AI for Medical Imaging: from weak supervision, unsupervised learning to combined computing

Xiahai Zhuang
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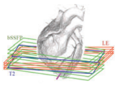
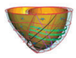
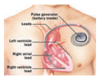
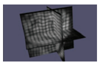


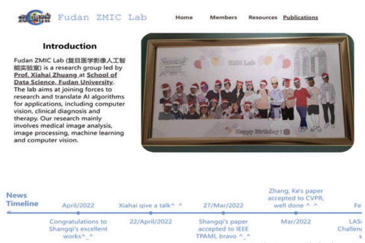


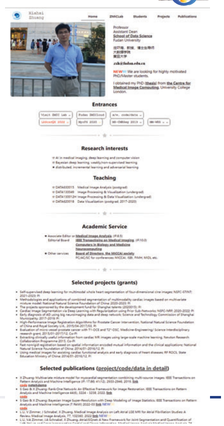




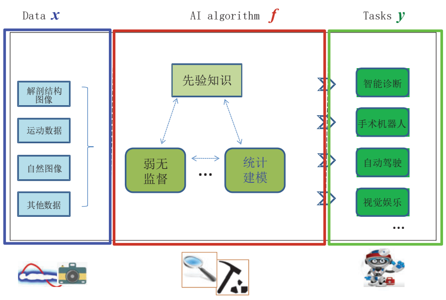
Xiahai Zhuang

- Personal Homepage
  https://zmiclab.github.io/zxh/
- ZMIC Lab
  https://zmiclab.github.io/





AI for medical imaging: $f(x)=y$



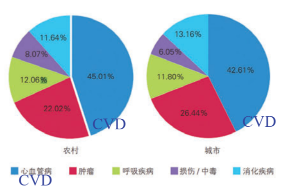
Content

- An example of intelligent medicine y
  - Combining multimodality images for cardiac and myocardial pathology segmentation
- Weakly/non-supervised segmentation f
- Image restoration and super-resolution x

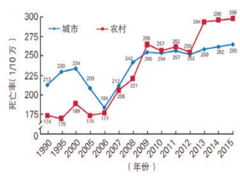
Facts about cardiovascular diseases (CVDs)

- ~17 000 000 Deaths in the world related to CVDs
- ~ 2 00 000 000 people in China suffering CVDs
- > 100 000 000 000 RMB Medical cost for healthcare related to CVDs in China

Major deadly diseases in China（%）



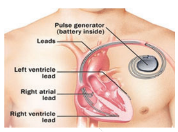
mortality due to CVDs

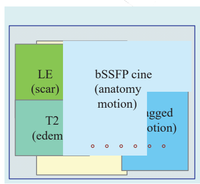


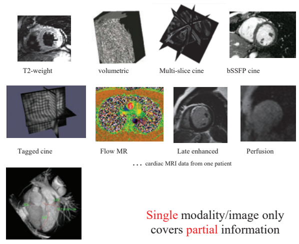
数据来源：《中国心血管病报告2016》，中国循环杂志2017年6月

Assessment of myocardial viability

- Imaging and challenges



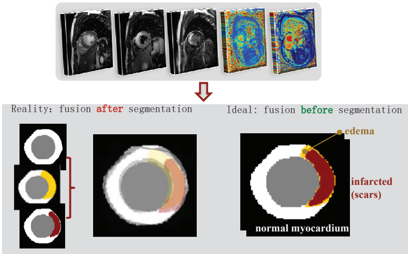




Single modality/image only covers partial information

Assessment of myocardial viability

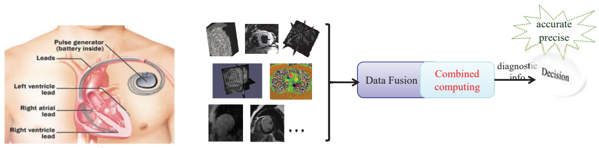
- Combining multi-modality images
  - Complementary information



Kim H W, et al. Cardiovascular magnetic resonance in patients with myocardial infarction: Current and emerging applications[J]. Journal of the American College of Cardiology, 2009
Hennemuth A, et at. A Comprehensive Approach to the Analysis of Contrast Enhanced Cardiac MR Images[J]. TMI , 2008

Assessment of myocardial viability

- Combining multi-modality images
  - Complementary information
  - Combined computing -> better accuracy and precision

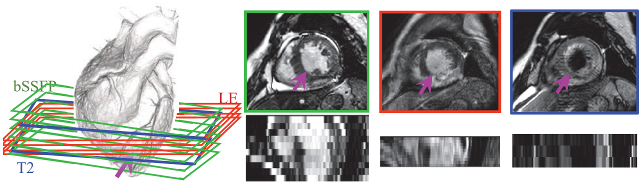


Kim H W, et al. Cardiovascular magnetic resonance in patients with myocardial infarction: Current and emerging applications[J]. Journal of the American College of Cardiology, 2009
Hennemuth A, et at. A Comprehensive Approach to the Analysis of Contrast Enhanced Cardiac MR Images[J]. TMI , 2008

Combined computing via multivariate mixture model

- For simultaneous segmentation and registration

$\boldsymbol{I}=[I_{bSSFP}, I_{LGE}, I_{T2}]$
$\boldsymbol{I}(x)=[I_{bSSFP}(x), I_{LGE}(x), I_{T2}(x)]$



x in common space x in bSSFP/C0 x in LGE x in T2

X Zhuang: Multivariate mixture model for myocardial segmentation combining multi-source images. IEEE T PAMI, 41(12): 2933-2946, 2019; Code&demo：https://github.com/xzluo97/MvMM-Demo

