Segmentation using Sparse Shape Composition and Minimally Supervised Method in Liver Surgery Planning System

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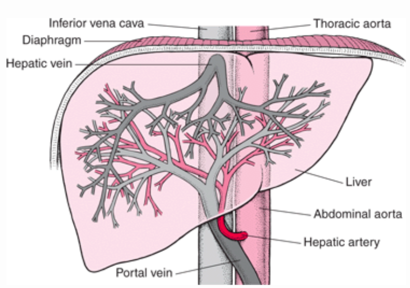
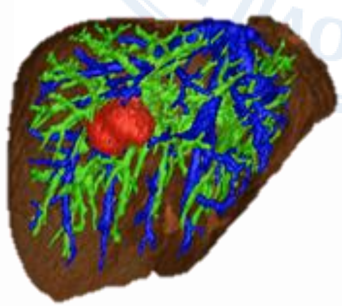
Background: Liver Surgery Planning

liver sugery planning system

function	significance
provide information of vascular distribution	Assist the optimized planning of the surgery strategy
Visualize tumors, vessels and liver segments	Improve the accuracy of treatment





framework

3D abdominal CT volume data

Segmentation

Hepatic parenchyma	Portal veins
Hepatic veins	Tumors

Liver segment approximation

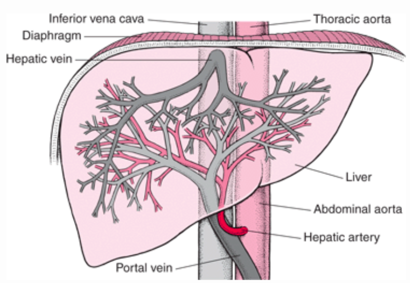
Visualization

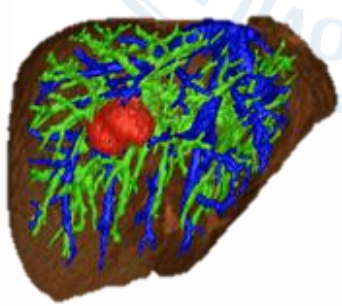
Quantitative analysis and surgery strategy decision

Guiding the implementation of the liver surgery

Background: Liver Surgery Planning

- **segmentation in liver surgery planning**
  - — User interaction
  - — Hard to achieve robust results
  - — Normal person VS patients





- **framework**

3D abdominal CT volume data

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Segmentation

Hepatic parenchyma	Portal veins
Hepatic veins	Tumors

↓

Liver segment approximation

↓

Visualization

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Quantitative analysis and surgery strategy decision	Guiding the implementation of the liver surgery

Background: Segmentation of Liver

Challenges of Segmentation

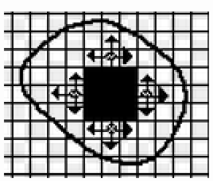

Low contrast

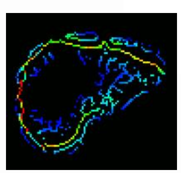

inhomogeneous

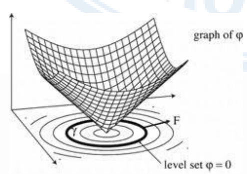

Shape variation

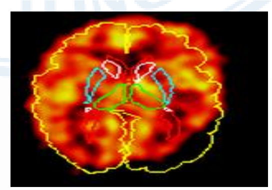
Liver segmentation method

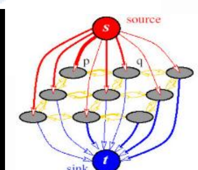
Region growing	Boundary localization	Snake/ Level set	Atlas matching	Graph cut	**Statistic shape model**	…

