

---

# Statistical Filtering of Indirect Illumination for Computer Graphics



---

Martin Benning, Edward Lee,  
Henry Pao, Karamatou Yacoubou-Djima  
Dr. John Anderson, Pixar Animation Studios  
Dr. Todd Wittman, IPAM

RIPS 2007



---

# Outline

- Introduction
    - Background
    - PCA
  - Motion detection
    - Global
    - Local
  - Denoising
    - Error Threshold Method
    - Moving Basis
    - Anisotropic Diffusion
    - Hybrid Method
    - Regression
  - Artifact detection
-

---

# Background

Direct Illumination (D)



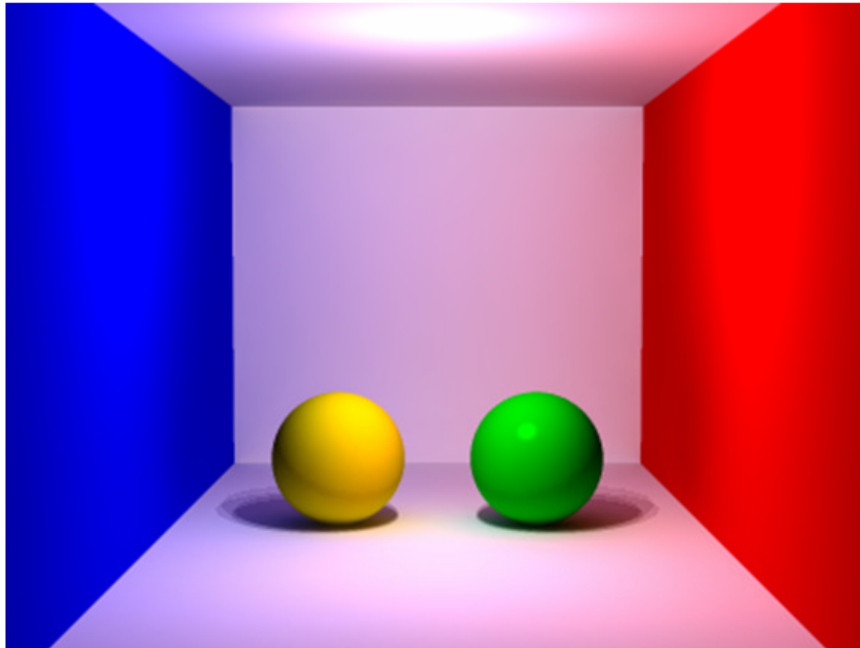
Global Illumination (G)



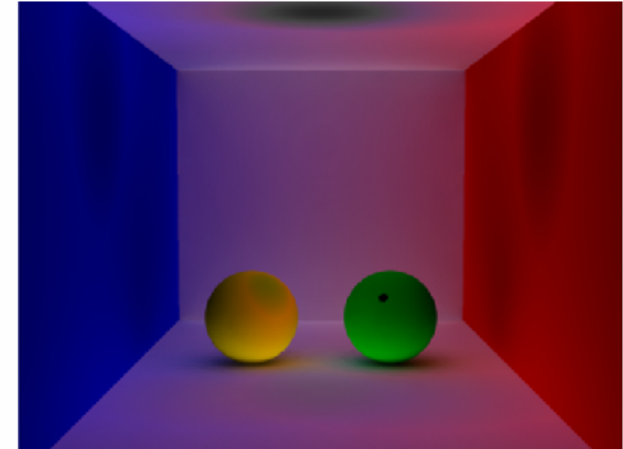
# Indirect Illumination

Global Illumination = Direct + Indirect

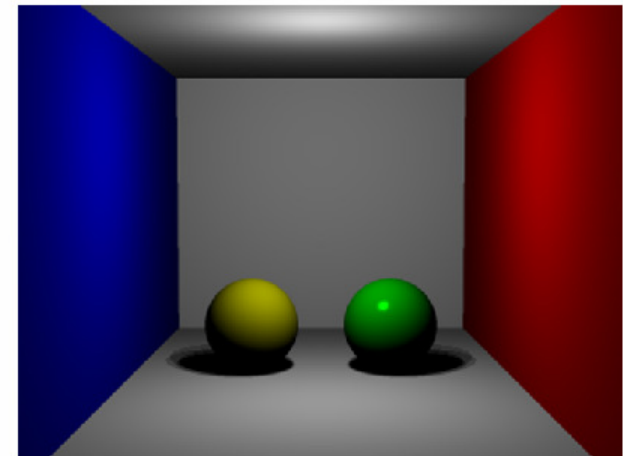
$$\Rightarrow G = D + I$$



Global Illumination (G)



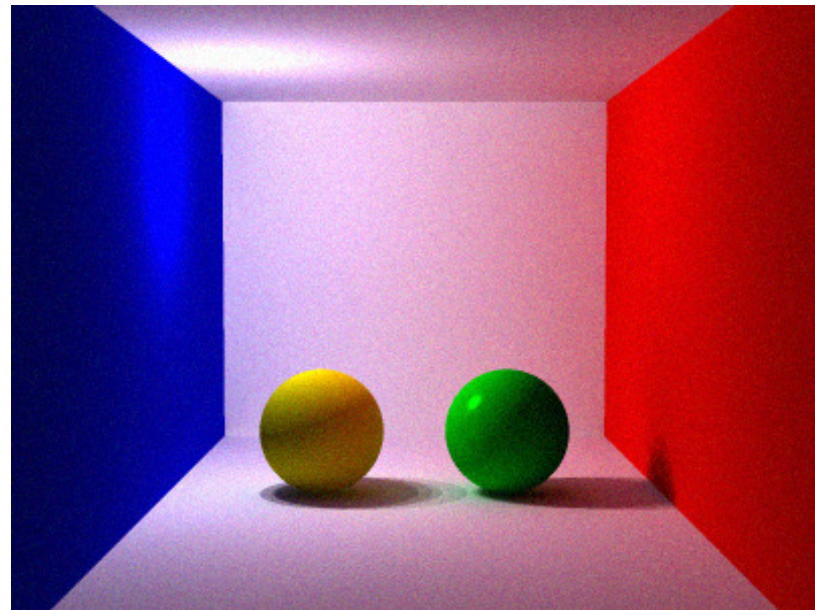
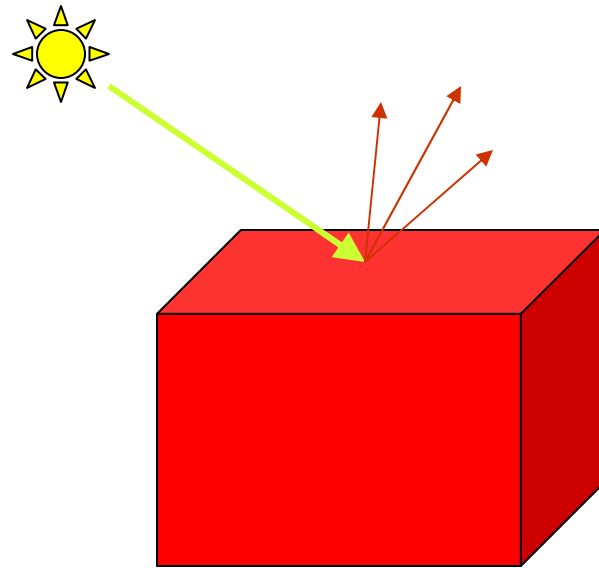
Indirect Illumination (I)



Direct Illumination (D)

# Photon Mapping

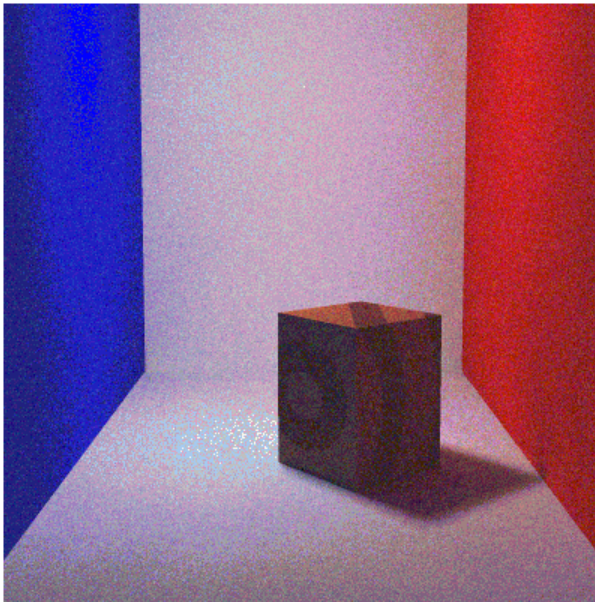
- Used for indirect illumination
- Method that Pixar wishes to use
- Algorithm is computationally expensive
- Lower sampling rates generates noisy images



