Regularization of CNN with Shape Priors

Seminar Machine Learning

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Outline

1. Regularization
2. GridNet
3. Anatomically Contrained Neural Networks (ACNN)
4. Anatomically Contrained Neural Networks (ACNN)
5. References

What is regularization?

- Ensures that model to generalizes well to the real world data.
- Reduces Overfitting.
- Techniques:
  - Dropout
  - Weight penalty L1 and L2
  - Dataset augmentation
  - Early stopping
- There is no best generic regularization technique.

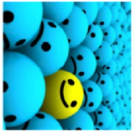
CNN Regularization

- Training data size is big.
- Number of features are very large.
- L2/L1 regularization or dropout like other neural networks.
- **L1/L2 regularization**: Add an extra term to the loss function.
  - L2 norm: Penalize the square weights ($|w|^2$).
  - L1 norm: Penalize the absolute values ($|w|$).

UNet: Regularization

- Training data size is very small.
- Data augmentation
  - Rotate
  - Scale
  - Flip
- Makes network invariant to certain transformations.

Image



Rotate

Scale

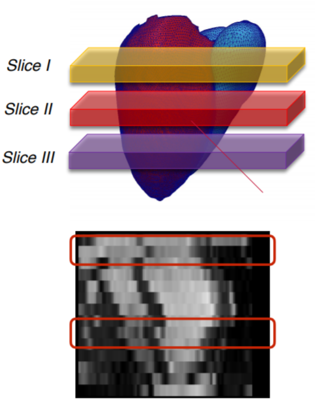
Flip

Shape priors

- A very specific type of "regularization" technique.
- Prior information related with the geometry of the object .
  - Boundries and edge polarity
  - Topology specification
  - Distance prior between the region
  - Atlas Prior (Most suitable for medical images)

.

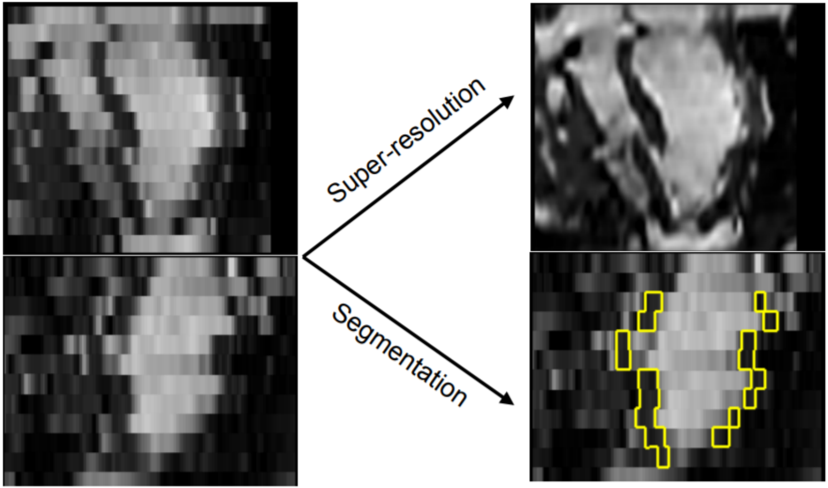
Shape priors



Cardiac MRI: 2D multislice data

- Useful where images are corrupted and contain artefact.
- Application in field of Medical image analysis.
- Improves the final reliability and accuracy of the segmentation result.