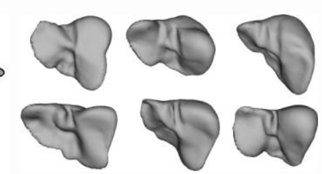






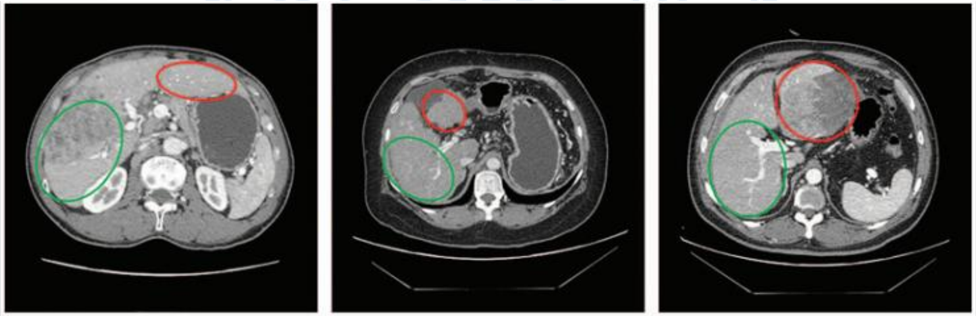






Background: Statistical Shape Model

- **Statistical shape model**
  - Better performance than methods using appearance cues
  - Address over-segmentation and under-segmentation
- **Problems in modeling liver shape**
  - Complex variation
  - gross errors and outliers
  - local details



Methods

Initial Segmentation

Shape Repository

Sparse Shape Composition

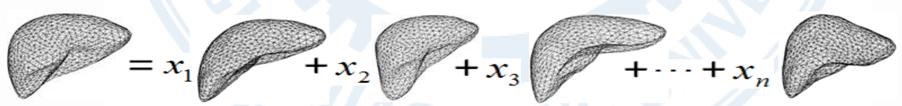
Shape prior

Fast Marching

Final Segmentation

1st, Sparse Shape Composition(SSC)

- Learn the shape from the shape repository
- optimized sparse linear combination of shapes in the repository
- Explicitly model gross errors



transformation

Gross errors

$$\arg\min_{x,e,\beta} \|T(y,\beta) - Dx - e\|_2^2 + \lambda_1 \|x\|_1 + \lambda_2 \|e\|_1$$

Liner combination

Sparse constraint

Methods

Initial Segmentation → Sparse Shape Composition
Shape Repository → Sparse Shape Composition
Sparse Shape Composition → Shape prior
Shape prior → Final Segmentation
Fast Marching → Final Segmentation

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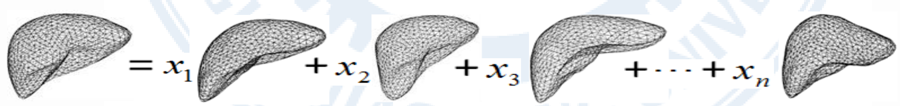

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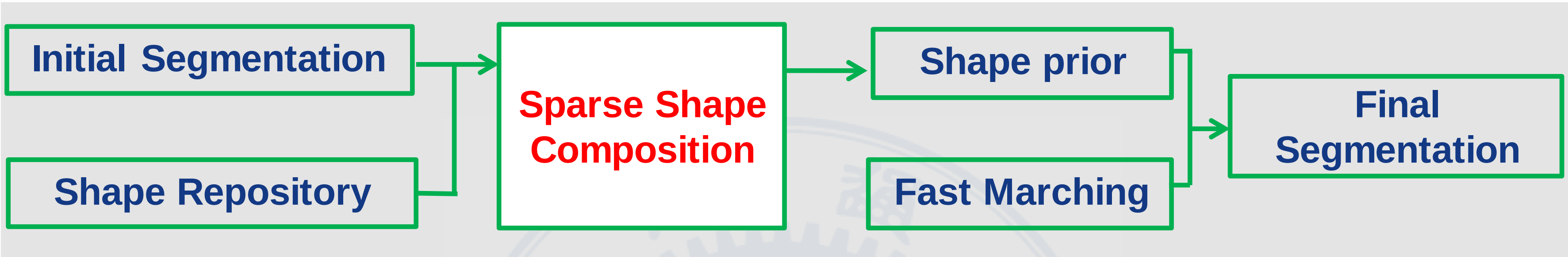
Gross errors

$$\arg\min_{x,e,\beta} \|T(y,\beta) - Dx - e\|_2^2 + \lambda_1 \|x\|_1 + \lambda_2 \|e\|_1$$