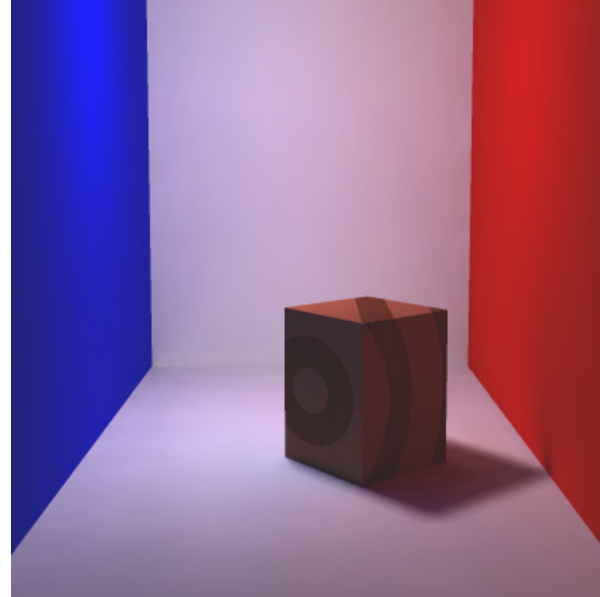
---

# Our Problem

- Remove noise generated by low sample photon mapping
- Detect and replace problematic pixels
- Re-render as few pixels as possible

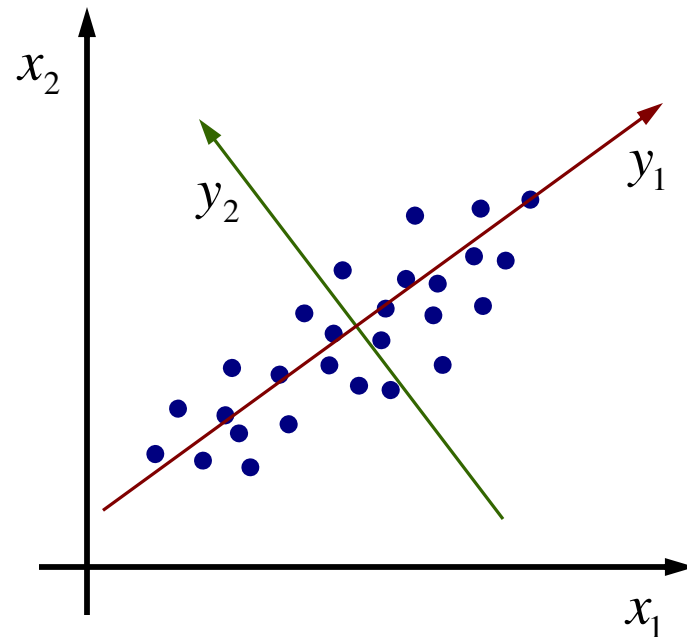


=>



# PCA: Basis

- PCA creates a variance-ordered basis
- Basis vectors point in direction of highest successive variance
- Noise-free pixels and noise are represented by different directions in the basis



Transformation of Basis  
using PCA



---

# PCA: Choosing the Basis

- Noisy animations are represented using PCA:

$$I(\bar{x}, t) = \sum_{i=1}^N w_i(t) B_i(\bar{x})$$

$I(\bar{x}, t)$  = Image sequence

$N$  = Number of frames

$B_i(x)$  = Basis Vectors

$w_i(t)$  = Observation Coefficients

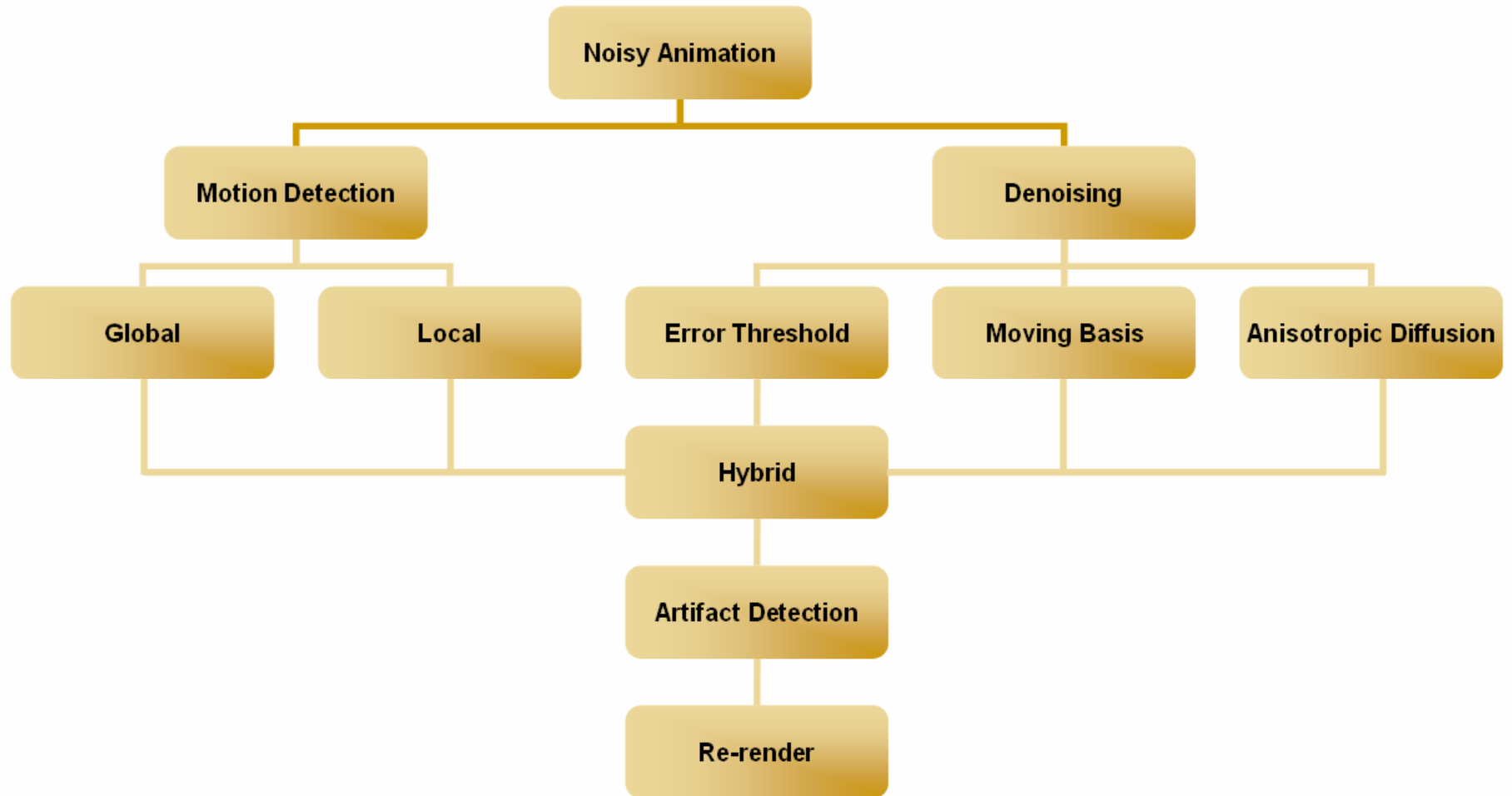
- The first vectors of the basis capture the noise-free indirect illumination
- The last vectors of the basis describe the noise
- Noise-free  $I(x, t)$  is determined with a truncated PCA basis:

$$I(\bar{x}, t) \approx I_k(\bar{x}, t) = \sum_{i=1}^k w_i(t) B_i(\bar{x})$$



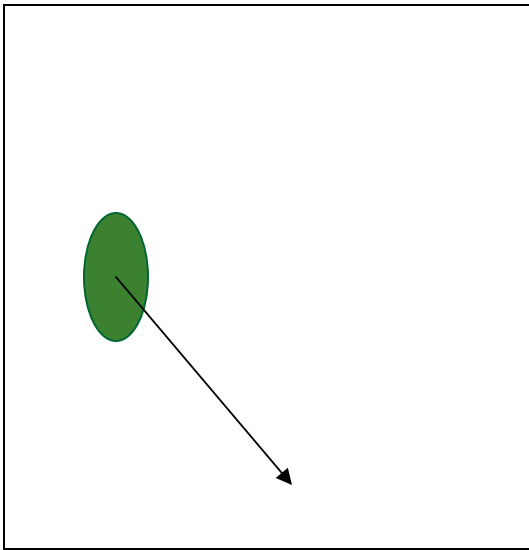


# Grand Scheme

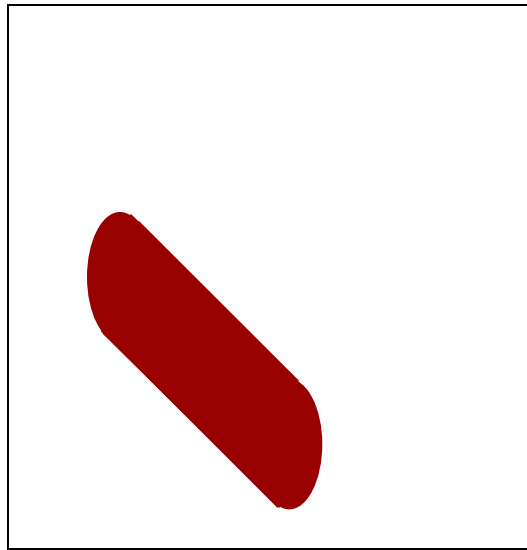


---

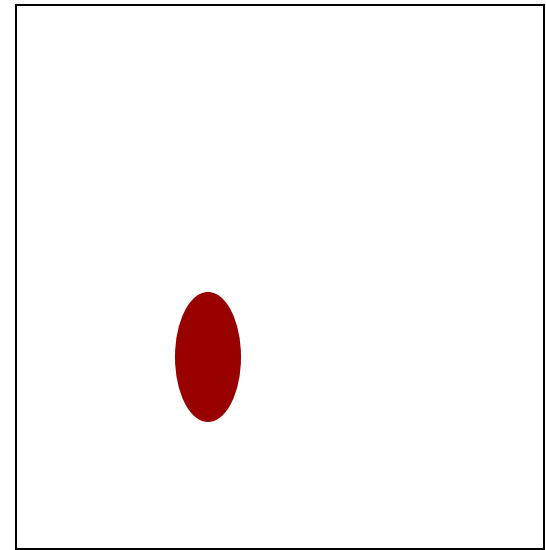
# Global vs. Local Motion



Original Animation



Global motion



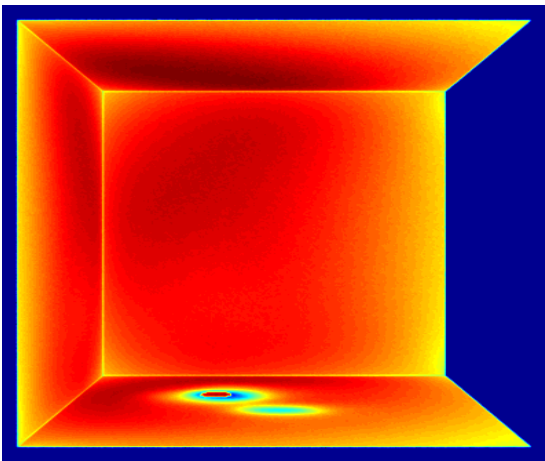
Local motion

---

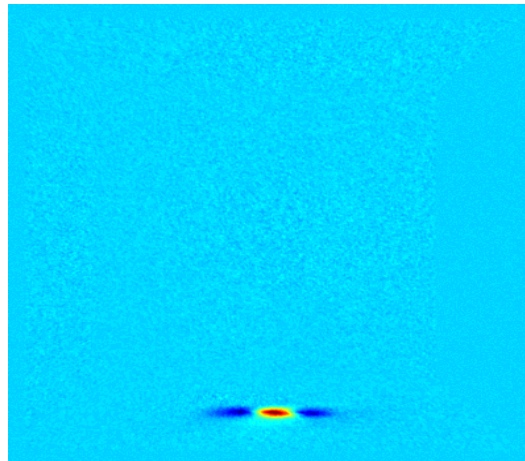
# Global Motion Detection

$$I(\vec{x}, t) = \sum_{i=1}^F w_i(t) B_i(\vec{x})$$

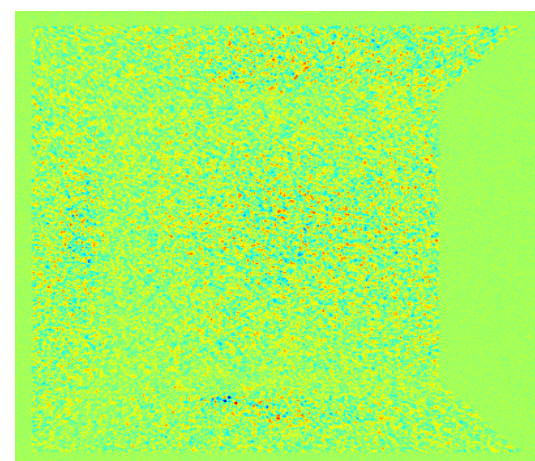
- PCA separates the animation sequence  $I(\vec{x}, t)$  into spatial and temporal bases
- The spatial basis vectors can be used for detecting global motion



B<sub>1</sub>



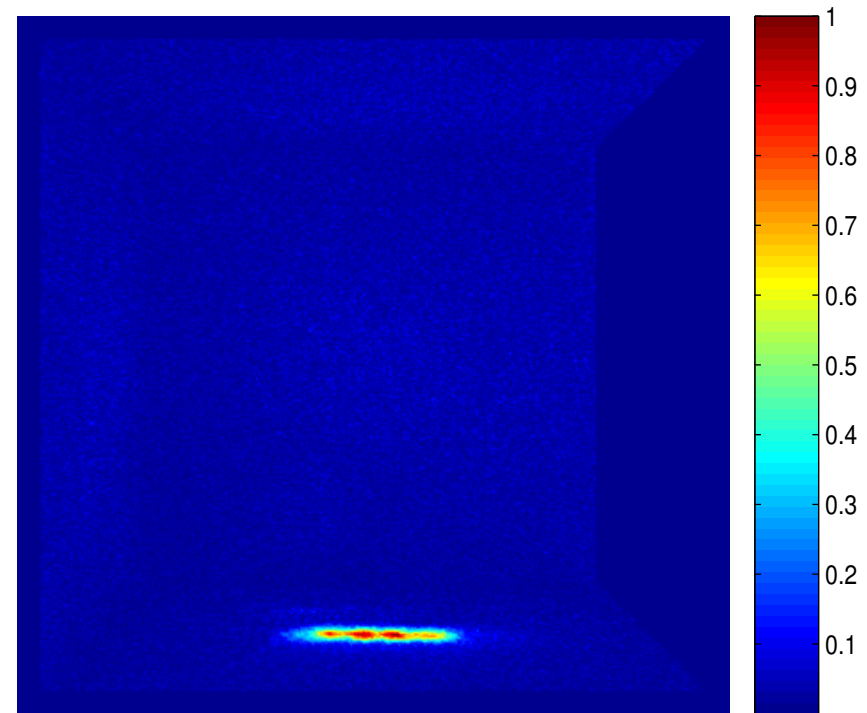
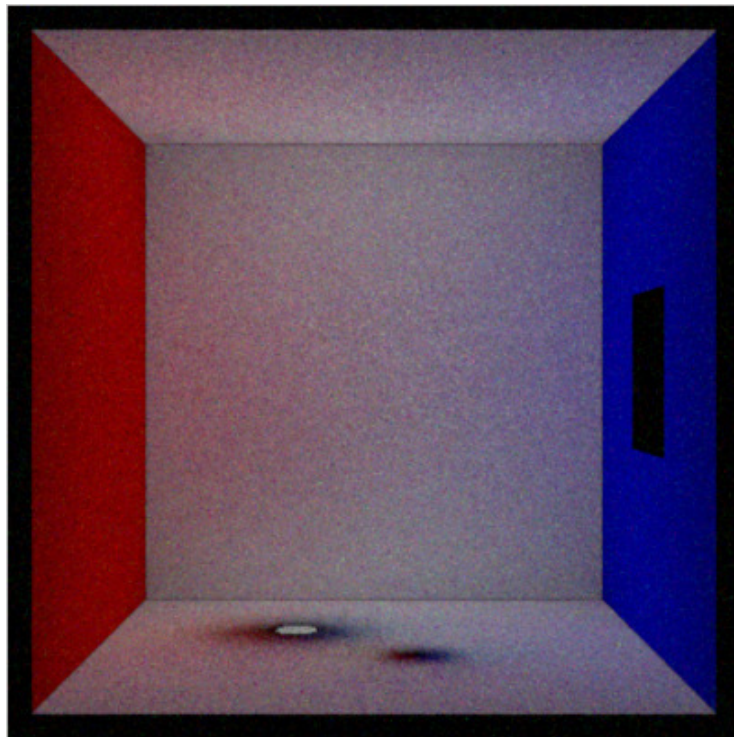
B<sub>3</sub>



B<sub>9</sub>

# Global Motion Detection

- The first basis vectors contain information of area of motion
- The last basis vectors contain only noise
- Adding up the absolute values of  $B_1$  to  $B_5$  results in

