Daniel Ruijters:
"Machine Learning in the Cathlab",
European Congress of Radiology - ECR 2022; July 13-17, 2022, Vienna (Austria), C-11045. doi:10.26044/ecr2022/C-11045

Machine Learning in the Cathlab

Authorblock: D. Ruijters; Best/NL

Authors:
1. Dr. Danny Ruijters [1] (presenter)

Disclosures:
Dr. Danny Ruijters: Employee: Philips

Keywords: Artificial Intelligence, Computer applications, Interventional vascular, Image manipulation / Reconstruction, Neural networks, Computer Applications-Detection, diagnosis, Computer Applications-General, Technology assessment, Image registration, Image verification

---

Purpose or Learning Objective:

In this article we will investigate the different categories of machine learning driven solutions that can provide added value in cathlab procedures. Categorizing machine learning applications in the cathlab, and structurally investigating their respective data needs, aids in developing a systematic approach to the data collection and algorithm development challenges. Machine learning applications in the cathlab can be divided in four data categories, dependent on the type of data they receive as input: 1) image-based, 2) 1D signals such as ECG, respiratory, etc., 3) natural language processing, 4) hybrid or other data sources. Machine learning algorithms, regardless of their input data type, typically address a fine-grained task, such as object detection, signal quality improvement, image registration, event detection, etc. These fine-grained algorithmic blocks then feed into high level applications, such as device navigation, lesion quantification, patient risk stratification, functional parametrization, etc.

The strengths and plasticity of machine learning techniques make them an attractive solution for many tasks that cannot easily be automated otherwise. Particularly, convolutional networks have demonstrated robust performance and versatility in segmentation tasks, and can be easily retrained to handle newly introduced devices. In this article we will investigate the different categories of machine learning driven solutions that can provide added value in cathlab procedures.

Methods or Background:

In recent years machine learning techniques have seen a tremendous increase in adoption, initially fueled by the massive use of social media leading to very large databases. A development which has also translated to the medical arena. For clinical applications, however, the sizeable data collections machine learning demands remains a challenge. Categorizing machine learning applications in the cathlab, and structurally investigating their respective data needs, aids in developing a systematic approach to the data collection and algorithm development challenges.

Categories

Machine learning applications in the cathlab can be divided in four data categories, dependent on the type of data they receive as input:

1. *Image-based*: This comprises interventional X-ray, ultrasound, transesophageal echocardiography, intravascular imaging, such as IVUS and OCT, etc.
2. *1D signals*: e.g., ECG, respiratory, blood pressure, intravascular measurements such fractional flow reserve FFR, etc.
3. *Natural language processing*: sources can be either audio fed speech to text (including voice commands and voice annotation), diagnostic patient reports, etc.
4. *Hybrid or other data sources*: e.g., combination of the input data types above (such as e.g., x-ray images, ECG and respiratory signals).

Machine learning algorithms, regardless of their input data type, typically address a fine-grained task, such as:

- *intra-vascular device detection*: such as catheter segmentation [1] (Figure 1), needle [2], valve (Figure 2), or stent (Figure 3) detection.
- *signal quality improvement*: e.g., noise reduction [3].
- *image registration*: which can be subdivided into rigid and elastic registration [4], and into 2D3Dand 3D-3D registration.
- *event detection*: such as adverse event detection [5], or valve deployment (Figure 2).
- *procedure phase recognition*: which segments the procedure into different time segments [6].
- *unstructured data to structured data translation*: such as the mining of unstructured text sources [5],
- etc.

These fine-grained algorithmic blocks then feed into high level applications, such as:

- *device navigation* [1,2],
- *lesion quantification* [7],
- *patient risk stratification* [8],
- *integrating pre-interventional planning data*,
- *functional parametrization* (e.g. blood flow quantification [9]),
- etc.

Results or Findings:

In this section several high level applications, and their machine learning building blocks will be further examined.

Device navigation

Typically, in minimally invasive procedures the in-body device can only be navigated and monitored through external imaging. Suitable imaging modalities are ultrasound, interventional x-ray, and realtime CT and MR. AI can be employed to detect and locate interventional devices, such as intravascular devices, and other percutaneous devices. Intra-vascular devices comprise catheters and guidewires [1] (Figure 1), intra-vascular valves (Figure 2), stents (Figure 3), etc. Other percutaneous devices entail needles [2], scalpels, etc. AI algorithms are particularly suited for detecting and segmenting devices since they are trained by a suitable set of examples [1,10,11]. This implies that the training set can contain a variety of devices with different visual properties, and it can be easily extended with new devices.