Combined computing via multivariate mixture model

- MvMM (Multivariate Mixture Model)

$\boldsymbol{I}=[I_{bSSFP}, I_{LGE}, I_{T2}]$
$\boldsymbol{I}(x)=[I_{bSSFP}(x), I_{LGE}(x), I_{T2}(x)]$

Combining LGE+T2+bSSFP

The likelihood (LH) of the MvMM parameters θ

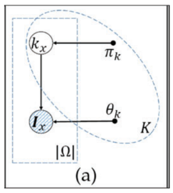
$LH_\Omega(\theta;\boldsymbol{I})=p(\boldsymbol{I}|\theta)$

Assuming independence of each location (pixel)

$LH_\Omega(\theta;\boldsymbol{I})=\prod_{x\in\Omega} p(\boldsymbol{I}(x)|\theta)$

$s(x)=k$, is the label information of pixel x

$p(\boldsymbol{I}(x)|\theta)=\sum_{k\in K}\pi_{kx}p(\boldsymbol{I}(x)|s(x)=k,\theta)$



graphical representation

X Zhuang: Multivariate mixture model for myocardial segmentation combining multi-source images. IEEE T PAMI, 41(12): 2933-2946, 2019; Code&demo：https://github.com/xzluo97/MvMM-Demo

Combined computing via multivariate mixture model

- Q1: computation of $p(\boldsymbol{I}|\theta)=p([I_1,\ldots,I_M]|\theta)$

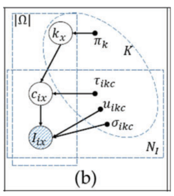
$\boldsymbol{I}=[I_{bSSFP}, I_{LGE}, I_{T2}]$
$\boldsymbol{I}(x)=[I_{bSSFP}(x), I_{LGE}(x), I_{T2}(x)]$

$$p(\boldsymbol{I}(x)|\theta)=\sum_{k\in K}\pi_{kx}p(\boldsymbol{I}(x)|s(x)=k,\theta)$$

when the tissue type of a position is known,
e.g. myocardium/ blood pool,
then the intensity distributions of different images
become independent

$$\boxed{p(\boldsymbol{I}(x)|s(x)=k,\theta)=\prod_{i=1,\ldots N_I}p(I_i(x)|k_x,\theta)}$$

$$p(I_i(x)|k_x,\theta)=\sum_{c\in C_{ik}}\tau_{ikc}\Phi_{ikc}(\mu_{ikc},\sigma_{ikc},I_i(x))$$



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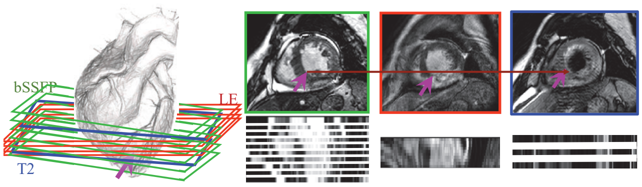
Combined computing via multivariate mixture model

- Q2: misalignments (inter-scan + intra-scan)

$\boldsymbol{I}=[I_{bSSFP}, I_{LGE}, I_{T2}]$, $\boldsymbol{I}(x)=[I_{bSSFP}(x), I_{LGE}(x), I_{T2}(x)]$
$\boldsymbol{I}=[I_{bSSFP}, I_{LGE}, I_{T2}]$, $\boldsymbol{I}(x)=[I_{bSSFP}(x+\delta x_1), I_{LGE}(x+\delta x_2), I_{T2}(x+\delta x_3)]$



x in common space x in bSSFP/C0 x in LGE x in T2

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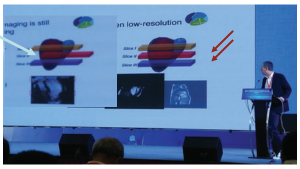
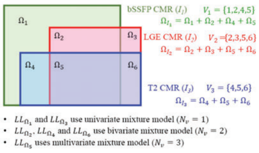
Combined computing via multivariate mixture model

- Q3: data missing/ incomplete data

Generalizing multivariate mixture model: mix of univariate + Ω_1, Ω_3 bivariate + $\Omega_2, \Omega_4, \Omega_6$ trivariate +….+ Ω_5 n-variate mixture model



[Daniel Rueckert, Imperial College London]



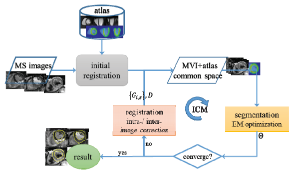
the log-likelihood $LL_{HC} = \sum_{v=1}^{6} LL_{\Omega_v}$

X Zhuang: Multivariate mixture model for myocardial segmentation combining multi-source images. IEEE T PAMI, 41(12): 2933-2946, 2019; Code&demo：https://github.com/xzluo97/MvMM-Demo

Combined computing via multivariate mixture model

- Challenges & solutions

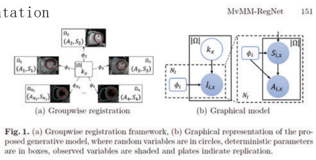
Q1: MLE of MvMM $p(I = [I_1 \dots I_n];\, \theta)$
Q2: Misalignment
Q3: Incomplete data (generalized MvMM)
Q4: Spatial encoding & regularization
Q5: Simultaneous optimization of two groups of parameters



X Zhuang: Multivariate mixture model for myocardial segmentation combining multi-source images. IEEE T PAMI, 41(12): 2933-2946, 2019; Code&demo：https://github.com/xzluo97/MvMM-Demo

Deep combined computing via DNN

- MvMM-RegNet
  - goal: Generalized MvMM model as loss for semi-supervised deep neural network for registration.
  - app:
    - Pairwise registration
    - Groupwise registration
    - Multi-atlas segmentation

