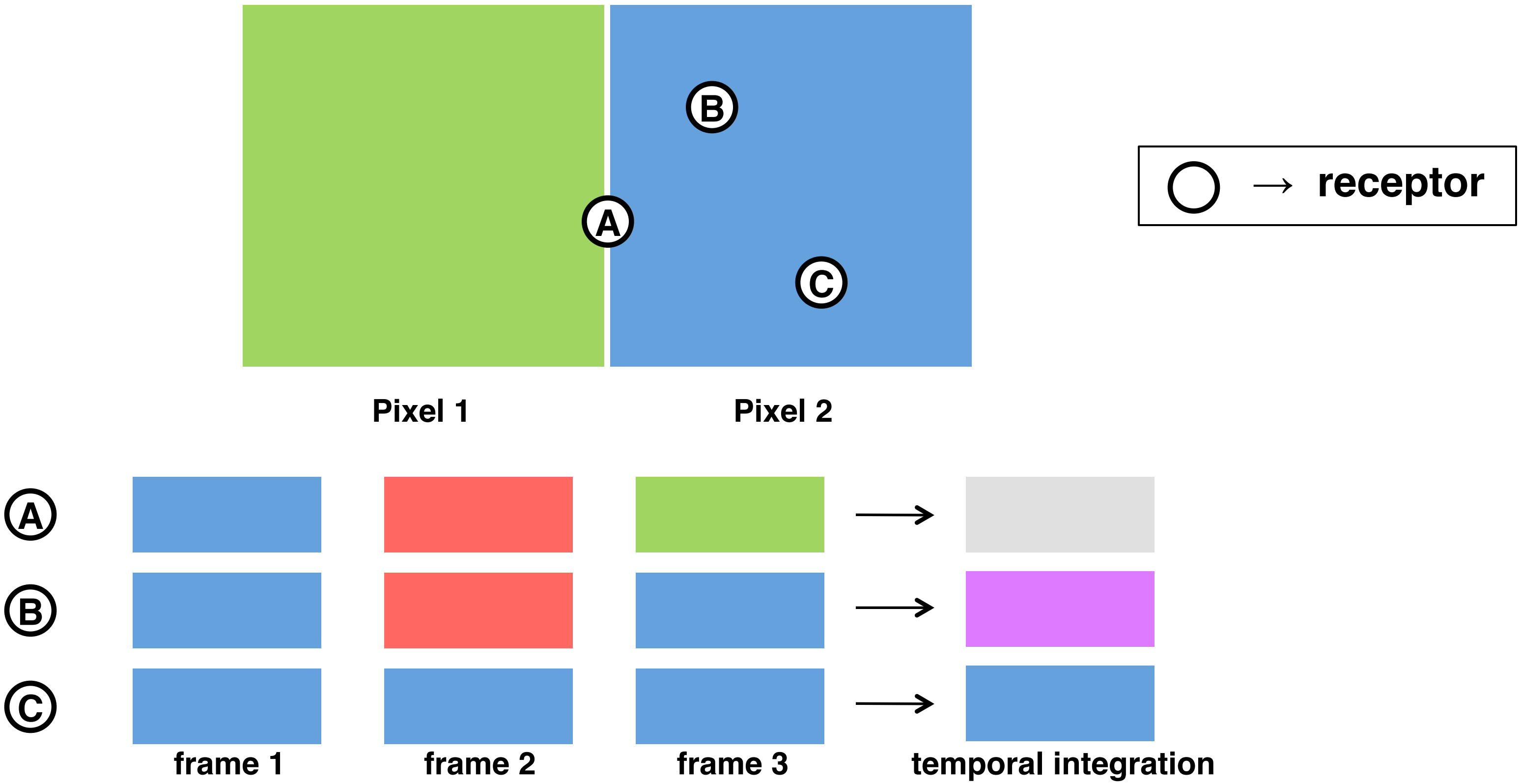


Temporal domain - dynamic case

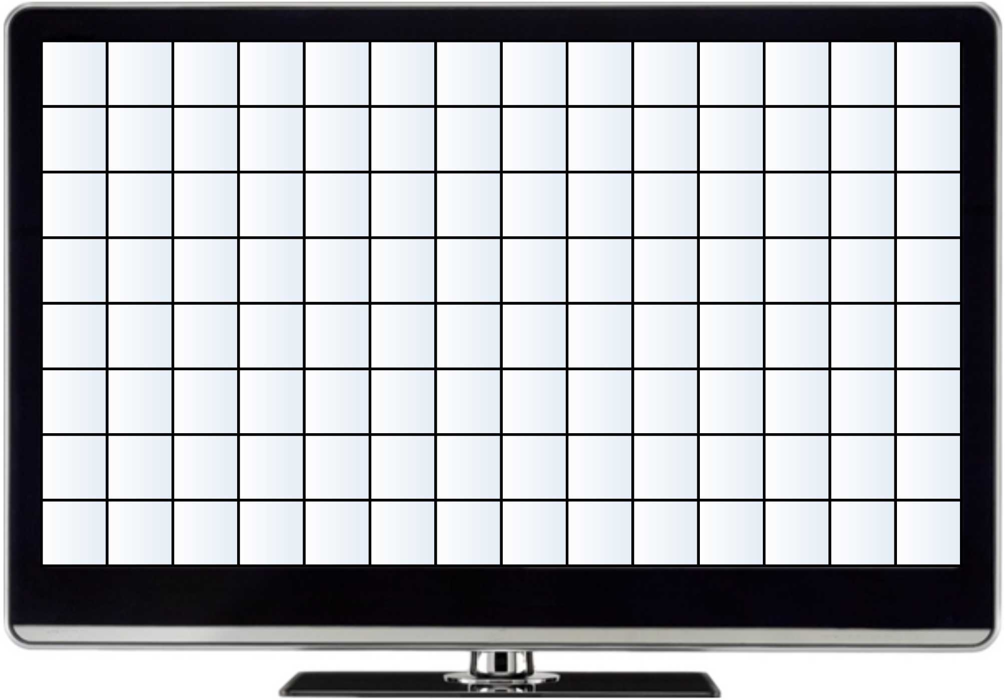


○ → receptor

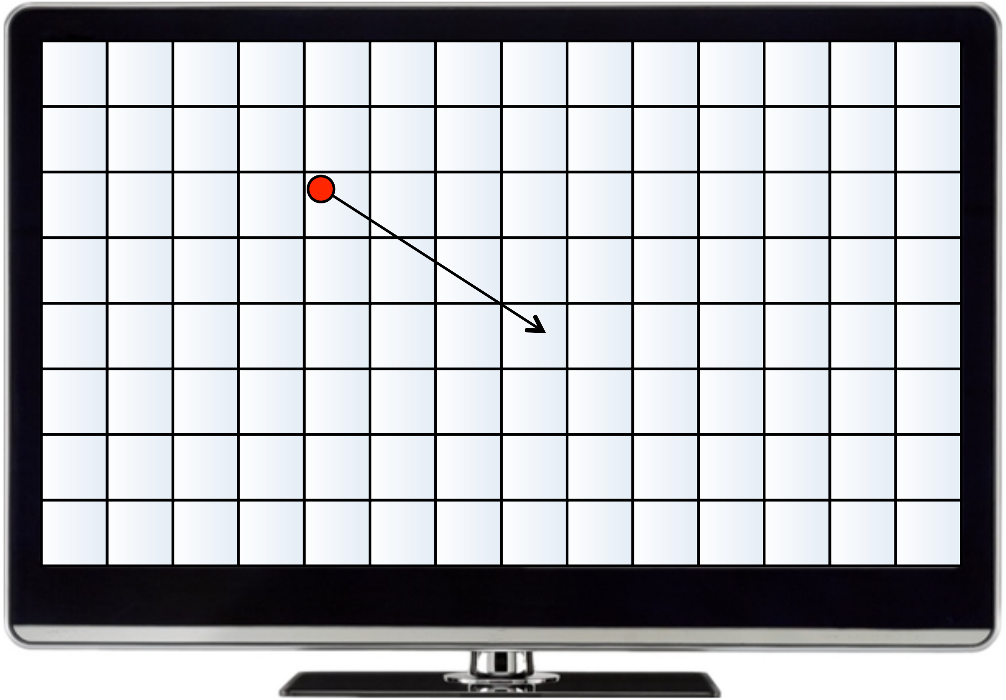
Temporal domain - dynamic case



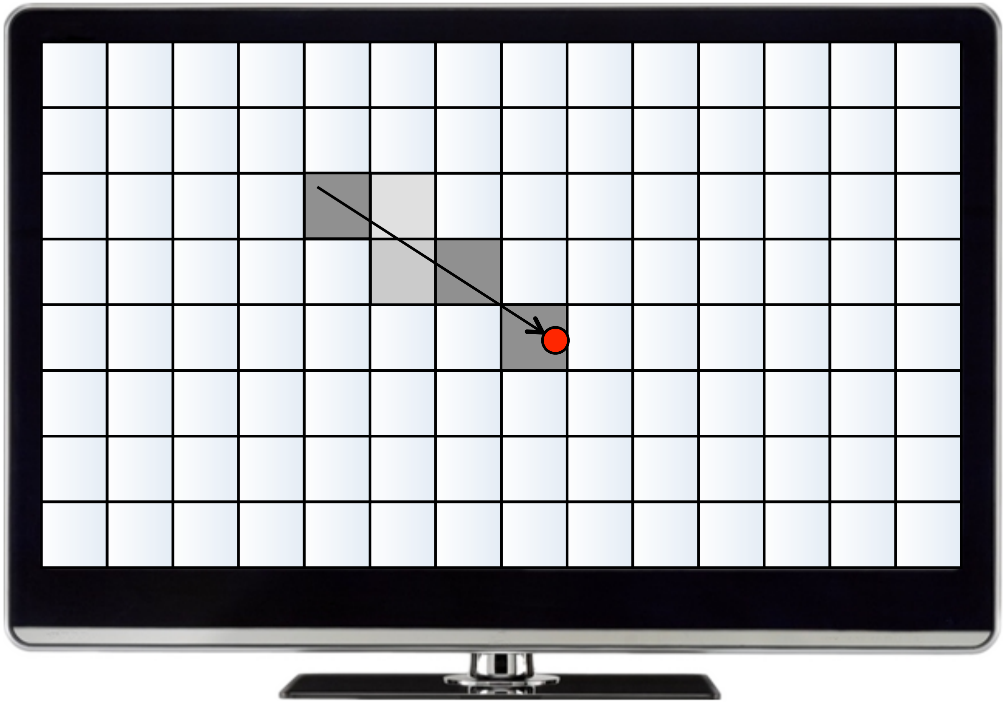
Temporal Integration Model



Temporal Integration Model

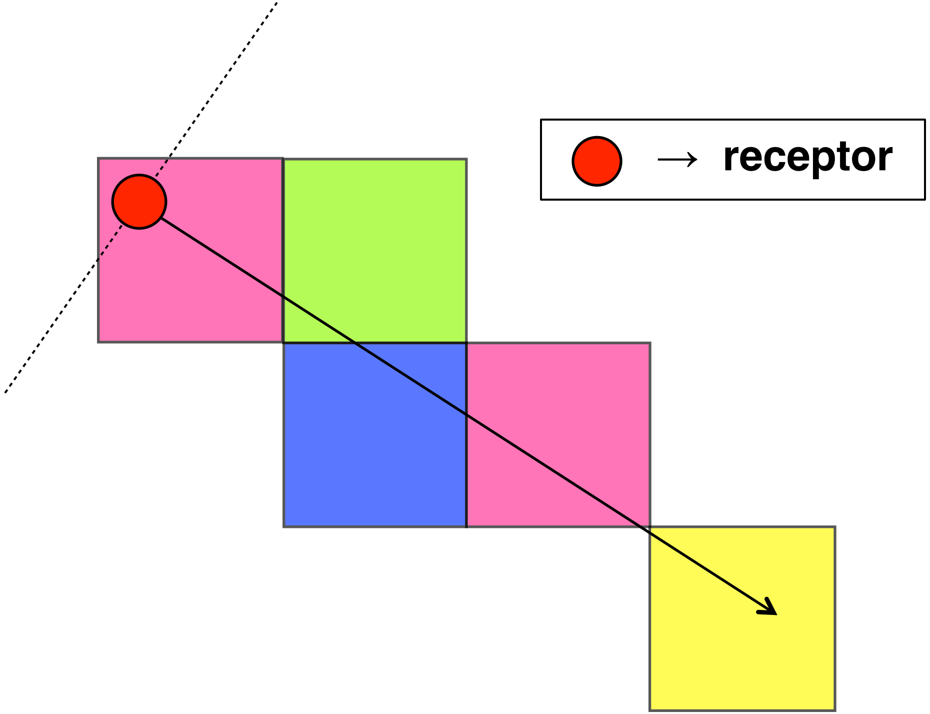


Temporal Integration Model



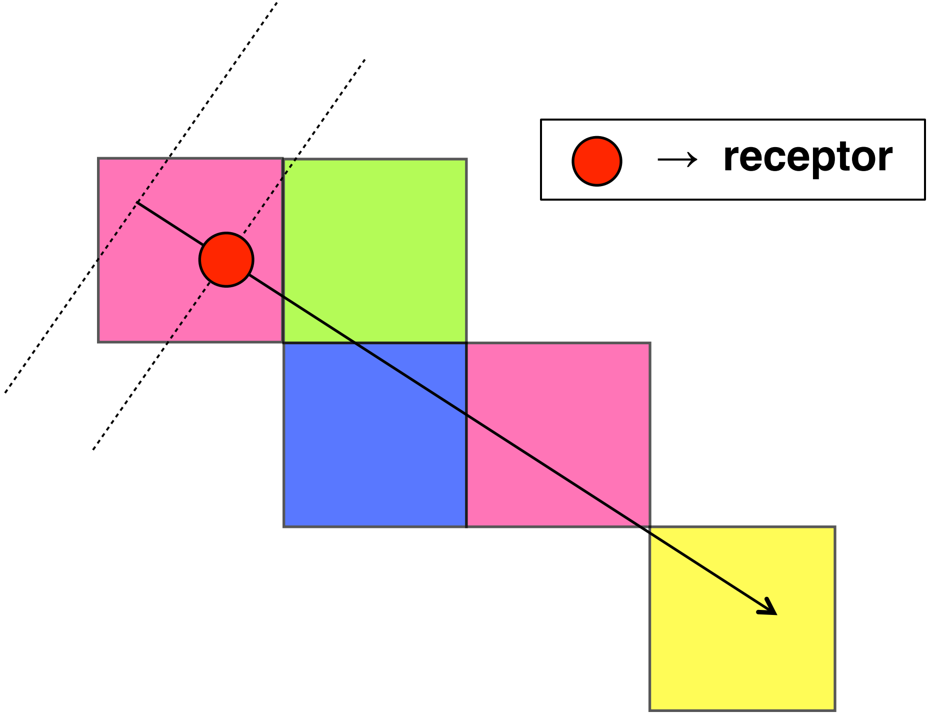
Temporal Integration Model

Receptor signal:



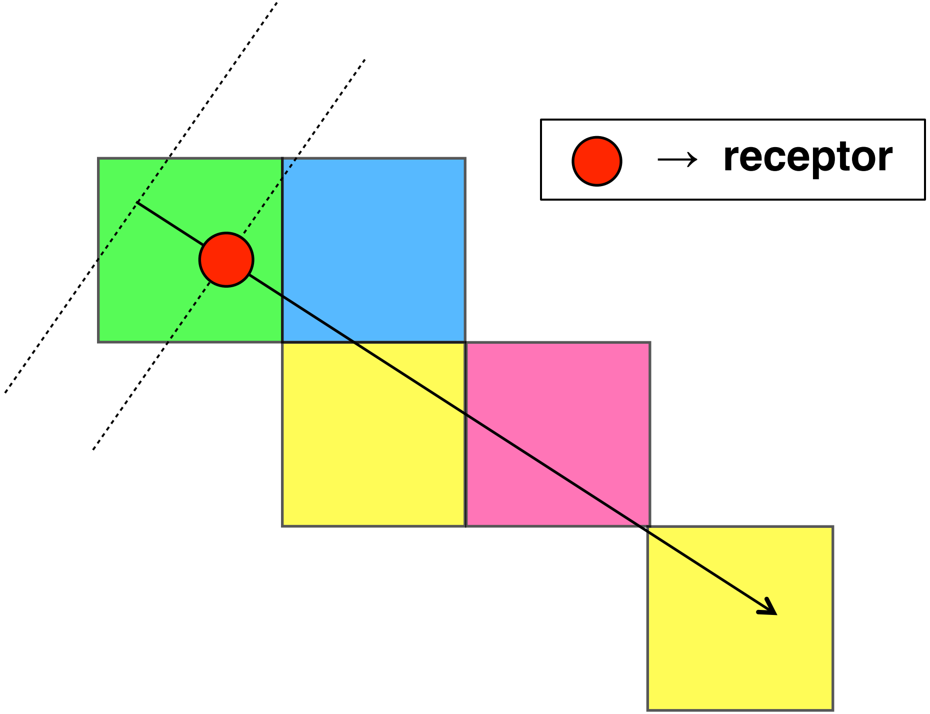
Temporal Integration Model

Receptor signal:



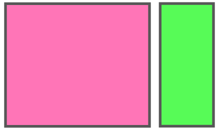
Temporal Integration Model

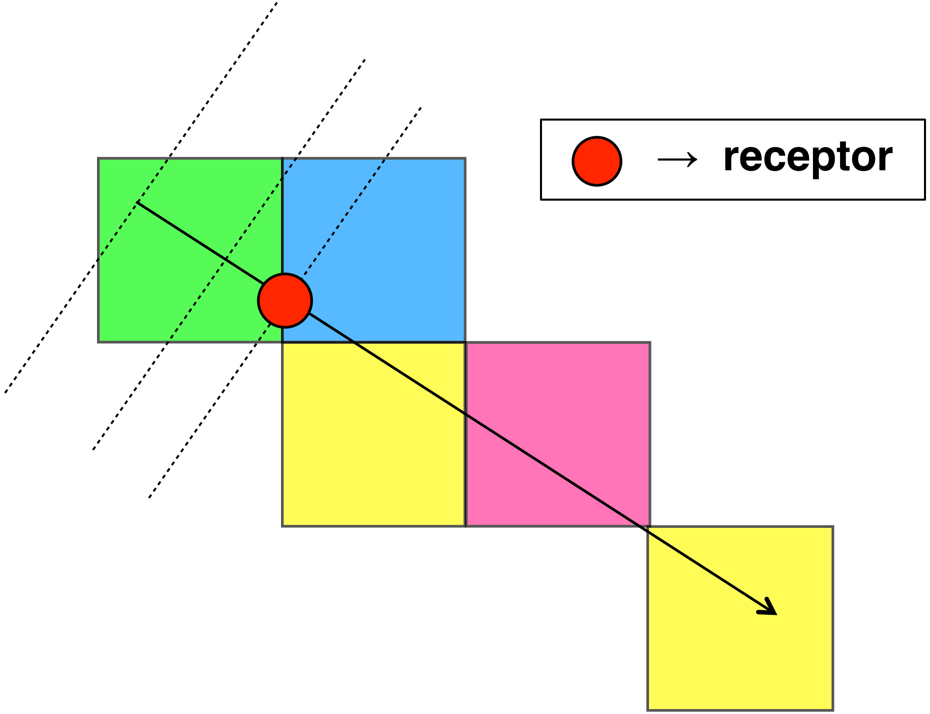
Receptor signal:



Temporal Integration Model

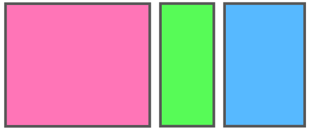
Receptor signal:

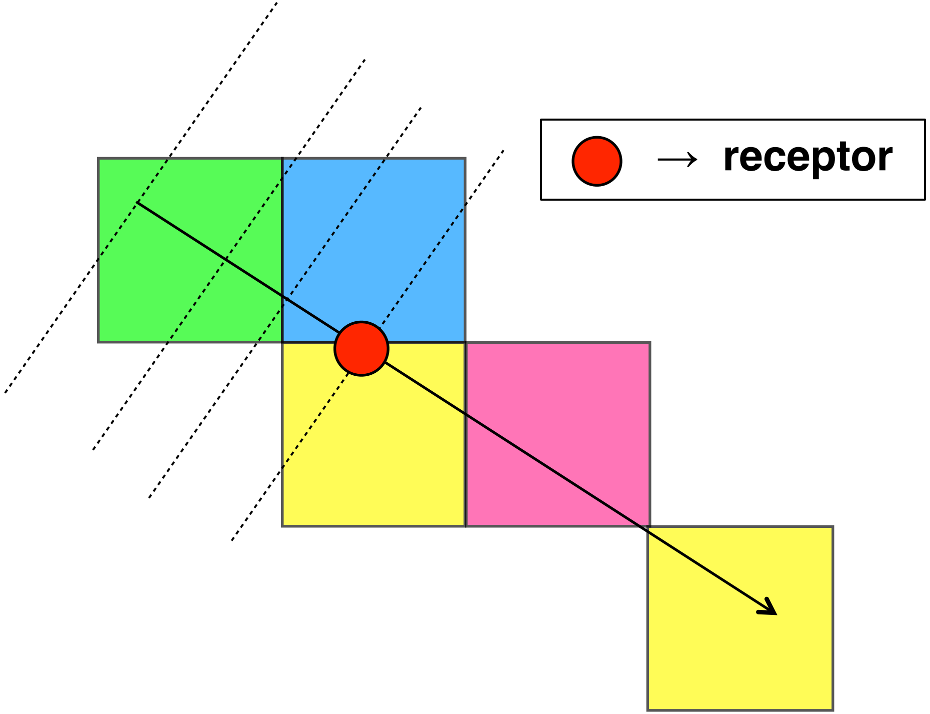




Temporal Integration Model

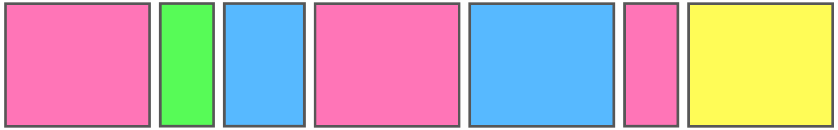
Receptor signal:

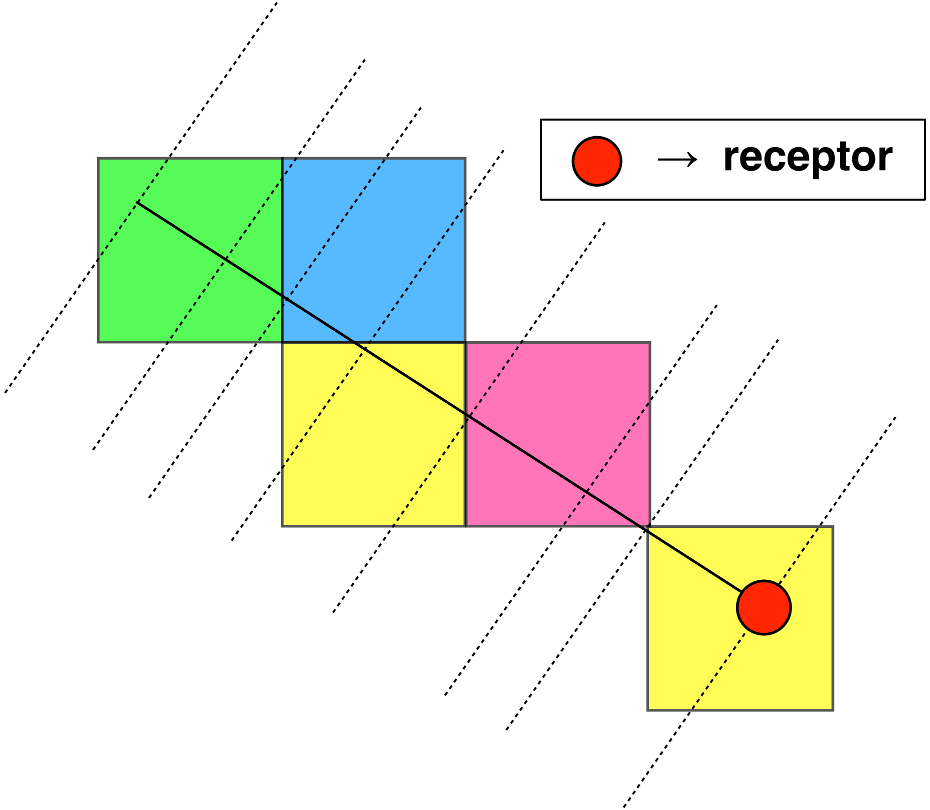




Temporal Integration Model

Receptor signal:



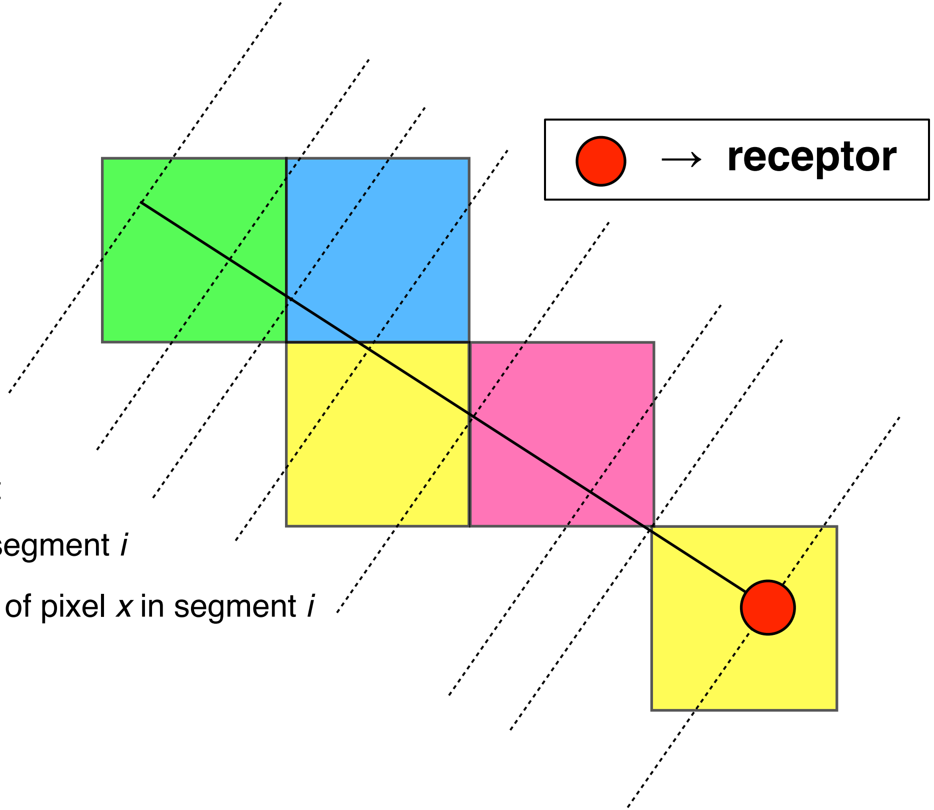


Temporal Integration Model

Receptor signal:

$$\sum_{i=0}^{N} w_i \, I(p(i), i)$$

i - segment
$p(i)$ - pixel in segment *i*
$I(x, i)$ - intensity of pixel *x* in segment *i*



Temporal Integration Model

Receptor signal:

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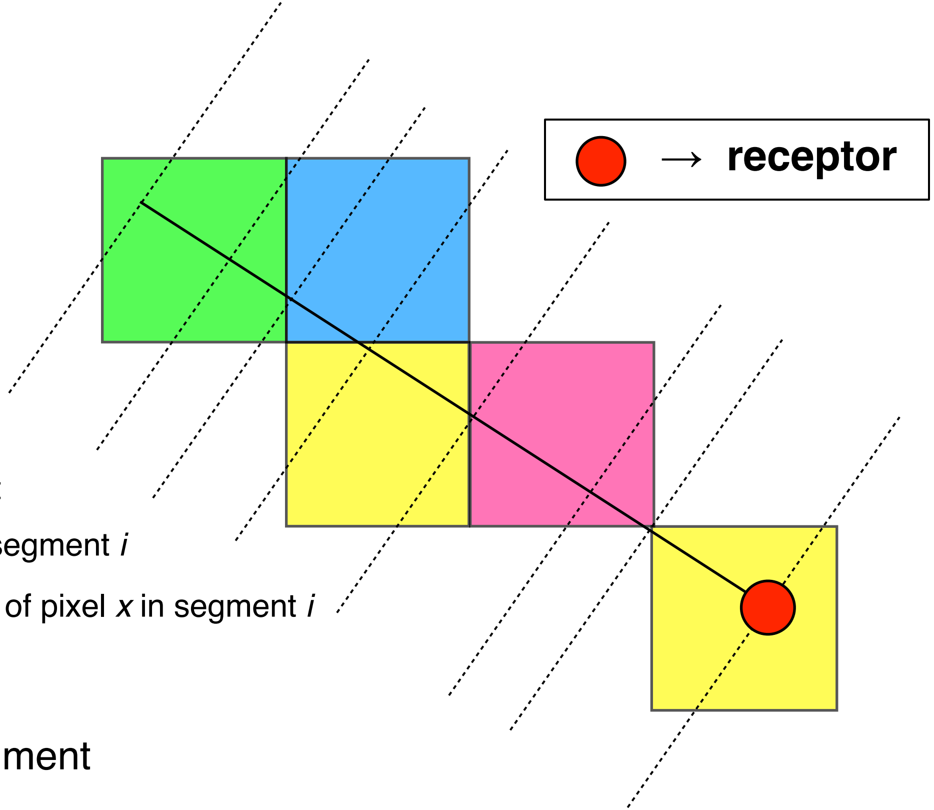

w_i - weights proportional to the length of the segment

Prediction of retina image

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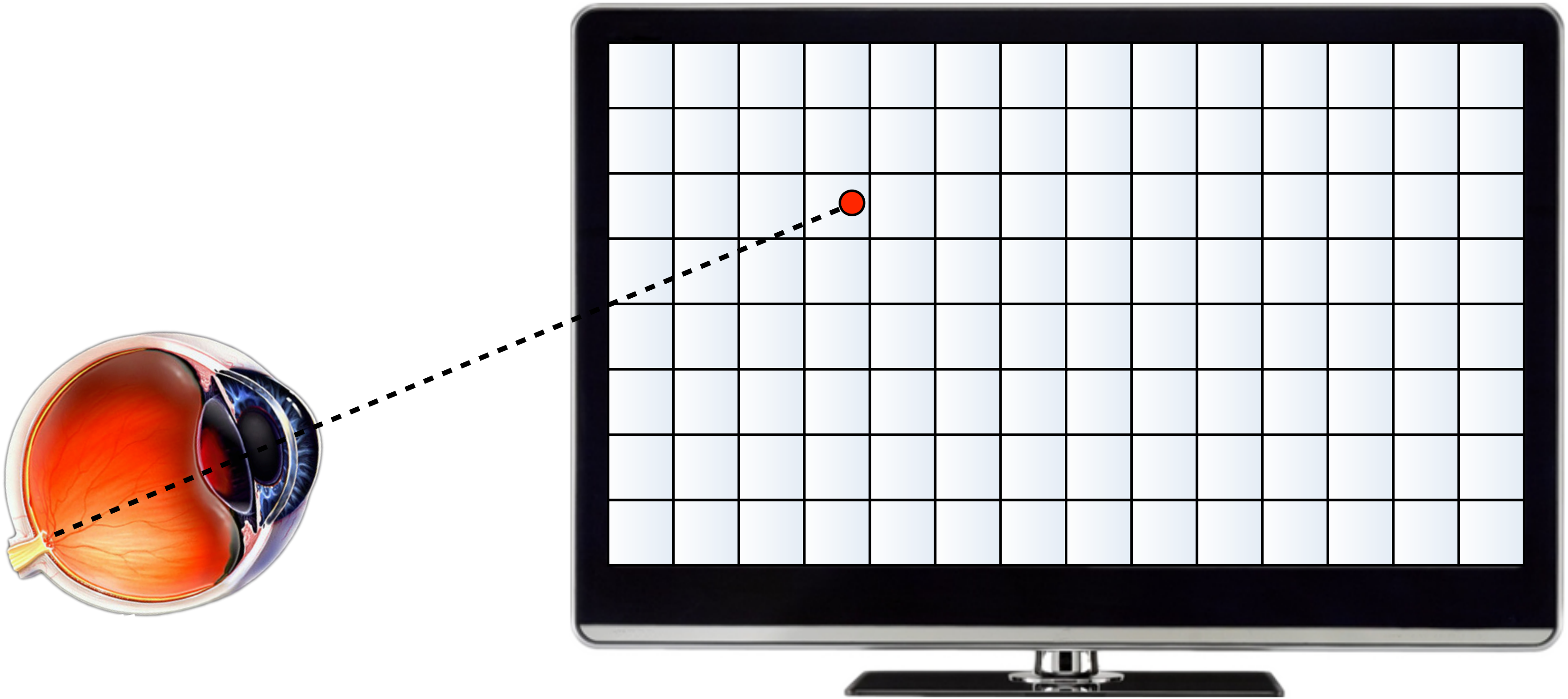
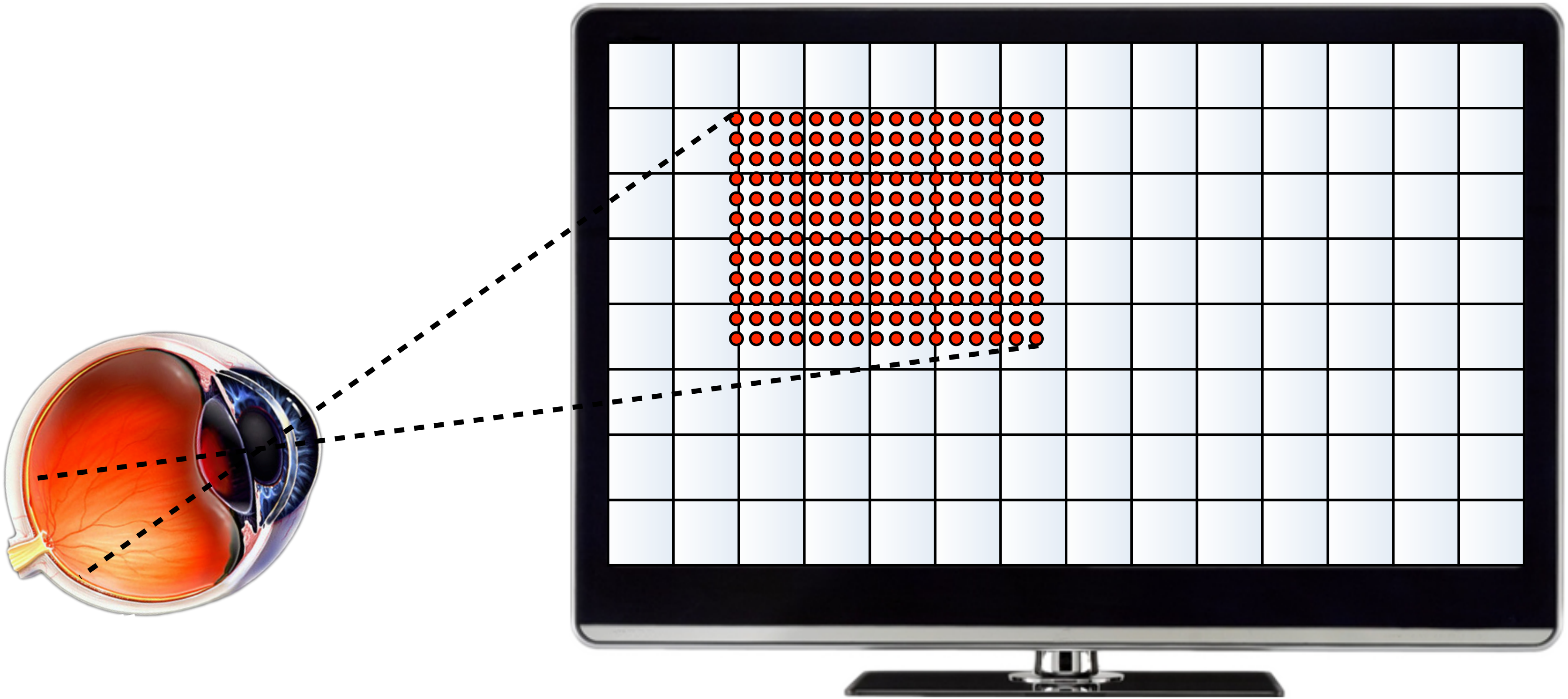
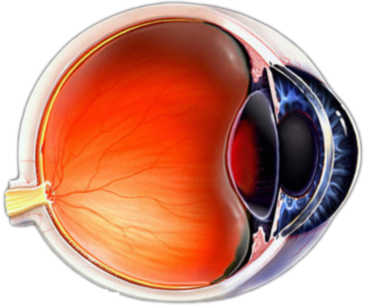
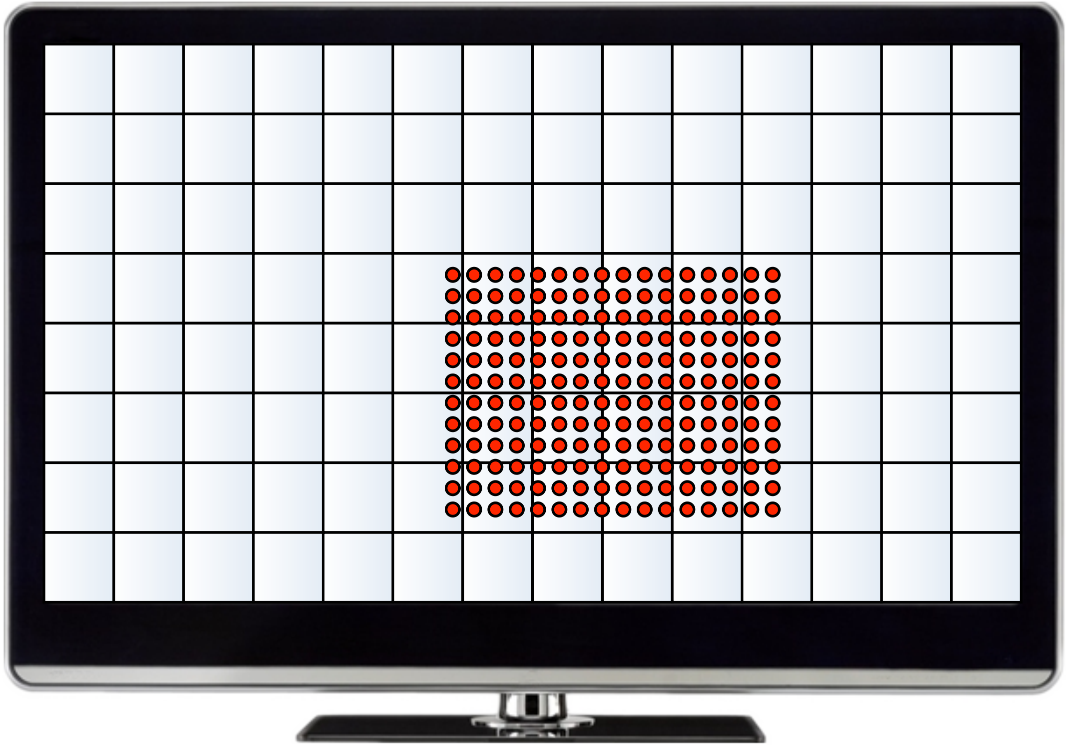