Liner combination

Sparse limitation

Methods



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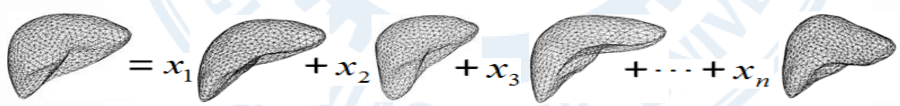


transformation   Gross errors

$$\arg\min_{x,e,\beta} \|T(y,\beta) - Dx - e\|_2^2 + \lambda_1 \|x\|_1 + \lambda_2 \|e\|_1$$

Liner combination   Sparse limitation

Methods

Initial Segmentation → Sparse Shape Composition
Shape Repository → Sparse Shape Composition
Sparse Shape Composition → Shape prior
Shape prior → Final Segmentation
Fast Marching → Final Segmentation

1st, Sparse Shape Composition(SSC)

- Learn the shape from the shape repository
- optimized sparse linear combination of shapes in the repository
- Explicitly model gross errors

$$\arg\min_{x,e,\beta} \boxed{\left\|T(y,\beta) - Dx - e\right\|_2^2} + \boxed{\lambda_1 \left\|x\right\|_1 + \lambda_2 \left\|e\right\|_1}$$

Assumption
Sparse representation of training shapes
Gross errors are sparse

Methods

Initial Segmentation

Shape Repository

Sparse Shape Composition

Shape prior

Fast Marching

Final Segmentation

2nd, Accurate segmentation

- Shape prior + Fast Marching Level Set
- Seeds points results from histogram analysis

$$V(x,c) = \omega V_{\text{intensity}}(x,c) + (1-\omega)V_{\text{shape}}(x).$$

$$V_{\text{shape}}(x) = \frac{\Phi(x)}{\max(\Phi(x))}$$

Speed function

Intensity term

Shape term

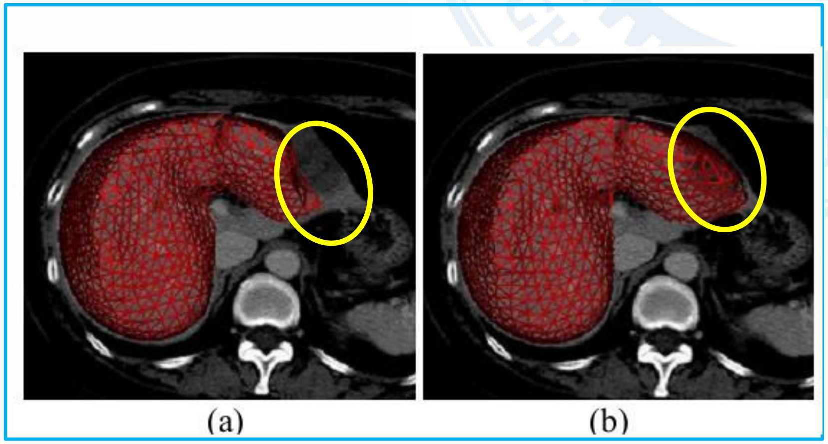
Results

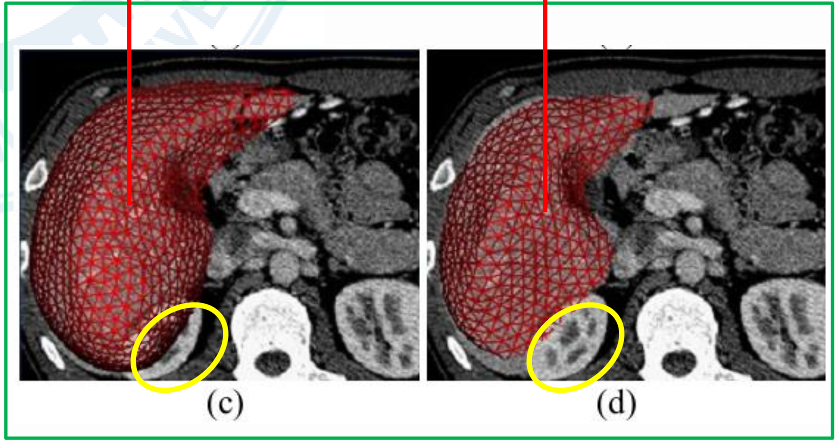
Shape repository: manually segmented result for training (50 shapes)

