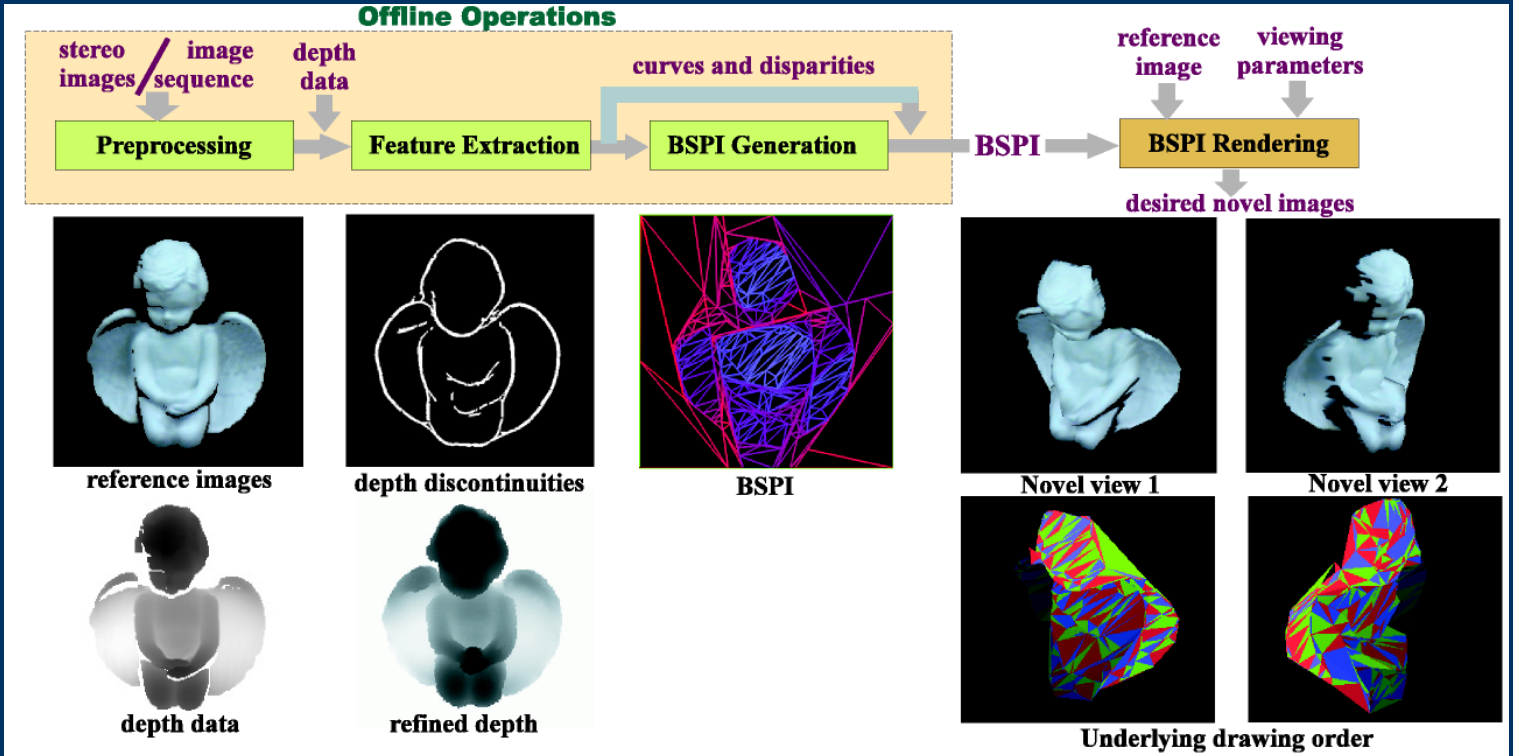
Overview

- Related Work
- Tensor Voting in 2-D
- Tensor Voting in 3-D
- Tensor Voting in N-D
- Application to Vision Problems
- Stereo
- Visual Motion
- Binary-Space-Partitioned Images
- 3-D Surface Extraction from Medical Data
- Epipolar Geometry Estimation for Non-static Scenes
- Image Repairing
- Range and 3-D Data Repairing
- Video Repairing
- Luminance Correction
- Conclusions

Overview of System

BSPI (Binary-Space-Partitioned Images)

(Courtesy of T.T. Wong & Philip Fu)



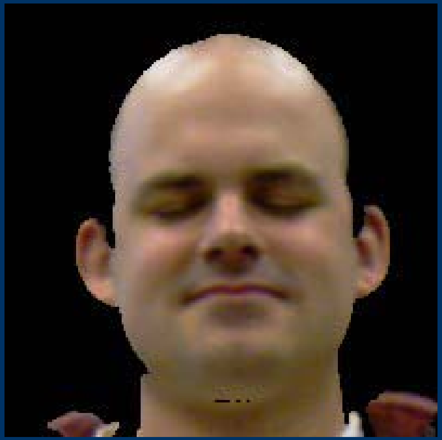
Criteria for partitioning

- Occlusion boundaries
- Depth and orientation discontinuity curves
- Give strong parallax effect when viewpoint changes
- Only depth data is considered
- Not reference image

Feature Curves Extraction for BSPI

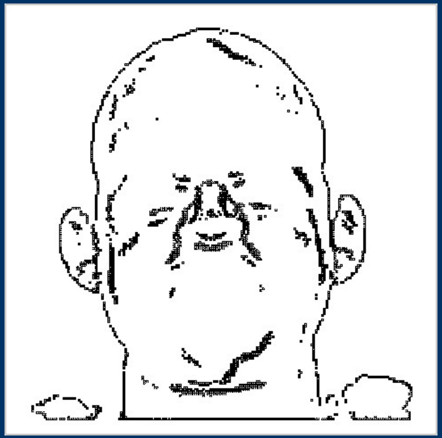
- Steps
  1. Refinement of the noisy depth map
  2. Estimate sign of curvature (simplified version)
     - since normal direction is estimated in step 1
     - sign of curvature will just have 2 choices
  3. Vote for endcurves
  4. Feature points extraction by simple thresholding of saliency

Feature Curves Extraction Results



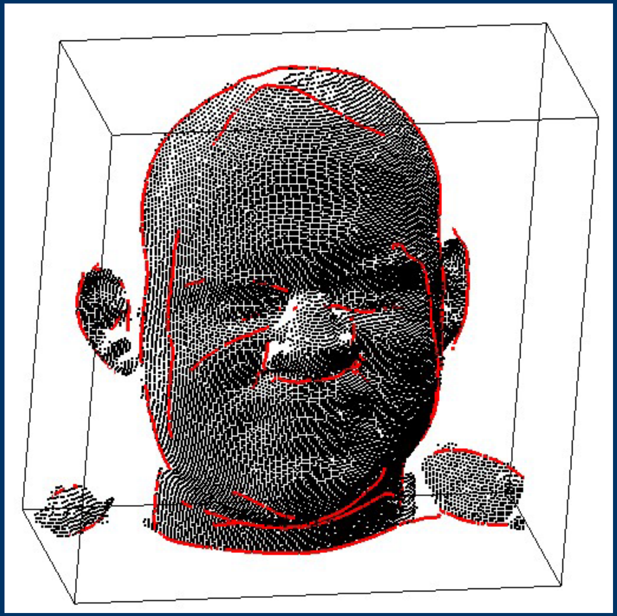
Reference image

Depth data



Depth discontinuity

Refined depth



Discontinuity curves

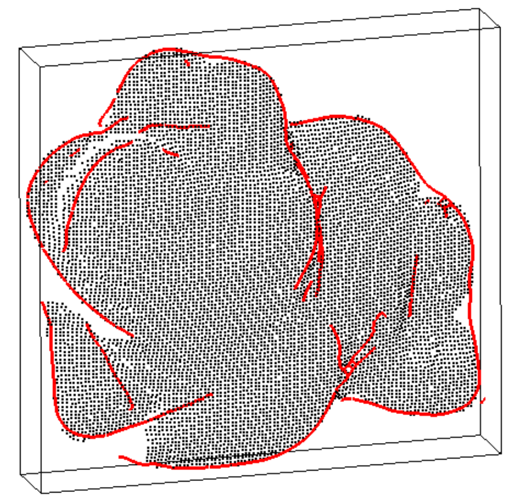
Feature Curves Extraction Results

Reference image

Depth data

Depth discontinuity

Refined depth



Discontinuity curves

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Motivation

- Surface models extraction is important
  - visualization
  - surgery planning
  - medical analysis
- Two major issues
  - segmentation with relevant tokens
  - surface fitting

Motivation

- Most methods require a knowledge model
  - easily break down to slightly abnormal case
- Propose to use tensor voting approach
  - enforcement of continuity constraint only
  - extract detail features with scale detection algorithm (CVPR’01)

Related Work

- Marching cubes algorithm
  - efficient, simple
  - good result only with accurate and dense data
  - Lorensen & Cline (Computer Graphics'87)
- Deformable model approach
  - initialization required
  - iterative
  - prior knowledge is often required
  - Kass, Witkin and Terzopoulous (IJCV'87)

Related Work

- Model or atlas based approach
  - a sub-class of deformable model approach
  - a patient specific model is required for deformation
  - model or training set must be obtained first
  - Leemput et al. (MICCAI'98)

Related Work

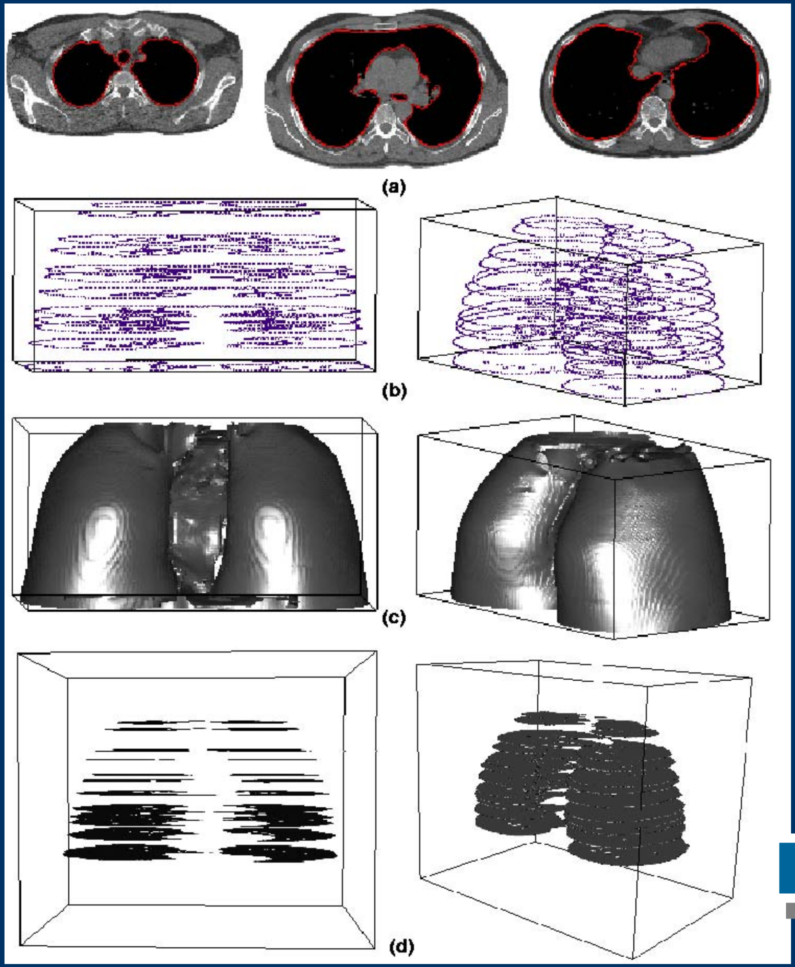
- Differential geometry approach
  - surface can be characterized if second-order differential properties are known
  - good result can be achieved for accurate data
  - Thirion & Gourdon (CVIU’95)
- Level set approach
  - zero crossings of higher dimensional space
  - allow topological changes, non-manifolds
  - methodology is iterative
  - require careful initialization
  - Duncan et al. (MICCAI’98)