Prediction of retina image

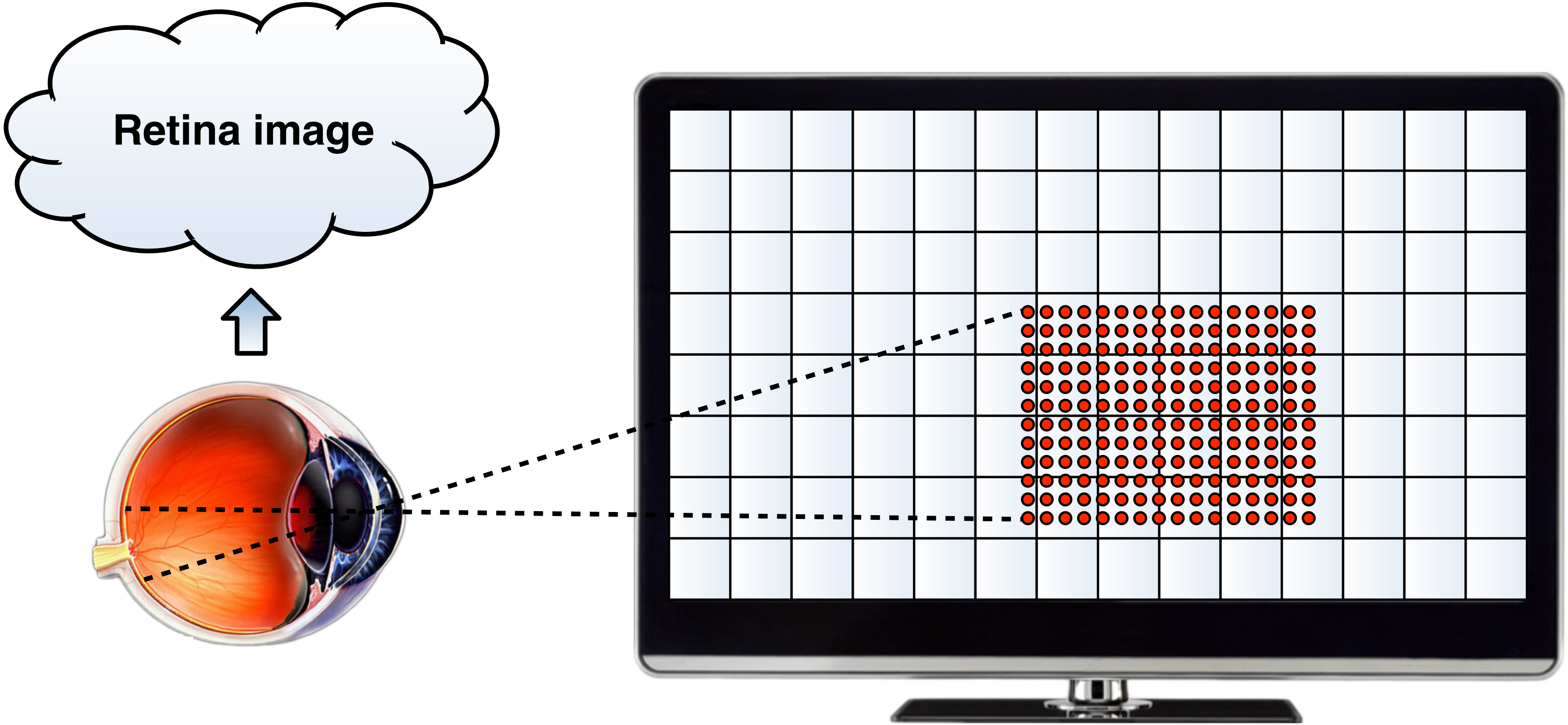


Prediction of retina image



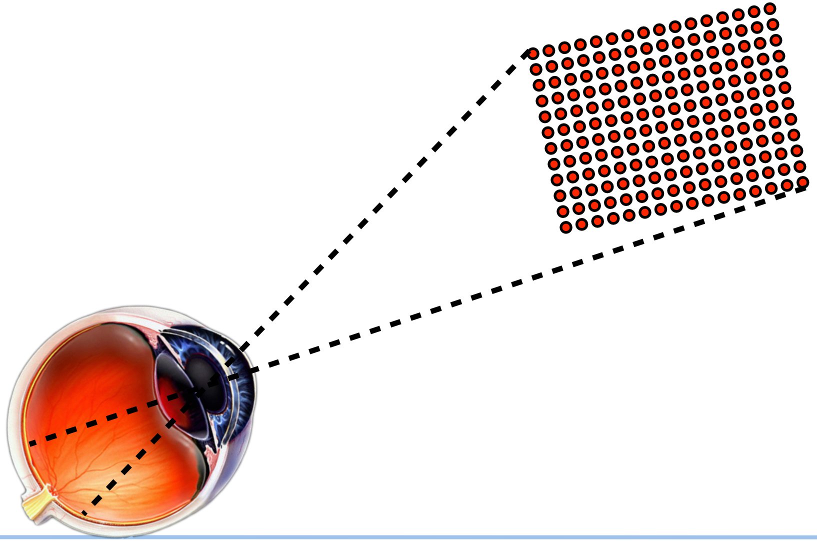


Prediction of retina image



Prediction of retina image

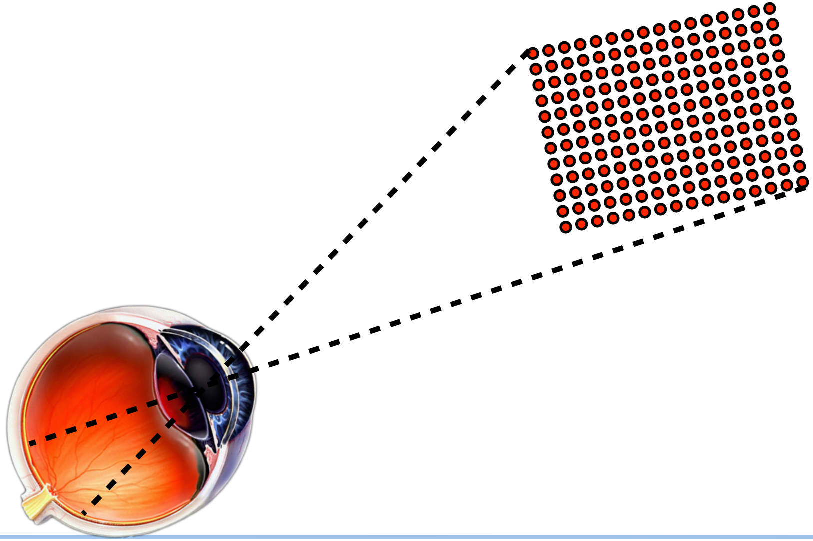
Assumptions:



Prediction of retina image

Assumptions:

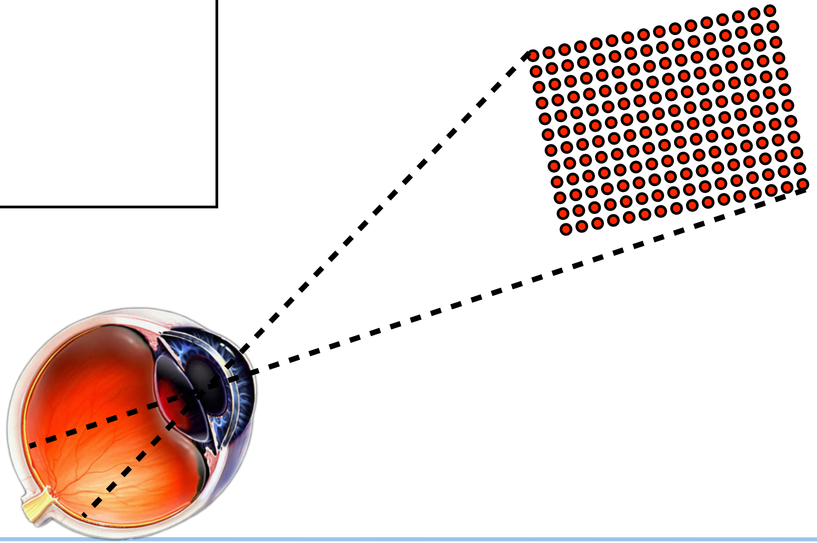
- Eye is tracking perfectly



Prediction of retina image

Assumptions:

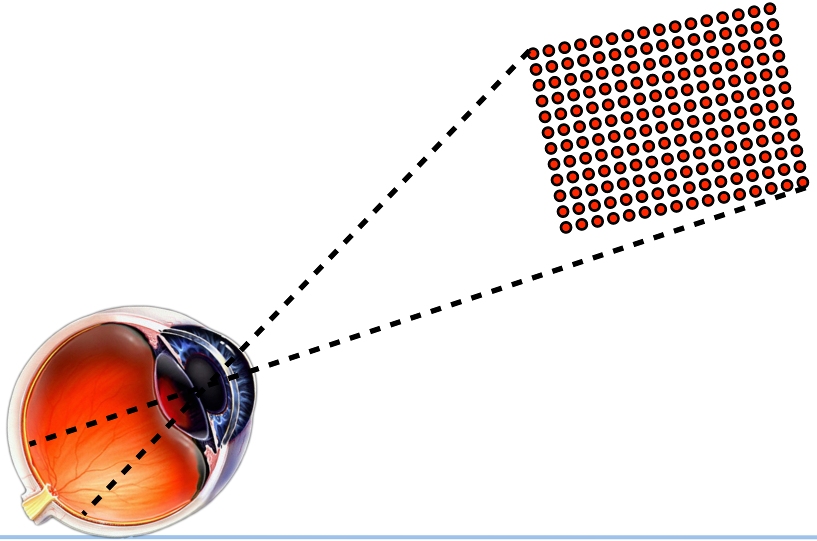
- Eye is tracking perfectly
  - HVS is trained to track (*smooth pursuit eye motion)*
    0.625 - 2.5 deg/s - perfect
    up to 7 deg/s - very good
  - switching and initialization fast



Prediction of retina image

Assumptions:

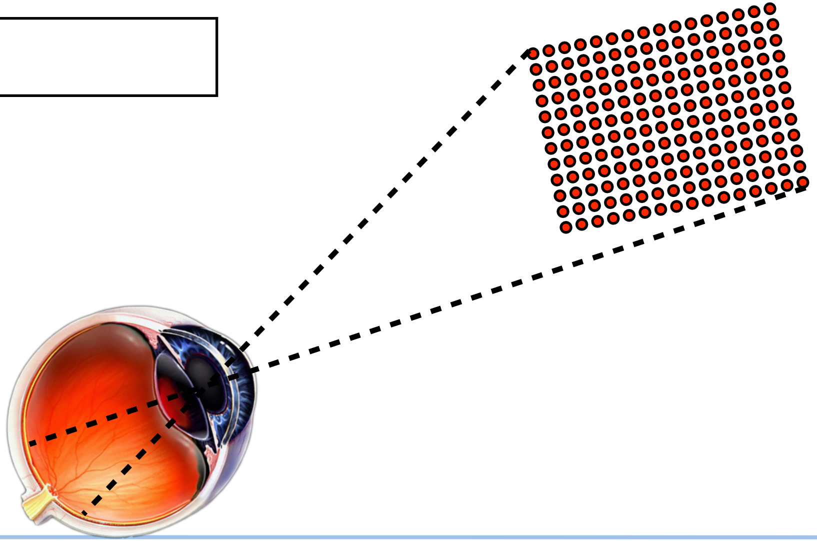
- Eye is tracking perfectly *OK*
- Retina represented as a grid of photoreceptors



Prediction of retina image

Assumptions:

- Eye is tracking perfectly ***OK***
- Retina represented as a grid of photoreceptors
  - should be dense enough



Prediction of retina image

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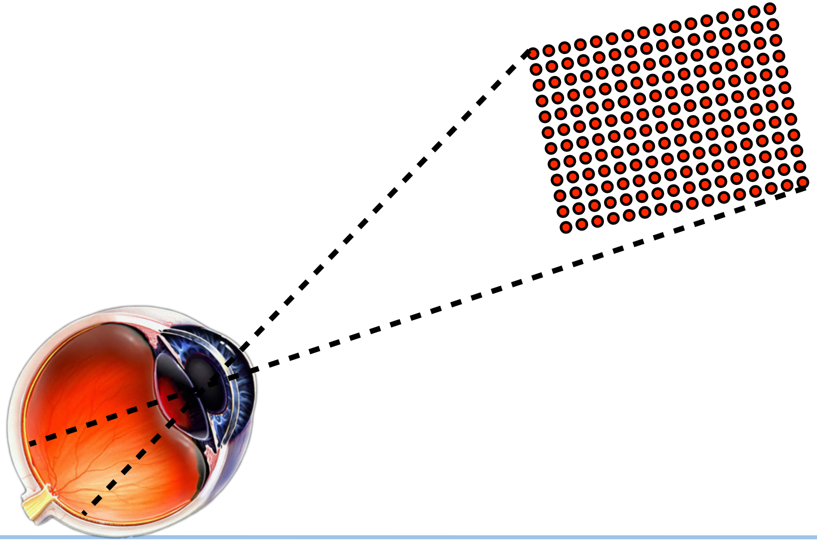
Assumptions:

- Eye is tracking perfectly ***OK***
- Retina represented as a grid of photoreceptors ***Reasonable***
- Temporal filter assumed to be a box filter



Prediction of retina image

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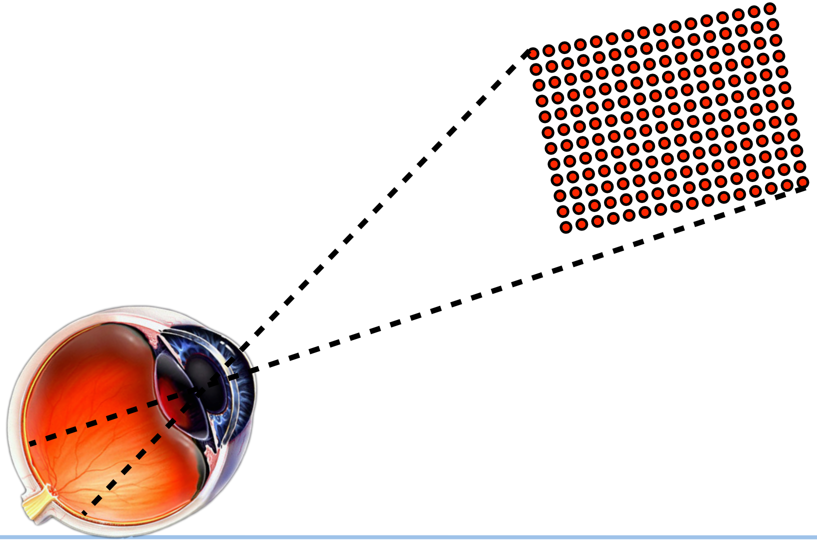
Assumptions:

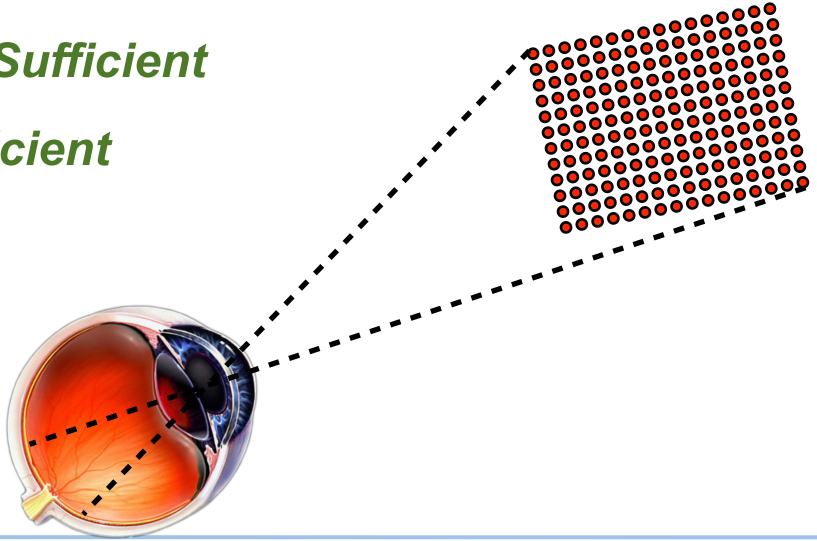
- Eye is tracking perfectly ***OK***
- Retina represented as a grid of photoreceptors ***Reasonable***
- Temporal filter assumed to be a box filter
- Simple display and eye optics model



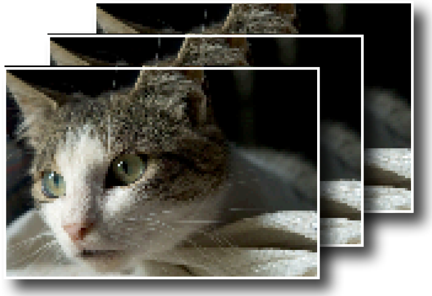
Prediction of retina image

Assumptions:

- Eye is tracking perfectly ***OK***
- Retina represented as a grid of photoreceptors ***Reasonable***
- Temporal filter assumed to be a box filter ***Sufficient***
- Simple display and eye optics model ***Sufficient***

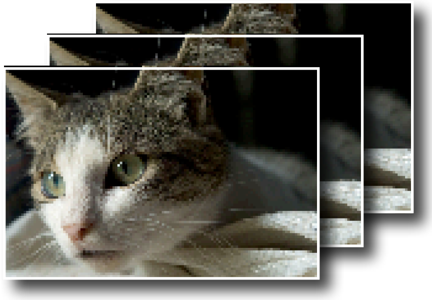


Prediction in equations



subimages

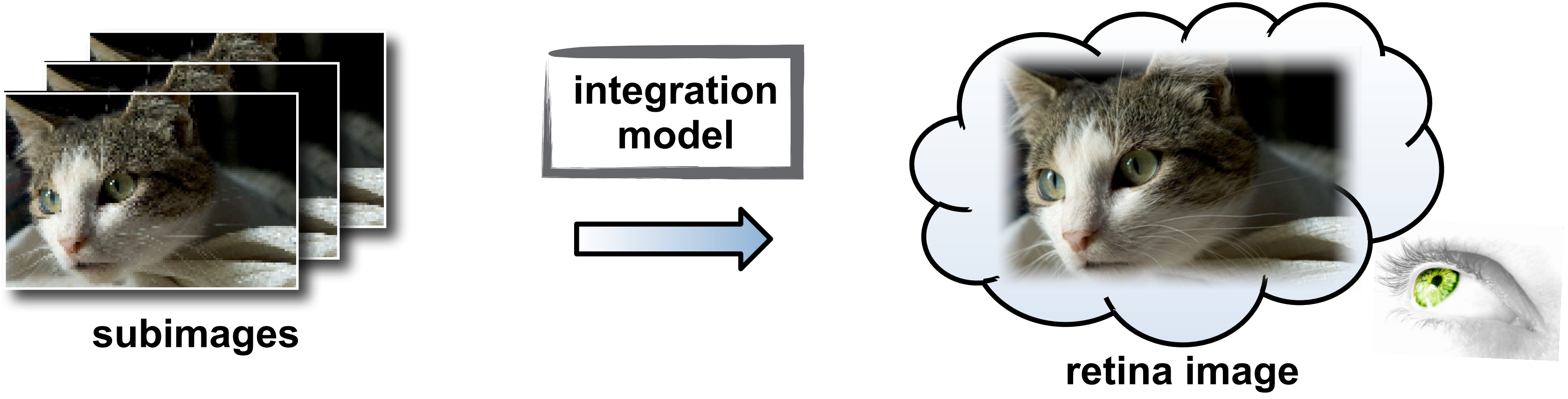
Prediction in equations



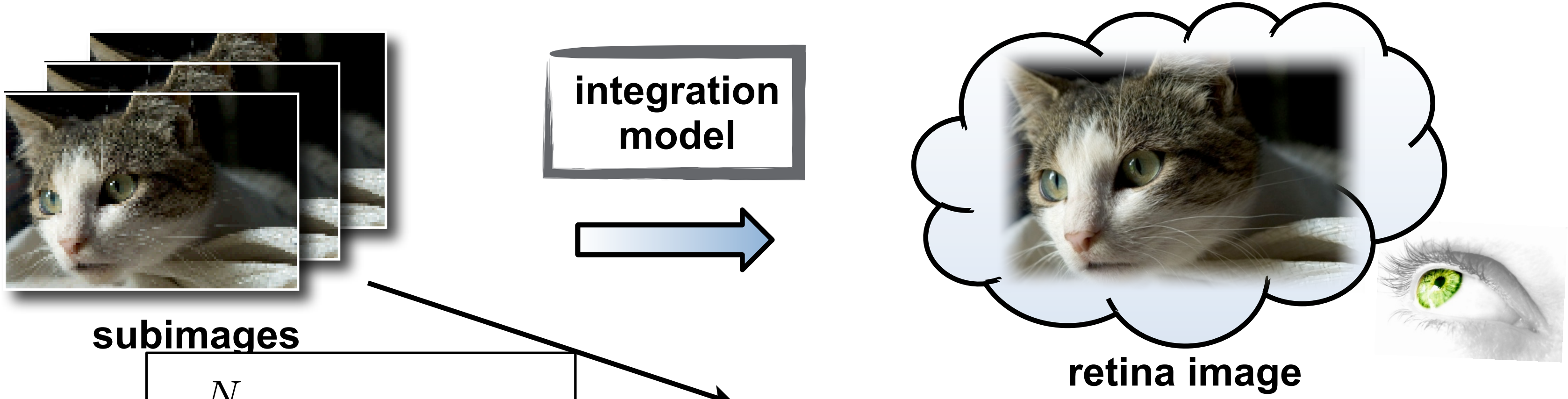
subimages

integration model

Prediction in equations



Prediction in equations



$$\sum_{i=0}^{N} w_i\, I(p(i), i)$$

$$\begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} I_1(1,1) \\ I_1(2,1) \\ \dots \\ I_1(m,k) \\ I_2(1,1) \\ \dots \\ I_n(m,k) \end{pmatrix}$$

Prediction in equations

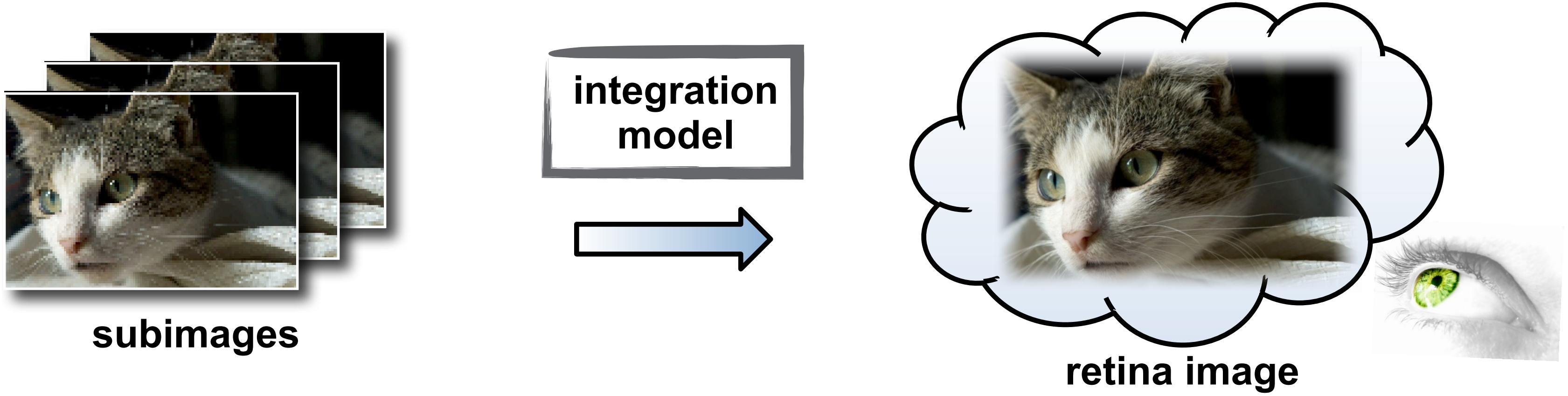
$$\sum_{i=0}^{N} w_i I(p(i), i)$$

integration model

retina image

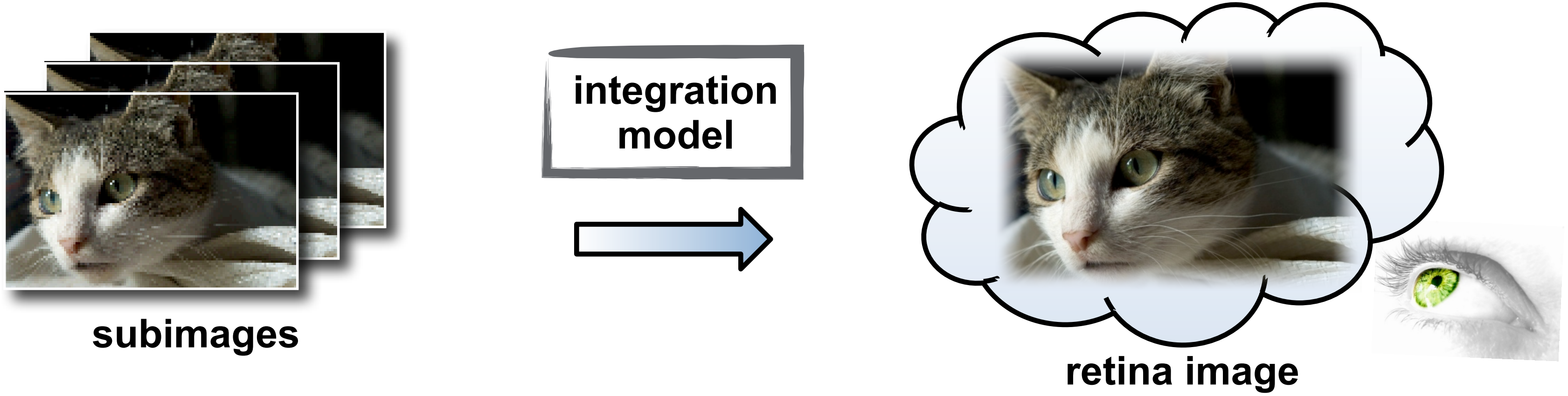
$$\left(\quad W \quad \right) \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix}$$

Prediction in equations



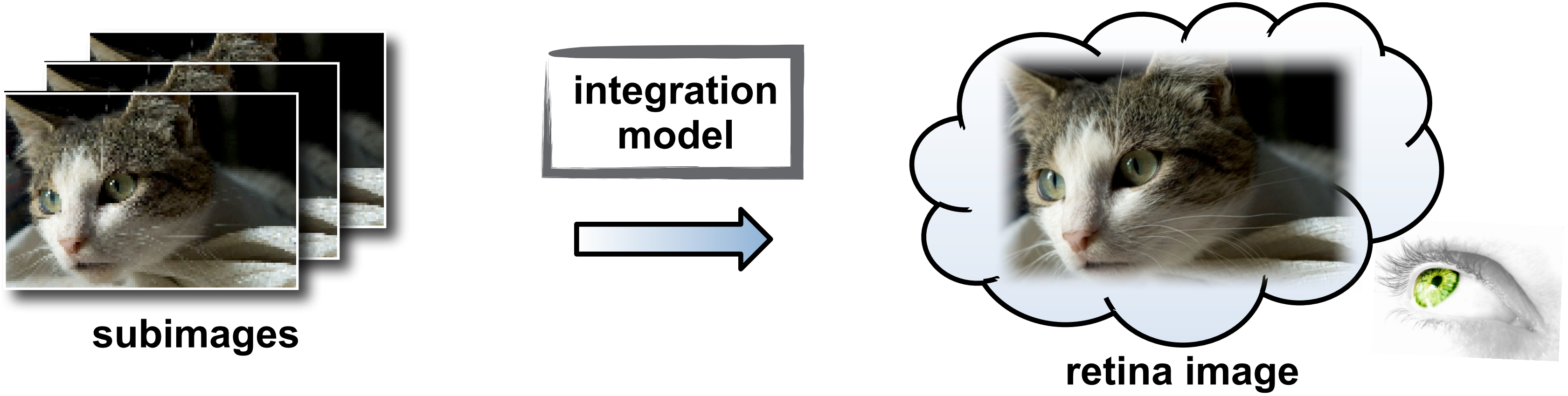
$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

Prediction in equations



$$\begin{pmatrix} w_{1,1},\ w_{1,2},\ \ldots,\ w_{n,m} \\ W \\ \\ \\ \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \ldots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

Prediction in equations

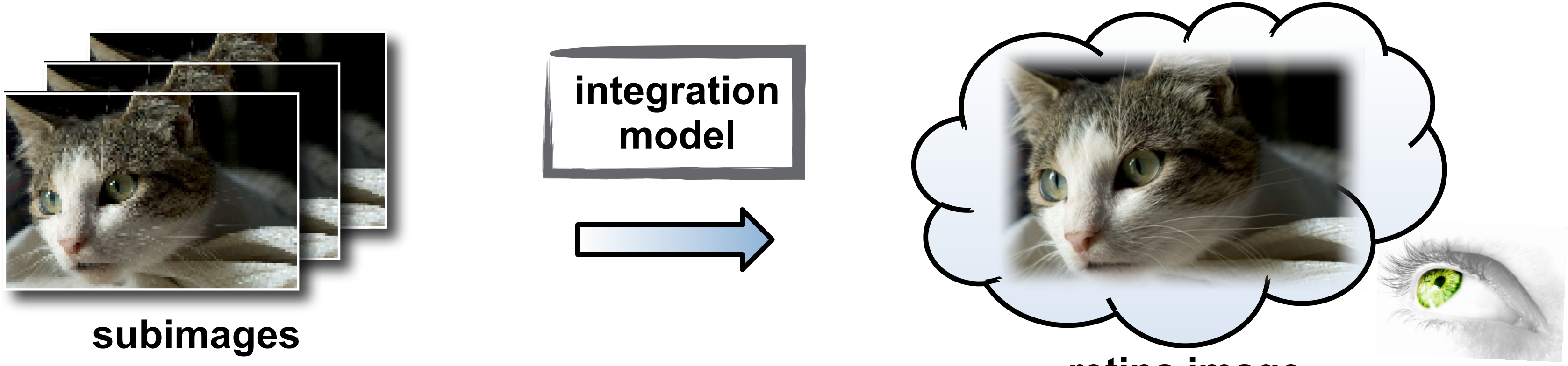


$$\begin{pmatrix} w_{1,1},\ w_{1,2},\ \ldots,\ w_{n,m} \\ \\ W \\ \\ \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \ldots \\ I_n^L \end{pmatrix} = \begin{pmatrix} i_{x,y} \\ I^H \\ \\ \end{pmatrix}$$

prediction for one receptor

$$\sum_{i=0}^{N} w_i \, I(p(i), i)$$

Optimization problem



subimages

retina image

$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} I^H \end{pmatrix}$$

Optimization problem

$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

Optimization problem

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$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

Optimization problem

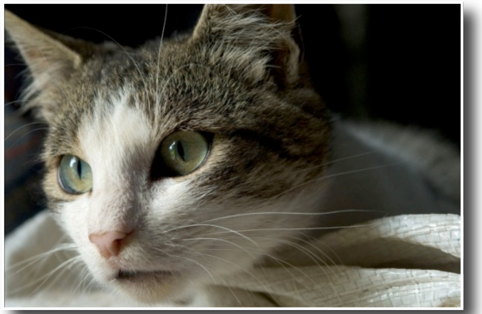
$$\left(\quad W \quad \right) \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \left(\quad I^H \quad \right)$$

integration model

Optimization problem

$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

integration model

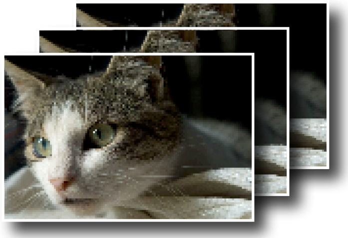


high resolution image

Optimization problem

$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} I^H \end{pmatrix}$$

integration model



subimages

high resolution image

Optimization problem

$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

Optimization problem

$$\begin{pmatrix} \\ & W & \\ \\ \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

We solve it with least square method

Optimization problem

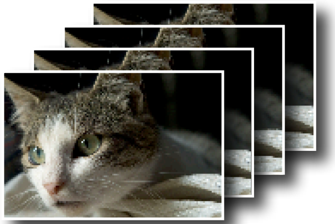
$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

Optimization problem

$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \dots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

Optimization problem

$$\begin{pmatrix} \\ & W & \\ \\ \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \cdots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$



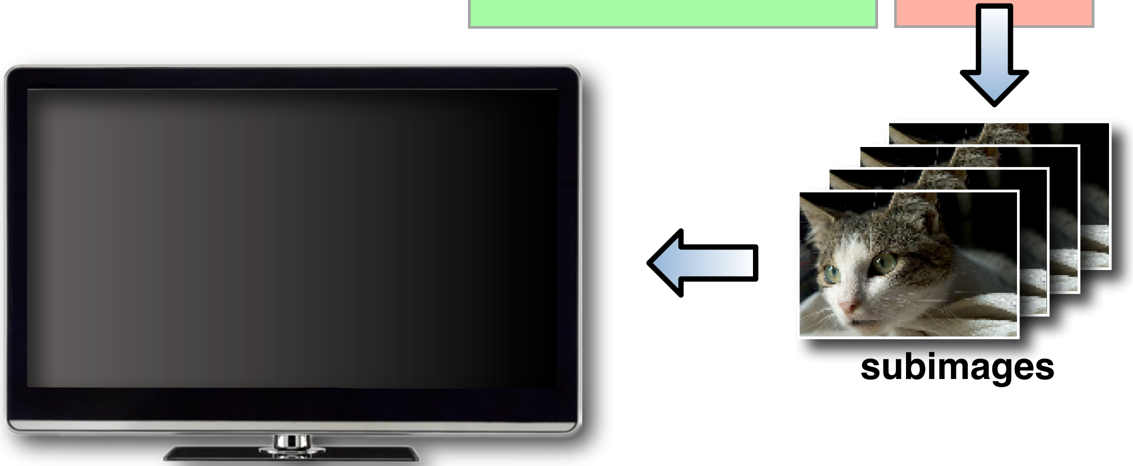
subimages

Optimization problem

We cannot display arbitrary values

➡ System needs to be constrained

$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \cdots \\ I_n^L \end{pmatrix} = \begin{pmatrix} I^H \end{pmatrix}$$



Optimization problem

We cannot display arbitrary values

➡ System needs to be constrained

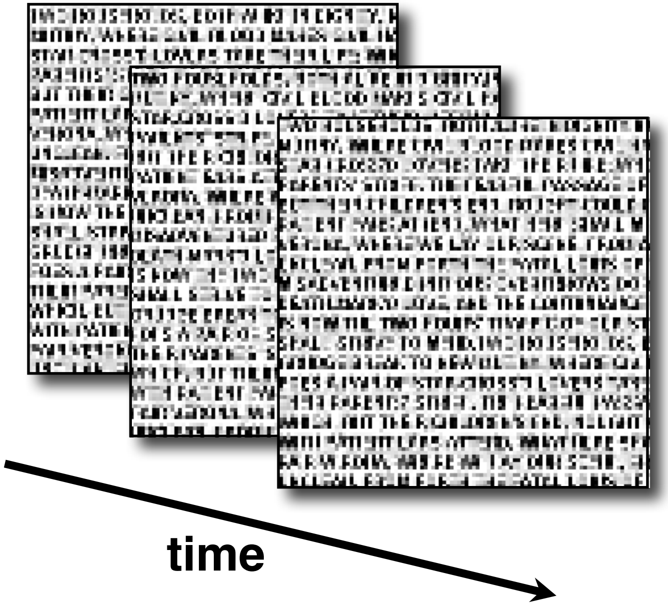
$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \cdots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