Initial liver segmentation: Simple region growing method

Output of SSC: robustness to outliers

Gross errors is corrected

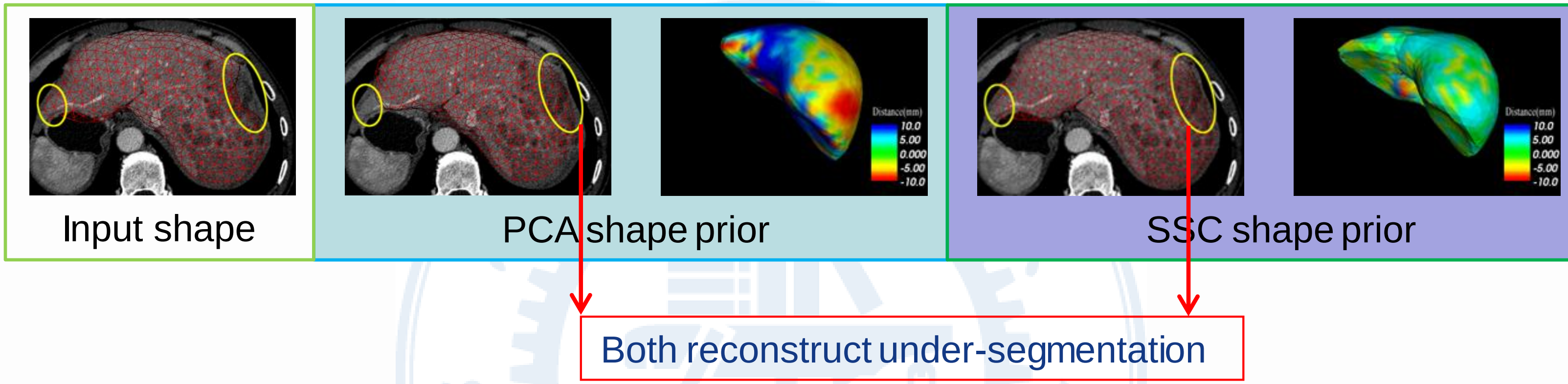




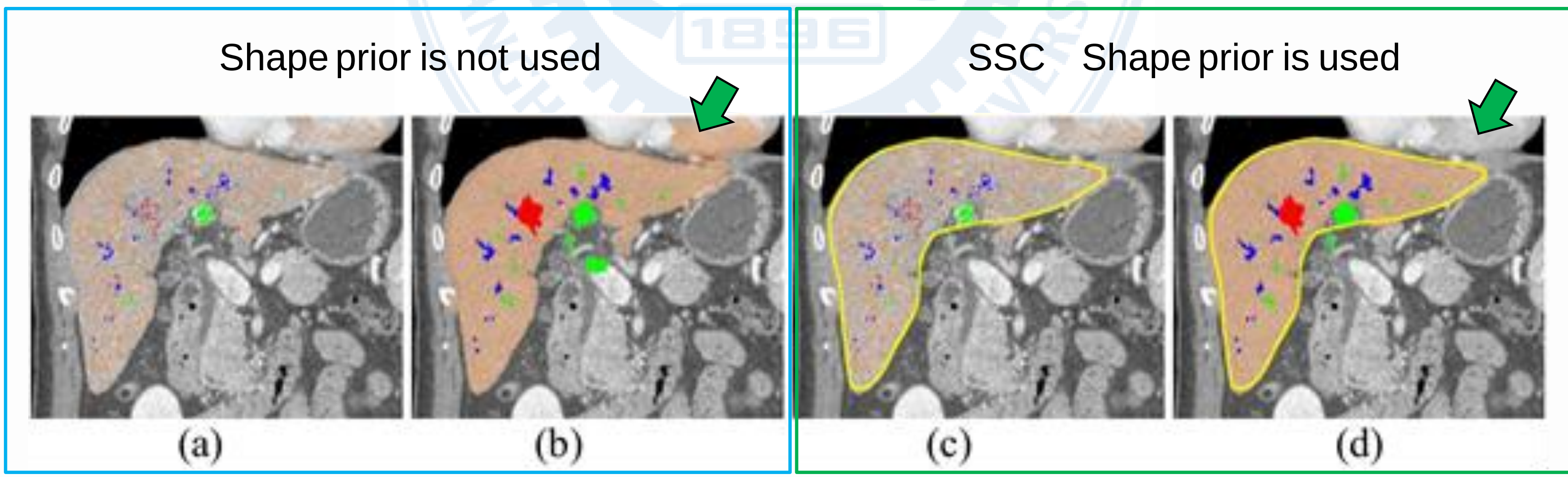
The initial segmentation results (a, c) and their corresponding shape priors (b, d).