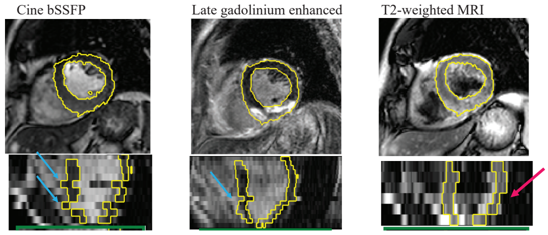


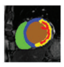
X Luo & X Zhuang: MvMM-RegNet: A new image registration framework based on multivariate mixture model and neural network estimation. In MICCAI'2020

Example

- Myocardial segmentation of 3 images

Cine bSSFP | Late gadolinium enhanced | T2-weighted MRI





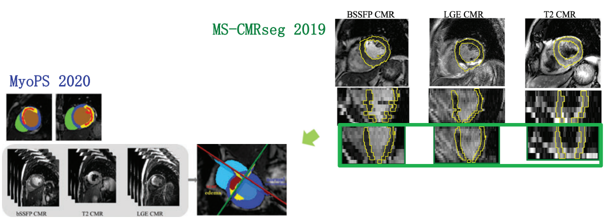
Data & new tasks

- Multi-sequence cardiac MR segmentation

-> Myocardial pathology segmentation

MS-CMRseg 2019

MyoPS 2020



MyoPS 2020: Myocardial pathology segmentation combining multi-sequence CMR
Code&Demo: https://zmiclab.github.io/projects.html

Content

- An example of intelligent medicine y
- Weakly/non-supervised segmentation f
- Image restoration and super-resolution x

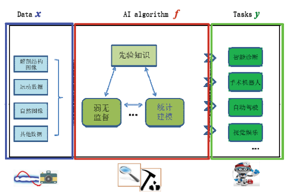
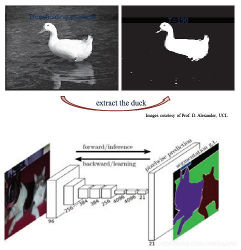


Image segmentation

- Weakly supervised/ unsupervised learning

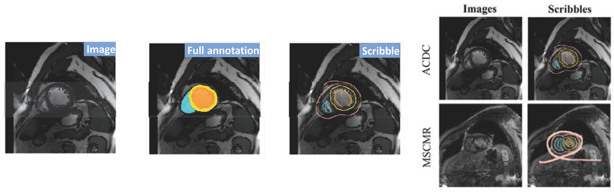


From the work of Fully Convolutional Network (FCN)

[图片来源不明]

S1: Weakly/semi-supervised segmentation

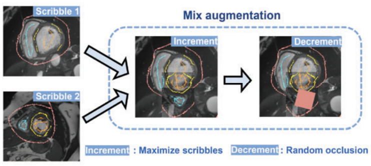
- Scribble annotation



[1] K Zhang & X Zhuang: CycleMix: A Holistic Strategy for Medical Image Segmentation from Scribble Supervision. CVPR 2022
https://github.com/BWGZK/CycleMix/
[2] Fuping Wu, Xiahai Zhuang: Minimizing Estimated Risks on Unlabelled Data: A New Formulation for Semi-Supervised Medical Image Segmentation. submitted to IEEE Transactions on Pattern Analysis and Machine Intelligence (In Revision)
https://fupingwu90.github.io/cv/

S1: Weakly/semi-supervised segmentation

- Scribble supervision
  - Augmentation and consistency regularization



Assumption: A segmentation model benefits from finer gradient flow via larger portion of annotated pixels.

Mix augmentation: maximize scribbles of mixed image, which increased the amount of supervision.

Random occlusion: Replace certain area with background, which enriches variants of supervision.

[1] K Zhang & X Zhuang: CycleMix: A Holistic Strategy for Medical Image Segmentation from Scribble Supervision. CVPR 2022
https://github.com/BWGZK/CycleMix/
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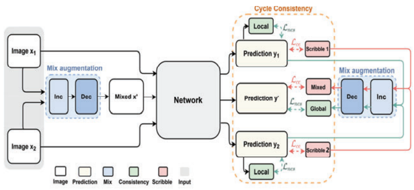

Cycle consistency:

Global consistency penalizes the inconsistent segmentation of the same image patch in two scenarios.

Local consistency loss minimizes the distance between prediction and its largest connected component.

[1] K Zhang & X Zhuang: CycleMix: A Holistic Strategy for Medical Image Segmentation from Scribble Supervision. CVPR 2022
https://github.com/BWGZK/CycleMix/
[2] Fuping Wu, Xiahai Zhuang: Minimizing Estimated Risks on Unlabelled Data: A New Formulation for Semi-Supervised Medical Image Segmentation. submitted to IEEE Transactions on Pattern Analysis and Machine Intelligence (In Revision)
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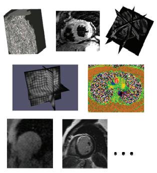
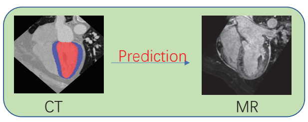
S2: Unsupervised domain adaptation segmentation

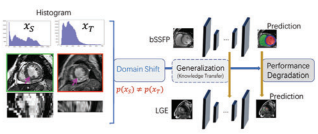
- Problem setting:
  - No labeled training images from new modality (MR)



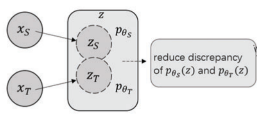


S2: Unsupervised domain adaptation segmentation

- Problem setting:
  - No labeled training images from new modality (MR)
  - Method target: reducing the distribution discrepancy



