Date: Dec 7, 2021

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| **Title** | Wang, D. D., Qian, Z., Vukicevic, M., Engelhardt, S., Kheradvar, A., Zhang, C., ... & Vannan, M. A. (2021). 3D printing, computational modeling, and artificial intelligence for structural heart disease. JACC: Cardiovascular Imaging, 14(1), 41-60. |
| **Area info** | * In transcatheter SHD interventions, the absence of a gold-standard open cavity surgical field deprives physicians of the opportunity for tactile feedback and visual confirmation of cardiac anatomy. * Adaptation of 3-dimensional (3D) printing in clinical care and procedural planning has demonstrated a reduction in early-operator learning curve for transcatheter interventions. * **3D printing in structure heart disease:**   + **Transcatheter aortic valve replacement (TAVR，经导管主动脉瓣置换术) interventions:** pre-procedural planning, the sizing of TAVR devices, and the estimation of possible risks for paravalvular leak; **CT data**   <https://www.mayoclinic.org/tests-procedures/transcatheter-aortic-valve-replacement/about/pac-20384698>   * + **Percutaneous mitral valve repair (经皮二尖瓣修复术):** transesophageal echocardiographic data   + Transcatheter mitral valve replacement (TMVR, **经导管二尖瓣置换术**): CT data   + Left atrial appendage (LAA) closure (**左心耳封堵术**): helped pave understanding of the different LAA device-specific landing zones within patients’ specific anatomy, and assisted in optimizing device sizing, and catheter and device selection; CT data   + Transcatheter tricuspid valve repair and replacement (**经导管三尖瓣修补术和置换术**): 3D transesophageal echocardiogram (TEE), a combination of 3D TEE and CT data   + Patient education；improved understanding and feedback * **Current limitation**: cannot mimic both the appearance and the mechanical property of the living organ; * **Role of AI:**   + Hyperrealism, a sort of augmented reality for training   + Training of interventionalists and interventional imaging physicians: auto-matic image quality grading, auto-mated skill assessment   + achieve fast and accurate segmentation in a clinically actionable time frame   + AI could be used to structure, share, and retrieve massive amounts of collected operative video, intraoperative imaging, and electronic medical records across many surgeons and interventionists around the world |
| **Notes** | * Structural heart interventions require in-depth understanding of cardiac pathophysiology. * 3D printing can decrease the early-operator learning curve for new technology adaptation. * Computational fluid modeling has potential to emulate dynamic physical and physiological properties of cardiac pathophysiology. * Application of AI has potential for patient-specific anatomic replica procedural simulation training. |
| **Comments** | * From technical view, there are also some research points about multi-modality-image based segmentation, and video-based surgery skill assessment that worth paying attention. |

Date: Dec 9, 2021

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| **Title** | Cheng K, Ma Y, Sun B, et al. Depth Estimation for Colonoscopy Images with Self-supervised Learning from Videos[C]//International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, 2021: 119-128. |
| **Area info** | * Depth estimation in colonoscopy images provides geometric clues for downstream medical analysis tasks, such as polyp detection, 3D reconstruction, and diagnosis * Compared with natural scenes where groundtruth depth can be obtained using depth cameras or LiDARs, acquiring the ground-truth depth for colonoscopy videos is arduous. |
| **Notes** | * We use synthetic data with ground truth depth maps to train a depth estimation network with a generative adversarial network model. * Despite the lack of ground truth depth, real colonoscopy videos are used to train the network in a self-supervision manner by exploiting temporal consistency between neighboring frames. * Furthermore, we design a masked gradient warping loss in order to ensure temporal consistency with more reliable correspondences. |
| **Comments** | * NA |

Date: Dec 9, 2021

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| **Title** | Rau A, Edwards P J E, Ahmad O F, et al. Implicit domain adaptation with conditional generative adversarial networks for depth prediction in endoscopy[J]. International journal of computer assisted radiology and surgery, 2019, 14(7): 1167-1176. |
| **Area info** | * NA |
| **Notes** | * propose to train a cGAN to translate real colonoscopy images to depth maps * Because training data are difficult to obtain during endoscopy, we avoid the necessity of paired colonoscopy images and corresponding depth maps altogether * we propose to **train a pix2pix network on paired simulated data and unlabelled real images**. * Prepare the Synthetic dataset   + We generate synthetic data based on a human CT colonography (CTC) scan (Fig. 1) from which we extract a surface mesh using manual segmentation and meshing.   + To render RGB endoscopic simulation images and corresponding depth maps, an environment developed using the game engine Unity is used.   + A virtual camera with two attached light sources, one on each side of the camera, can be scripted to follow a desired path through the virtual model with varying textures and lighting conditions; * Prepare the real validation data: 目的是找到真实图片对应的unity系统中的深度图片   + Unity系统：大量数据pair（摄像头位置-假图片-深度信息图），以及有若干marker   + da Vinci系统：若干真图片，且有若干marker，   + 以上两个系统的marker是一一对应的，这是两个系统对应上的基础   + 流程：da Vinci系统中的图片A，基于Procrustes analysis方法通过marker位置计算得到图片A对应的摄像头位置；在这个位置获得相应的假图片以及深度信息图；这样就得到了da Vinci系统的真实图片（当然还是假的手术）对应的深度信息图。   + 上述过程比较繁琐，该paper只采集了16个2d图。 |
| **Comments** | * NA |

Date: Dec 24, 2021

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| **Title** | Medical Image Segmentation Using 3d Convolutional Neural Networks: A Review |
| **Area info** | * Most of the published studies on 3D medical image analysis have used 2D CNN models. * CNN is designed to learn spatial features using higher-dimensional data space (2D, 3D, etc.) and analyze the images adaptively without using any handcrafted features； * A typical CNN model uses multiple convolutions and pooling layers for extracting multi-scale features; the complexity of image features advances as the model depth increases. * Medical images use different modalities based on the imaging principles. The characteristics of these images differ, in terms of spatial resolution, image intensity range, size of the image, and noise. In addition, they vary in terms of dimensionality and its way of representation. * The 3D image visualization has provided a great opportunity for clinicians to evaluate the cross-section of anatomic structures. |
| **Notes** |  |
| **Comments** |  |