"A reflective Newton method for minimizing a quadratic function subject to bounds on some of the variables"

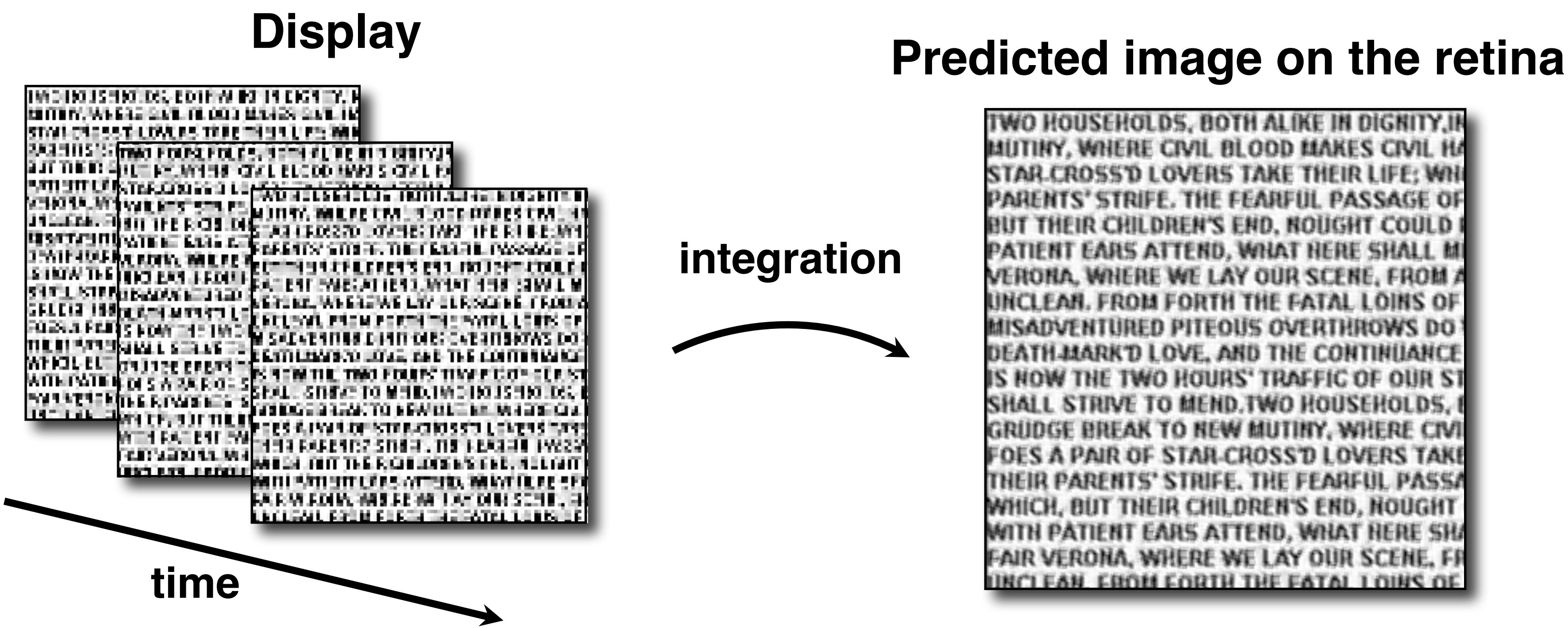
[Coleman et al. 2005]

Optimization results

Display

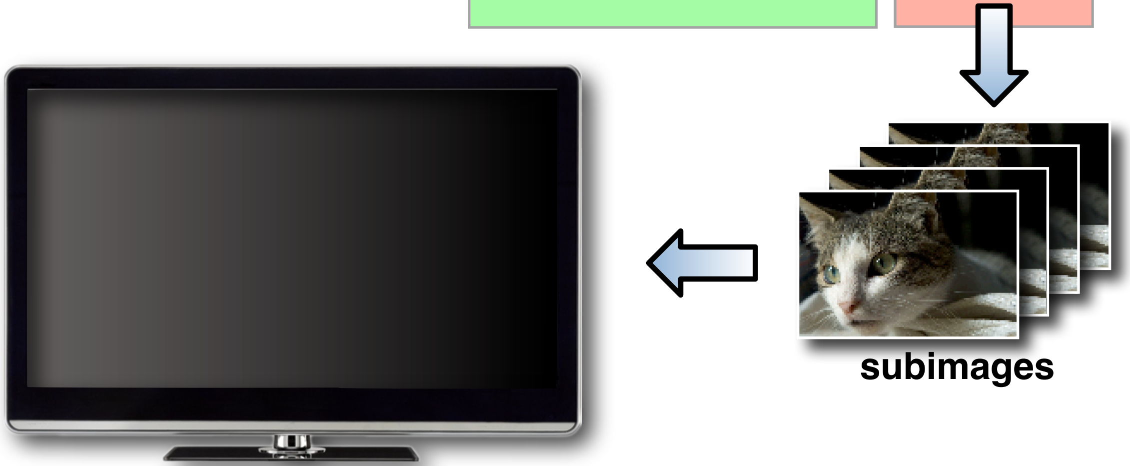


Optimization results



Subimages

$$W \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \cdots \\ I_n^L \end{pmatrix} = \begin{pmatrix} I^H \end{pmatrix}$$

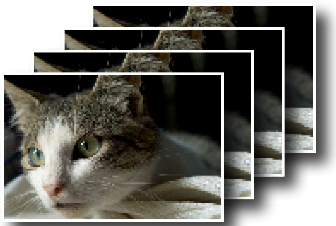


subimages

Subimages

Human Visual System

$$\begin{pmatrix} & & \\ & W & \\ & & \end{pmatrix} \begin{pmatrix} I_1^L \\ I_2^L \\ I_3^L \\ \cdots \\ I_n^L \end{pmatrix} = \begin{pmatrix} \\ I^H \\ \\ \end{pmatrix}$$

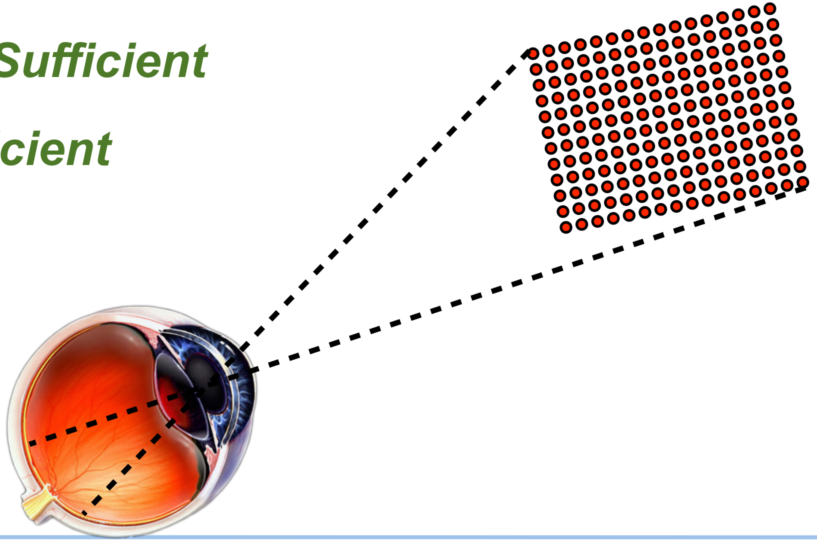


subimages

Prediction of retina image

Assumptions:

- Eye is tracking perfectly ***OK***
- Retina represented as a grid of photoreceptors ***Reasonable***
- Temporal filter assumed to be a box filter ***Sufficient***
- Simple display and eye optics model ***Sufficient***



Prediction of retina image

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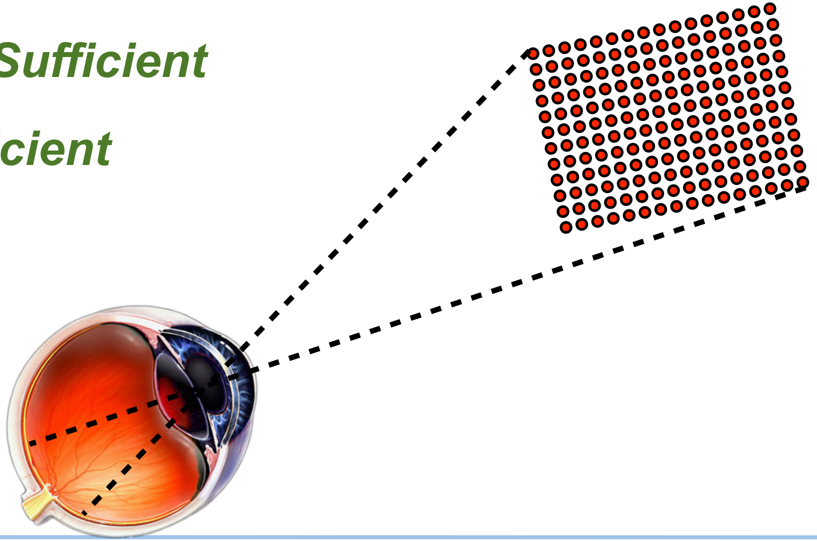
Assumptions:

- Eye is tracking perfectly ***OK***
- Retina represented as a grid of photoreceptors ***Reasonable***
- Temporal filter assumed to be a box filter ***Sufficient***
- Simple display and eye optics model ***Sufficient***
- **All frames are fused**



Prediction of retina image

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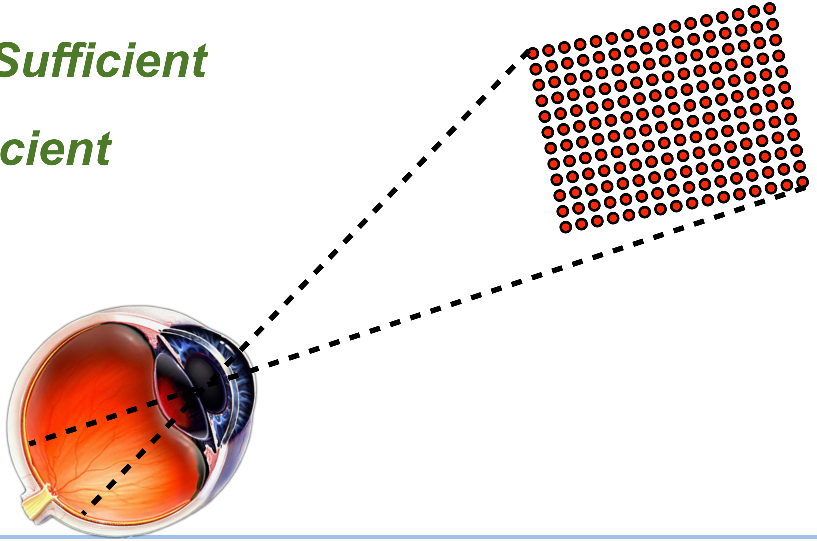
Assumptions:

- Eye is tracking perfectly ***OK***
- Retina represented as a grid of photoreceptors ***Reasonable***
- Temporal filter assumed to be a box filter ***Sufficient***
- Simple display and eye optics model ***Sufficient***
- **All frames are fused** ***We will solve it***



Fusing frames

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Fusing frames

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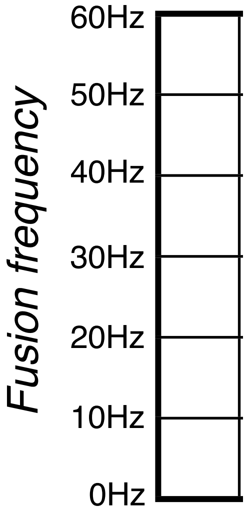
Fusing frames

When do we start fusing the subimages?

Fusion frequency

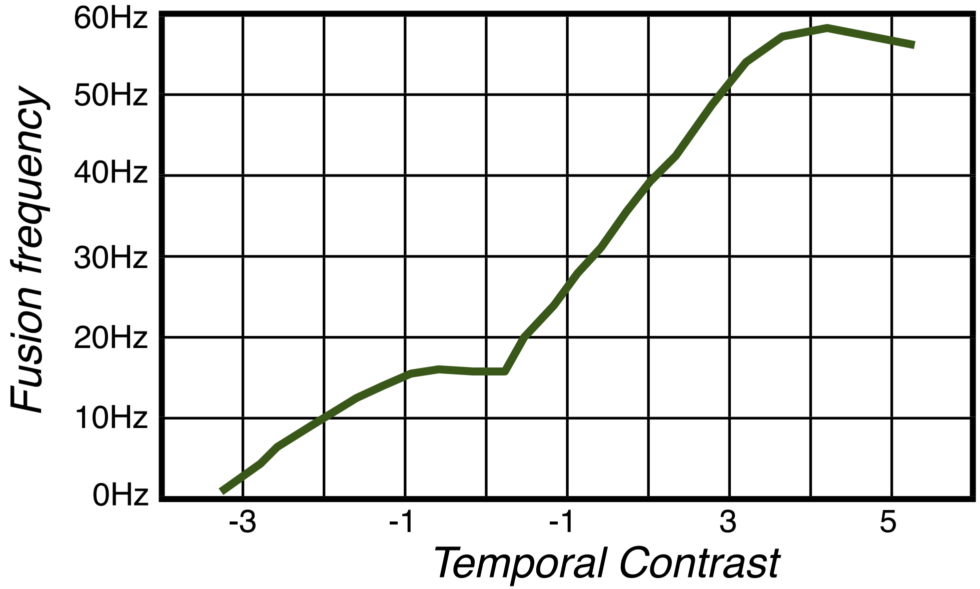
Fusion frequency depends on:



Fusion frequency

Fusion frequency depends on:

- temporal contrast

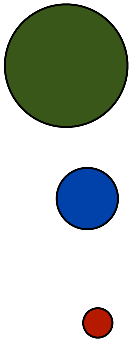


Critical Flicker Frequency - Hecht and Smith's data from
Brown J. L. *Flicker and Intermittent Simulation*

Fusion frequency

Fusion frequency depends on:

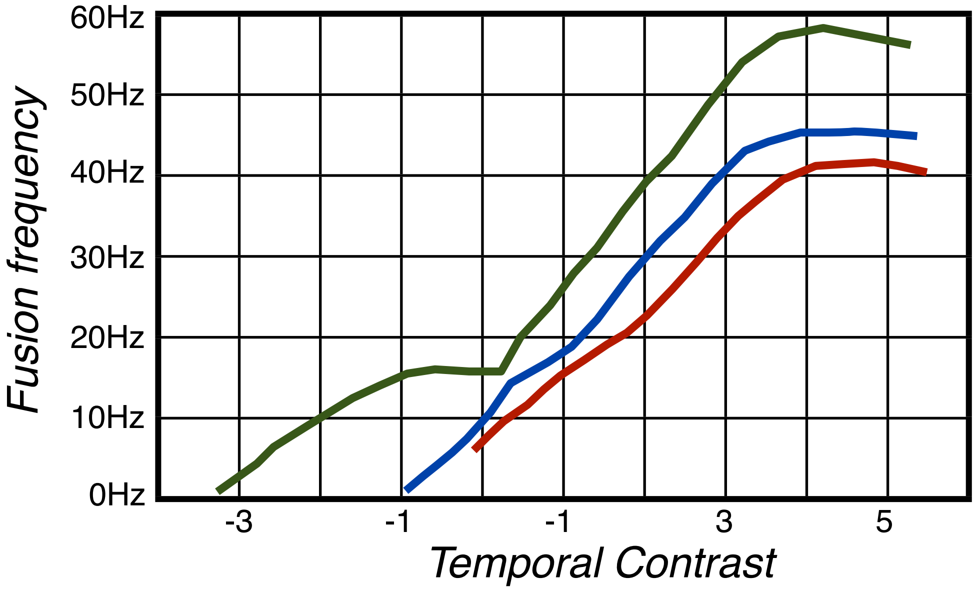
- temporal contrast
- spatial extent of the pattern



19 deg

2 deg

0.3 deg



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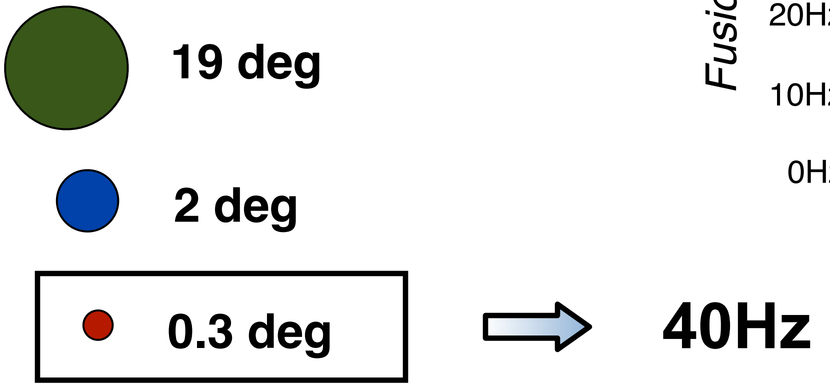

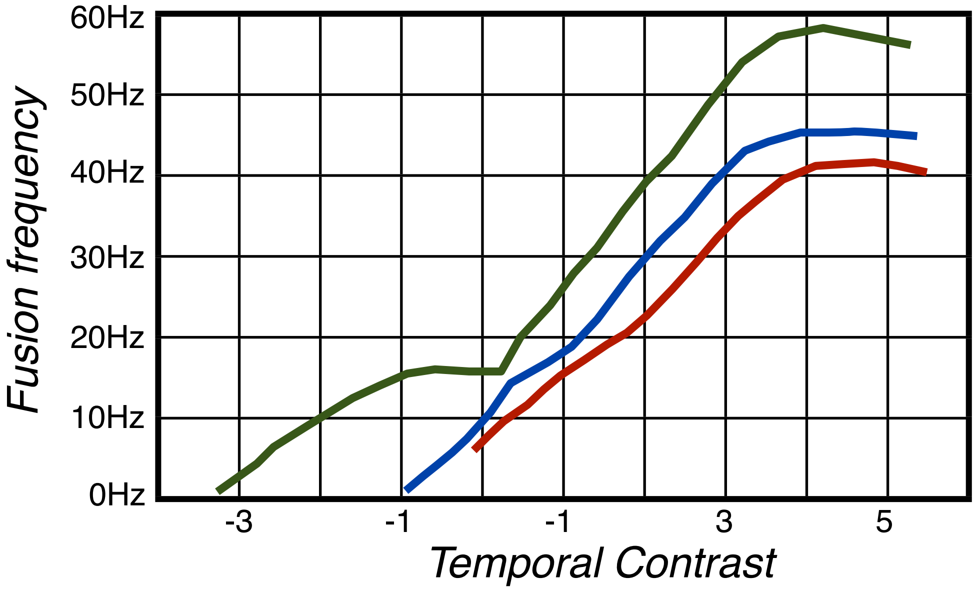

Critical Flicker Frequency - Hecht and Smith's data from
Brown J. L. *Flicker and Intermittent Simulation*

