SMPL-A: Modeling Person-Specific Deformable Anatomy

Hengtao Guo[1,2], Benjamin Planche[1], Meng Zheng[1], Srikrishna Karanam[1], Terrence Chen[1], Ziyan Wu[1]

[1]United Imaging Intelligence, Cambridge MA, USA, [2]Rensselaer Polytechnic Institute, Troy NY, USA

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Abstract

A variety of diagnostic and therapeutic protocols rely on locating in vivo target anatomical structures, which can be obtained from medical scans. However, organs move and deform as the patient changes his/her pose such the clinicians have to conduct frequent intraoperative scans, resulting in higher exposition to radiations. We present a learning-based approach to estimate the patient-specific internal organ deformation for arbitrary human poses to assist with radiotherapy and similar medical protocols.

Keywords: SMPL Model, Deformable Registration, Point Cloud Analysis, Deep Neural Networks

Highlights

- We propose SMPL-A ("A" for anatomy) to extend SMPL [1] for pose/shape-dependent organ deformation estimation.
- We unify the shape representation for organs by setting up anatomical correspondences through deformable registration.
- Results suggests the organ's shape and elastic properties can be encoded into lower-dimensional representations.

Data Processing

- Inspired by the SMPL models, we propose to parameterized the organ segmentation into points cloud with fixed length.
- We apply Elastix [2], an intensity-based image registration, to set up the correspondences between the same type of organs:

$$\hat{\mu}_k = \arg\min_{\mu} C(I_k, T(\hat{I}; \mu)),$$

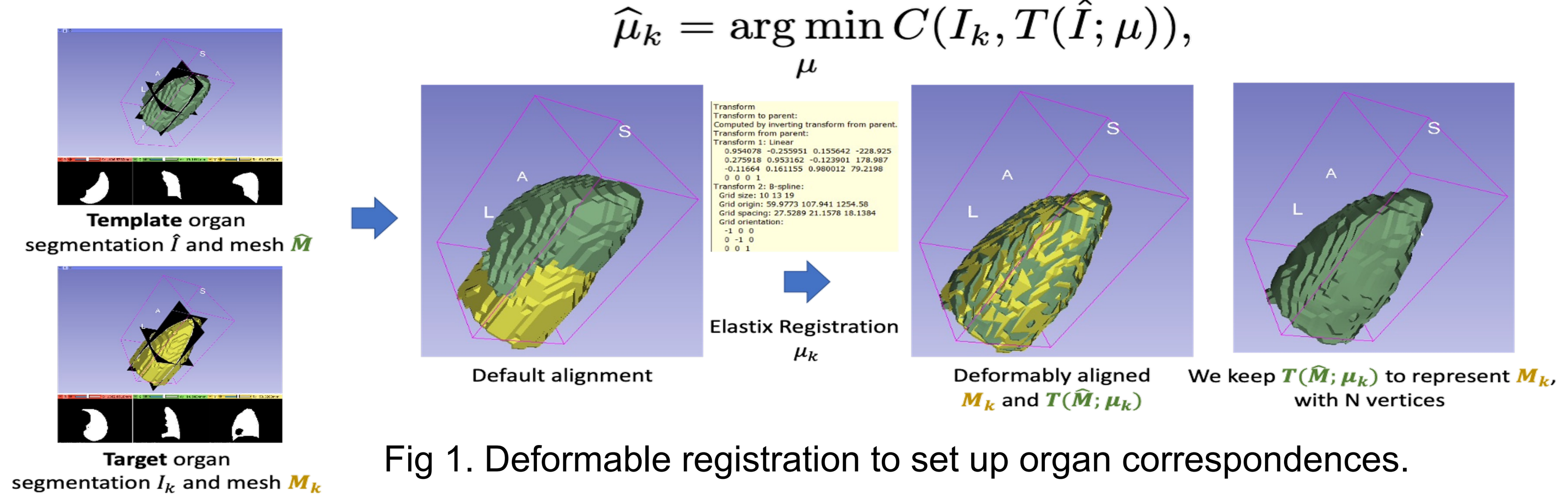

Fig 1. Deformable registration to set up organ correspondences.