Conventional CNNs without shape prior



CNNs with shape prior

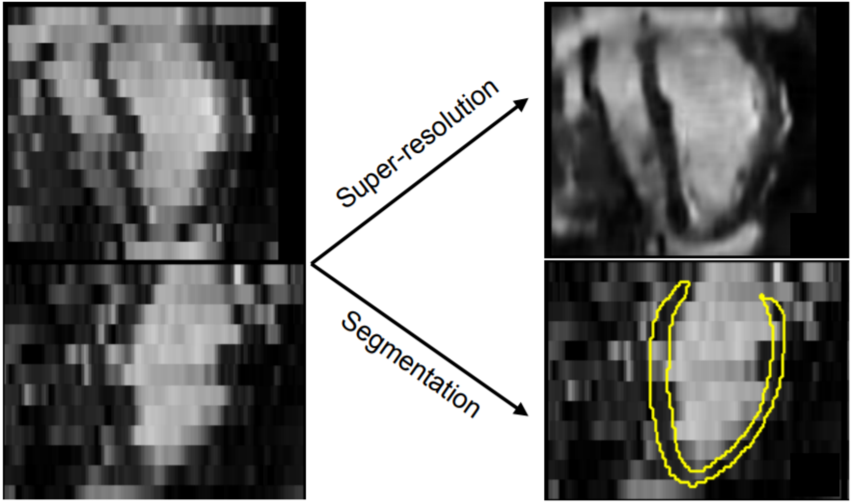
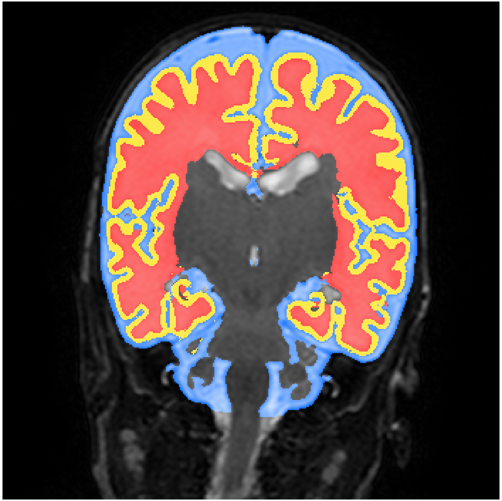


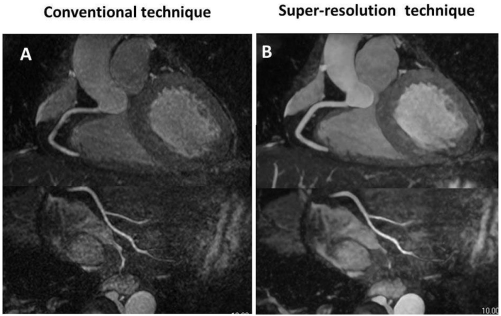
Figure: Using prior/expert knowledge about the shape result into anatomically more meaningful and smooth image.

Applications

a) Segmenation



b) Image Enhancement



GridNet

- Generalization of U-Net.
- Incorporate shape prior (S_i) regularization: via alignment of S_i on top of input.
- Specific to MRI cardiac segmentation.
- Extract both global and local contexts.
  - Global context: Distinguishes among the organs.
  - Local context: For segmentation.

GridNet: Comparison with U-Net

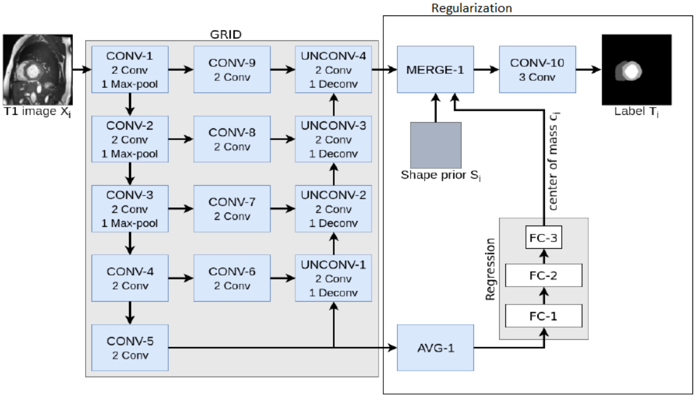


Fig. : Our network architecture.

- Additional
  CONV-6 to 9: Feature extraction at different resolution.
  CONV-5: Estimate CoM.
- 8 millions params in U-Net as compare to 32 millions in U-Net.

GridNet: Architecture

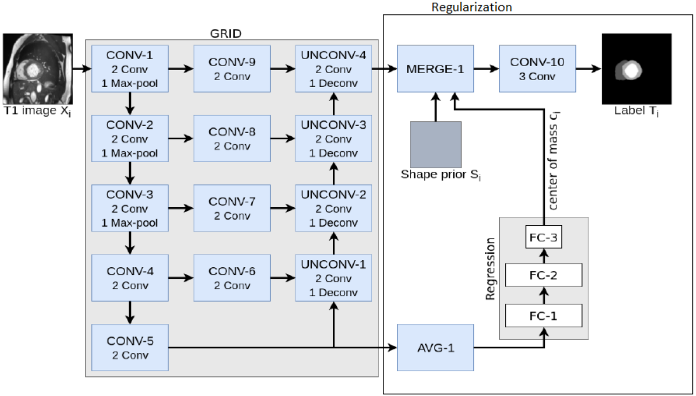


Fig. : Our network architecture.

Input:

- 256 x 256 MR image (X_i)
- Shape prior (S_i) of the corresponding slice.