Fusion

120 Hz display
(common for 3D applications)

Fusion

120 Hz display
(common for 3D applications)

40Hz - 3 subimages

Fusion

120 Hz display
(common for 3D applications)

40Hz - 3 subimages

- fine details are fused
- bigger not necessary

Fusion

120 Hz display

(common for 3D applications)

40Hz - 3 subimages

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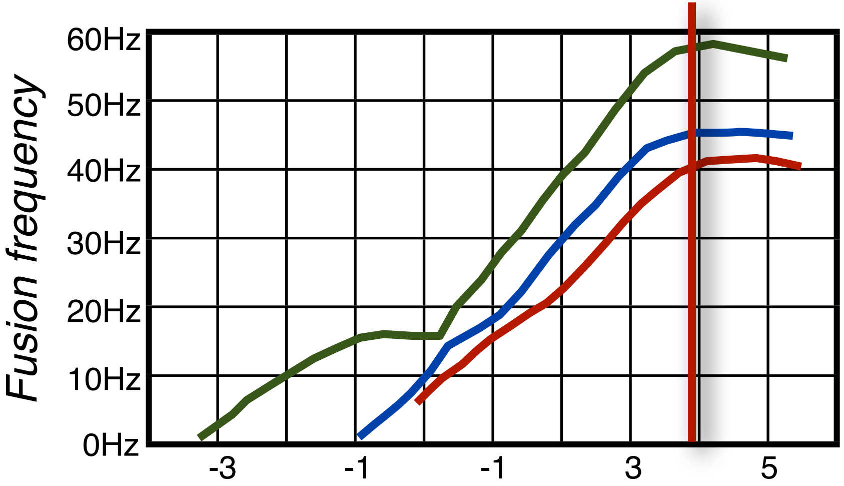

Fusion

120 Hz display

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40Hz - 3 subimages

- fine details are fused
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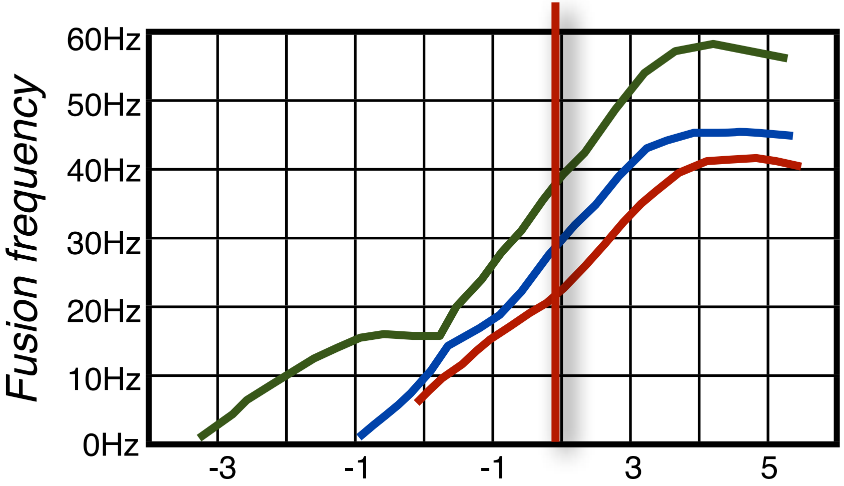
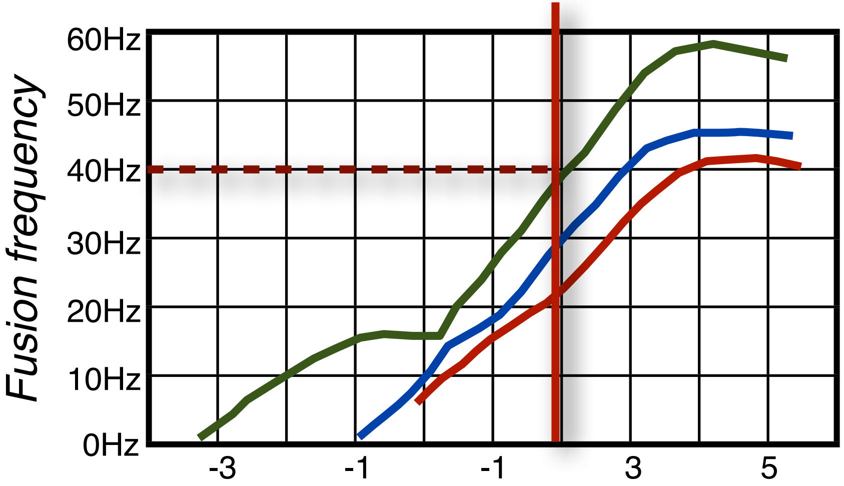


Fusion

120 Hz display
(common for 3D applications)

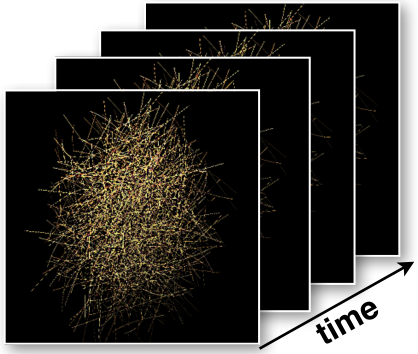
40Hz - 3 subimages

- fine details are fused
- bigger not necessary



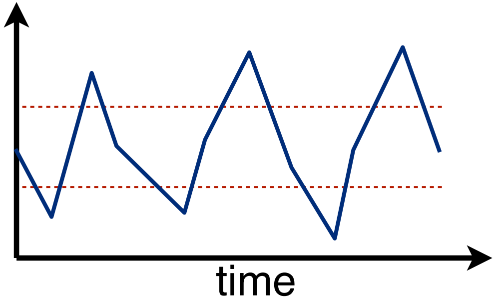
Flickering reduction

Flickering reduction



subimages

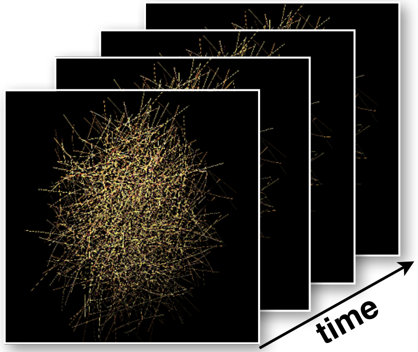
- ➡ local flickering
- ➡ improved resolution



Flickering reduction

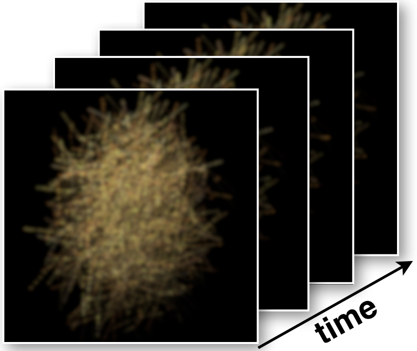
subimages

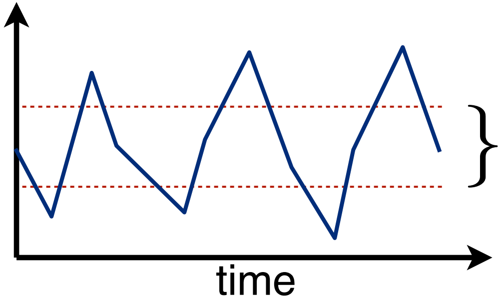
➡ local flickering
➡ improved resolution



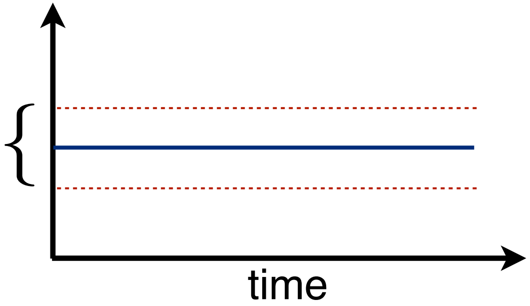
standard solution
(e.g.,Lanczos)

➡ no flickering
➡ low resolution





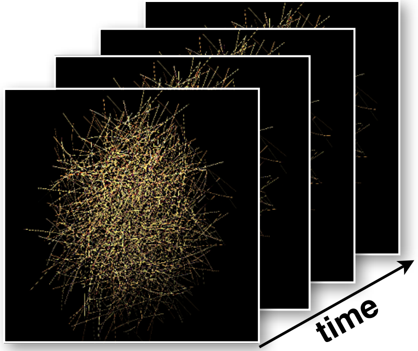
fusion at 40Hz



Flickering reduction

subimages

- ➡ local flickering
- ➡ improved resolution



standard solution

(e.g.,Lanczos)

- ➡ no flickering
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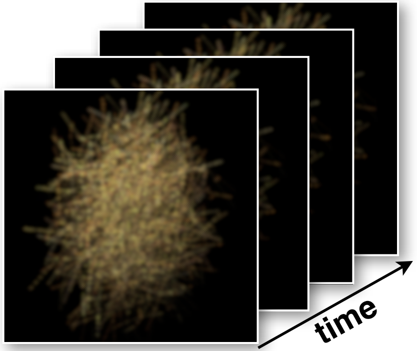
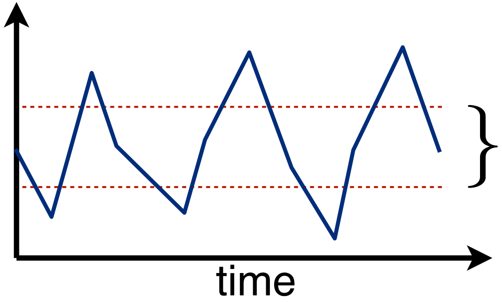
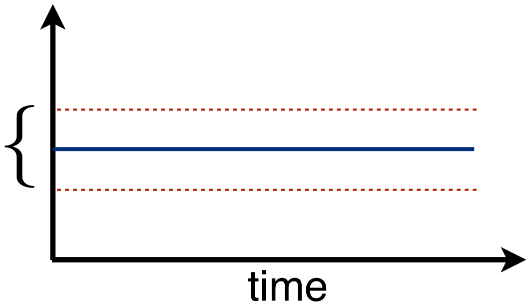


blending



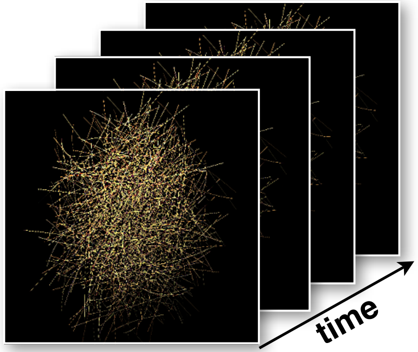
fusion at 40Hz



Flickering reduction

subimages

- ➡ local flickering
- ➡ improved resolution



standard solution

(e.g.,Lanczos)

- ➡ no flickering
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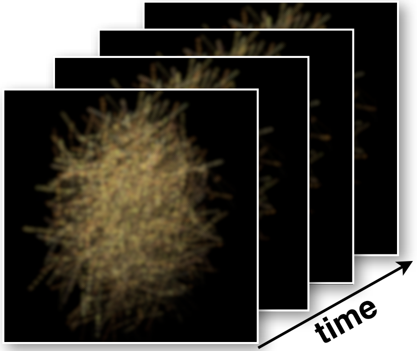
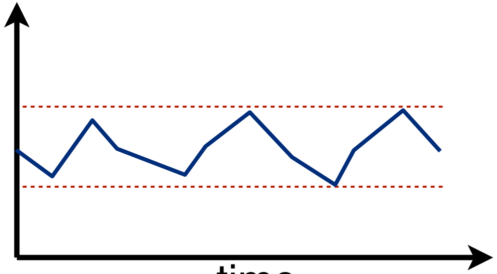


blending



Flickering reduction

subimages

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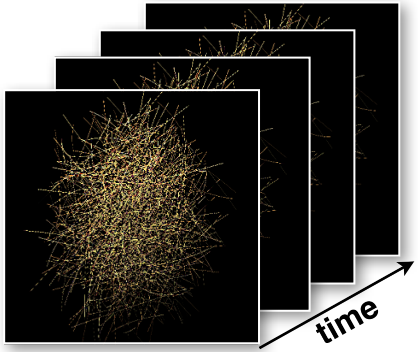
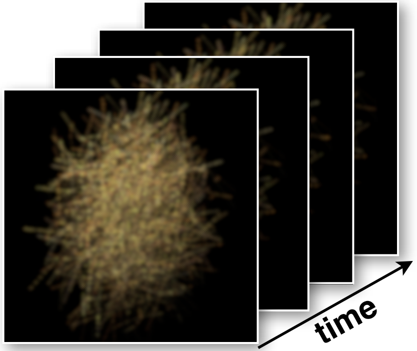


standard solution
(e.g.,Lanczos)

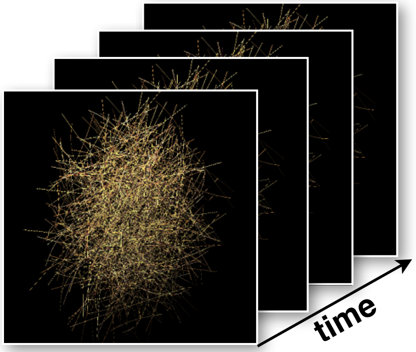
➡ no flickering
➡ low resolution



blending

final solution

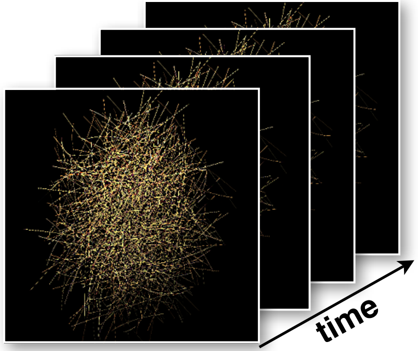
➡ no flickering
➡ improved resolution



Flickering reduction

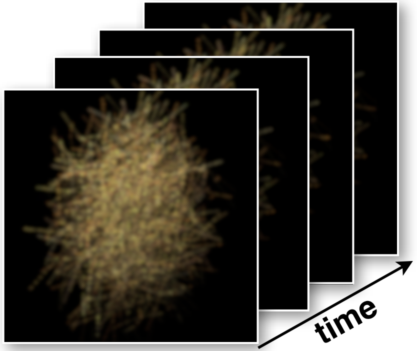
subimages

➡ local flickering
➡ improved resolution

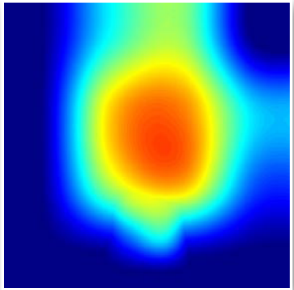


standard solution
(e.g.,Lanczos)