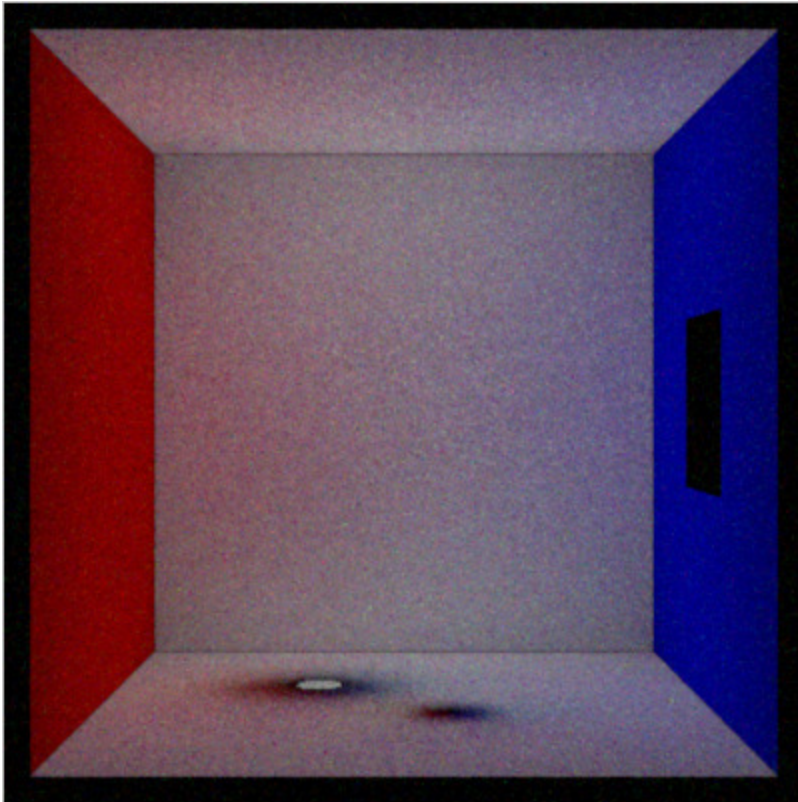


$$\alpha(\vec{x}) = \sum_{i=1}^5 |B_i(\vec{x})|$$

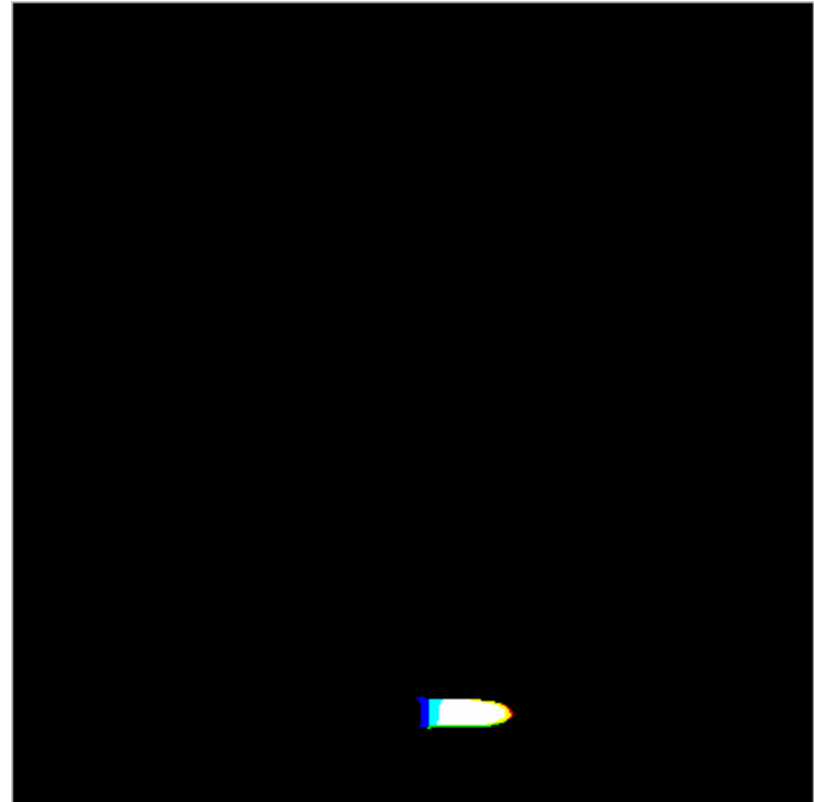
---

# Local Motion Detection using z-scores

$$z(\vec{x}, t) = \frac{I(\vec{x}, t) - \mu(\vec{x})}{\sigma(\vec{x})}$$



Original animation



Threshold z-scores

---

---

# Denoising using PCA

- It represents data with a variance ordered basis

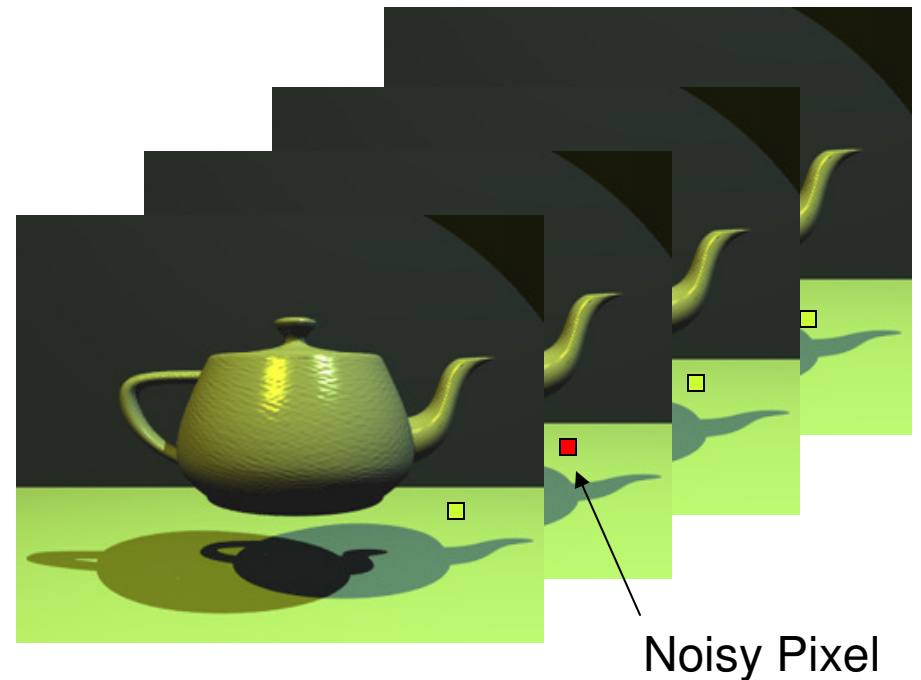
$$I(\bar{x}, t) = \sum_{i=1}^F w_i(t) B_i(\bar{x})$$

- First basis vectors contain the noise-free indirect illumination
  - Last basis vectors contain noise and motion
  - Noise in animation sequence can be filtered using truncated temporal PCA basis
-

---

# PCA: Motivation

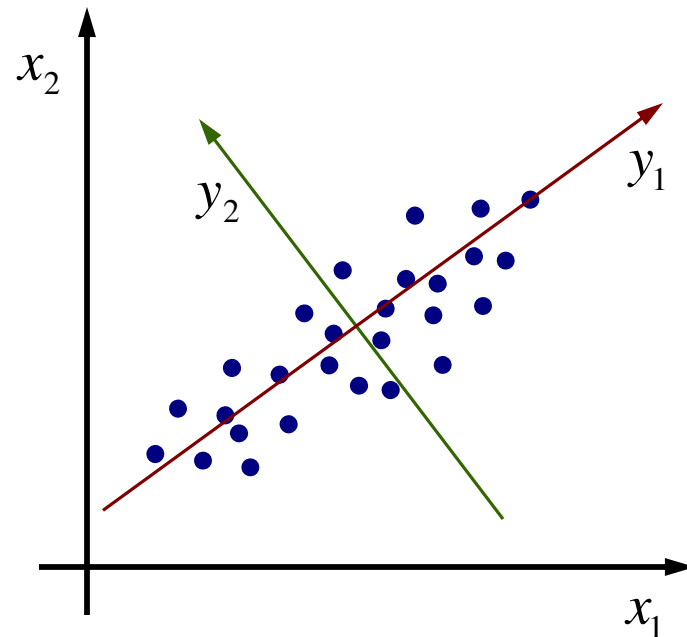
- Most methods denoise individual frames
- Our approach uses temporal correlation of pixel values
- PCA finds a new basis which separates meaningful pixels from noisy ones
- PCA is fast and inexpensive





# PCA: Basis

- PCA creates a variance-ordered basis
- Basis vectors point in direction of highest successive variance
- Noise-free pixels and noise are represented by different directions in the basis



Transformation of Basis  
using PCA

---

# PCA: Choosing the Basis

- Noisy animations are represented using PCA:

$$I(\bar{x}, t) = \sum_{i=1}^N w_i(t) B_i(\bar{x})$$

$I(\bar{x}, t)$  = Image sequence

$N$  = Number of frames

$B_i(x)$  = Basis Vectors

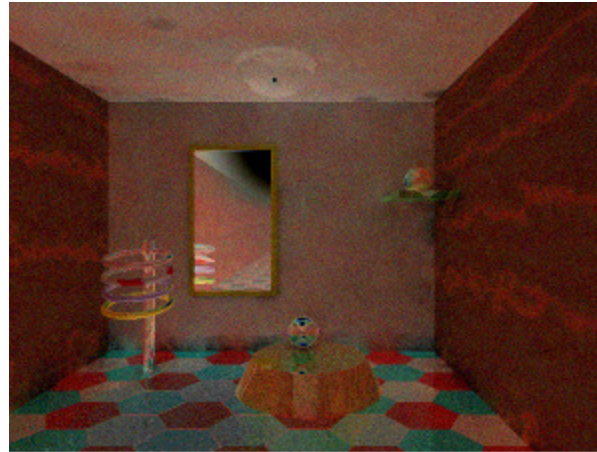
$w_i(t)$  = Observation Coefficients

- The first vectors of the basis capture the noise-free indirect illumination
- The last vectors of the basis describe the noise
- Noise-free  $I(x, t)$  is determined with a truncated PCA basis:

$$I(\bar{x}, t) \approx I_k(\bar{x}, t) = \sum_{i=1}^k w_i(t) B_i(\bar{x})$$



# Image Sequence Reconstruction



Noisy animation sequence



Reconstruction with  $k = 2$



Reconstruction with  $k = 10$

# Error Threshold Method\*

- Compute the PCA basis
- Create reconstructions for each truncation  $T_k$

$$I_k(\vec{x}, t) = \sum_{i=1}^k w_i(t) B_i(\vec{x})$$

- Calculate the error (between the reconstruction and the noisy image)