Results

Compare with PCA



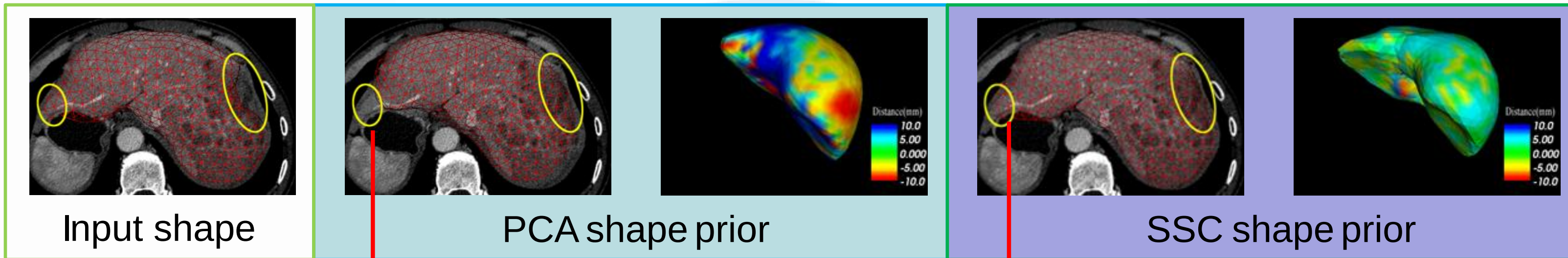
Segmentation results



Accurate segmentation of hepatic parenchyma, portal veins and hepatic veins.

Results

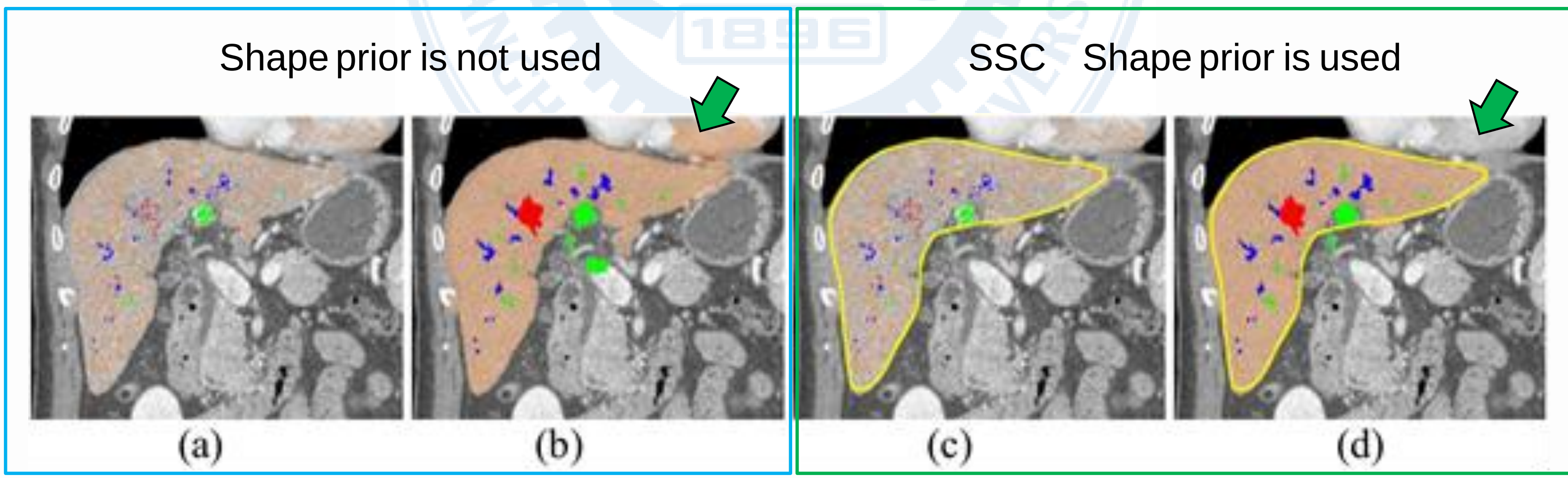
Compare with PCA



Local detail is lost

Local detail is preserved

Segmentation results



Accurate segmentation of hepatic parenchyma, portal veins and hepatic veins.