Output:

- CoM (c_i) (bottom right)
- label field (T_i) (top right)

GridNet: Architecture

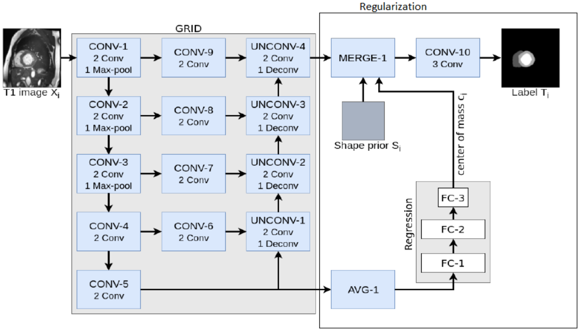


Fig. : Our network architecture.

Segmentation network (GRID) :

- **Column 1(from CONV-1 to CONV-5)**: Global context increases as we move down.
- **Column 2** : 4 convolution layers to compute the features at various resolutions.
- **Column 3**: UNCONV-4 layer contains entire information, used to segment the image.

GridNet: Architecture

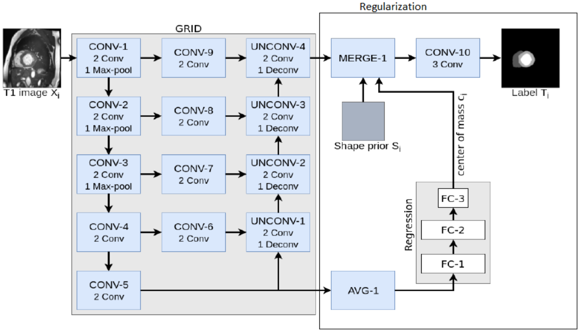


Fig. : Our network architecture.

Regularization :

- CoM (c_i) is the output of regression module (from FC-3).
- "Merge-1" realigns shape prior based on predicted CoM.

GridNet with shape prior: Loss

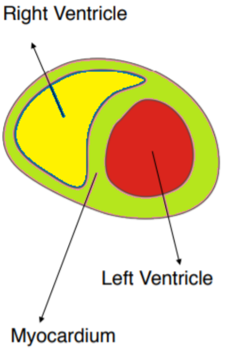
Standard loss for segmentation:

Cross-Entropy

Regularization:

- Contour loss.
- "Shape regularization loss" as difference between CoMs

GridNet: Results



- Regularization improved the results significantly especially close to boundaries.
- Outperforms popular segmentation networks like U-Net, ConvDeconv.
- Measures:
  - Clinical metric:
    - Correlation coefficient for cavity volume
    - Ejection fraction(EF) of LV and RV
  - Geometric metric:
    - Dice coefficient
    - Hausdorff distance.

GridNet: Results

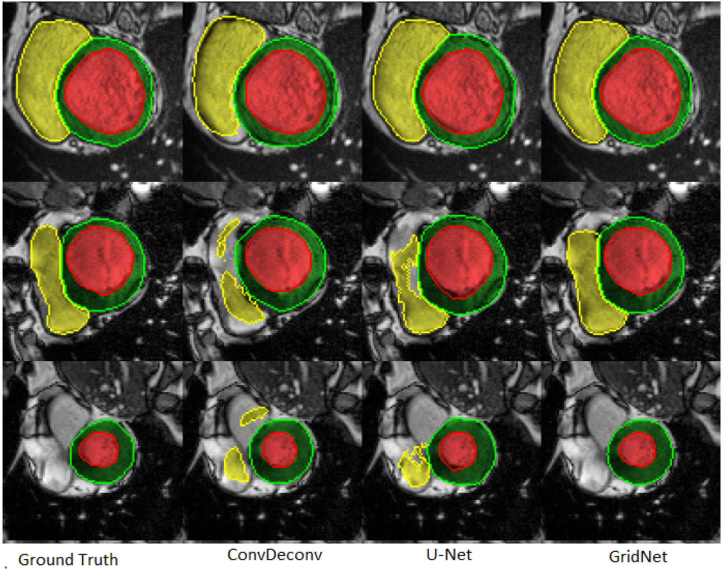
Table : Results for the validation dataset.