$$error(k, \vec{x}) = [I(\vec{x}, t) - I_k(\vec{x}, t)]^2$$

- Calculate the difference of the error

$$\Delta(error(k, \vec{x})) = error(k, \vec{x}) - error(k+1, \vec{x})$$

---

# Error Threshold Method



Noisy Animation



Error Threshold Method

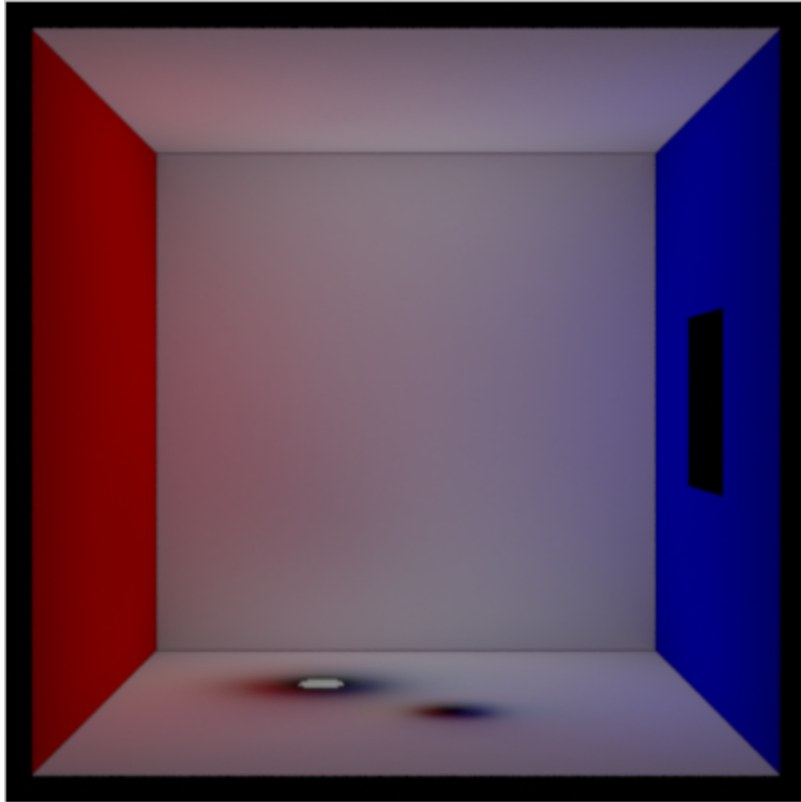
$$I_{PCA}(\bar{x}, t)$$

---

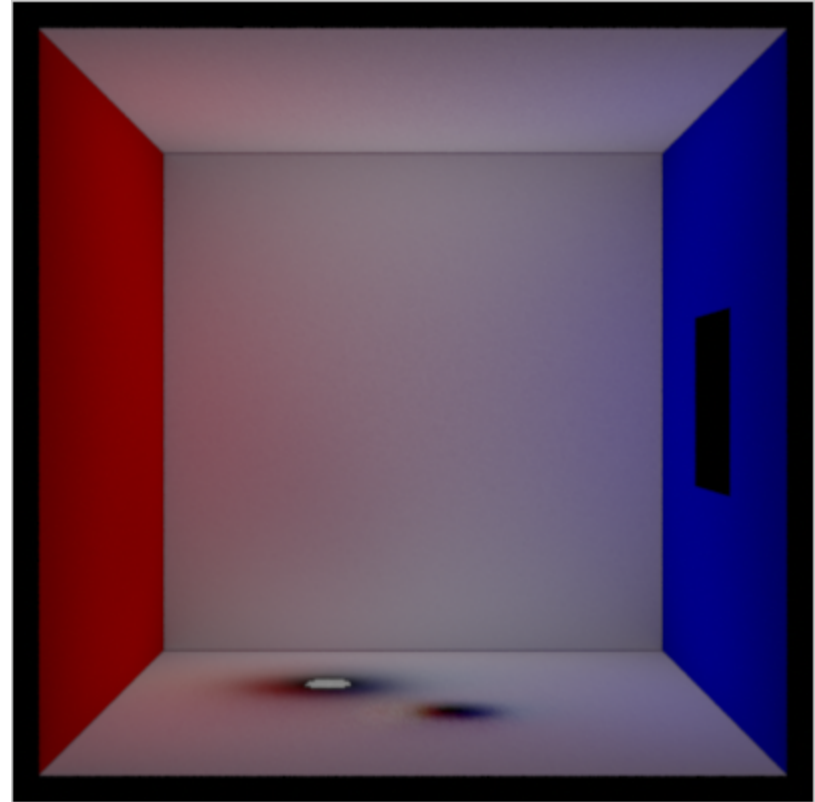


---

# Error Threshold Method



Noisy Animation



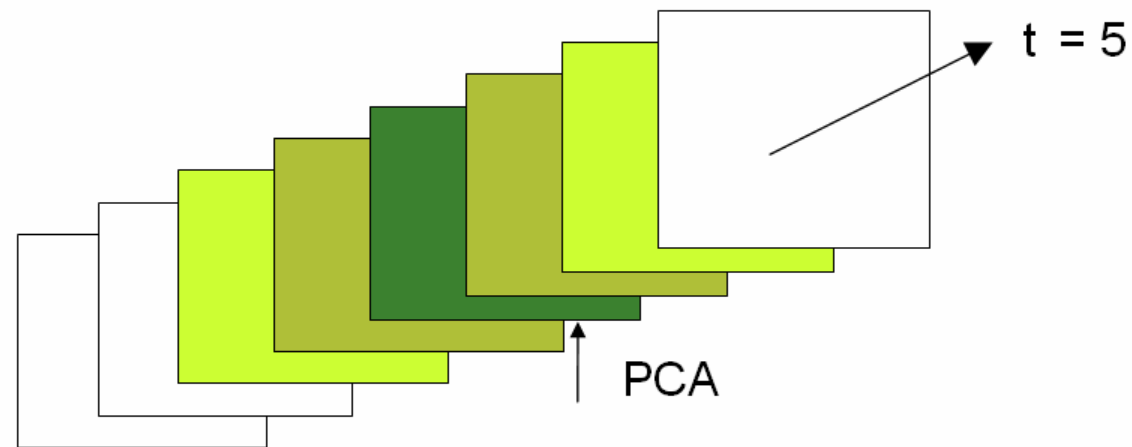
Error Threshold Method

---

---

# Moving Basis

- Pick a single frame
- Select former and following  $P$  frames and apply Gaussian weights
- Compute PCA for selected frames
- Pick out the middle frame of the reconstruction
- Move on to next frame and repeat procedure