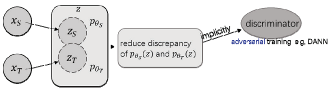
Domain shift in bSSFP and LGE CMR images
Performance degradation



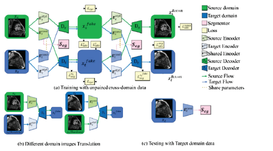
[F Wu & X Zhuang: Unsupervised Domain Adaptation with Variational Approximation for Cardiac Segmentation.. IEEE Transactions on Medical Imaging 2021]

S2: Unsupervised domain adaptation segmentation

- Problem setting:
  - No labeled training images from new modality (MR)
  - Method target: reducing the distribution discrepancy
- Adversarial training for domain adaptation



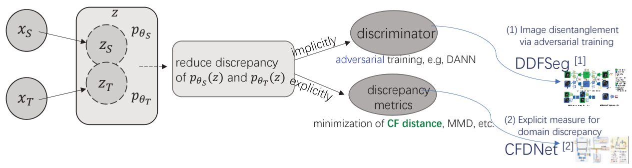
[F Wu & X Zhuang: Unsupervised Domain Adaptation with Variational Approximation for Cardiac Segmentation.. IEEE Transactions on Medical Imaging 2021]



C Pei, F Wu, L Huang, X Zhuang: Disentangle domain features for cross-modality cardiac image segmentation. Medical Image Analysis 2021.
https://github.com/Endless-Hao/DDFSeg

S2: Unsupervised domain adaptation segmentation

- Adversarial ->implicit minimize distribution discrepancy
- CF distance ->explicit minimize distribution distance



F Wu, X Zhuang: Unsupervised Domain Adaptation with Variational Approximation for Cardiac Segmentation.. IEEE Transactions on Medical Imaging 2021 https://github.com/FupingWu90/VarDA

S2: Unsupervised domain adaptation segmentation

- CFDNet: distance of characteristic function of distribution

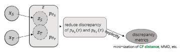
Techniques

B. CF Distance: Characteristic Function Distance for Explicit Domain Adaptation

We explicitly compute the domain discrepancy for explicit domain adaptation. The intuitive idea is to calculate the distance between the latent feature distributions, i.e., $p_{z_S}(z)$ and $p_{z_T}(z)$, as a measurement of the discrepancy. However, computing this distance with the limited training samples can be difficult. As $p_{z_S}(z)$ and $p_{z_T}(z)$ can be taken as information in space domain z, we transform them into frequency domains with CFs, $f_{z_S}(\vec{t})$ and $f_{z_T}(\vec{t})$, defined in Eq.3. Note that replacing $\vec{t}$ with $(-\vec{\omega})$ in Eq.3 leads to Fourier Transformation $\mathcal{F}$, i.e., $F_S(\vec{\omega}) = \mathcal{F}(p_{z_S}(z)) = \int p_{z_S}(z)e^{-i\vec{\omega}z}dz = \mathbb{E}_{p_{z_S}(z)}(e^{-i\vec{\omega}z})$, and $F_T(\vec{\omega}) = \mathcal{F}(p_{z_T}(z)) = \int p_{z_T}(z)e^{-i\vec{\omega}z}dz = \mathbb{E}_{p_{z_T}(z)}(e^{-i\vec{\omega}z})$, where $\vec{\omega}$ is frequency. Since CFs and probability distribution functions (PDFs) are mutually determined [27], meaning $p_{z_S}(z) = p_{z_T}(z)$ if and only if $f_{z_S}(\vec{t}) = f_{z_T}(\vec{t})$, one can use the distance between $f_{z_S}(\vec{t})$ and $f_{z_T}(\vec{t})$ as a surrogate measurement of the distance between $p_{z_S}(z)$ and $p_{z_T}(z)$. Here, f is the CF of p,

$$f_{z_S}(\vec{t}) = \mathbb{E}_{p_{z_S}(z)}(e^{i(\vec{t})'z}),\ \text{and}\ f_{z_T}(\vec{t}) = \mathbb{E}_{p_{z_T}(z)}(e^{i(\vec{t})'z}) \quad (3)$$

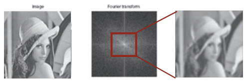
where, i denotes the imaginary unit, $\vec{t} \in \mathbb{R}^n$, and $(\vec{t})'$ is the transpose of $\vec{t}$.



Framework

Particularly, in the view of frequency domain, the information of high frequency signals usually can be ignored.

Hence, to align the two distributions we mainly reduce the discrepancy of the low frequency signals of the two domains.



F Wu, X Zhuang: CF Distance: A new domain discrepancy metric and application to explicit domain adaptation for cross-modality cardiac image segmentation. IEEE Transactions on Medical Imaging 39 (12), 4274 - 4285, 2020
https://github.com/FupingWu90/CFDnet

S2: Unsupervised domain adaptation segmentation

- CFDNet: distance of characteristic function of distribution

Techniques

CF distance $\mathcal{D}_{CF}(z_S, z_T; U) = \int_{-U}^{U} ||f_{z_S}(\vec{t}) - f_{z_T}(\vec{t})||^2 dt.$