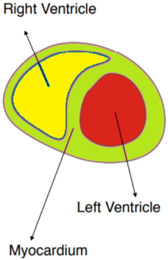
	Dice LV		Dice RV		Dice MYO	
	ED	ES	ED	ES	ED	ES
ConvDeconv	0.92	0.87	0.82	0.64	0.76	0.81
UNet	**0.96**	0.92	0.88	0.79	0.78	0.76
GridNet	**0.96**	**0.94**	**0.94**	**0.87**	**0.89**	**0.90**

	HD LV (mm)		HD RV (mm)		HD MYO (mm)	
	ED	ES	ED	ES	ED	ES
ConvDeconv	8.77	10.34	22.59	28.45	13.92	11.64
UNet	6.17	8.29	20.51	21.20	15.25	17.92
GridNet	**5.96**	**6.57**	**13.48**	**16.66**	8.68	**8.99**

	Corr EF LV	Corr EF RV	Corr MYO ED	Corr LV vol	Corr RV vol
ConvDeconv	0.988	0.764	0.927	0.990	0.957
UNet	0.991	0.824	0.921	0.995	0.821
GridNet	**0.992**	0.898	**0.975**	**0.997**	**0.978**

GridNet: Results





Anatomically Contrained Neural Networks

- PCA based statistical model unlike aligment in GridNet
  - Learns latent represenation of anatomy via auto-encoders.
  - Final prediction follows the learnt space.
- Components :

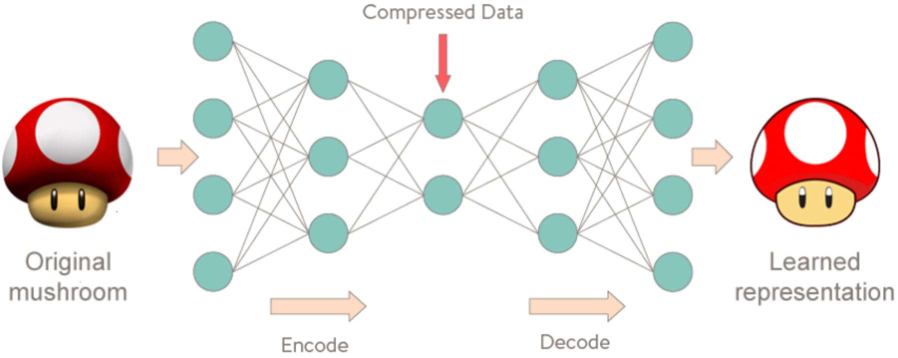
  - For Segmenation:

  Segmenation Network + TL Network (for shape regularization)

  - For Image Enhancement:

  SR Network + TL Network(for shape regularization)

AutoEncoder: Overview



- NN that aim to learn intermediate representation.
- Output could be reconstructed from this intermediate representation.
- Used for dimensionality reduction.
- Integrated as regularization model., s.t. prediction (y) will be anatomically meaningful and more accurate

AutoEncoder: Loss

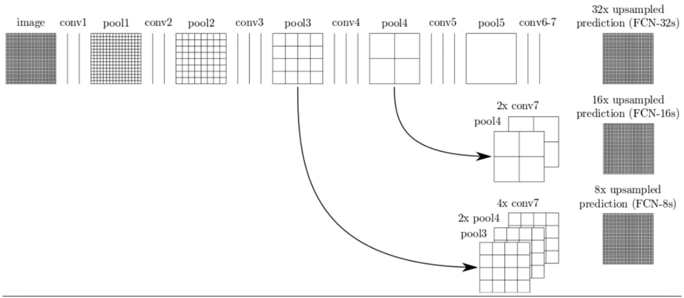
$f(y_s)$: Encoder component of AE.
$g(f(y_s))$: Decoder component of AE.

Loss: $L_x(y_s, g(f(y_s)))$

L_x is penalising $g(f(y_s))$ being dissimilar from y_s

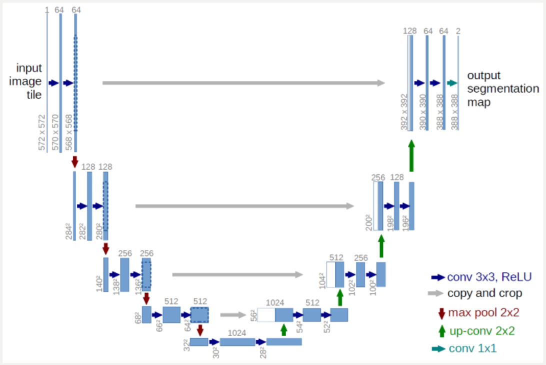
Segmentation networks

- We can use any segmentation network.
- Aim: To get per pixel classification.
- Popular segmentation networks we discussed:
  FCN:



Segmentation networks

U-Net:



Anatomically Contrained Neural Networks

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TL Network

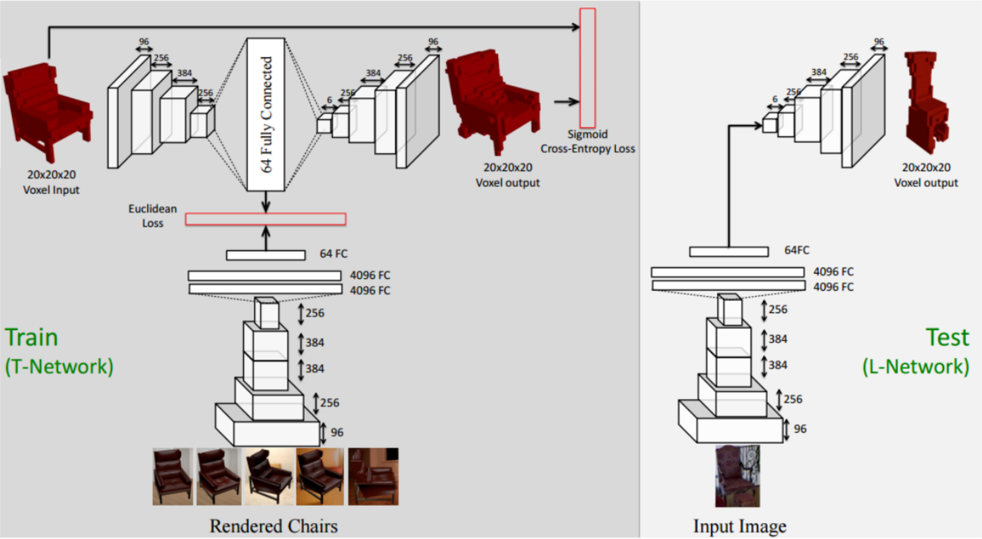


Figure: (a) T-Network (training time) : Takes 2 inputs 3D voxel map and 2D image (b) L-Network (test time) : Removes encoder part and uses image as input.

TL network

- Requirements:
  a. Generative: Should be able to generate voxel in 3D from latent space.
  b. Predictable: Should be able to predict the 3D represenation from 2D image of the object.

- **T Network**

  Components:

  - Auto-encoder: 3D voxel map -> latent space -> 3D voxel map
  - CNN

Total Loss = Reconstruction loss + Regression loss

  - Reconstruction loss: For voxel output
  - Regression loss: For 64D embeddings

- **L Network**: Remove encoder part only use image as input.

TL networks:Training

Three stage training:

1. Stage 1: Train the auto-encoder part of the network independently.
2. Stage 2: Train ConvNet to regress 64D representation generated by auto-encoder.
3. Stage 3: Fine tune the network jointly with both the losses.

Shape prediction using TL-Network vs PCA

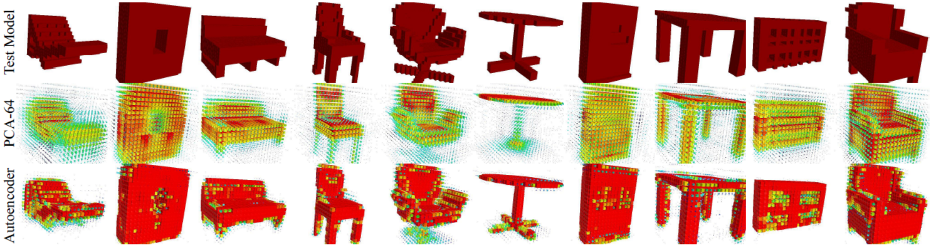
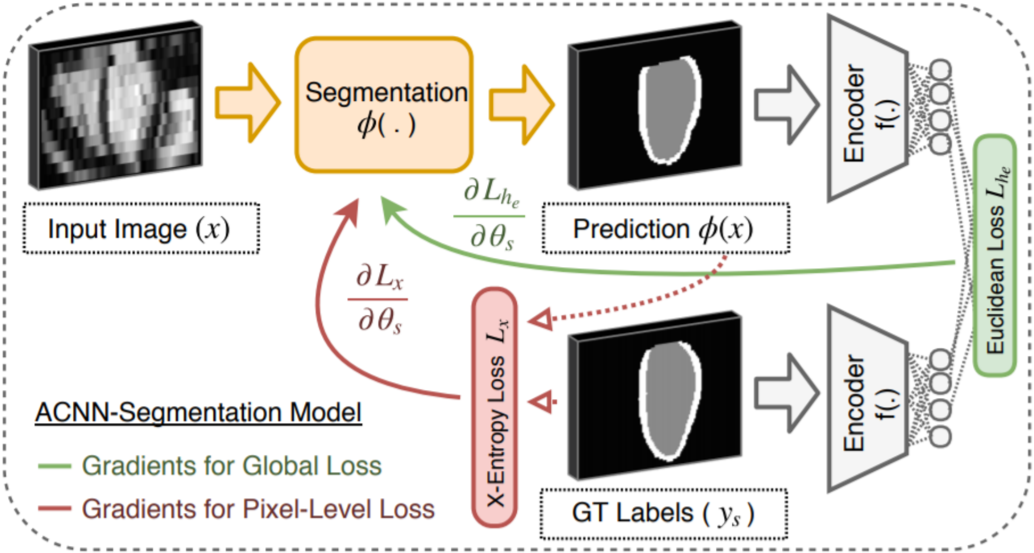