# Moving Basis Reconstruction



Noisy animation sequence

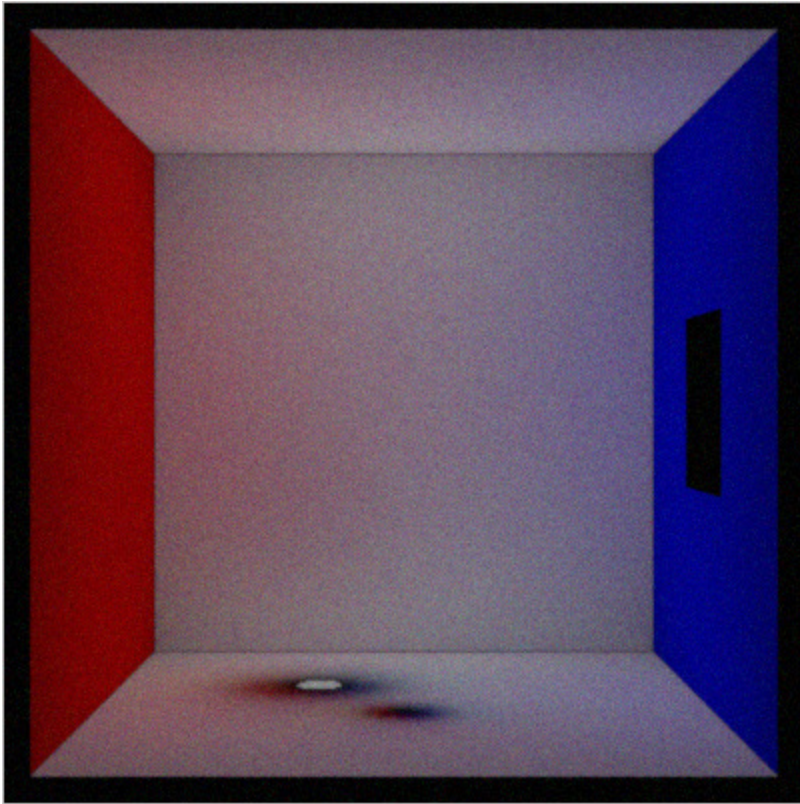


Moving Basis

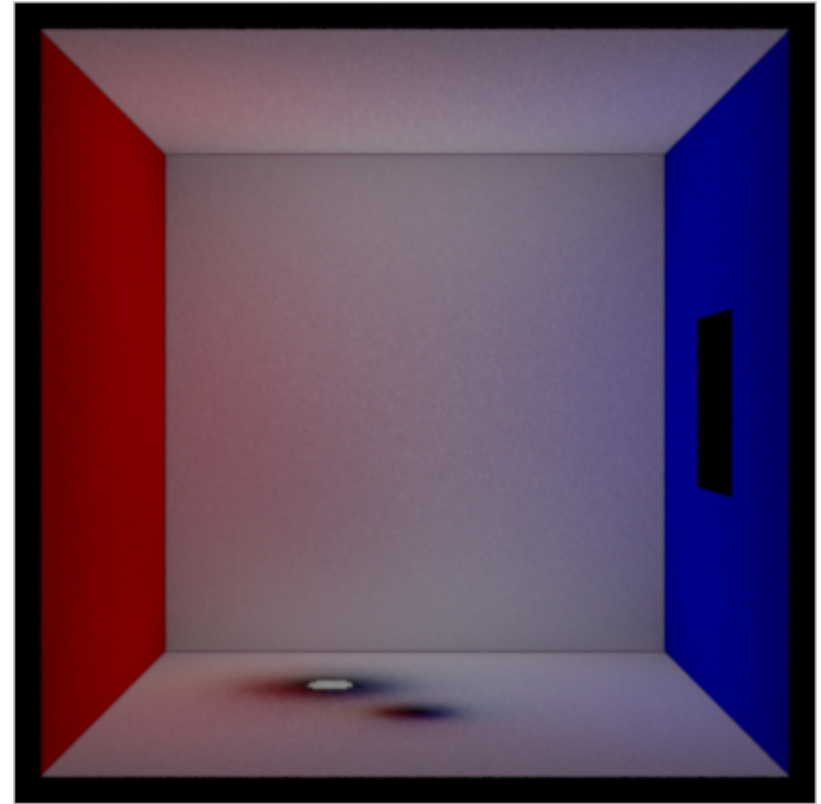
$$I_{MB}(\bar{x}, t)$$

---

# Moving Basis



Noisy animation sequence



Reconstruction using Moving Basis

---



# Single Frame Denoising\*

- Each frame of the image sequence is denoised using anisotropic diffusion:

$$u_t = \nabla \cdot \left( \frac{1}{\sqrt{1 + |\nabla u|^2}} \nabla u \right)$$

- Motion is preserved
- Little noise is removed

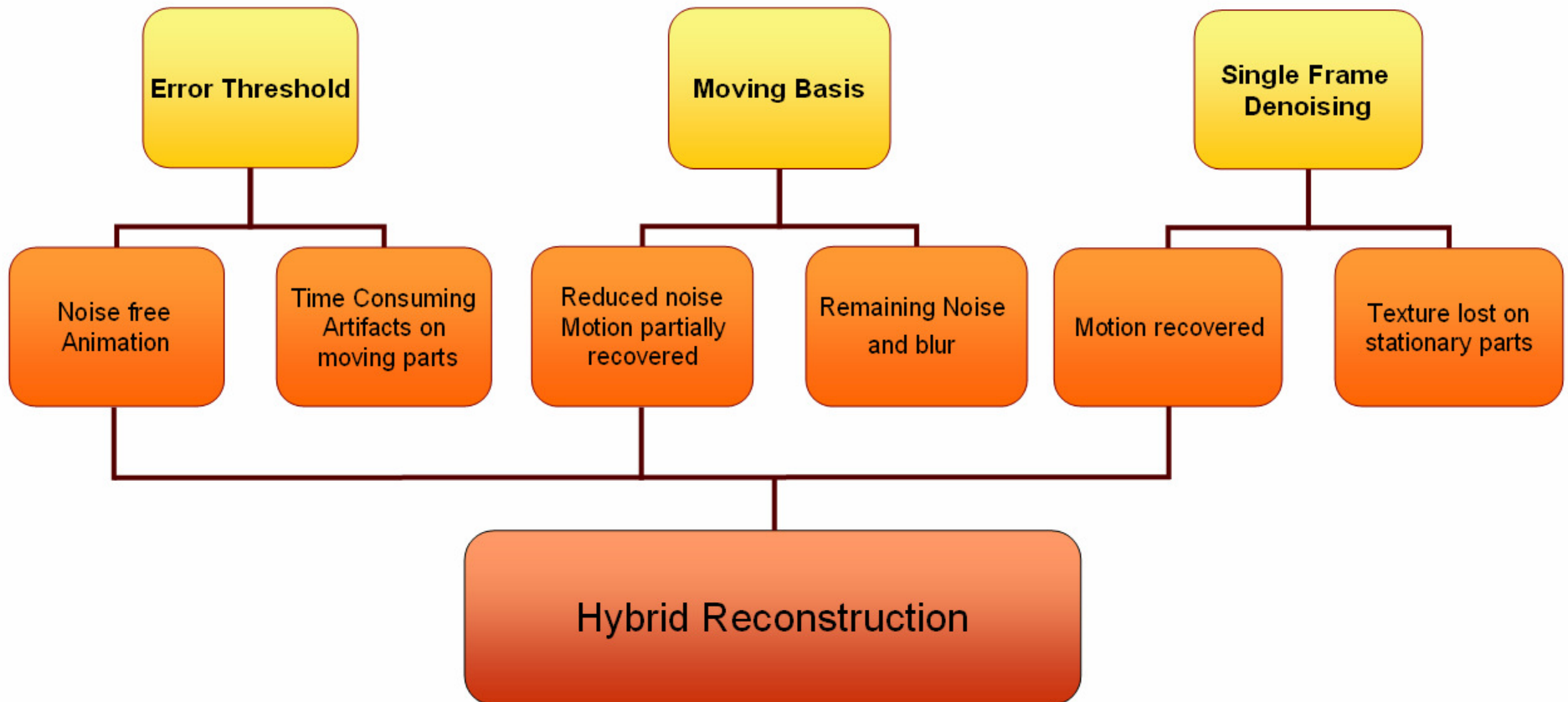


$I_{SF}(\bar{x}, t)$

\* P. Perona, J. Malik, "Scale-Space and Edge Detection Using Anisotropic Diffusion," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 12, no. 7, pp. 629-639, Jul., 1990

---

# Denoising Methods



---

# Hybrid Method

- Combination of:
  - Denoising methods
  - Motion detection
- Formulation

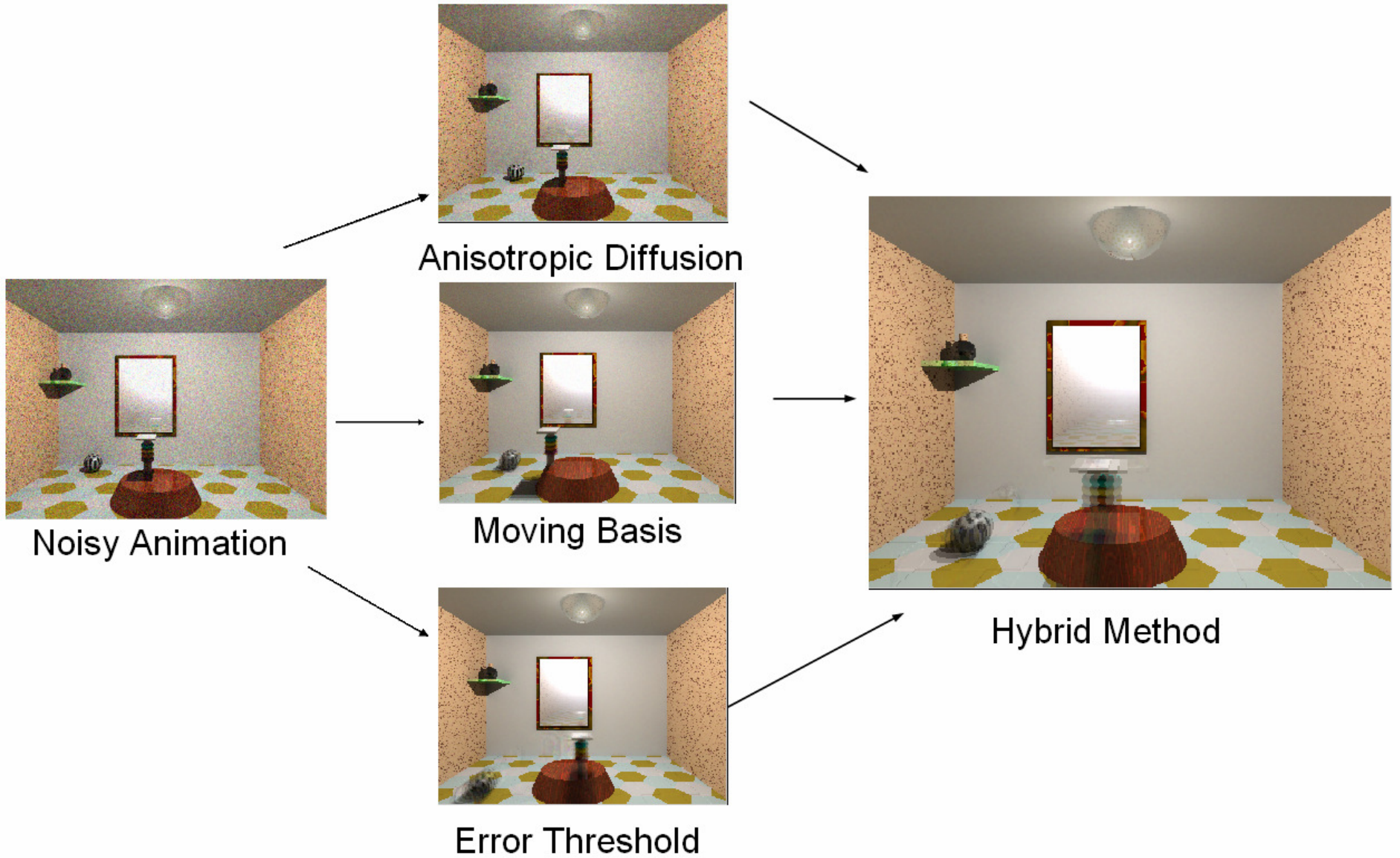
Global Motion:  $\alpha(\vec{x}) = \begin{cases} 0, \text{ motion} \\ 0 < \sigma < 1, \text{ motion at some point} \\ 1, \text{ stationary} \end{cases}$