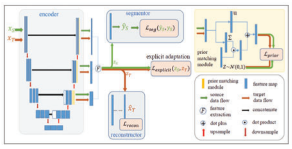
(a) $\mathcal{D}_{CF}(z_S, z_T; U_a) \approx \frac{1}{M^2}\sum_{p=1}^{M}\sum_{q=1}^{M} k(z_S^p, z_S^q) + \frac{1}{M^2}\sum_{p=1}^{M}\sum_{q=1}^{M} k(z_T^p, z_T^q) - \frac{2}{M^2}\sum_{p=1}^{M}\sum_{q=1}^{M} k(z_S^p, z_T^q)$

$$k(z_S, z_T) = \prod_{k=1}^{n} \frac{2\sin[(z_{S_k} - z_{T_k})a]}{z_{S_k} - z_{T_k}}$$

(b) Property: Kernel $\frac{\sin(x-y)}{x-y}$ is positive semi-definite, but not universal

(c) Substitution: $\mathcal{L}_{SCF}(z_S, z_T; U) \approx \frac{1}{n}\sum_{i=1}^{n} \mathcal{D}_{CF}(z_{S_i}, z_{T_i}; U).$

Framework



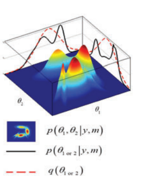
$$\mathcal{L} = \alpha_1\mathcal{L}_{seg} + \alpha_2\mathcal{L}_{prior} + \alpha_3\mathcal{L}_{recon} + \alpha_4\mathcal{L}_{explicit}$$

1 million times $\mathcal{D}(p(x_i), p(y_i))$ is far better than $\mathcal{D}(p(x_1, \ldots, x_{100}), p(y_1, \ldots, y_{100}))$

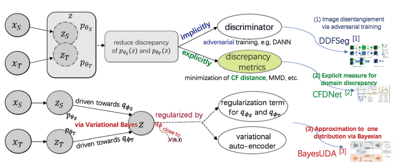
F Wu, X Zhuang: CF Distance: A new domain discrepancy metric and application to explicit domain adaptation for cross-modality cardiac image segmentation. IEEE Transactions on Medical Imaging 39 (12), 4274 - 4285, 2020
https://github.com/FupingWu90/CFDnet

S2: Unsupervised domain adaptation segmentation

- Adversarial ->implicit minimize distribution discrepancy
- CF distance ->explicit minimize distribution distance
- Parameterized distribution with variation Bayes -> explicit minimize distance by driving to same distribution and using marginalized distributions



https://mbb-team.github.io/VBA-toolbox/wiki/The-variational-Bayesian-approach/



F Wu, X Zhuang: Unsupervised Domain Adaptation with Variational Approximation for Cardiac Segmentation.. IEEE Transactions on Medical Imaging 2021

S2: Unsupervised domain adaptation segmentation

- VarDA: Unsupervised Domain Adaptation with Variational Approximation

Techniques

(1) Regularization term (domain discrepancy)

(a) $D(\phi_S, \phi_T) = \int [q_{\phi_S}(z) - q_{\phi_T}(z)]^2 dz \approx \frac{1}{M^2}\sum_{i=1}^{M}\sum_{j=1}^{M}\left[k(x_S^i, x_S^j) + k(x_T^i, x_T^j) - 2k(x_S^i, x_T^j)\right]$

$$k(x_S^i, x_T^j) = \frac{e^{-\frac{1}{2}\sum_{l=1}^{n}\frac{(u_{S_l}^i - u_{T_l}^j)^2}{\lambda_{S_l}^i + \lambda_{T_l}^j}}}{(2\pi)^{\frac{n}{2}} \cdot (\prod_{l=1}^{n}(\lambda_{S_l}^i + \lambda_{T_l}^j))^{\frac{1}{2}}}$$

(b) $\mathcal{D}(\phi_S, \phi_T) = \frac{1}{n}\sum_{i=l}^{n} D_{Slice}(\phi_S, \phi_T; \eta^l).$

(2) Source VAE

$$\begin{aligned} LB_{VAE}(\theta_S, \phi_S) &= -D_{KL}(q_{\phi_S}(z|x) \,\|\, p_{\theta_S}(z)) \\ &+ E_{q_{\phi_S}(z|x)}[p_{\theta_S}(x|y,z)] + E_{q_{\phi_S}(z|x)}[\log[p_{\theta_S}(y|z)] \\ &\leq \log p_{\theta_S}(x, y) \end{aligned}$$

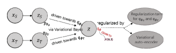
prior matching

reconstruction

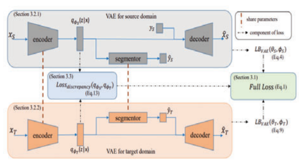
prediction

(3) Target VAE

$$\begin{aligned} LB_{VAE}(\theta_T, \phi_T) &= -D_{KL}(q_{\phi_T}(z|x) \,\|\, p_{\theta_T}(z)) \\ &+ E_{q_{\phi_T}(z|x)} \log[p_{\theta_T}(x|\hat{y}, z)] + E_{q_{\phi_T}(z|x)}[\log[p_{\theta_T}(\hat{y}|z)]. \end{aligned}$$



Framework



$$\mathcal{L}_{total}(\omega) = -\alpha_1 LB_{VAE}(\theta_S, \phi_S) - \alpha_2 LB_{VAE}(\theta_T, \phi_T) + \alpha_3 Loss_{discrepancy}(q_{\phi_S}, q_{\phi_T})$$

F Wu, X Zhuang: Unsupervised Domain Adaptation with Variational Approximation for Cardiac Segmentation.. IEEE Transactions on Medical Imaging 2021
https://github.com/FupingWu90/VarDA

S2: Unsupervised domain adaptation segmentation

- Adversarial ->implicit minimize distribution discrepancy
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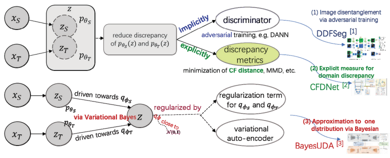