Figure: Predicted voxel are colored by level of prediction confidence i.e. from red to blue.

Anatomically Contrained CNN: Segmenation framework



Anatomically Contrained CNN: Segmenation

Standard Loss for segmentation: Cross- Entropy per pixel

Issues?

Anatomically Contrained CNN: Segmenation

Standard Loss for segmentation: Cross- Entropy per pixel

Issues?

Individual pixel level class prediction

- No guarantee about the global consistency

Anatomically Contrained CNN: Segmenation

Standard Loss for segmentation: Cross- Entropy per pixel

Issues?

Individual pixel level class prediction

- No guarantee about the global consistency
- No idea of possible anatomical shapes.

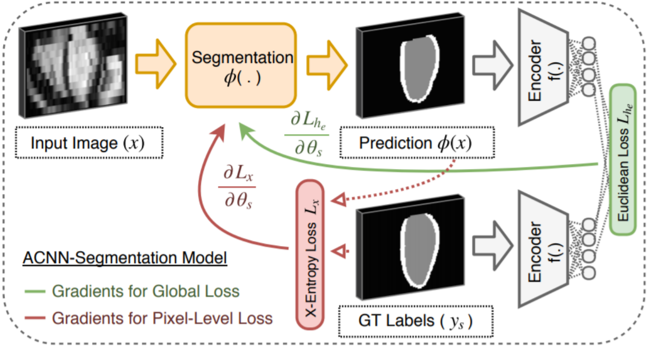
Anatomically Contrained CNN: Additional Regularization

L_{h_e} : Shape regularization loss
θ_f : Model parameter to be trained.
$\phi(x)$: Predicted output labels.
y : Ground truth labels.

$$L_{h_e} = ||f(\phi(x); \theta_f) - f(y; \theta_f)||^2$$

L_{h_e} : Ensures that **latent space of generated segmentations** are similar to that of **Ground Truth**.

Anatomically Contrained CNN: Total Loss

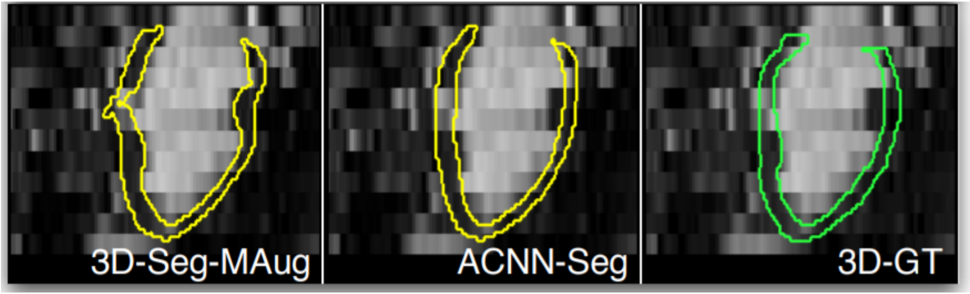


Segmenation Loss with shape regularization

L_x: Cross-entropy (L_x)