Related Work

- Non-iterative approach
  - tensor voting approach
  - no model or other specific assumption is needed
  - Tang, Medioni, Duret (MICCAI’98)

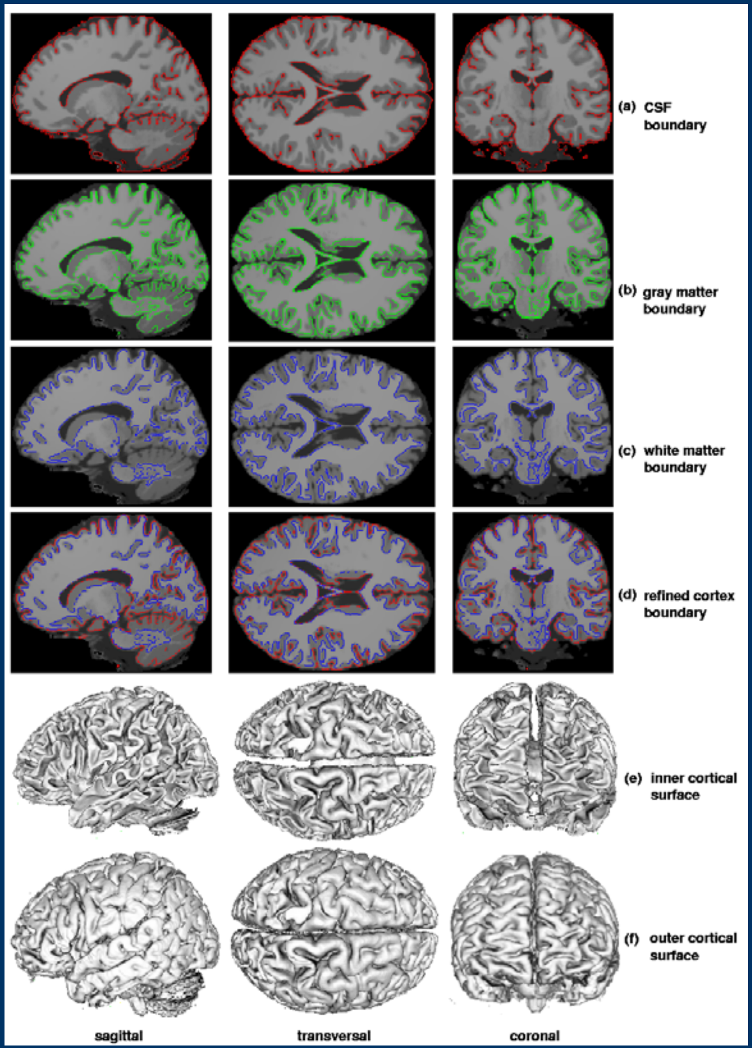
Results (Thorax Dataset)

- 12 real set of CT scans of the thorax is used
- Extract thorax by simple thresholding
- Region boundary inference
- Second order tensor voting is used to refine normal
- Sign of curvatures is detected
- Extraction of surface model is done with scale detection algorithm (CVPR’01)



Results (McGill Brain Dataset)

- MRI dataset of a brain is used
- The CSF, gray matter and white matter are extracted with simple thresholding
- Region boundary inference
- Inference of CSF/GM boundary and GM/WM boundary is done by intersection
- Surface model is generated with similar methods as the thorax
- Ground truth comparison shows our method is comparable with others (CVPR'01)



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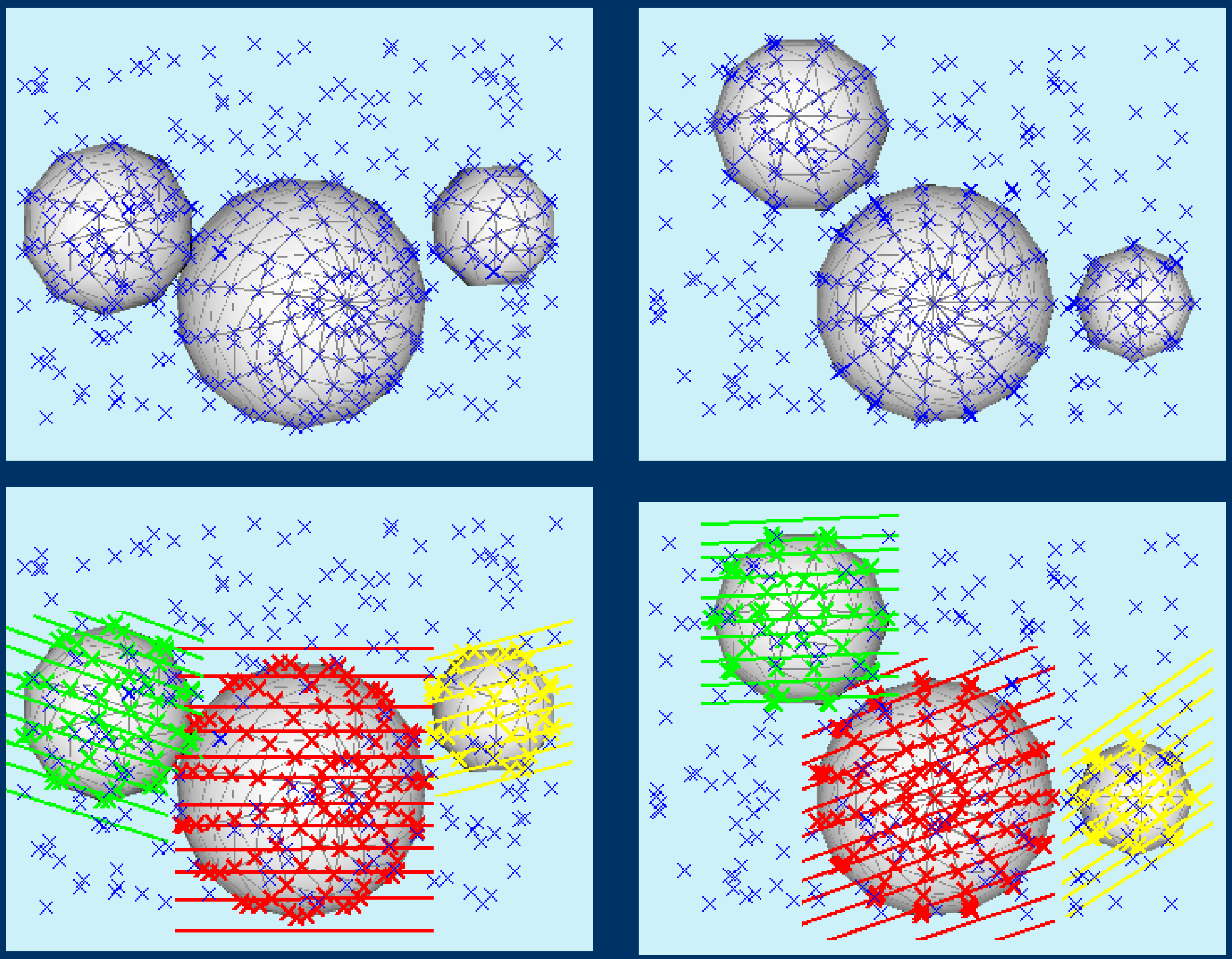
Motivation

- Epipolar geometry is an important constraint
  - stereo registration
  - stereo reconstruction
- Matching points are used for estimation
  - corresponding matching program are never accurate enough
  - false matches are unavoidable
  - non-static scene is even more complicated

Motivation

- Estimate epipolar constraint corresponding to:
  - not only background
  - but also salient motion
  - in the presence of large amount of false matches
  - quite difficult for most of the previous method

Example



Previous Work

- Eight Point Algorithm
  - earliest, simplest, most efficient
  - become inaccurate with large amount of noise contamination
  - Hartley suggest: normalization of data set (PAMI'97)
  - more accurate and comparable to non-linear approach - but still sensitive to outlier noise

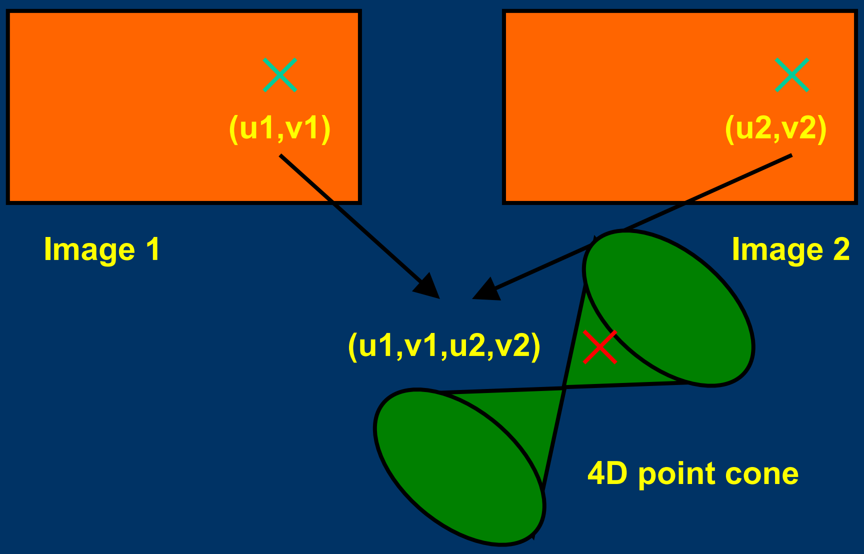
Previous Work

- Robust Algorithms
  - non-linear iterative optimization methods
    - LMedS by Zhang et al. (IJCV’98)
  - random sampling approach
    - RANSAC by Torr and Murray (IJCV’97)
  - good with static scene but unstable with non-static scenes and false matches contamination
- Local Homography Assumption
  - by Pritchett and Zisserman (ICCV’98)
  - point matches are generated by homography
  - but does not apply to curved surfaces

Previous Work

- Noise Removal Techniques
  - ROR by Adam and Rivlin (PAMI'01)
    - with proper rotation of image points
    - correct matching pairs will create line segments pointing in approx same direction
    - require intensive search of the correct rotation
  - 8D Tensor Voting by Tang and Medioni (PAMI'01)
    - voting for the most salient hyperplane in the 8D parameter space
    - the 8D space is not isotopic
    - high dimension require multi-passes of voting