[1] F Wu, X Zhuang: Unsupervised Domain Adaptation with Variational Approximation for Cardiac Segmentation.. IEEE Transactions on Medical Imaging 2021 https://github.com/FupingWu90/VarDA
[2] C Pei, F Wu, L Huang, X Zhuang: Disentangle domain features for cross-modality cardiac image segmentation. Medical Image Analysis 2021.https://github.com/Endless-Hao/DDFSeg
[3] F Wu, X Zhuang: CF Distance: A new domain discrepancy metric and application to explicit domain adaptation for cross-modality cardiac image segmentation. IEEE Transactions on Medical Imaging 39 (12), 4274 - 4285, 2020 https://github.com/FupingWu90/CFDnet

Content

- An example of intelligent medicine y
- Weakly/non-supervised segmentation f
- Image restoration and super-resolution x
  - Deep decomposition and reconstruction

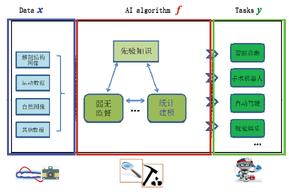
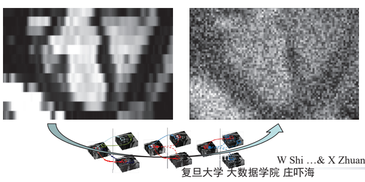


Image restoration and super resolution

- Natural images

From Y Chen, S Liu, X Wang (https://yinboc.github.io/liif/)

- Medical images (unsupervised)

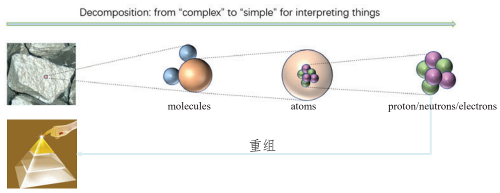


现实不存在这种高分辨图像作为训练数据

W Shi …& X Zhuang et al; H Zhou & X Zhuang

Deep decomposition and reconstruction

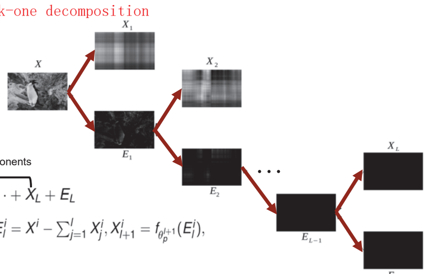
- 先分解成可解释建模的“原子”（如秩一分量、统计分量）
- 再从“原子”组合重建新的物质（图像）



S Gao & X Zhuang: Rank-One Network: An Efficient Framework for Image Restoration. IEEE T PAMI Dec 2020
Code: https://github.com/shangqigao/RONet
S Gao & X Zhuang: Bayesian Image Super-Resolution with Deep Modeling of Image Statistics. IEEE T PAMI 2022
Code: https://github.com/shangqigao/BayeSR

Method 1: RO-Net

- Rank-One Network for image restoration
  - New representation for low-ranked matrix
    - Rank-one decomposition



Low rank components

$$X = \underbrace{X_1 + X_2 + \cdots + X_L}_{\text{Low rank components}} + E_L$$

$$X_1^i = f_{\theta_p^1}(X^i), \cdots, E_j^i = X^i - \sum_{j=1}^{l} X_j^i, X_{l+1}^i = f_{\theta_p^{l+1}}(E_l^i),$$

S Gao & X Zhuang: Rank-One Network: An Efficient Framework for Image Restoration. IEEE T PAMI Dec 2020
Code: https://github.com/shangqigao/RONet

Method 1: RO-Net

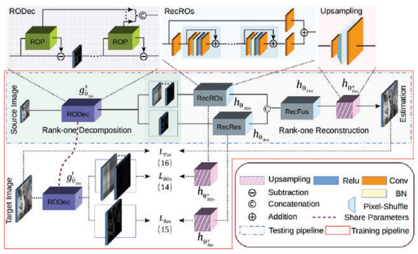
- Rank-One Network

$$L_{Fus} = \frac{1}{N}\sum_{i=1}^{N} \| h_{\theta_{Rec}} \circ g^s_{\hat{\theta}_{Dec}}(S^i) - T^i \|_\alpha^\alpha + \eta L_{Per}\left(h_{\theta_{Rec}} \circ g^s_{\hat{\theta}_{Dec}}(S^i), T^i\right),$$

$$L_{ROs} = \frac{1}{N}\sum_{i=1}^{N} \| h_{\theta^u_{ROs}} \circ h_{\theta_{ROs}}(\hat{S}^i_{ROs}) - \hat{T}^i_{LR} \|_\alpha^\alpha,$$

$$L_{Res} = \frac{1}{N}\sum_{i=1}^{N} \| h_{\theta^u_{Res}} \circ h_{\theta_{Res}}(\hat{S}^i_{Res}) - \hat{T}^i_{Res} \|_\alpha^\alpha.$$

Low rank (LR) components, i.e., rank-one matrices of T



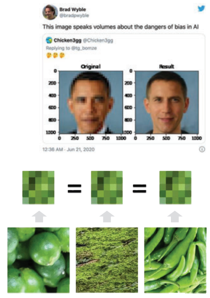
S Gao & X Zhuang: Rank-One Network: An Efficient Framework for Image Restoration. IEEE T PAMI Dec 2020
Code: https://github.com/shangqigao/RONet

Deep decomposition and reconstruction

- Multiple HR images downsampled to one LR image
- Solution

  learning/infer distribution

  $\mathbf{x} = \mathbf{f}_{\theta}(y)$ $\quad$ $p(\mathbf{x}|y) \sim \mathbf{f}_{\theta}(y).$