- Considering the template mesh $\widehat{M}$ has m vertices, every other case in the dataset can all be represented by m vertices correspondingly.

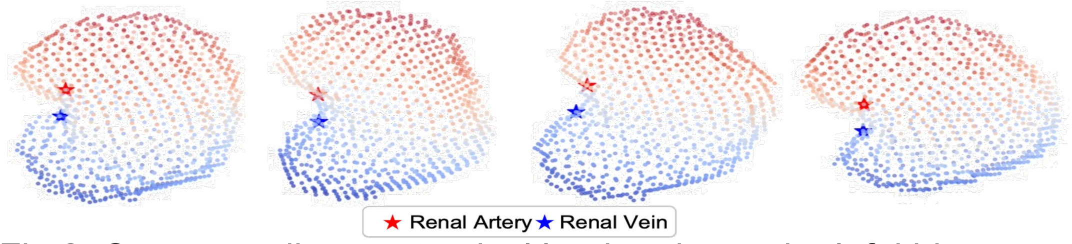

Fig 2. Corresponding anatomical landmarks on the left kidneys

Methodology

SMPL-A network extracts the organ's shape representation α specific to each patient, and predict its deformed shape, conditioned on different pose parameters:

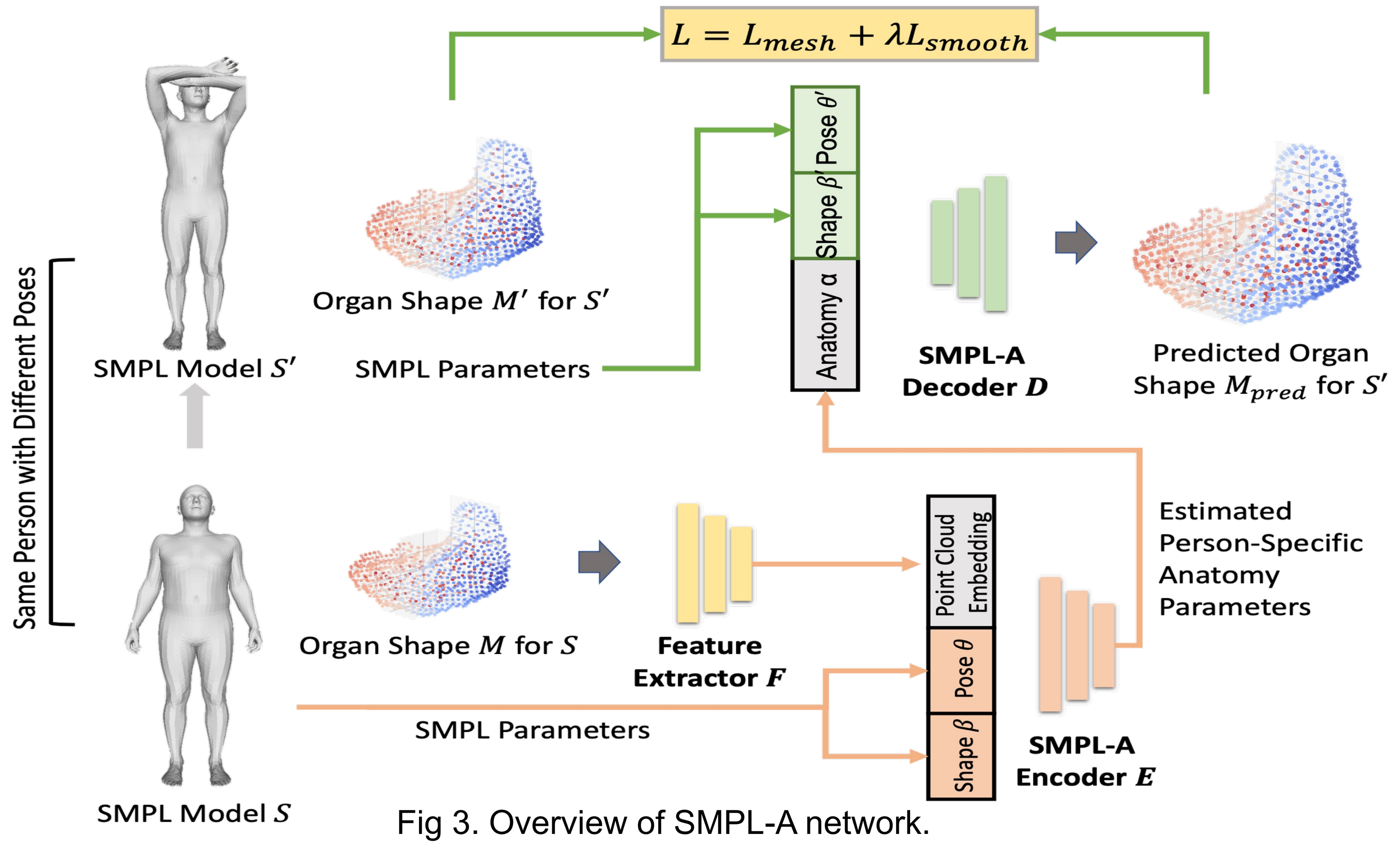

Fig 3. Overview of SMPL-A network.

Patient-Specific Organ Shape Encoder *E* aims to map the organ's 3D mesh to a low-dimensional feature representation α:

$$E(\theta, \beta, M) = MLP\big(\theta, \beta, F(M)\big) = \alpha$$

Pose-Conditioned Organ Shape Decoder *D* aims to recover the deformed organ mesh conditioned on different poses of the same patient:

$$D(\theta, \beta, \alpha) = M_{pred}$$

Since multiple scans from the same patient with different poses are difficult to acquire, we apply finite element modeling to simulate organ deformation based on pose changes for training data augmentation:

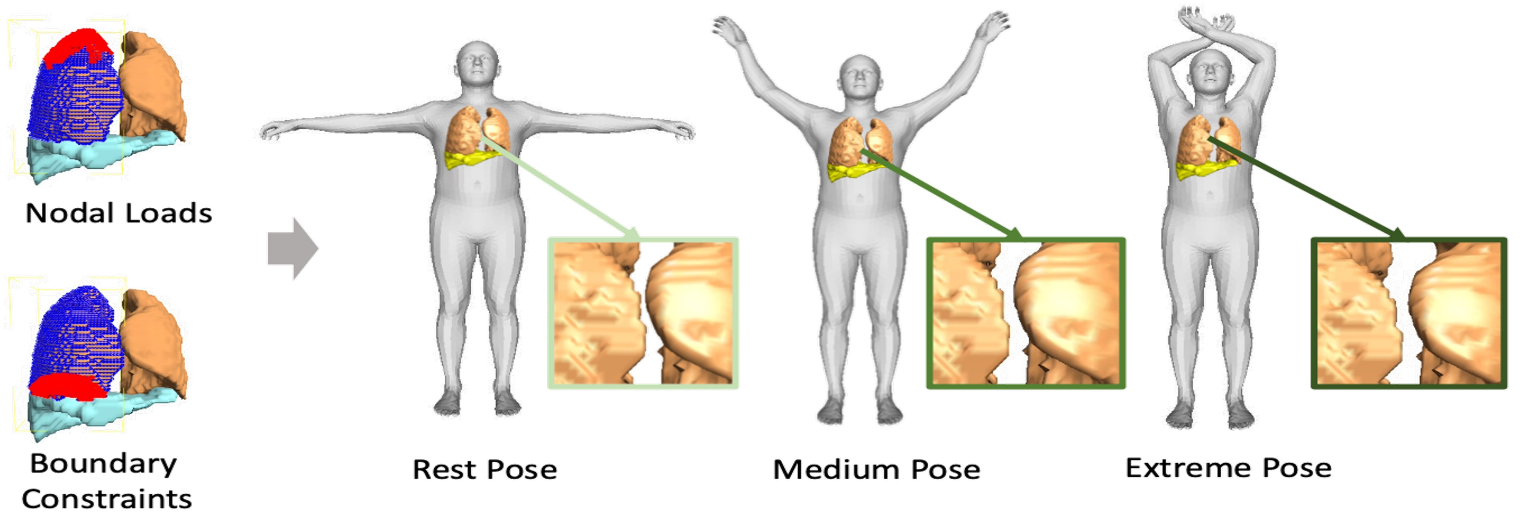

Fig 4. Synthetic data augmentation using finite element modeling.

Results

Table 1. Reconstruction error (mm) for the deformation of six organ parts. The baseline method computes the error between mean and ground-truth shape.

	Baseline Error	SMPL-A Error
Spleen	2.5353 ± 0.1088	1.4496 ± 0.0949
Liver	2.9810 ± 0.1395	1.7832 ± 0.1012
Left Kidney	2.2364 ± 0.1174	1.2694 ± 0.0974
Right Kidney	2.4608 ± 0.1207	1.2504 ± 0.1088
Left Lung	4.4784 ± 0.2586	2.2475 ± 0.1688
Right Lung	4.9846 ± 0.2407	2.3716 ± 0.1942

Table 2. We train a point-cloud autoencoder to reconstruct the organ's shape for α's ablation study, without pose-conditioned deformation.

k_α	Reconstruction Error (mm)			
	Spleen	Liver	Lung_left	Kidney_left
5	1.45 ± 0.23	2.45 ± 0.23	2.65 ± 0.21	1.65 ± 0.24
10	1.09 ± 0.17	1.76 ± 0.20	1.75 ± 0.23	1.33 ± 0.14
20	0.78 ± 0.13	1.21 ± 0.15	1.22 ± 0.18	0.84 ± 0.12
40	**0.74 ± 0.16**	**1.05 ± 0.19**	**1.15 ± 0.16**	**0.82 ± 0.14**