Joint Image Space

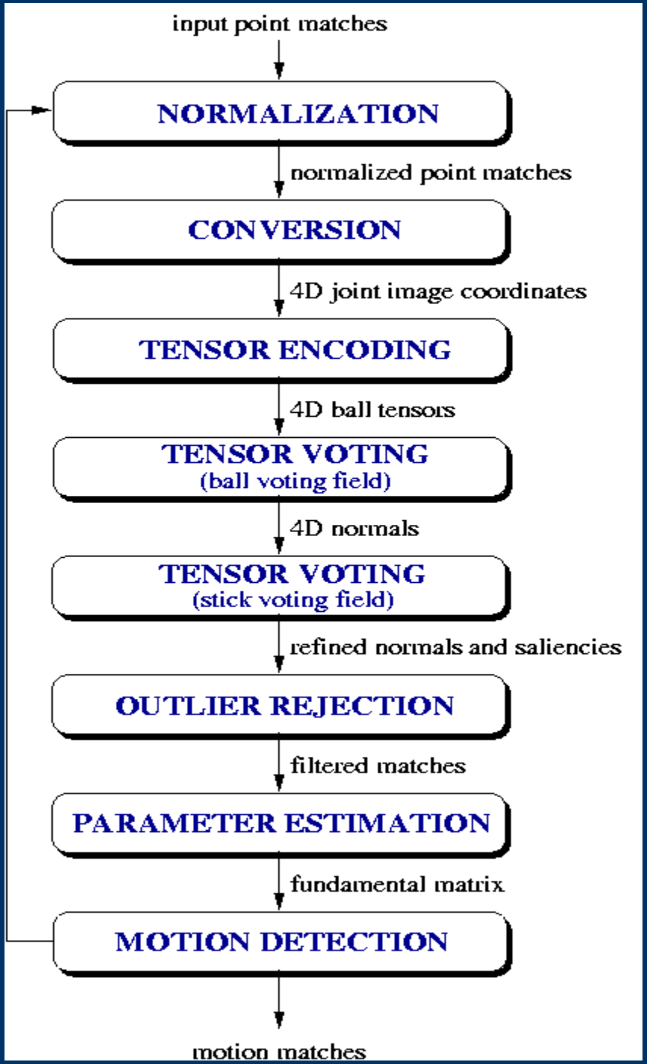


- Suggested by Anandan that the epipolar geometry defines a 4D point cone in the joint image space (ECCV'00)

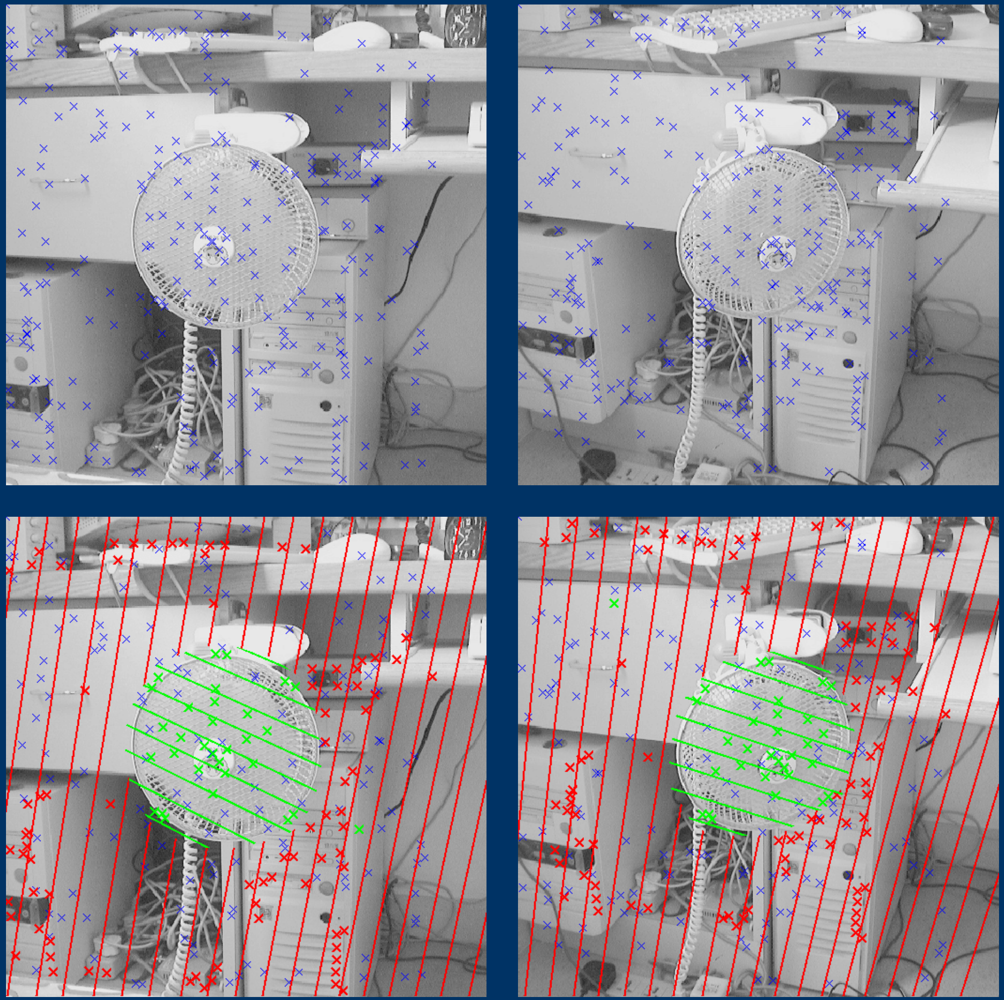
Our Approach

- Use 4D tensor voting to filter off matches not likely on a smooth structure
- Use robust methods: such as RANSAC to estimate epipolar geometry correspond to different motions
- Epipolar geometry of motion object is just the combination of camera and their motions

Algorithm


input point matches
NORMALIZATION
normalized point matches
CONVERSION
4D joint image coordinates
TENSOR ENCODING
4D ball tensors
TENSOR VOTING
(ball voting field)
4D normals
TENSOR VOTING
(stick voting field)
refined normals and saliencies
OUTLIER REJECTION
filtered matches
PARAMETER ESTIMATION
fundamental matrix
MOTION DETECTION
motion matches

Results



Results

Results

	Three Spheres			Fan		Umbrella		Car	
	most salient	2nd salient	3rd salient	most salient	2nd salient	most salient	2nd salient	most salient	2nd salient
No. of correct data points S_i	192	83	33	111	30	84	21	93	34
No. of incorrect data points	192	192	191	151	150	101	99	101	100
noise/signal ratio	1.000	2.313	5.788	1.360	5.000	1.202	4.714	1.086	2.941
(A) Results on 4D tensor voting									
No. of correct inliers T_i	150	72	33	80	27	61	19	71	20
No. of incorrect inliers	2	1	0	3	9	3	7	7	2
(B) Results on parameter estimation									
No. of correct inliers R_i	109	50	33	81	30	63	21	59	30
No. of incorrect inliers	0	1	0	1	1	2	2	1	0
Scale used in 4D analysis σ	400			400		400		400	
No. of random trials	1000			10000		10000		10000	
No. of points in each subset	10			15		15		15	

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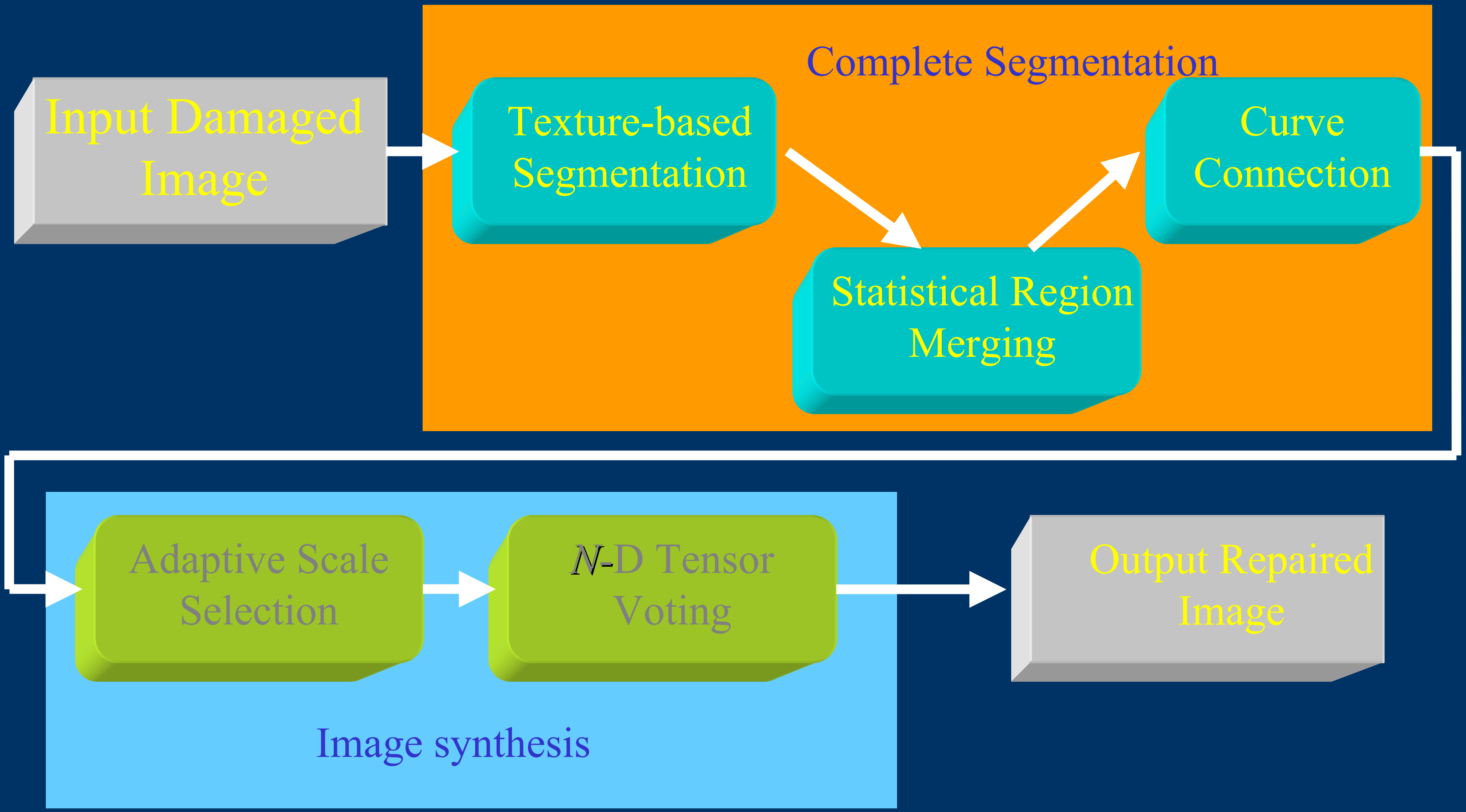
Motivation

- Main difficulties to repair a severely damaged image of natural scene
  - Mixture of texture and colors
  - Inhomogeneity of patterns
  - Regular object shapes

Motivation

- Given as few as one image without additional knowledge, we address:
  - How much color and shape information in the existing part is needed to seamlessly fill the hole?
  - How good can we achieve in order to reduce possible visual artifact when the information available is not sufficient?