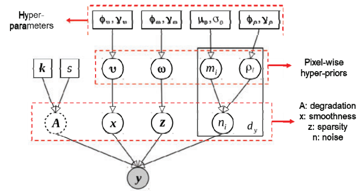
https://data.vision.ee.ethz.ch/cvl/ntire21/

Method 2: BayeSR

- Unsupervised Bayesian Image Super-Resolution

  Deep modeling of image statistics:

  (1) smoothness (2) sparsity (3) noise components (variables)



S Gao & X Zhuang: Bayesian Image Super-Resolution with Deep Modeling of Image Statistics. IEEE T PAMI 2022
Code: https://github.com/shangqigao/BayeSR

Method 2: BayeSR

- Unsupervised Bayesian Image Super-Resolution

  Deep modeling of image statistics:

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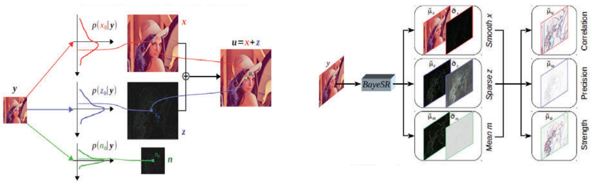


S Gao & X Zhuang: Bayesian Image Super-Resolution with Deep Modeling of Image Statistics. IEEE T PAMI 2022
Code: https://github.com/shangqigao/BayeSR

Method 2: BayeSR

- Unsupervised ideal SR

TABLE 4

Evaluation on the task of *ideal* SISR ×4. We test all methods on Set5 [69], Set14 [70], BSDS100 [71], and Urban100 [72], and report the average PSNR (↑), SSIM (↑), LRPSNR (↑), LPIPS (↓), and Div. score (↑). The bold font indicates the best performance for the models trained without ground truth, and and the italic value represents the second best performance. Note that the supervised methods are just for reference.

Model	#Paras	Set5				Set14				BSDS100				Urban100				Div. score
		PSNR	SSIM	LRPSNR	LPIPS	PSNR	SSIM	LRPSNR	LPIPS	PSNR	SSIM	LRPSNR	LPIPS	PSNR	SSIM	LRPSNR	LPIPS	
Bicubic	–	28.42	0.8105	35.02	0.3357	26.10	0.7048	34.62	0.4320	25.96	0.6676	35.86	0.5175	23.15	0.6579	32.73	0.4677	0
ZSSR	0.23M	29.46	0.8319	42.15	0.2062	27.05	0.7413	42.33	0.3186	26.66	0.7058	43.54	0.4101	24.02	0.7045	41.13	0.3363	0
MZSR	0.23M	28.12	0.8029	41.46	0.2589	25.77	0.7089	41.14	0.3471	25.83	0.6782	42.88	0.4183	23.02	0.6659	39.75	0.3782	0
Baseline	2.63M	*30.56*	*0.8738*	48.85	*0.1785*	*27.33*	*0.7656*	47.30	*0.2962*	*26.88*	*0.7267*	48.97	*0.3905*	*24.58*	*0.7468*	46.28	*0.2751*	0
U-BayeSR	2.63M	30.86	0.8809	*45.81*	0.1088	27.51	0.7679	*45.14*	0.2123	27.08	0.7284	*46.10*	0.2986	24.91	0.7614	*44.33*	0.2171	7.70
Supervised model for reference																		
EnhanceNet	0.48M	28.56	0.8093	40.06	0.1014	25.04	0.6528	36.41	0.1656	24.09	0.6006	34.47	0.2055	22.30	0.6504	33.21	0.1692	0
SRGAN	0.95M	28.19	0.8163	33.18	0.0906	25.97	0.7001	33.87	0.1746	24.63	0.6416	33.16	0.2066	23.67	0.6984	33.44	0.1791	0
ESRGAN	16.7M	30.44	0.8505	40.74	0.0750	26.28	0.6974	38.65	0.1341	25.30	0.6494	40.05	0.1615	24.35	0.7322	37.70	0.1231	0
SRFlow	39.5M	30.26	0.8416	42.17	0.0771	26.82	0.7130	42.03	0.1314	26.04	0.6704	43.13	0.1825	25.25	0.7493	40.87	0.1271	22.70

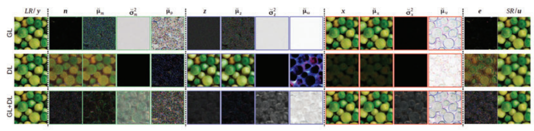


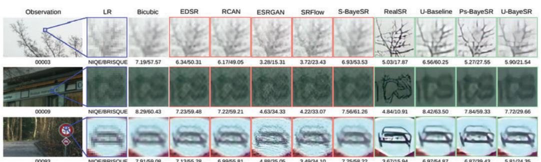
Fig. 5. Visualization of variational posteriors inferred by three typical models. The five columns split by dotted lines represent LR observations, inferences w.r.t. the noise $\mathbf{n}$, estimations w.r.t. the sparsity residual $\mathbf{z}$, approximations w.r.t. the smoothness component $\mathbf{x}$, and outputs. Here, $\mathbf{e} = \mathbf{y} - \mathbf{A}(\mathbf{x} + \mathbf{z})$ denotes the residual error in LR space, and $\mathbf{m}$ is a sample follows $\mathcal{N}(\breve{\mu}_m, \mathrm{diag}(\breve{\sigma}_m^2))$. Please zoom in for more details.