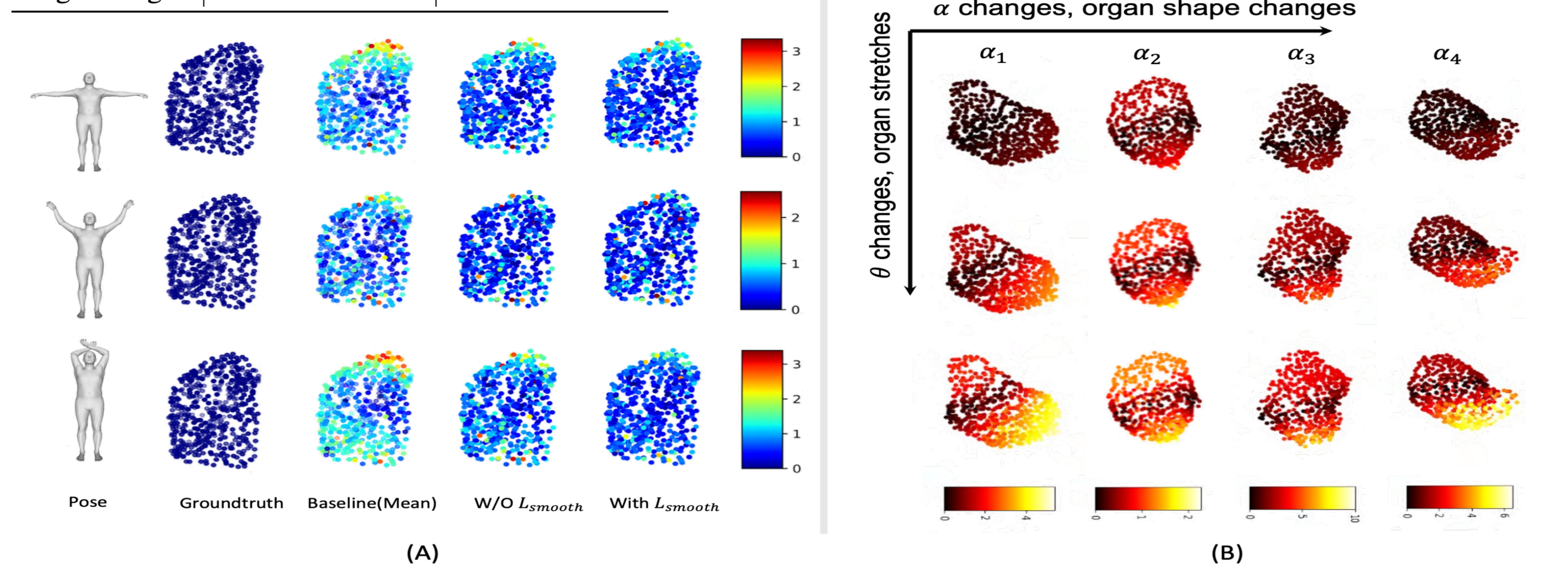

Fig 5. (A) Predicted deformation error for the left lung; (B) Impact of θ and α on spleen shape.

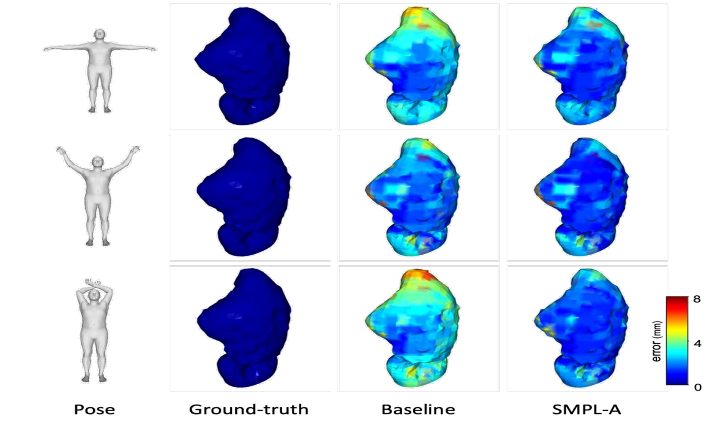

Fig 6. Predicted deformation error for a left lung

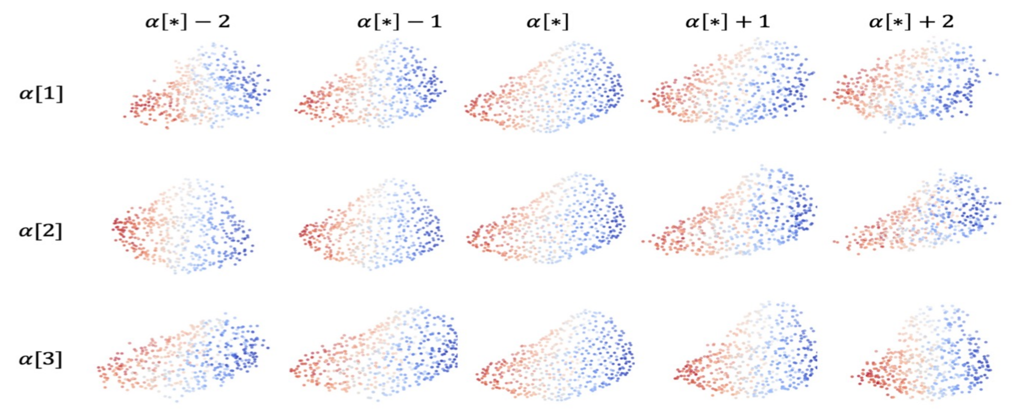

Fig 7. Impact of the first three values of α

Conclusion

Using our parameterized organ mesh models, the proposed SMPL-A network can extract the organ's shape representation α specific to each patient, and predict its deformed shape conditioned on different pose/shape parameters for a proof-of-concept study.

References

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