➡ no flickering
➡ low resolution



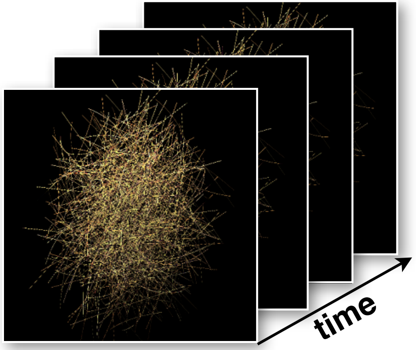
blending



reduction map

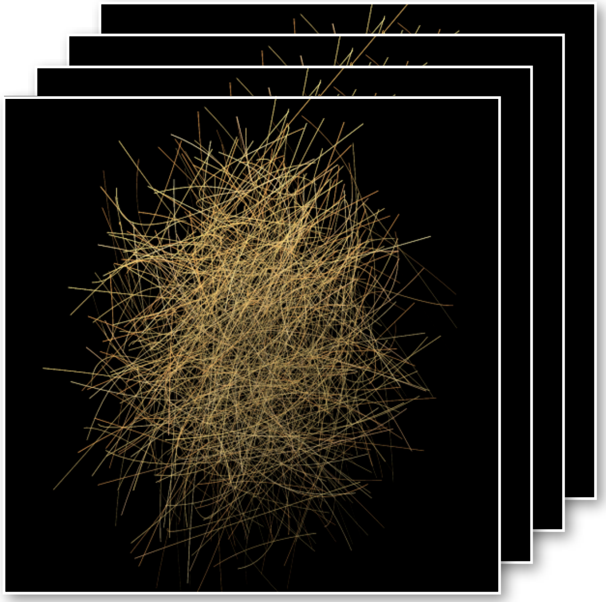
final solution

➡ no flickering
➡ improved resolution

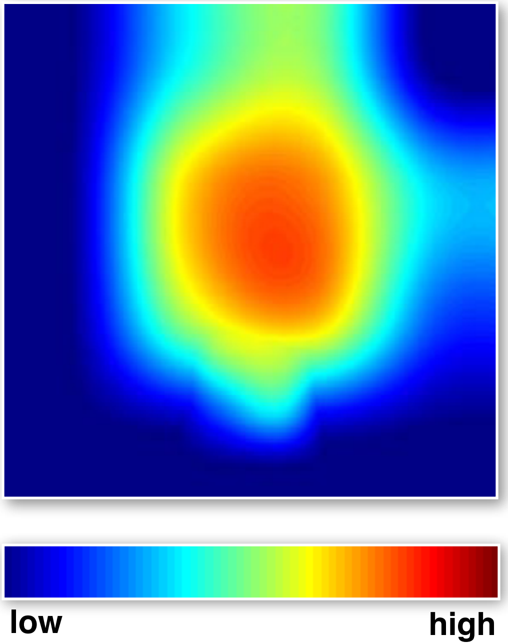


Flickering reduction

subimages

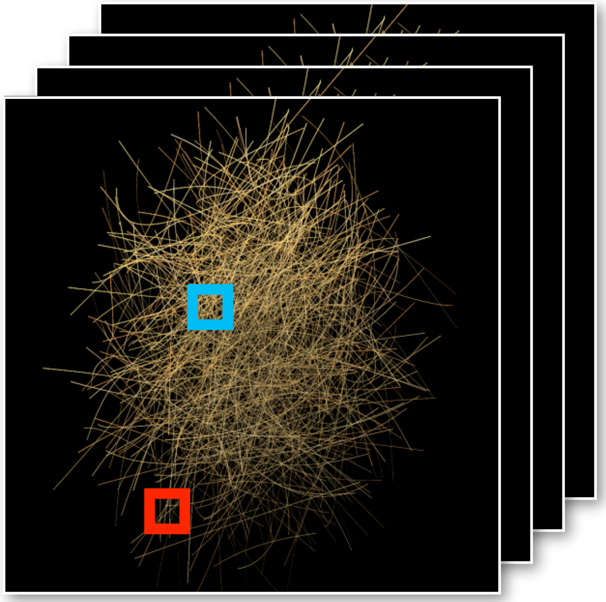


contrast reduction map

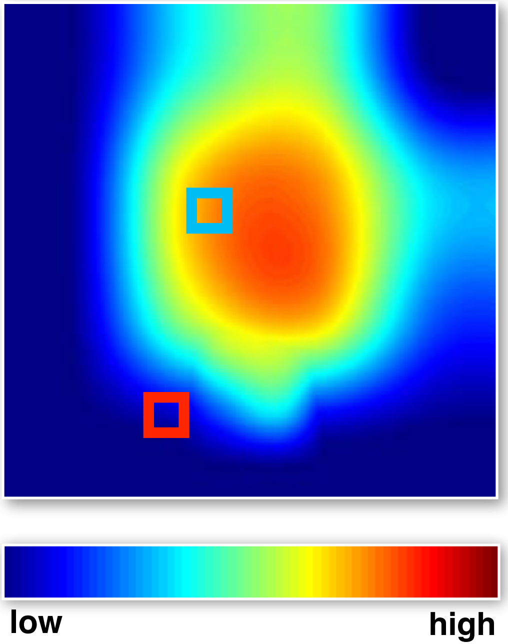


Flickering reduction

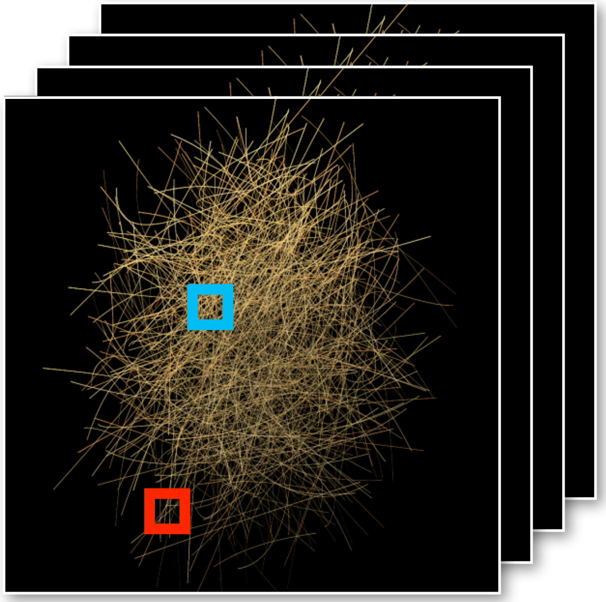
subimages

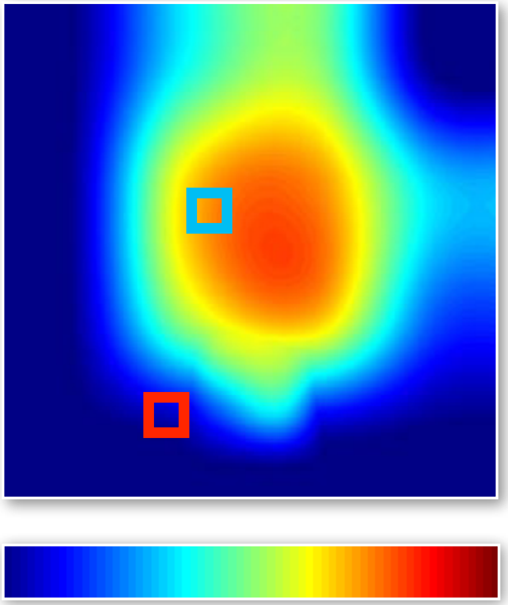


contrast reduction map

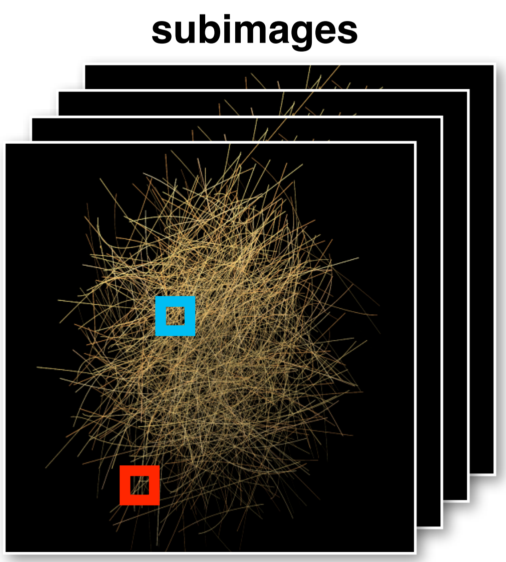


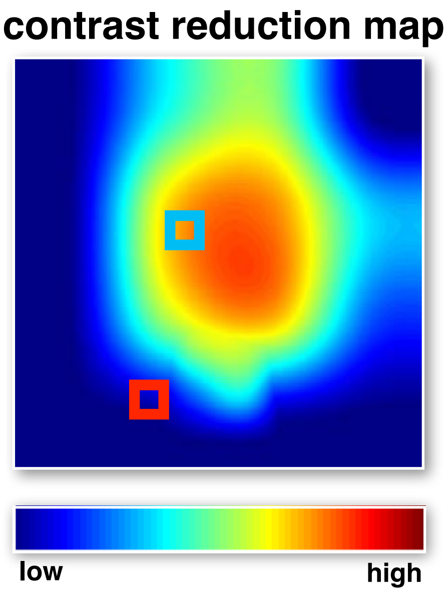
Flickering reduction





Flickering reduction



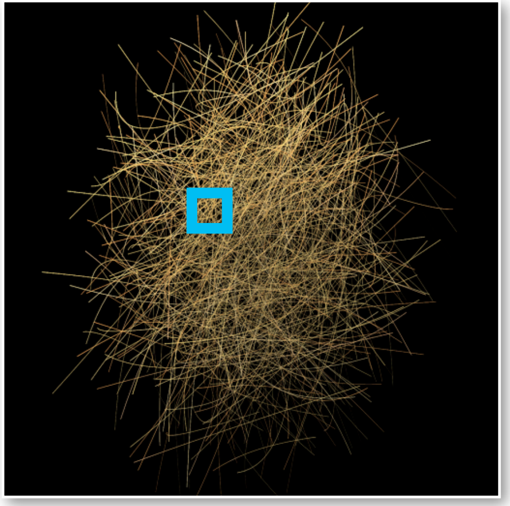


The reduction map: How much we need to reduce temporal contrast

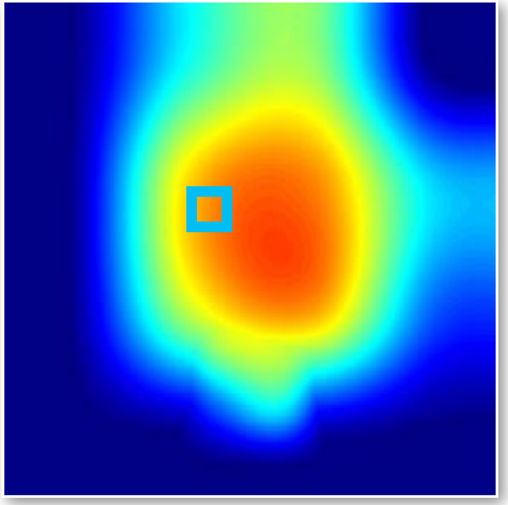
“Effects of luminance and external temporal noise on flickering sensitivity as a function of stimulus size at various eccentricities”
[Mäkelä et al. 1994]