Image repairing system



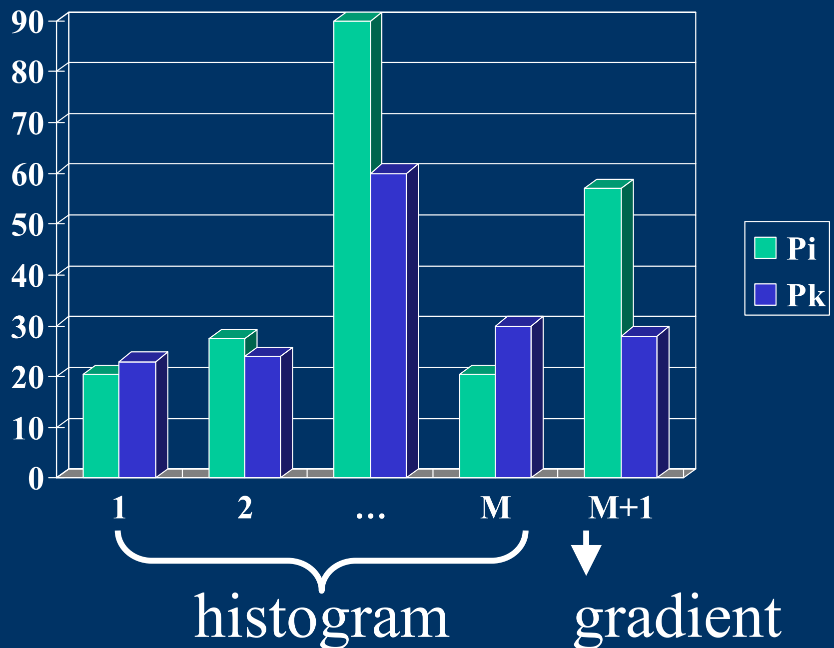
Segmentation

- JSEG [Deng and Manjunath 2001]
  - color quantization
  - spatial segmentation
- Mean shift [Comanicu and Meer 2002]
- Deterministic Annealing Framework [Hofmann et al 1998]

Texture-based Segmentation

Statistical Region Merge

- $(M+1)$D intensity vector V_i^{M+1} for each region P_i, where M is the maximum color depth in the whole image.



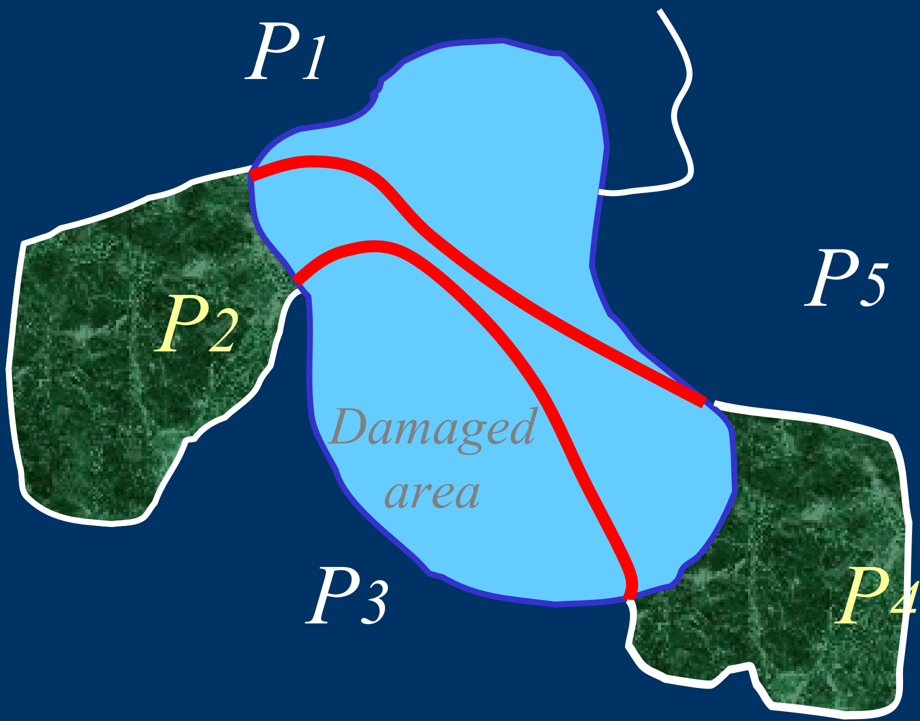
$$V_i\ (M+1) = \frac{\alpha}{N_i} \sum_{j \in P_i} \| \nabla j \|$$

$$P = P_i \cup P_k \qquad \text{if}$$

$$s_{i,k} = \| V_i - V_k \| < Threshold$$

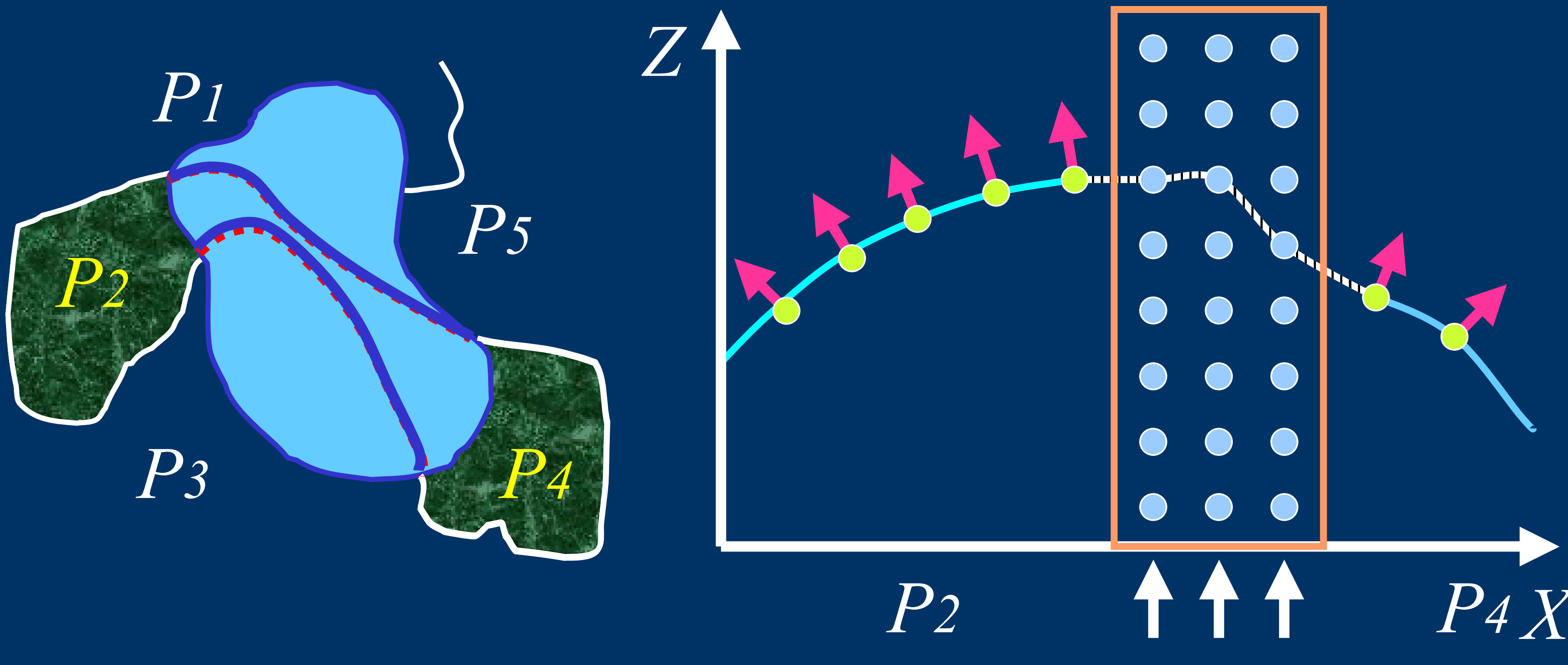
Why Region Merge?

- Decrease the complexity of region topology
- Relate separate regions



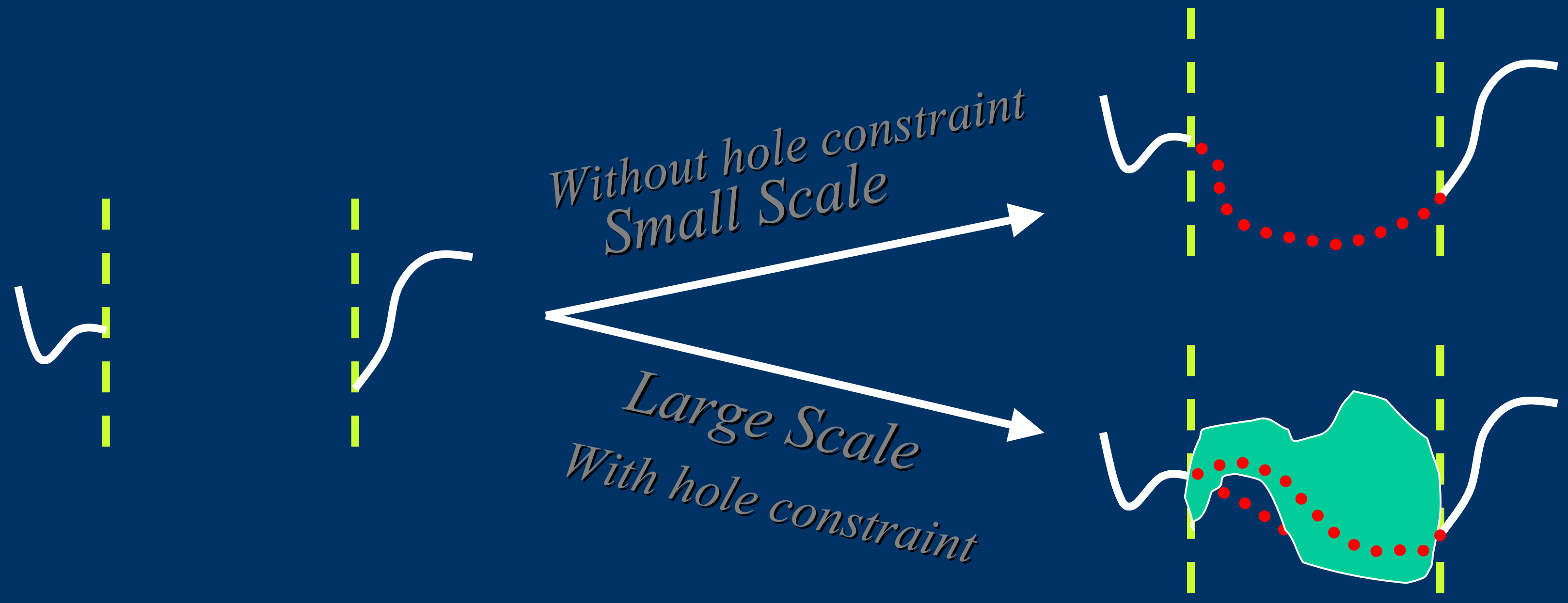
Curve Connection

- 2-D tensor voting method



Why Tensor Voting?