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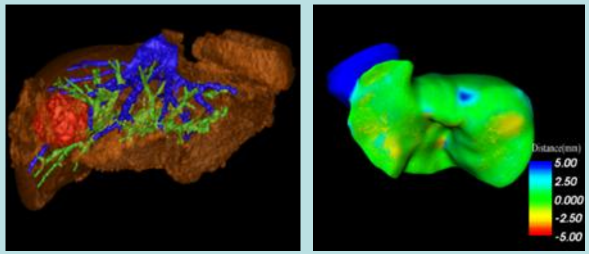
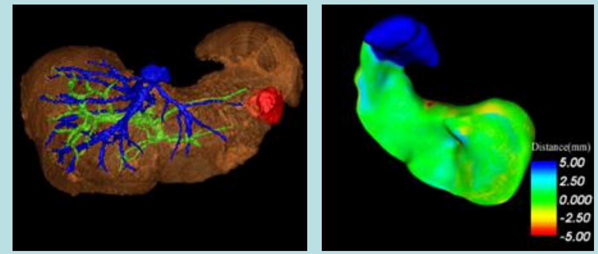
Results

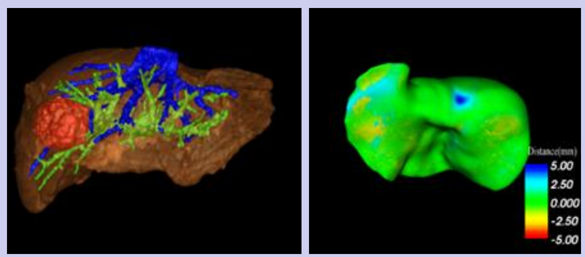
Segmentation results:

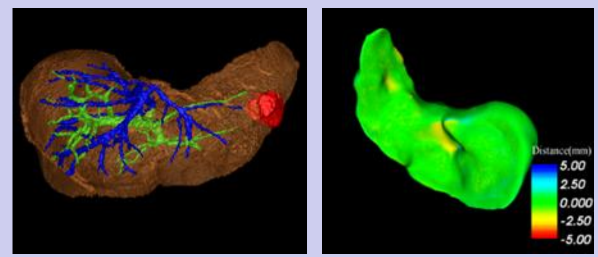
Shape prior not used



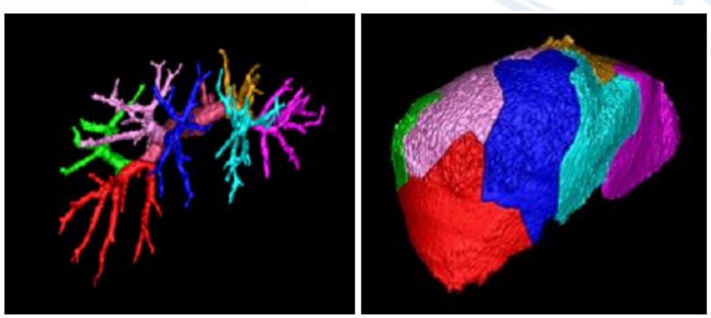


SSC
Shape prior
is used

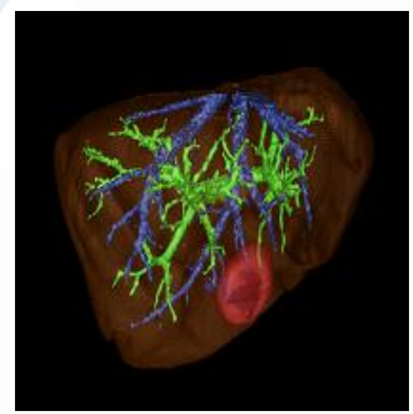




Liver segment approximation



(a) (b)