Local Motion:  $\beta(\vec{x}, t) = \begin{cases} 0, \text{ currently no motion} \\ 0 < \sigma < 1, \text{ motion at some time} \\ 1, \text{ motion} \end{cases}$

$$\begin{aligned} I_{Hybrid}(\vec{x}, t) &= I_{PCA}(\vec{x}, t)\alpha(\vec{x}) \\ &+ I_{MB}(\vec{x}, t)(1 - \alpha(\vec{x}))\beta(\vec{x}, t) \\ &+ I_{SF}(\vec{x}, t)(1 - \alpha(\vec{x}))(1 - \beta(\vec{x}, t)) \end{aligned}$$

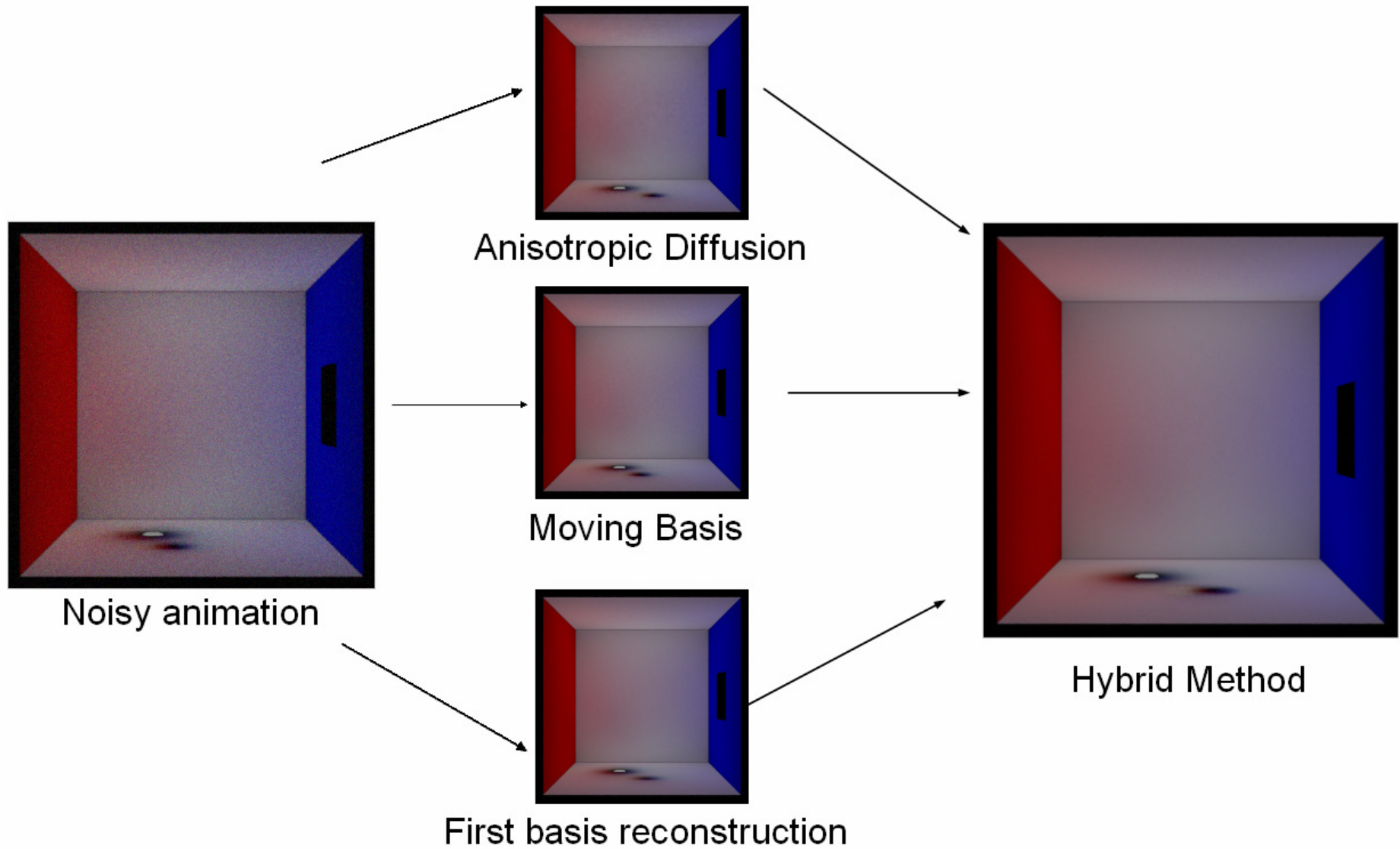
---

# Hybrid Method





# Hybrid Method

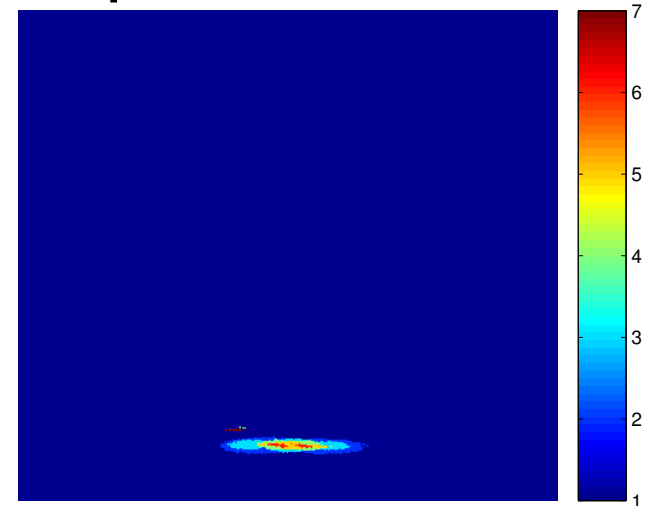




# Artifact Detection using Regression

- Artifact – any pixel that looks bad ☹️
- Regression methods used to detect pixels that have to be re-rendered
- Polynomial regression on all pixels over time
- Degree is determined by a threshold

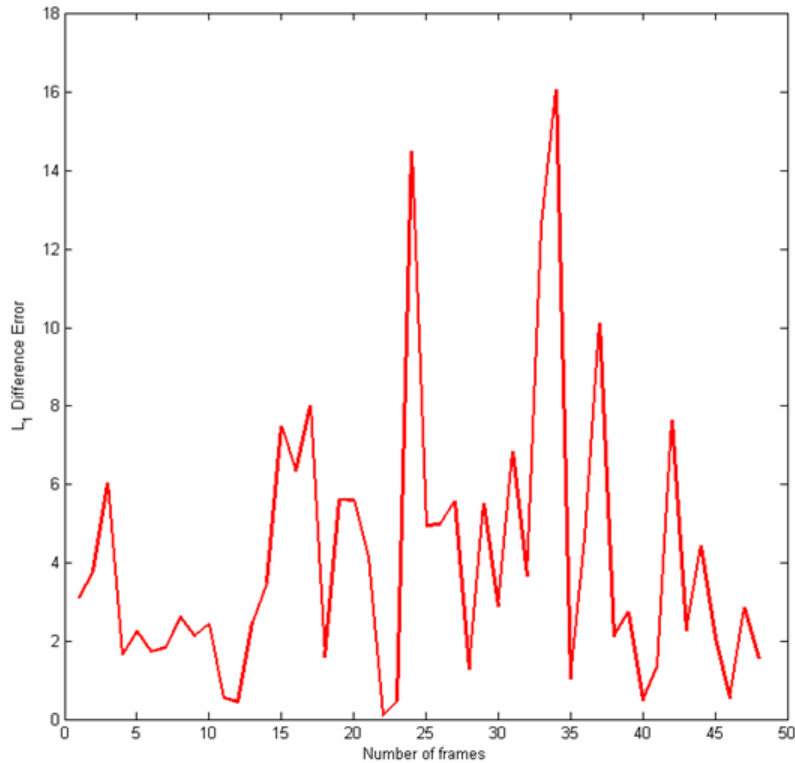
$$n = \arg \min_i \left( \frac{1}{F} \left| I(\vec{x}, t) - R_{i, \vec{x}}(t) \right| < \delta \right)$$