$$\text{Total Loss} = L_x + L_{h_e}$$

Anatomically Contrained CNN: Segmenation results

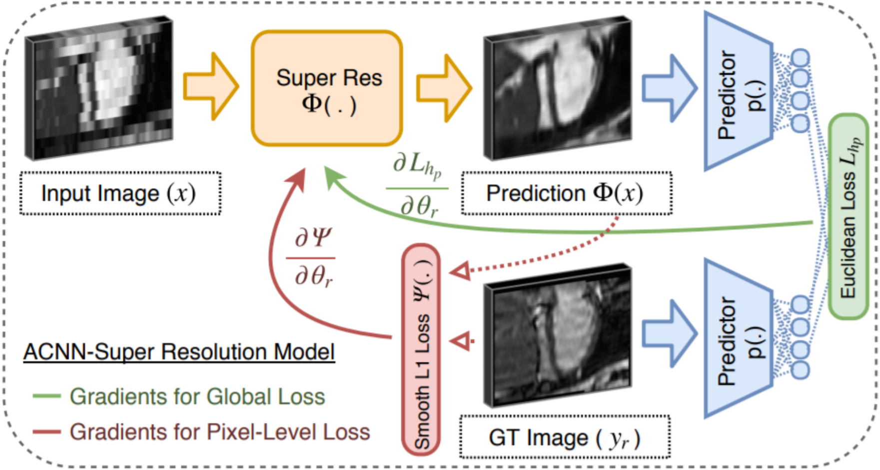


Anatomically Contrained CNN: Segmenation results

	Endocardium			Myocardium			Capacity
	Mean Dist. (mm)	Hausdorff Dist. (mm)	Dice Score (%)	Mean Dist. (mm)	Hausdorff Dist. (mm)	Dice Score (%)	# Trainable Parameters
2D-FCN	2.07±0.61	11.37±7.15	.908±.021	1.58±0.44	9.19±7.22	.727±.046	1.39×10^6
3D-Seg	1.77±0.84	10.28±8.25	.923±.019	1.48±0.51	10.15±10.58	.773±.038	1.60×10^6
3D-UNet	1.66±0.74	9.94±9.22	.923±.019	1.45±0.47	9.81±11.77	.764±.045	1.64×10^6
AE-Seg	1.75±0.58	8.42±3.64	.926±.019	1.51±0.29	8.52±2.72	.779±.033	1.68×10^6
3D-Seg-MAug	1.59±0.74	8.52±8.13	.928±.019	1.37±0.41	9.41±9.17	.785±.041	1.60×10^6
AE-Seg-M	1.59±0.48	**7.52±3.78**	.927±.017	1.32±0.26	**7.12±2.79**	.791±.036	1.91×10^6
ACNN-Seg	**1.37±0.42**	7.89±3.83	**.939±.017**	**1.14±0.22**	7.31±3.59	**.811±.027**	1.60×10^6
p-values	$p \ll 0.001$	$p \approx 0.890$	$p \ll 0.001$	$p \ll 0.001$	$p \approx 0.071$	$p \ll 0.001$	-

Figure: Dataset of 2D cardiac MR images and segmentation accuracy measured in terms of "Dice Metric" and "Surface to Surface distances"

Anatomically Contrained CNN: Super-resolution framework



Anatomically Contrained CNN: Loss

- Standard loss for SR Network: Smooth l_1 loss

Anatomically Contrained CNN: Loss

- **Standard loss for SR Network**: Smooth l_1 loss

- **Shape regularization loss**:

$$L_{h_p} = ||p(\phi(x);\theta_p) - p(y_r;\theta_p)||_2^2$$

Anatomically Contrained CNN: Loss

- **Standard loss for SR Network**: Smooth l_1 loss

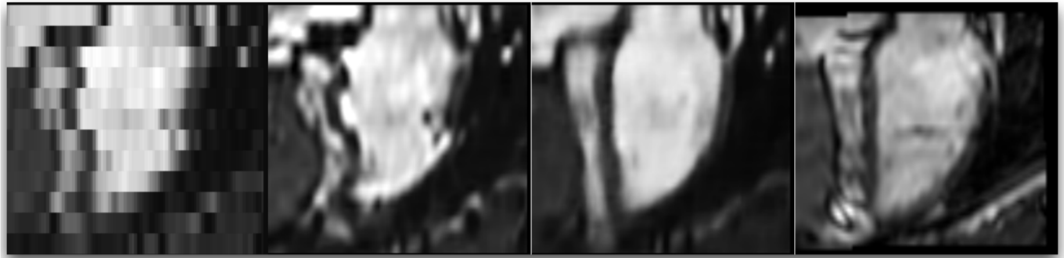
- **Shape regularization loss**:

$$L_{h_p} = ||p(\phi(x);\theta_p) - p(y_r;\theta_p)||_2^2$$

- **Segmenation Loss using shape regularization**:

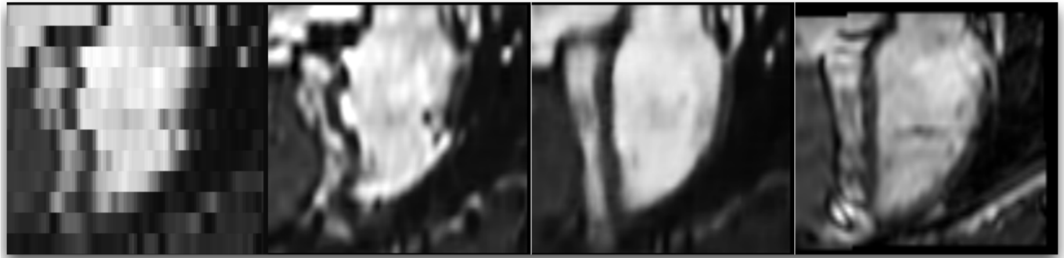
$$\text{Total Loss} = \Psi_{l_1} + L_{h_p}$$

Anatomically Contrained CNN: Super-resolution results



Original LR image | Baseline SR approach | Anatomically constrained SR model | Ground-truth HR image

Anatomically Contrained CNN: Super-resolution results



Original LR image

Baseline SR approach

Anatomically constrained SR model

Ground-truth HR image

Summary

- Prior knowledge about the anatomy provided guidance and robustness to models.
- Discussed two major models that used shape priors regularization:
  - GridNet
  - Anatomically constrained NN
- Future Research:
  - Human pose estimation.
  - Landmark localization on partially occluded images.

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Thank You!

APPENDIX A

GridNet

i: Corresponds to slice.

l: Classes (4 classes: RV, LV, MYO, Back)

v: Pixel location

$T_{i,l,v}$: True probability that for slice i pixel v is in class l

$\hat{T}_{i,l,v}$: Output of our model for slice i pixel v is in class l

$C_i, \hat{C}_i$: Countour extracted from T_i, $\hat{T}_i$

γ_T, γ_C: Constants

Loss functions:

$L_T = -\gamma_T \sum_{l=1}^{4} \sum_{v} T_{i,l,v} \ln \hat{T}_{l,v}$ (Cross-entropy of predicted labels)

$L_C = -\gamma_C \sum_{l=1}^{4} \sum_{v} C_{i,l,v} \ln \hat{C}_{l,v}$ (Cross-entropy of predicted contour)

$L_c = \gamma_c ||c_{i,w} - \hat{c}_i||^2$ (Euclidean distance between predicted CoM $c_{i,w}$ and true CoM)

$L_w = \gamma_w ||w||^2$ (Prior loss)

Total Loss:

$$L = \sum_i (-\gamma_T \sum_{l=1}^{4} \sum_{v} T_{i,l,v} \ln \hat{T}_{i,l,v} - \gamma_C \sum_{l=1}^{4} \sum_{v} C_{i,l,v} \ln \hat{C}_{l,v} + \gamma_c ||c_{i,w} - \hat{c}_i||^2) + \gamma_w ||w||^2$$

APPENDIX B

Anatomically Contrained CNN

Standard Loss for segmentation: Cross- Entropy

C : Set of classes.

$$L_x = -\sum_{c=1}^{C}\sum_{i\in S}\log(\frac{e^{f_{(c,i)}}}{\sum_j e^{f_{(j,i)}}})$$

Segmenation Loss with shape regularization:

L_x: Cross-entropy

θ_s: All the trainable parameters of segmentation model

λ_1 , λ_2: Weight of 'shape regularization loss' and 'weight decay term'

$$Loss = min\theta_s(L_x(\phi(x;\theta_s),y) + \lambda_1.L_{h_e} + \frac{\lambda_2}{2}||w||_2^2)$$

Super Resolution Loss using shape regularization:

Ψ_{l_1}: Smooth l_1 loss defined as { $0.5k^2$ if |k|<1 , |k| - 0.5 otherwise }

θ_r : All the trainable parameters in SR model.

λ_1 , λ_2: Weight of 'shape regularization loss' and 'weight decay term'

$$Loss = min\theta_s(\Psi_{l_1}(\phi(x;\theta_r) - y_r) + \lambda_1.L_{h_p} + \frac{\lambda_2}{2}||w||_2^2)$$