Evaluation (8 patients)

Sensitivity and specificity

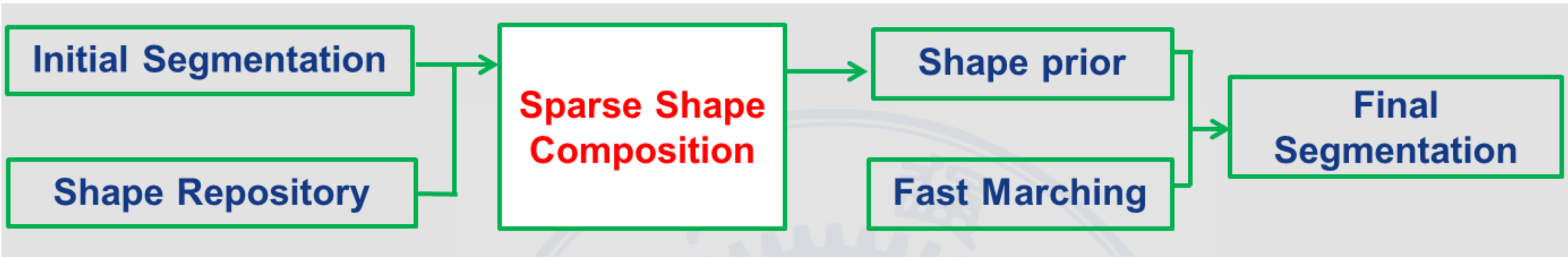
	hepatic parenchyma	portal veins	hepatic veins	tumours
Sensitivity	0.902	0.878	0.925	0.896
Specificity	0.961	0.983	0.994	0.987

symmetric surface distance (ASD), mm

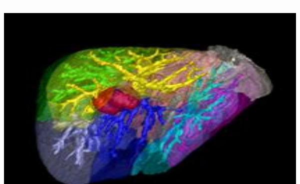
hepatic parenchyma	portal veins	hepatic veins	tumours
1.08	1.06	0.90	1.15

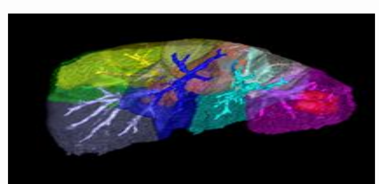
$$ASD(A,B) = \frac{1}{|S(A)| + |S(B)|}\left(\sum_{S_A \in S(A)} d(S_A, S(B)) + \sum_{S_B \in S(B)} d(S_B, S(A))\right)$$

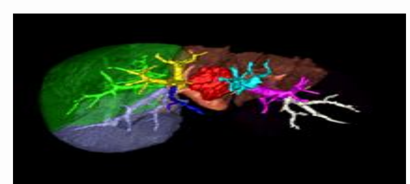
Conclusion



- **Advantage of Sparse Shape Composition for liver**
  - Model the complex variation of liver
  - Address outliers and preserve details
- **The proposed segmentation framework**
  - Accurate segmentation of liver and intrahepatic vessels
  - Robust to clinical liver image data







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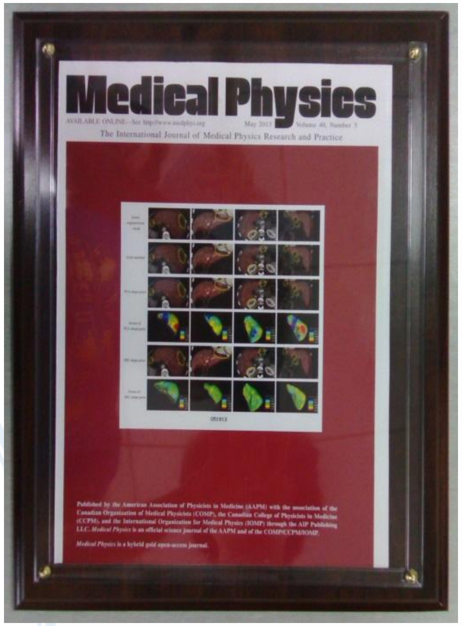

Thanks!

Reference

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