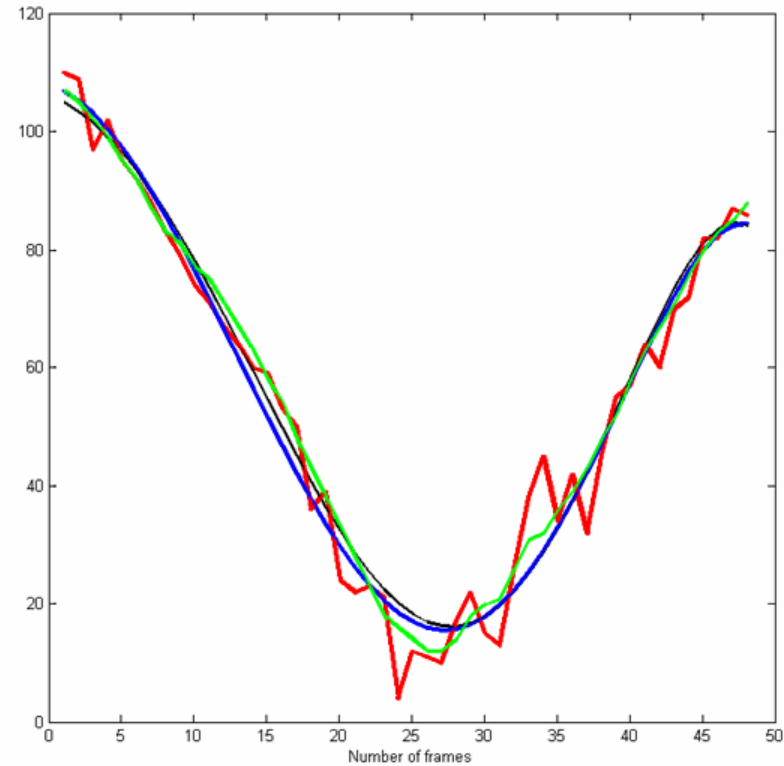
Degree map

# Artifact Detection Using Regression

Noisy – noisy regression



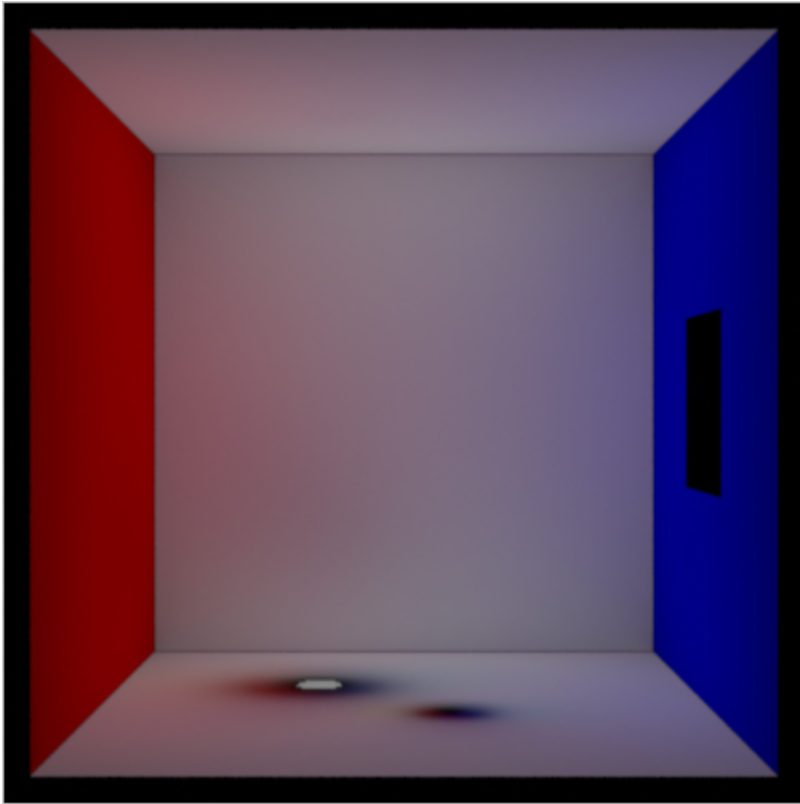
Pixel over time



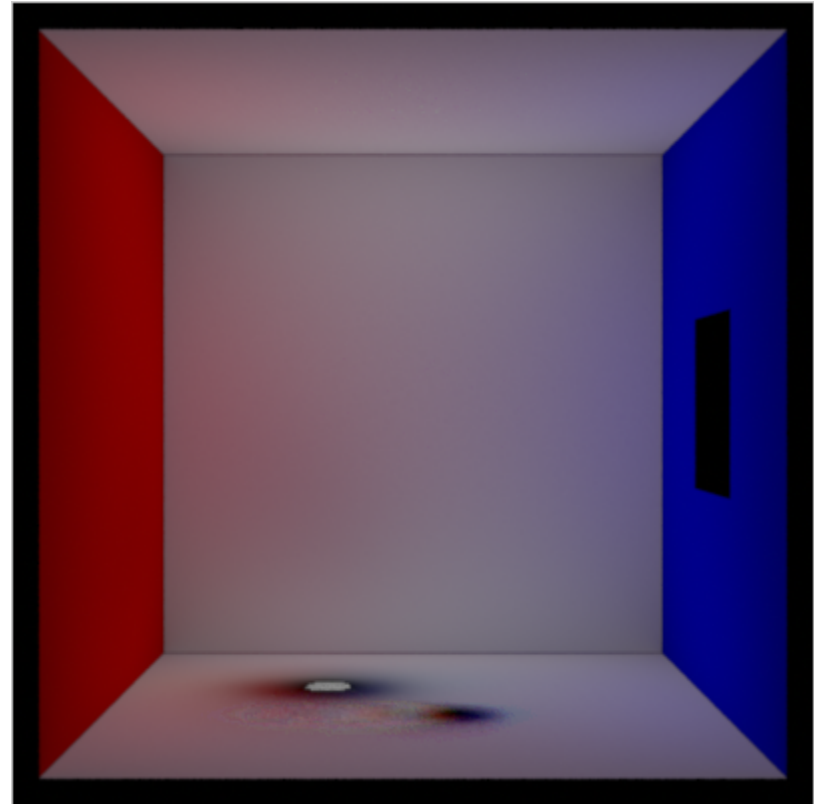
- Noisy sequence
- Noisy sequence regression
- High-sample render
- High-sample render regression

---

# Regression Results



Noise-free Animation



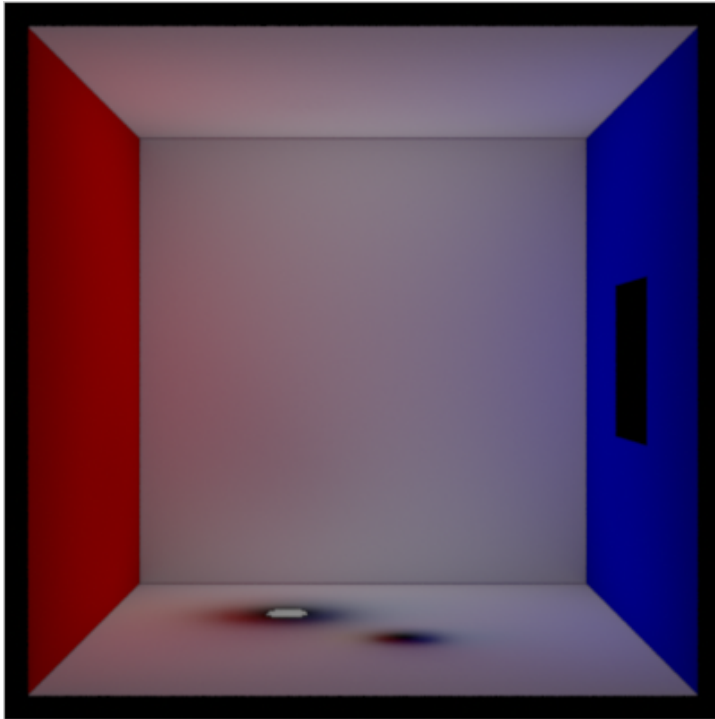
Polynomial Regression

---

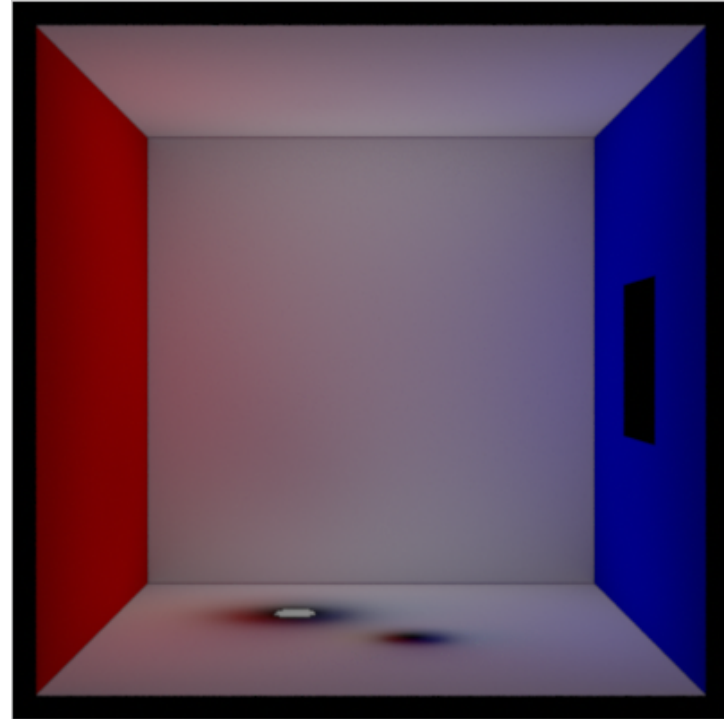
---

# Summary

- Detect motion using spatial PCA basis vectors and z-scores
- Denoise image sequence with hybrid method
- Detection artifacts using regression
- Re-render artifacts



High sample data



Reconstructed data

---

---

# Future work

- Artifacts detection
    - Improvement of regression
    - Difference between hybrid and regression denoising
  - Motion detection
    - Localization of motion using VARIMAX
-

---

# Acknowledgements

- Todd Wittman, IPAM
  - John Anderson, PIXAR
  - PIXAR Animation Studios
  - IPAM
  - RIPS Students 2007
-