S Gao & X Zhuang: Bayesian Image Super-Resolution with Deep Modeling of Image Statistics. IEEE T PAMI 2022
Code: https://github.com/shangqigao/BayeSR

Method 2: BayeSR

- Unsupervised real-world SR

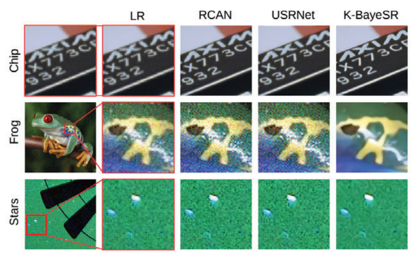
Model	Bicubic	EDSR	RCAN	SRGAN	ESRGAN	SRFlow	S-BayeSR	RealSR	U-Baseline	Ps-BayeSR	U-BayeSR
LRPSNR	36.74	37.78	37.80	27.89	36.83	37.52	36.93	33.08	36.82	38.59	35.65
NIQE	7.99	6.89	6.91	3.83	4.02	3.84	7.26	4.85	7.69	6.96	6.73
BRISQUE	60.41	55.74	55.12	15.68	27.50	25.66	58.60	16.42	60.45	47.67	31.46
#Paras	–	43.1M	15.6M	2.03M	16.7M	39.5M	2.63M	16.7M	2.63M	2.63M	2.63M
–	–	Model transferred from ideal SISR						Model trained without ground truth			



S Gao & X Zhuang: Bayesian Image Super-Resolution with Deep Modeling of Image Statistics. IEEE T PAMI 2022
Code: https://github.com/shangqigao/BayeSR

Method 2: BayeSR – Generalizability

- to noise
- to **degradation** kernel

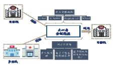


S Gao & X Zhuang: Bayesian Image Super-Resolution with Deep Modeling of Image Statistics. IEEE T PAMI 2022
Code: https://github.com/shangqigao/BayeSR

Content

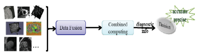
$f(x)=y$

1 Multi-center left atrial analysis



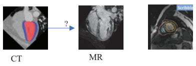
MedIA2020/2022a/b, MICCAI2020/2021等;

2 Combined computing for multi-modality images



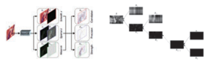
IEEE T PAMI2019, MICCAI2020等;

3 Weakly/non-supervised segmentation



IEEE TMI2020/2021, MedIA2019/2021等;

4 Deep image restoration/reconstruction



IEEE T PAMI2020/ 2022等

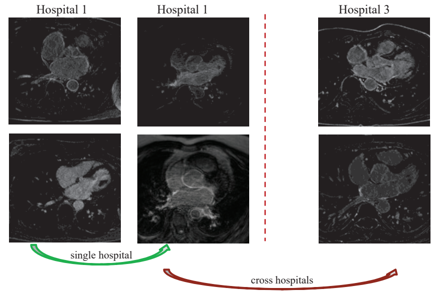
Our Challenges (visit us @ www.zmiclab.github.io)

- LAScarQS 2022 Challenge – open now ☺
- MM-WHS2017: Multimodality whole heart segmentation
- MSCMRSeg2019: Multisequence cardiac MR segmentation
- MyoPS2020: Myocardial Pathology segmentation

AtrialGeneral

Target: test generalizability across domains/ hospitals

- Multi-center LGE MRIs of left atrium SQ



Lei Li, et al. & Xiahai Zhuang: AtrialGeneral: Domain Generalization for Left Atrial Segmentation of Multi-Center LGE MRIs. *MICCAI*, 2021
Lei Li et al & Xiahai Zhuang: Medical Image Analysis on Left Atrial LGE MRI for Atrial Fibrillation Studies: A Review. Medical Image Analysis 2022

AtrialGeneral

Results

- Comparisons of Different Semantic Segmentation Networks

	Center	Metrics	U-Net	U-Net++	DeepLab v3+	MAnet
Single hospital	Same	Dice	0.908±0.039	0.908±0.037	0.900±0.041	0.904±0.057
		ASD (mm)	1.35±0.722	1.26±0.577	1.31±0.557	1.37±0.849
		HD (mm)	36.3±12.3	28.5±14.9	15.3±5.78	32.7±12.6
Cross hospital	Diff	Dice	0.652±0.107	0.633±0.104	0.678±0.089	0.610±0.116
		ASD (mm)	6.86±1.51	7.12±1.60	6.19±1.65	8.26±1.98
		HD (mm)	48.2±7.93	51.1±7.62	42.7±8.62	53.3±7.45

- Comparisons of Different Generalization Models

Method	Dice	ASD (mm)	HD (mm)
DeepLab v3+ (baseline)	0.678±0.089	6.19±1.65	42.7±8.62
HM	0.772±0.089	3.76±1.04	26.5±5.30
MID-Net	0.741±0.064	4.83±1.12	42.6±9.66
RST-Net	0.756±0.090	4.20±1.15	30.3±6.90

Lei Li, et al. & Xiahai Zhuang: AtrialGeneral: Domain Generalization for Left Atrial Segmentation of Multi-Center LGE MRIs. *MICCAI*, 2021
Lei Li et al & Xiahai Zhuang: Medical Image Analysis on Left Atrial LGE MRI for Atrial Fibrillation Studies: A Review. Medical Image Analysis 2022

LAScarQS 2022 Challenge

关注：域泛化、分布式、增量学习

https://zmiclab.github.io/projects/lascarqs22

- 200+ subjects
  - training images with LA and scar gold standard
  - different vendors and centers (from different continents)
  - a global effort involving teams from 4 continents
- Two tasks
  - Cross domain
  - Scar quant&seg

Visit our website

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