- The parameter of the voting field can be used to control the smoothness of the resulting curve.
- Adaptive to various hole shapes



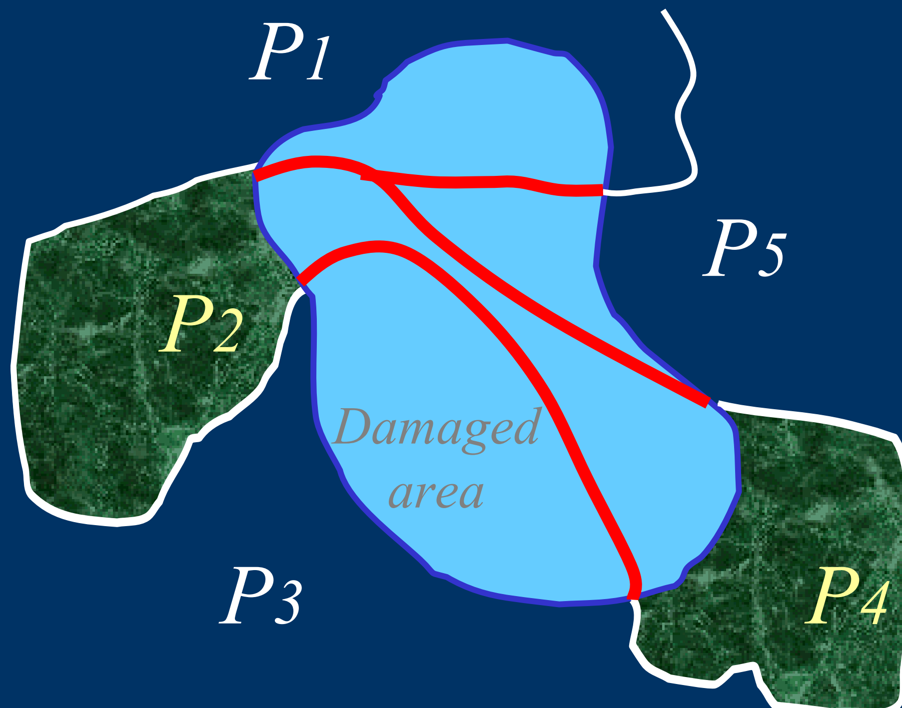
Connection Sequence

- Greedy algorithm
  - Always connect the most similar regions

P2 **and** *P4*

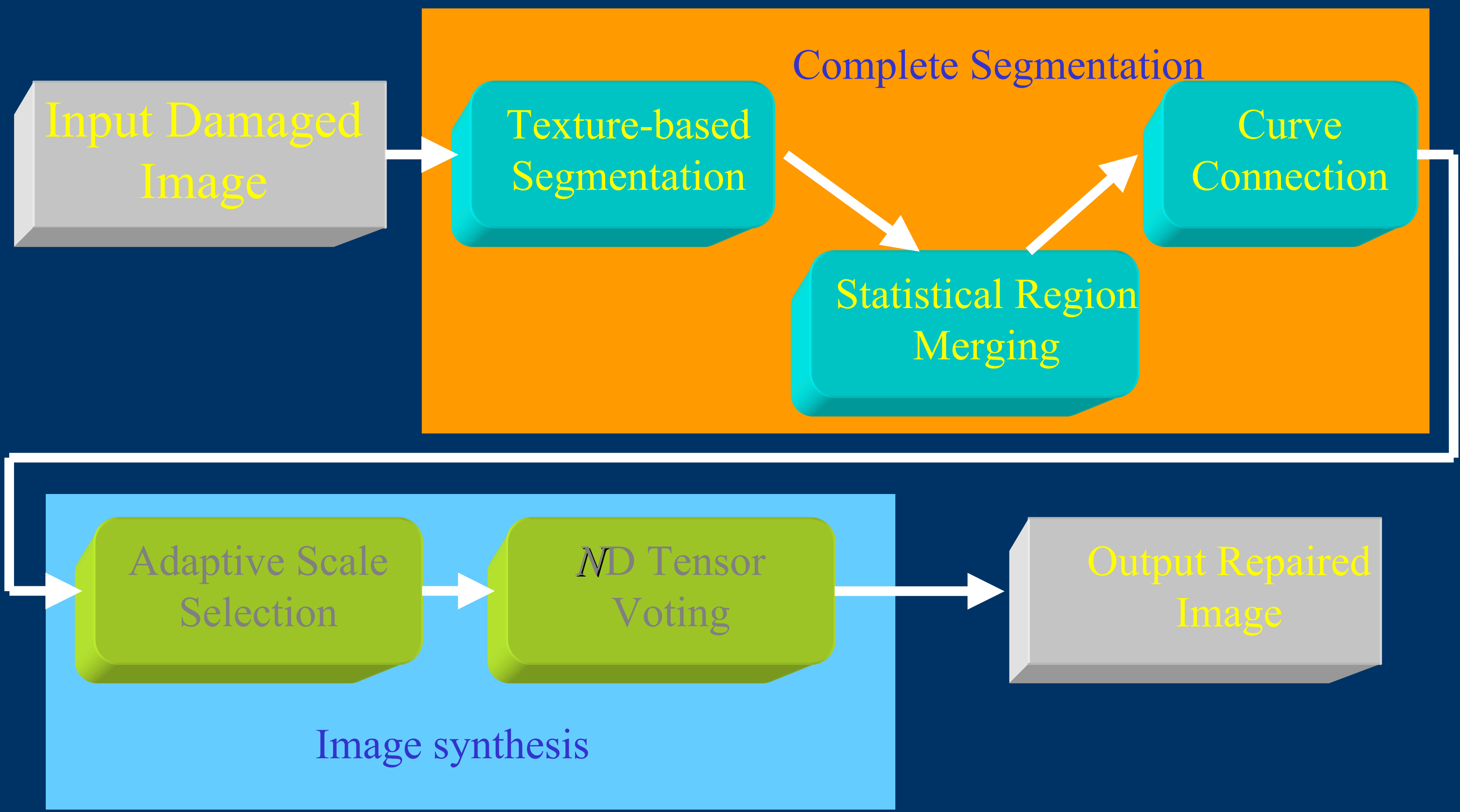
P3 **and** *P5*

P1



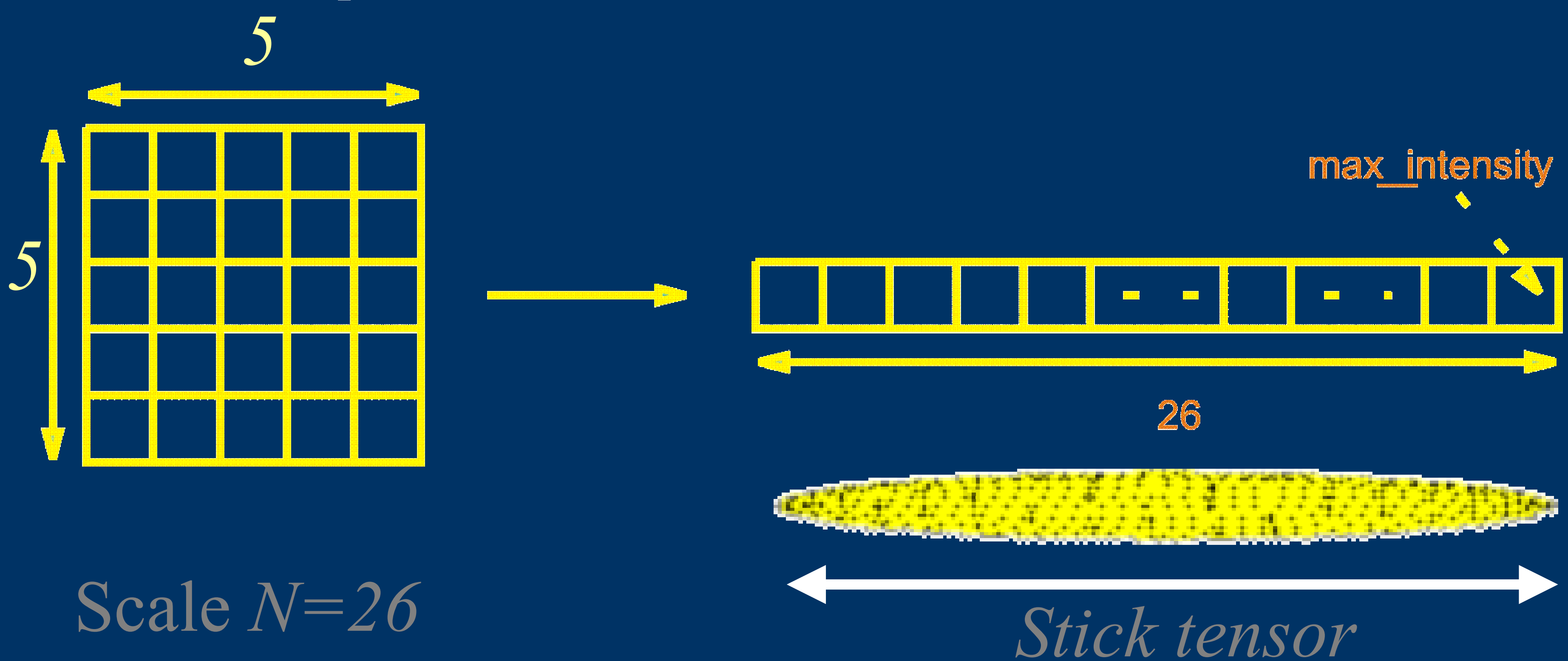
Complete Segmentation

Image repairing system



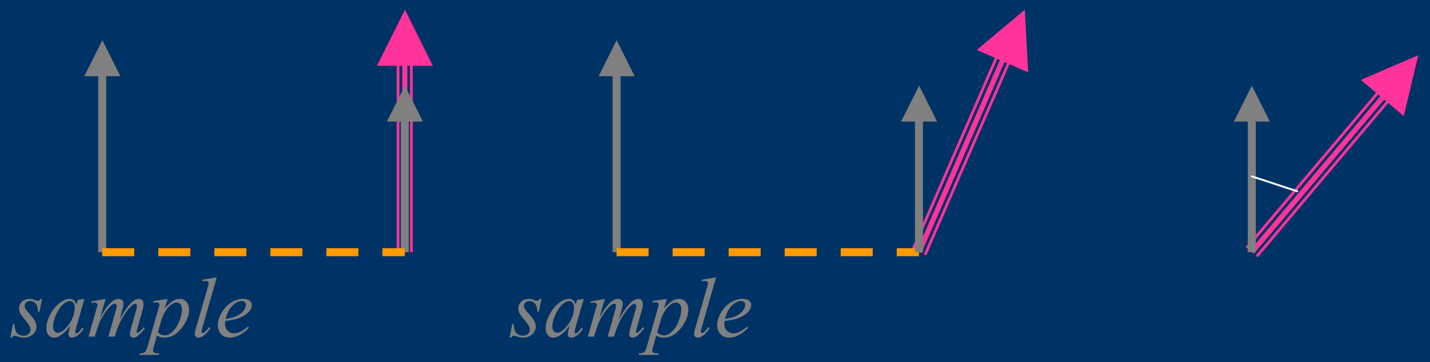
N-D Tensor Voting

- Tensor encoding
  - Each pixel is encoded as an *N*-D stick tensor



N-D Tensor Voting

- Voting process in *N*-D space
  - An osculating circle becomes an osculating hypersphere.
  - *N*-D stick voting field is uniform sampling of normal directions in the *N*-D space.