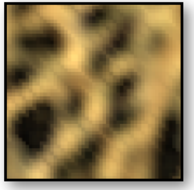
Flickering reduction

original image

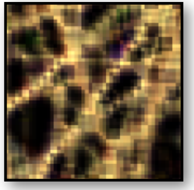


reduction map

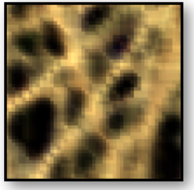




Downsampling



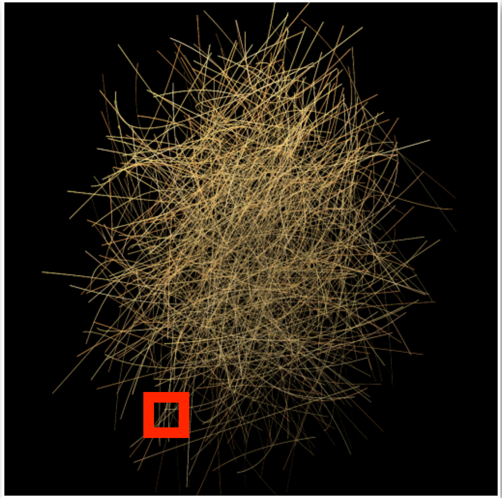
Our
before reduction



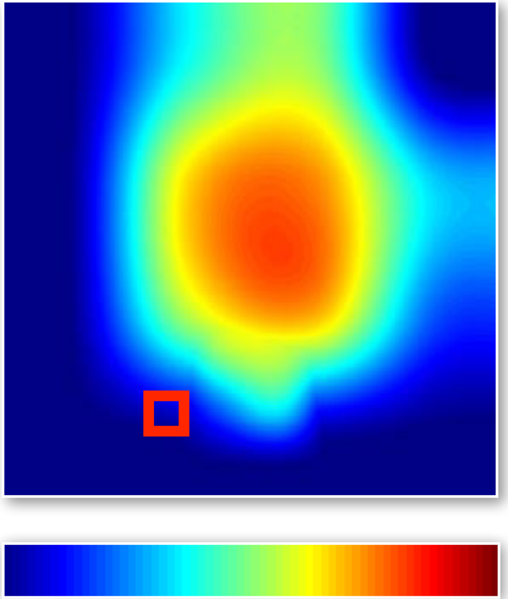
Our
after reduction

Flickering reduction

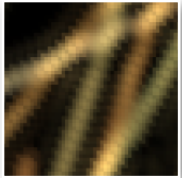
original image



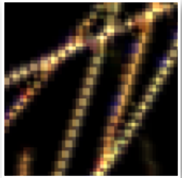
reduction map



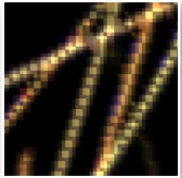
low **high**



Downsampling

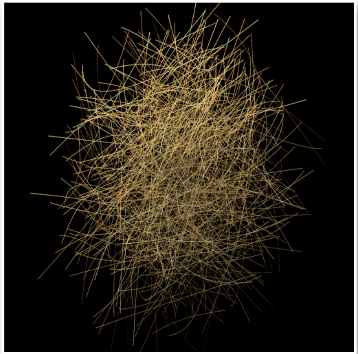


Our
before reduction



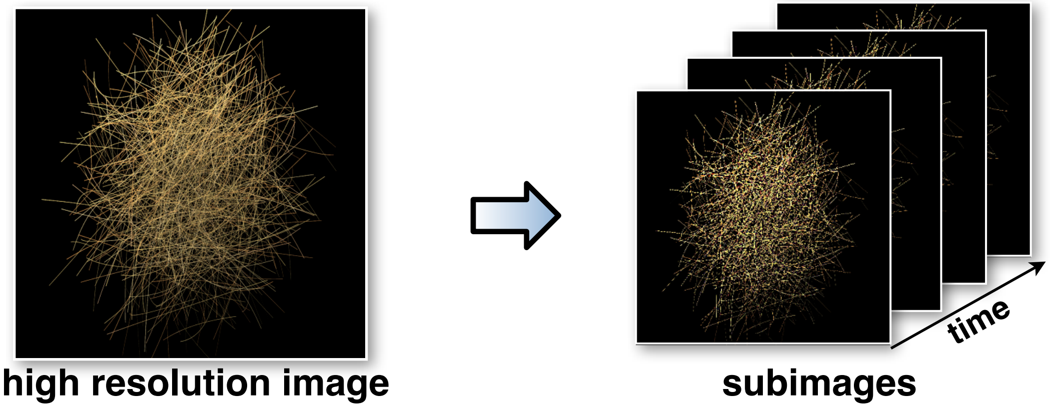
Our
after reduction

Full pipeline

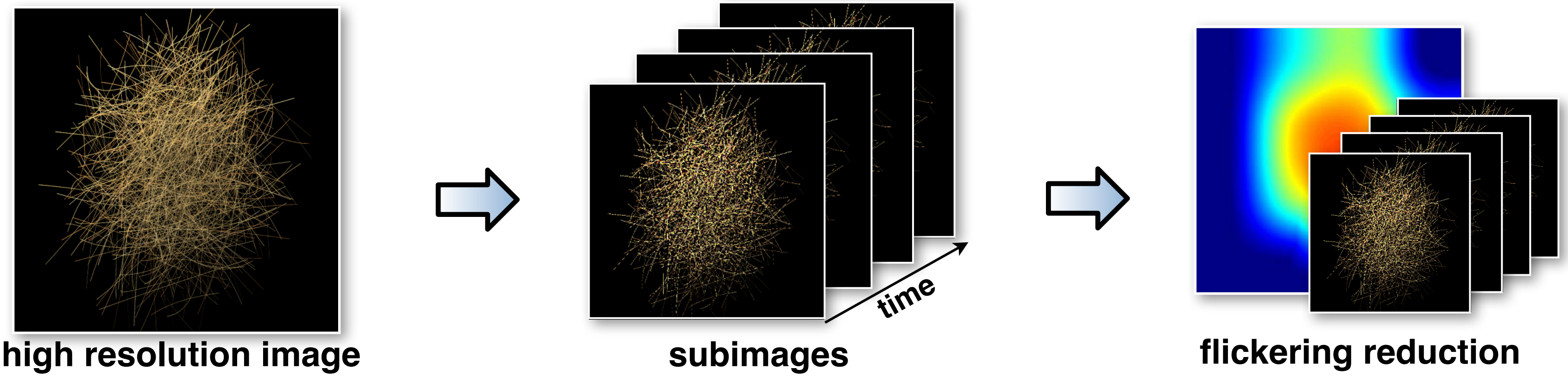


high resolution image

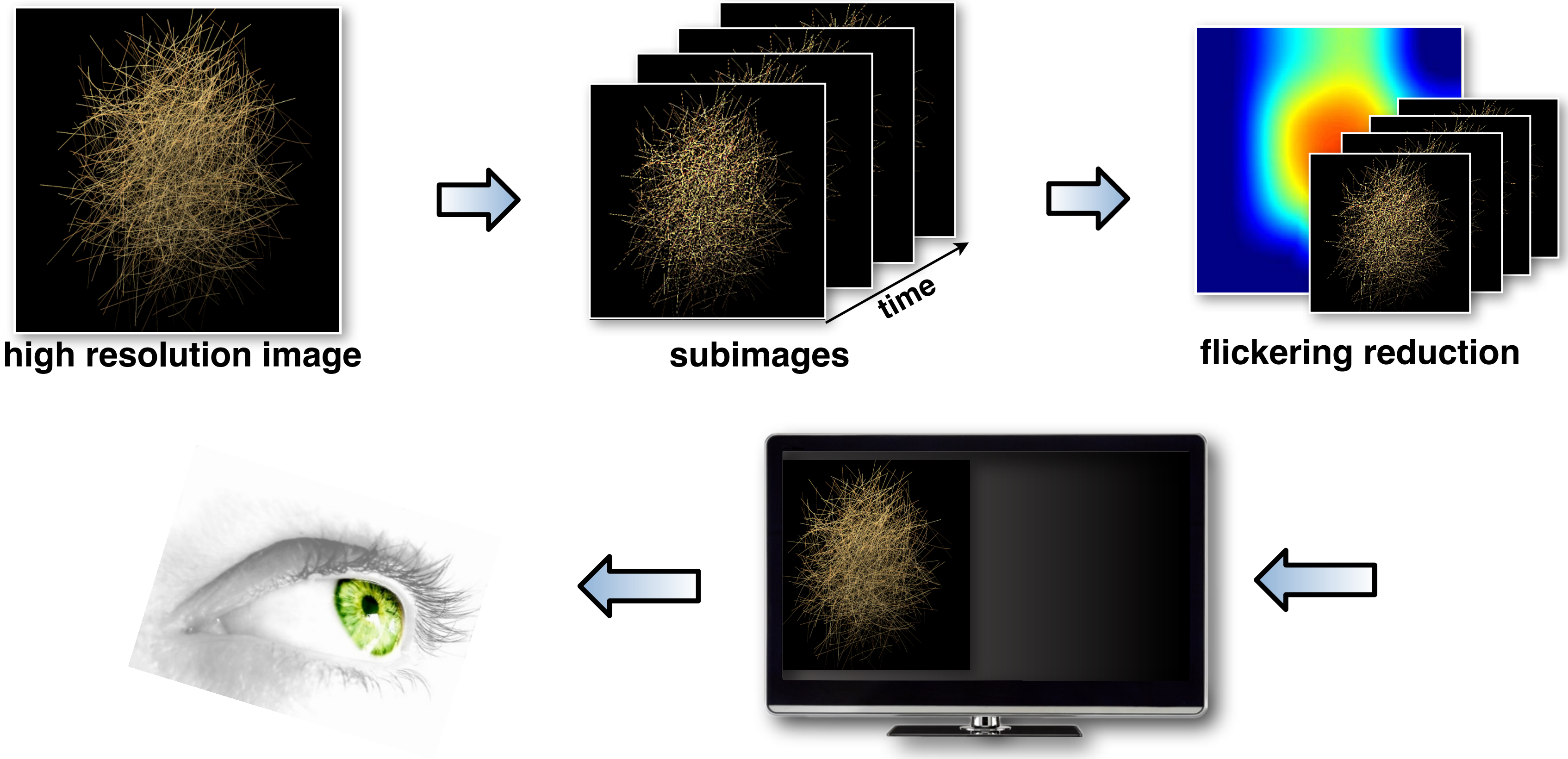
Full pipeline



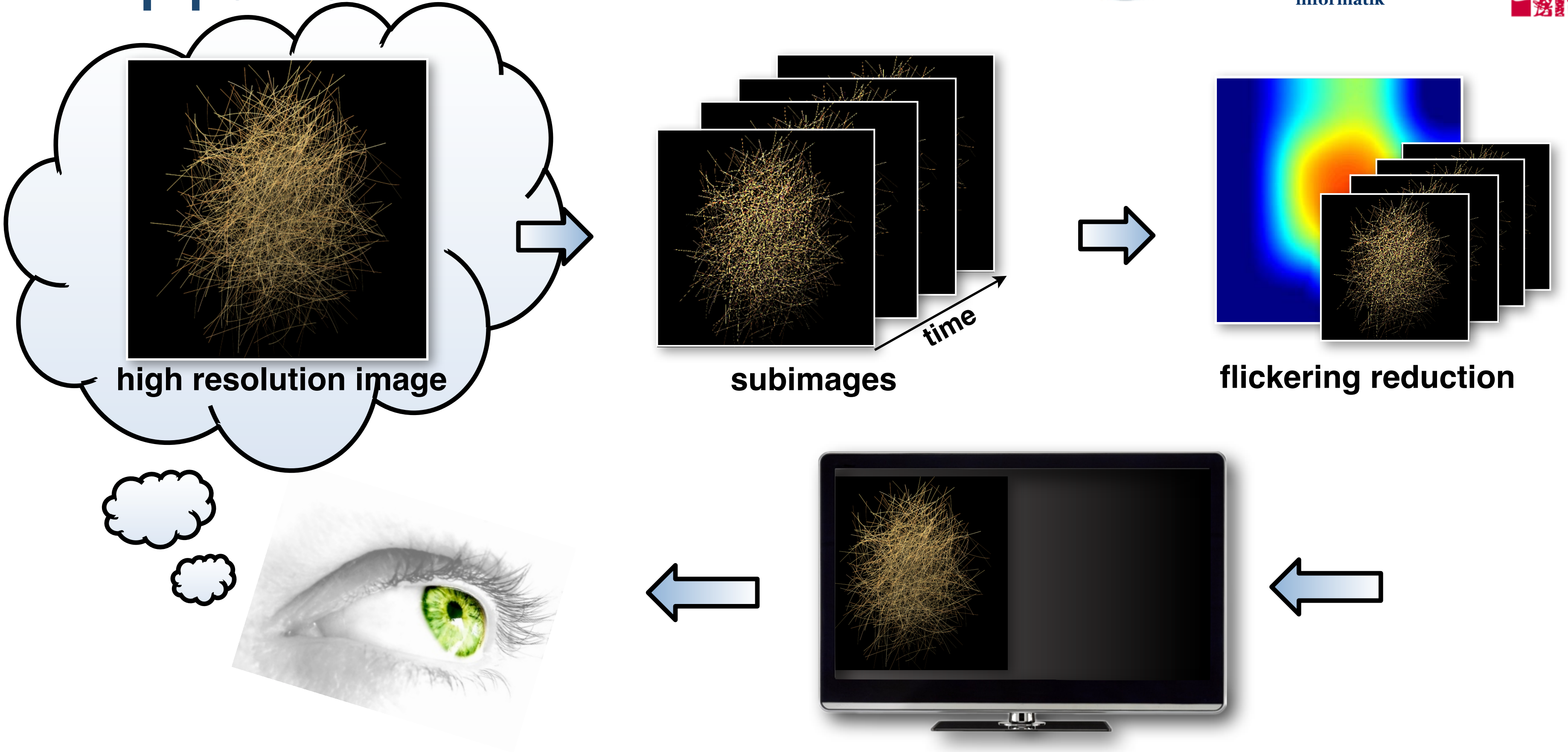
Full pipeline



Full pipeline



Full pipeline



Experiments

Experiments

- 5 images - detailed photographs and rendering

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- different velocities

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- different velocities
- decomposition into 3 subimages

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Experiments

- 5 images - detailed photographs and rendering
- different velocities
- decomposition into 3 subimages
- 14 participants
- comparison to Lanczos and Mitchell downsampling

Experiments

Our vs. Static case

our

standard downsampling

Experiments

Our vs. Static case

our

standard downsampling

Experiments

Our vs. static case

our

standard downsampling

Experiments

Our vs. static case

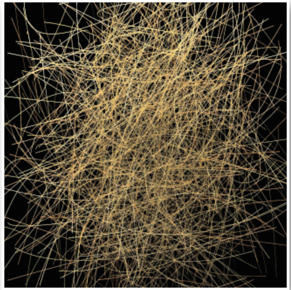
our

standard downsampling

All participants preferred our solution

Experiments

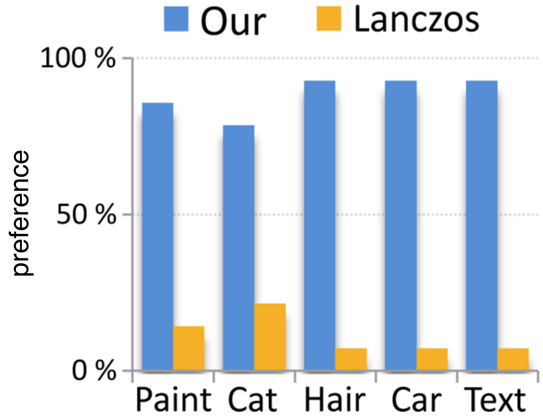
Our vs. Lanczos



- compare to moving image
- each frame downsample separately
  - ➡ slightly different information over time

Experiments
Our vs. Lanczos

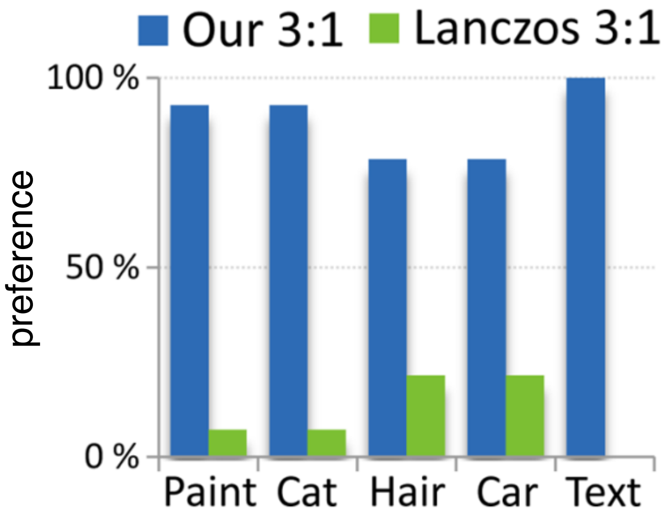
- compare to moving image
- each frame downsample separately
    - ➡ slightly different information over time



Experiments

Lanczos scale 3:1

Experiments
Lanczos scale 3:1



Experiments

Our vs. Mitchell

Mitchell downsampling

➡ participants adjusted parameters
to match high resolution image

Experiments

Our vs. Mitchell

Mitchell downsampling

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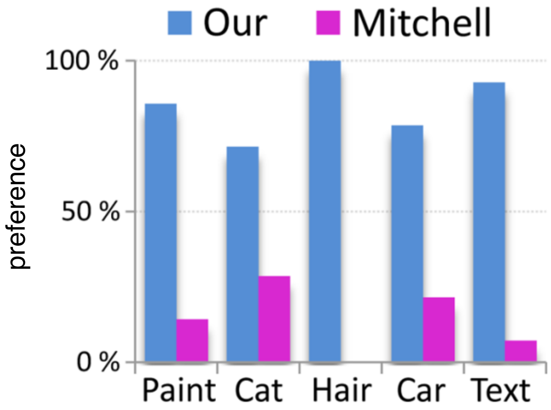
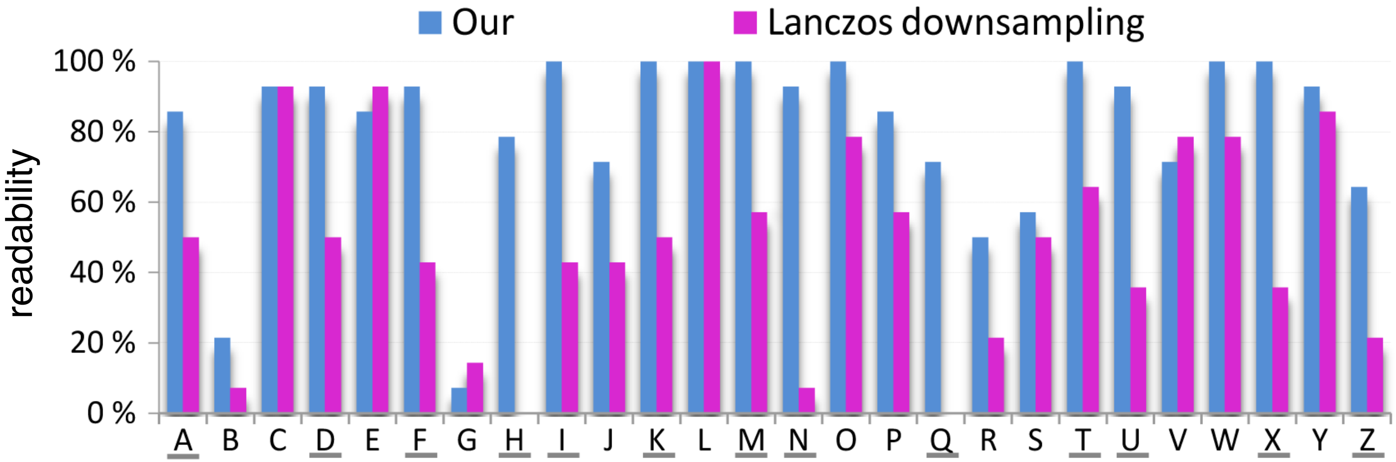


Results

Alphabet

Size: 2 x 3 pixels



Results

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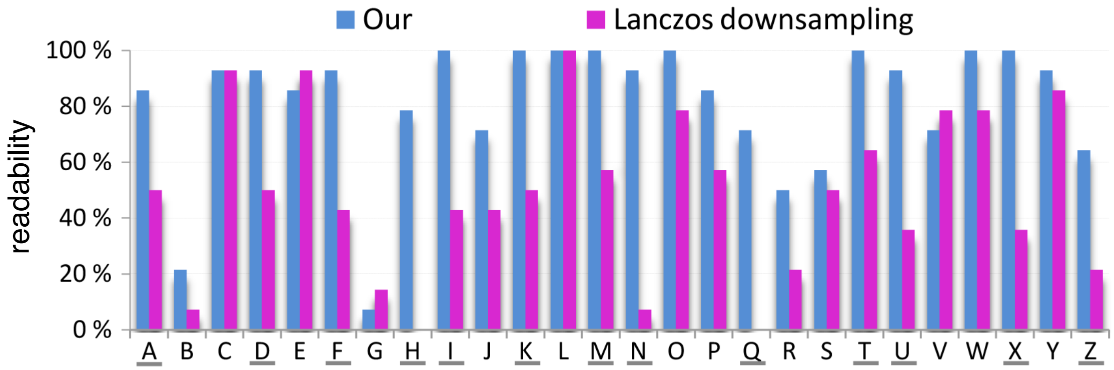
Size: 2 x 3 pixels



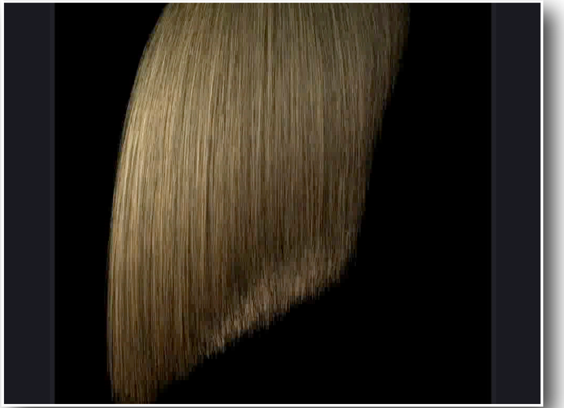
Applications:

- scrolling text or maps on low resolution devices
- stock tickers, news headlines

Experiment (small)

Rendering

Experiment (small)
Rendering



- 2 highly detailed rendering
- 5 participants
- comparison to Lanczos

Experiment (small)
Rendering

- 2 highly detailed rendering
- 5 participants
- comparison to Lanczos

Result:
all subjects preferred our solution

Limitations

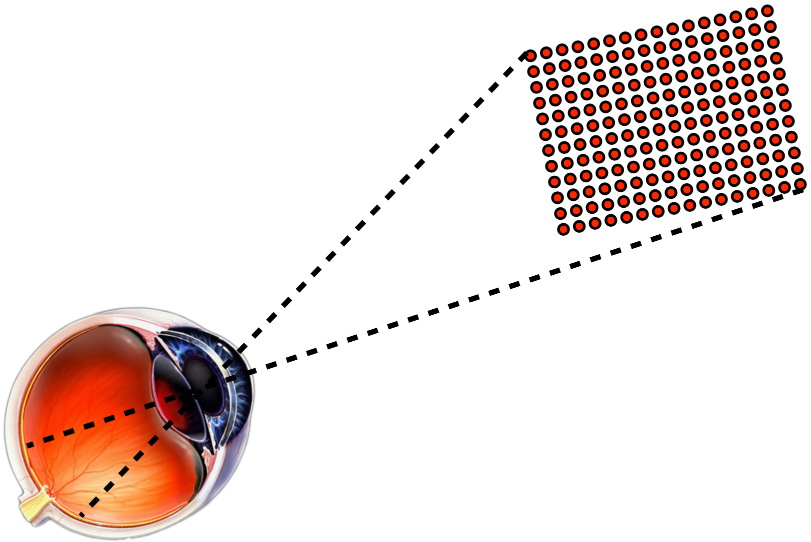
Limitations

- The resolution improvement is velocity dependent

Limitations

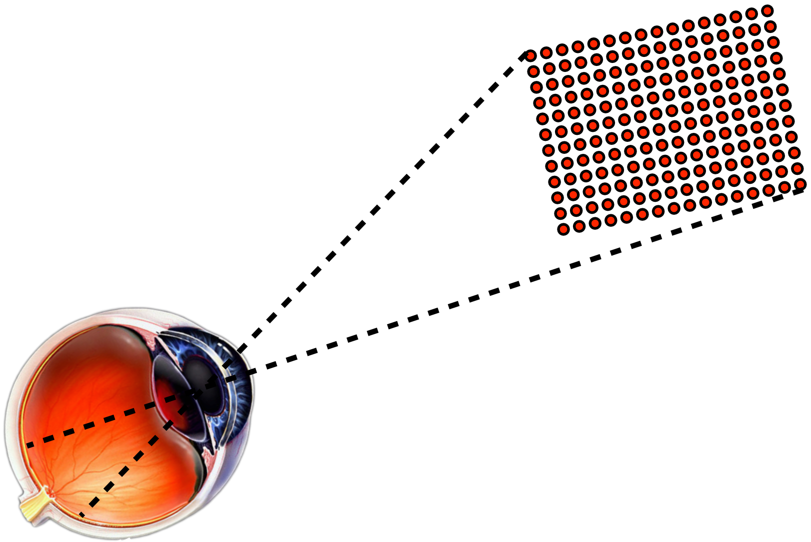
- The resolution improvement is velocity dependent
- For complex motion optimization of whole sequence is required

Conclusions



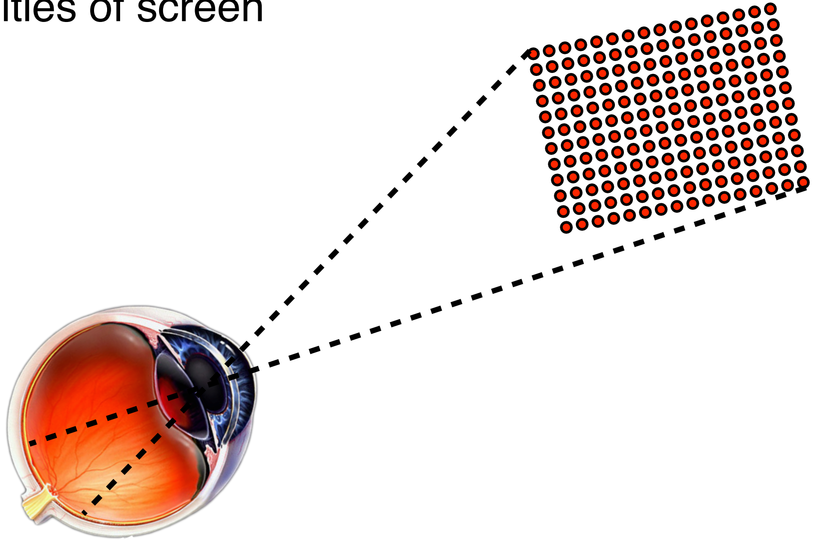
Conclusions

- We presented apparent resolution enhancement using human perception



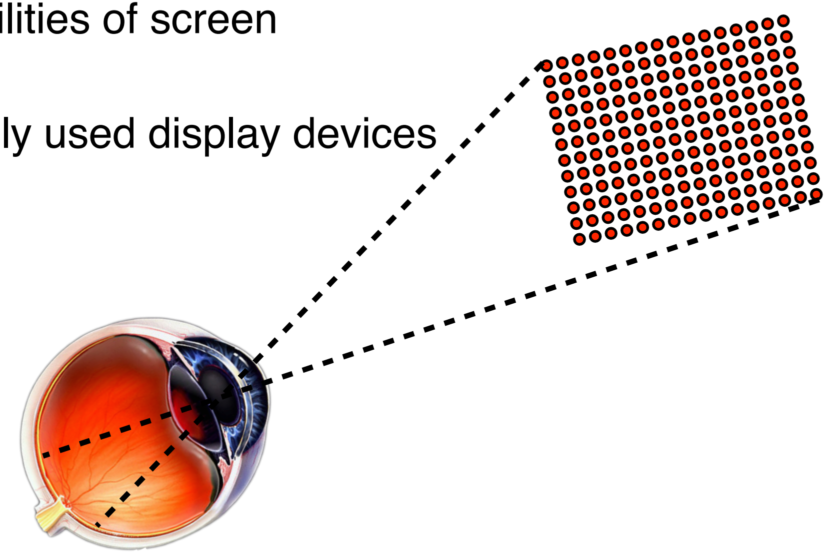
Conclusions

- We presented apparent resolution enhancement using human perception
- We can show resolution beyond physical capabilities of screen



Conclusions

- We presented apparent resolution enhancement using human perception
- We can show resolution beyond physical capabilities of screen
- Our method works with whole range of commonly used display devices



Acknowledgments

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Acknowledgments

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The work was partially supported by the **Cluster of Excellence MMCI** (www.m2ci.org)

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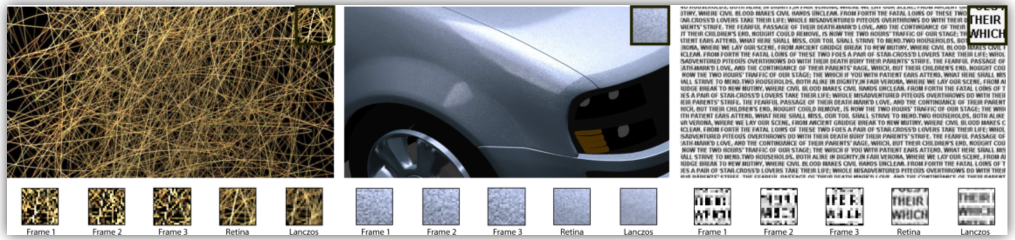
Apparent Display Resolution Enhancement for Moving Images

Piotr Didyk, Elmar Eisemann, Tobias Ritschel, Karol Myszkowski, Hans-Peter Seidel



Thank you!

Additional materials: http://www.mpii.de/resources/ResolutionEnhancement/