Adaptive Scaling

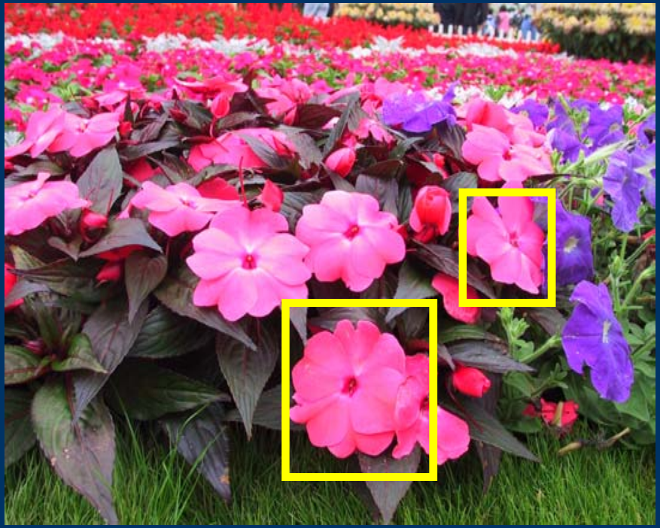
- Texture inhomogeneity in images gives difficulty to assign only one global scale *N* [Lindeberg et al 1996].
- For each pixel *i* in images, we calculate:

$$M_{N_i} = AVG_{N_i}\{(\nabla I)(\nabla I)^T\}$$

- *trace*(*M*) measures the average strength of the square of the gradient magnitude in the window of size *Ni*

Adaptive Scaling

- For each sample seed:
  - Increase its scale *Ni* from the lower bound to the upper bound
  - If $trace(M_{N_i}) < trace(M_{N_i - 1}) - \alpha$ where α is a threshold to avoid small perturbation or noise interference, set $Ni - 1 \rightarrow Ni$ and return
  - Otherwise, continue the loop until maxima or upper bound is reached



Results

Results

Results

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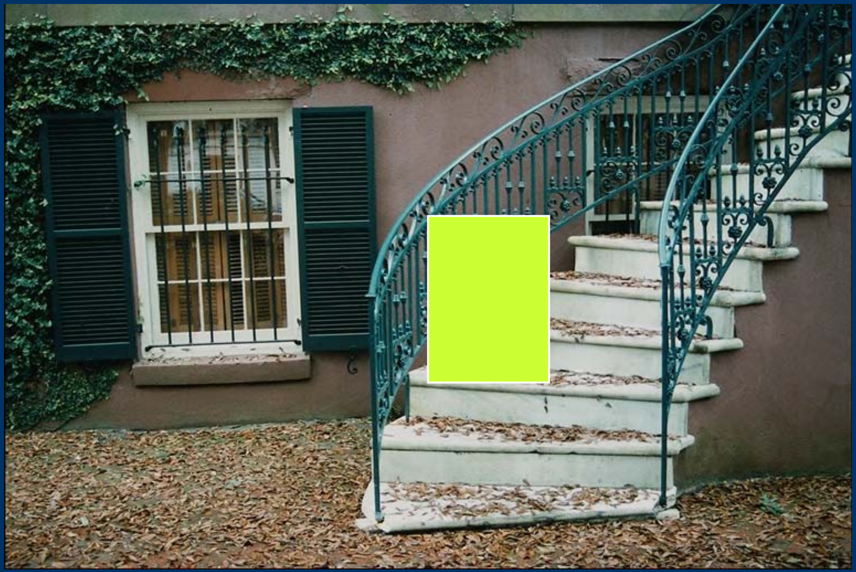
Results

Limitations

- Lack of samples.
- Meaningful and semi-regular objects.



Conclusion

- An automatic image repairing system.
- Region partition and merging.
- Curve connection by 2D tensor voting.
- *N*D tensor voting based image synthesis.
- Adaptive scale.

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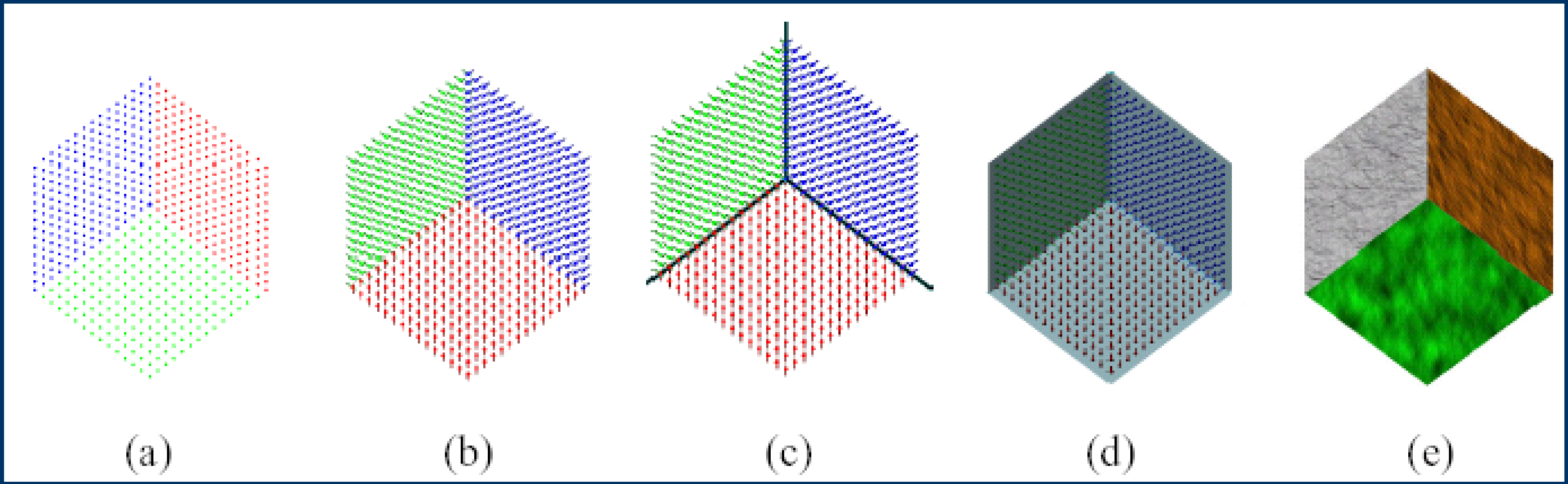
Introduction

- Geometric hole filling
- Range data: one depth value for a pixel
- Extension of 2-D curve connection

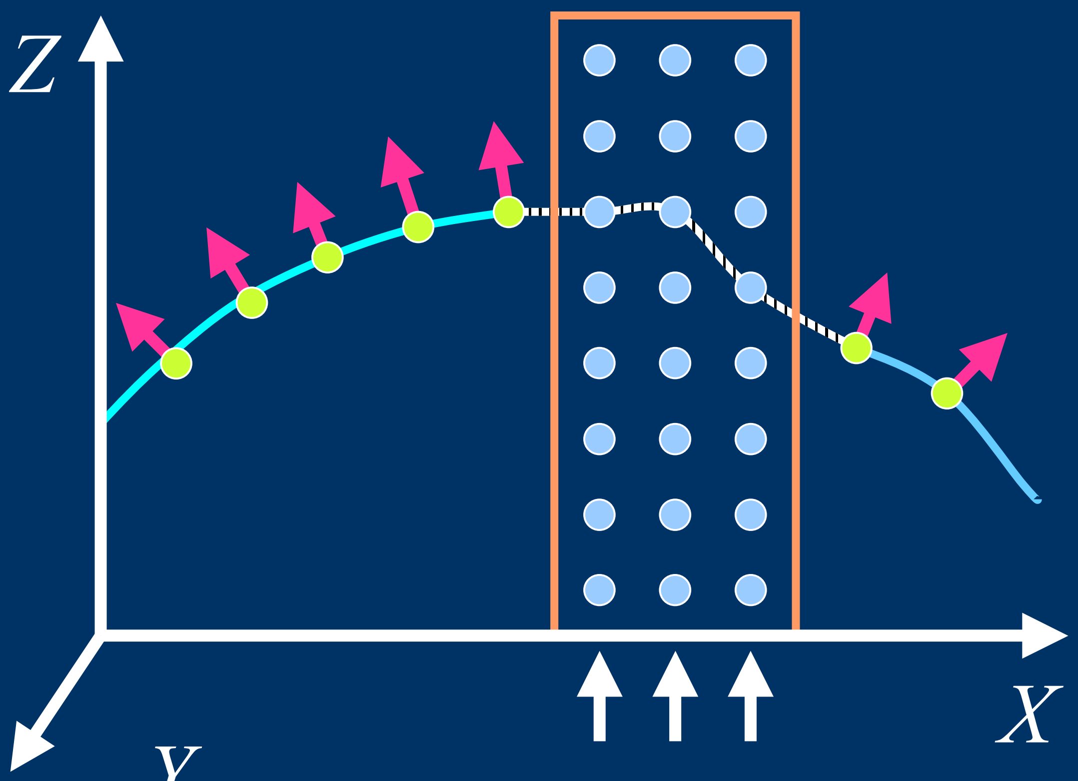
Procedure



- Data inference
- Normal estimation
- Curve junctions
- Surface mesh
- Texture synthesis

Range data

- 3-D data synthesis with additional Y axis



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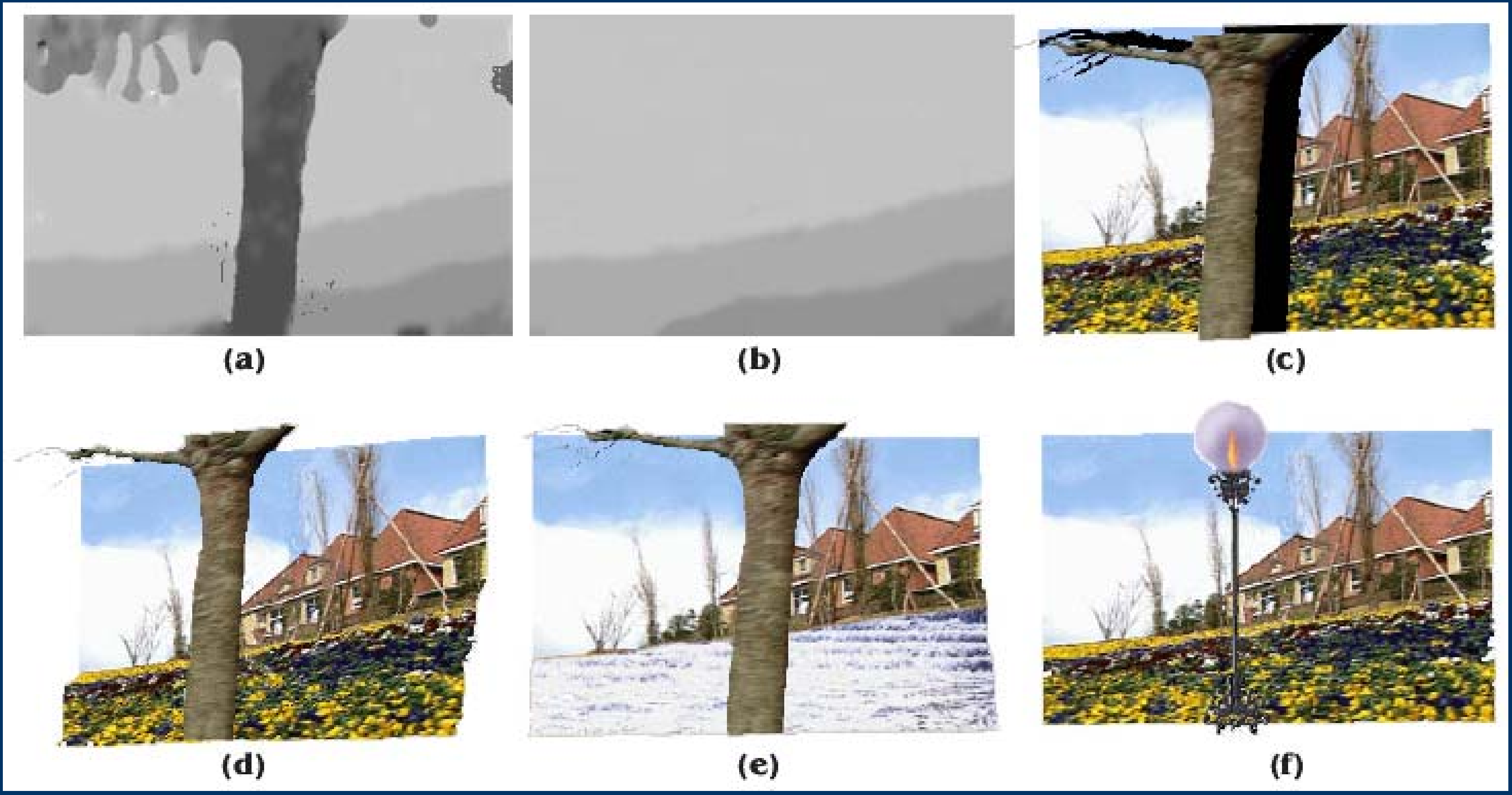

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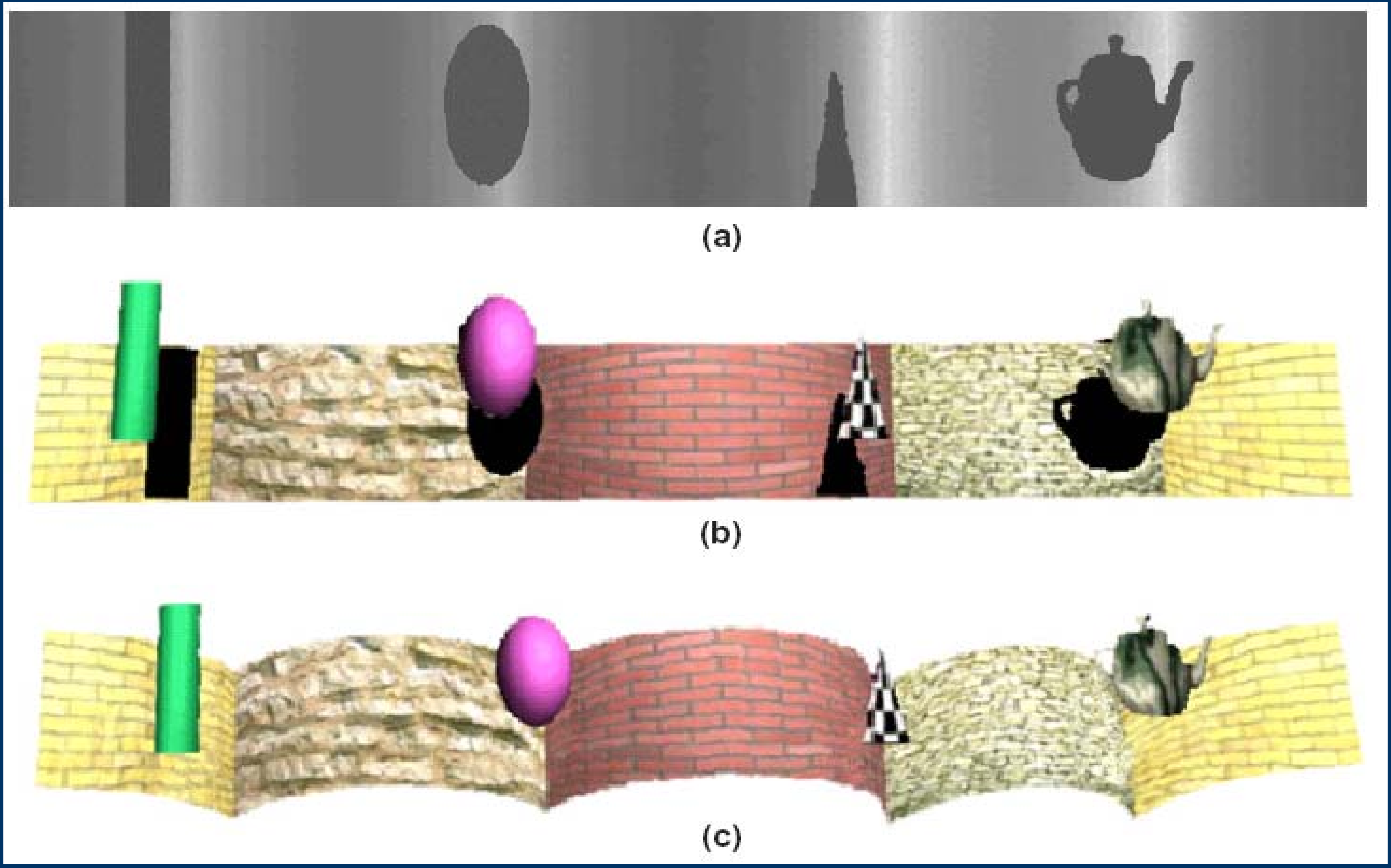

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Motivation

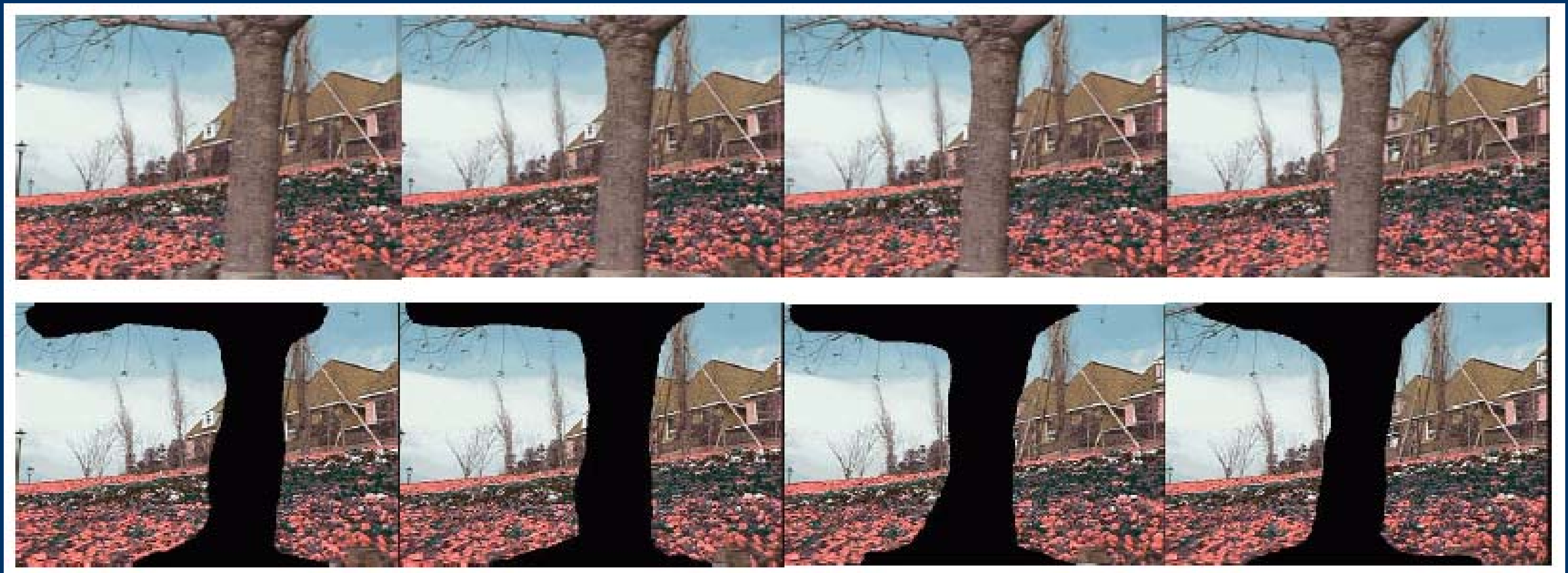
- Video Retouching
- Difficulties:
  - Frame-by-frame repairing can not maintain temporal coherence
  - Single mosaic has limitations

Our approach

- Hole propagation
- Layer propagation
- Layered reference mosaic
- Image repairing
- Homography blending

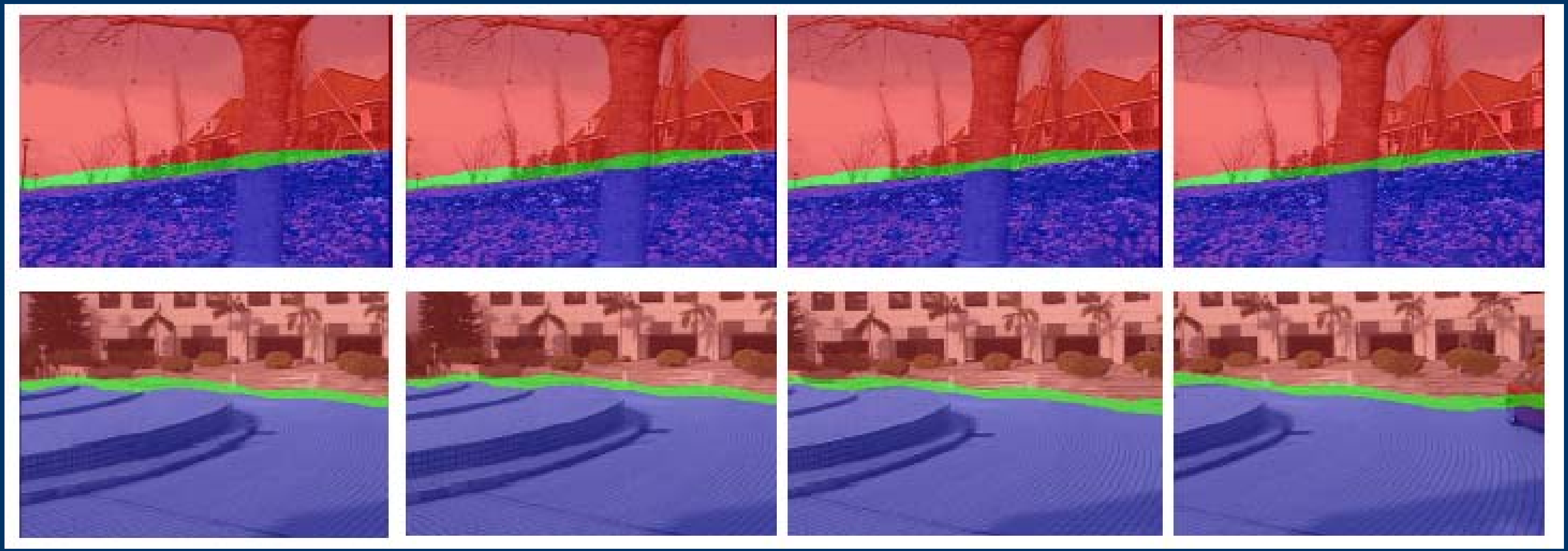
Hole Propagation

- Frame-by-frame segmentation
- Mean shift tracking



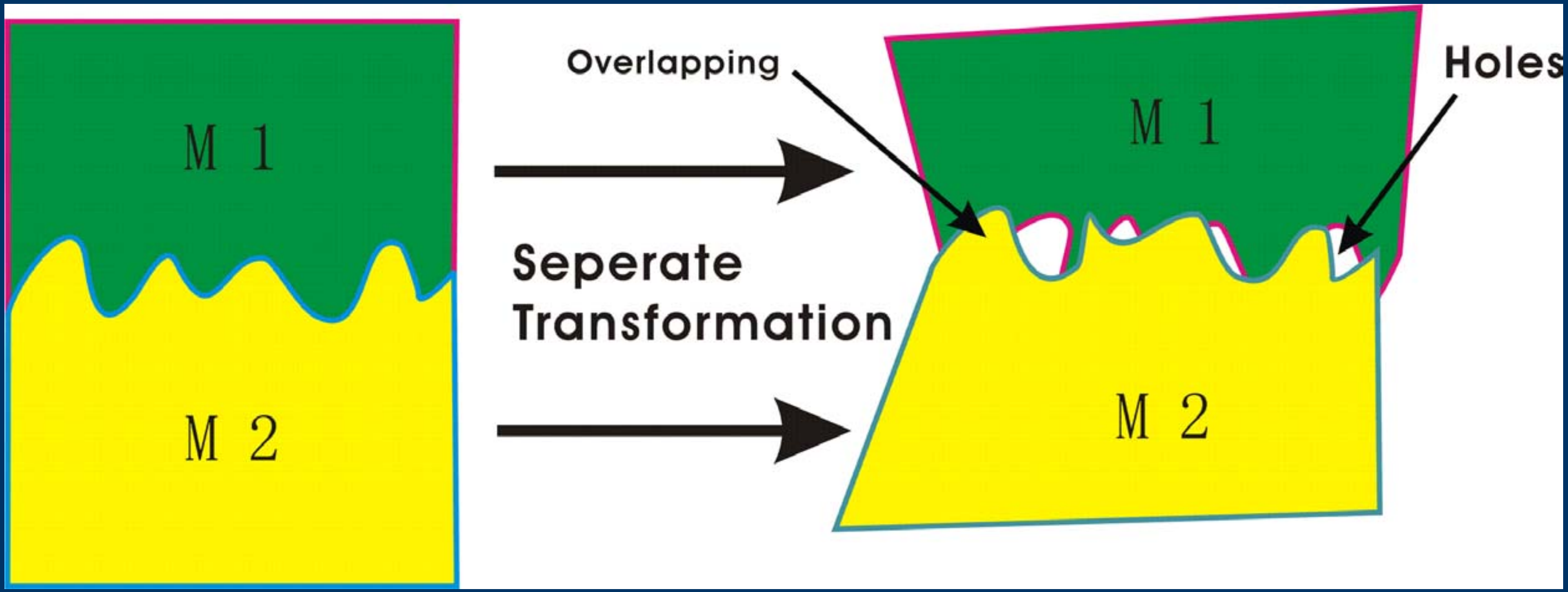
Layer Propagation

- Users only need to specify rough layer boundaries in key frames
- Optical Flow method to track the boundaries



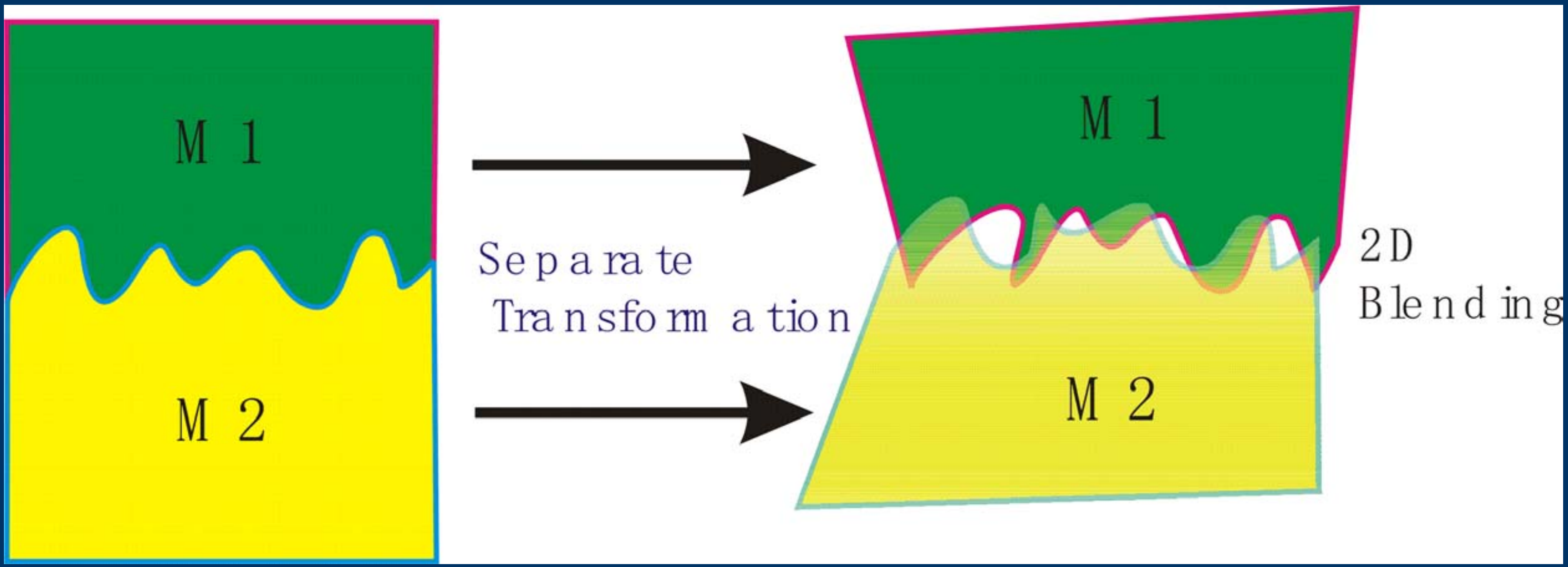
Homography Blending

- Overlapping and small holes are obtained by warping two layers, using their respective homographic transform



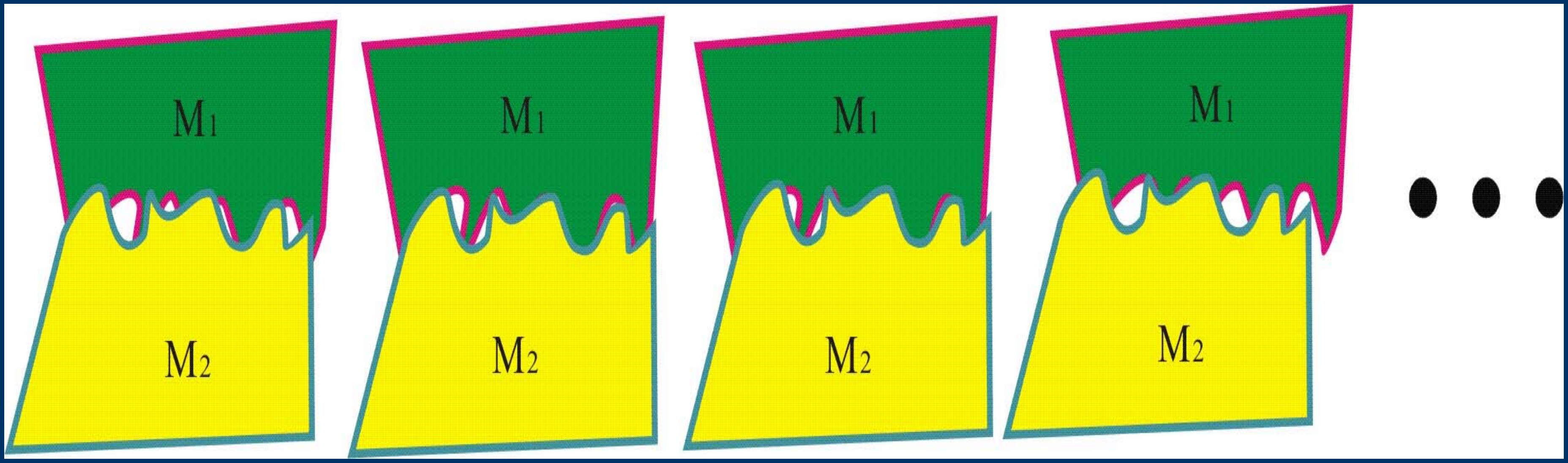
Homography Blending

- Normal 2-D blending



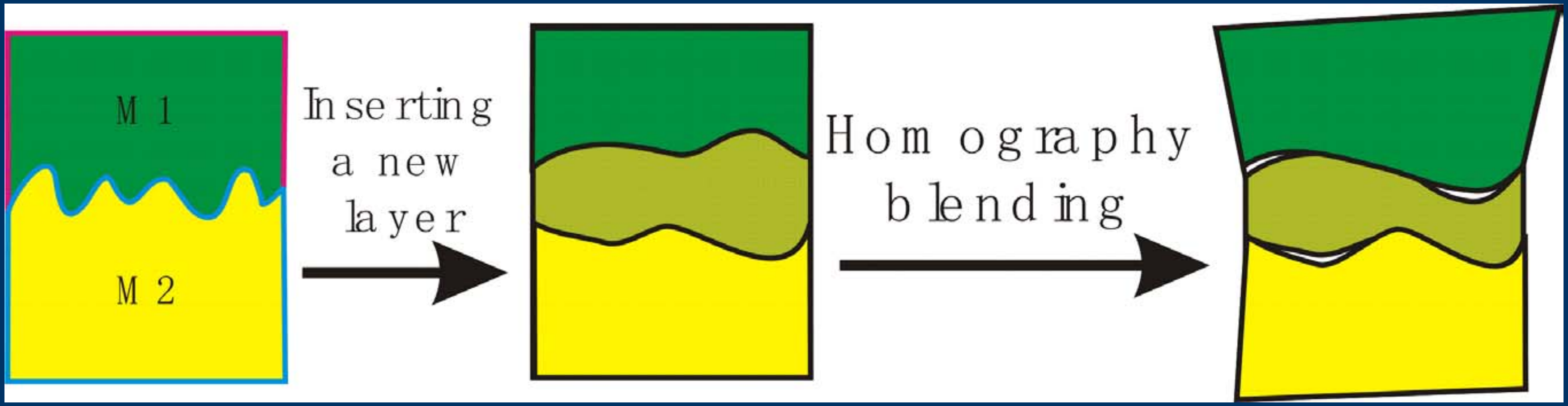
Homography Blending

- 2-D blending is performed on single frame
- 2-D blending can not solve the boundary shifting problem for a video sequence



Homography Blending

- Blending homography matrices
- Weighting function is calculated according to the distance to the boundary of two regions



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