Integrating pre-interventional planning data

Integrating data from various imaging modalities can aid the interventional treatment procedure. E.g., pre-interventional planning conducted on diagnostic images can be utilized during the procedure [12], see Figure 4. The spatial registration of the pre-interventional and peri-interventional images can then bring the pre-interventional planning into the coordinate space of the interventional equipment. This allows to overlay the planning, such as a needle path, on the live images containing the interventional devices. Also, multiple complementary imaging modalities, such as e.g. ultrasound and x-ray, can be combined to create richer more informative data [13]. The combination of the images can show interfaces between tissues and objects that can only be visualized by a different imaging modality.

The spatial co-registration process can be conducted based on explicit markers and other external knowledge, on image content alone, or a combination of those. The resulting spatial mapping can be rigid, affine, elastic, or other deformable, depending on the clinical application. E.g., for intra-cranial applications a rigid registration is often sufficient, while registering pre- and intra-interventional abdominal images may require elastic registration to account for respiratory motion, etc. [4].

AI based approaches may play a role in establishing the spatial co-registration mapping either by detecting explicit landmarks and/or identifying landmark features in images, or by integrally addressing the registration task [14,15].

Functional parametrization

Functional imaging has as purpose to characterize the functioning of biological processes, rather than visualizing the anatomy (though it is typically combined with anatomical imaging in order to localize the functional aspects). Examples of the functions that are imaged peri-interventionally are blood flow in vessels and aneurysms [9,16], blood perfusion of the parenchymal tissue, valve motion, etc. Functional imaging is typically based on intensive processing of raw measurements. For e.g. blood flow vector fields through digital subtraction angiography (see Figure 5), the motion of contrast through the vascular structures is followed in the consecutive frames, while for valve motion the valve leaflets are segmented and followed over time. These segmentations and motion of carrier substances are very well suited for AI approaches, such as convolutional networks [1,10].

Conclusion:

Machine learning employed in the cathlab can be categorized along multiple dimensions. The segmentation can be performed based on input data type, fine-grained algorithmic tasks, and high level applications. An overview of the data categories aids in structurally addressing data needs and development efforts.

Acknowledgements

Pierre Ambrosini, Fred van Nijnatten and Marco Verstege are acknowledged for the development, annotation and training of the machine learning algorithms used in the figures.

References:

1. P. Ambrosini, I. Smal, D. Ruijters, W. Niessen, A. Moelker, and T. van Walsum, “A Hidden Markov Model for 3D Catheter Tip Tracking with 2D X-ray Catheterization Sequence and 3D Rotational Angiography”, IEEE Transactions on Medical Imaging, vol. 36(3), pp. 757-768, March 2017. https://doi.org/10.1109/TMI.2016.2625811
2. L. Spelle, D. Ruijters, D. Babic, R. Homan, P. Mielekamp, J. Guillermic, and J. Moret, “First clinical experience in applying XperGuide in embolization of jugular paragangliomas by direct intratumoral puncture”, International Journal of Computer Assisted Radiology and Surgery, vol. 4(6), pp. 527-533, November 2009. https://doi.org/10.1007/s11548-009-0370-6
3. E. Kang, J. Min, and J.C. Ye. "A deep convolutional neural network using directional wavelets for low-dose X-ray CT reconstruction." Medical physics 44(10): e360-e375, 2017. https://doi.org/10.1002/mp.12344
4. D. Ruijters, B.M. ter Haar Romeny, and P. Suetens, “Efficient GPU-Accelerated Elastic Image Registration”, in Proceedings of the Sixth International Conference on BIOMEDICAL ENGINEERING (BioMed), February 13-15, 2008, Innsbruck (Austria), pp. 419-424.
5. B. Fan, W. Fan, and C. Smith. “Adverse drug event detection and extraction from open data: A deep learning approach”. Information Processing & Management, 57(1):102131, 2020. https://doi.org/10.1016/j.ipm.2019.102131
6. C. Garrow, K.-F. Kowalewski, L. Li, M. Wagner, M. Schmidt, S. Engelhardt, D.A. Hashimoto, H.G. Kenngott, S. Bodenstedt, S. Speidel, B.P. Müller-Stich, and F. Nickel. “Machine Learning for Surgical Phase Recognition: A Systematic Review”, Annals of Surgery 273(4): 684-693, 2021. https://doi.org/10.1097/SLA.0000000000004425
7. Y. Hong, F. Commandeur, S. Cadet, M. Goeller, M.K. Doris, X. Chen, J. Kwiecinski, D.S. Berman, P.J. Slomka, H.J. Chang, and D. Dey. “Deep learning-based stenosis quantification from coronary CT Angiography”. Proc SPIE Int Soc Opt Eng.: 109492I, 2019. https://doi.org/10.1117/12.2512168
8. J.M. Kwon, K.H. Jeon, H.M. Kim, M.J. Kim, S. Lim, K.H. Kim, P.S. Song, J. Park, R.K. Choi, and B.H. Oh. “Deep-learning-based risk stratification for mortality of patients with acute myocardial infarction”, PloS one, 14(10), e0224502, 2019. https://doi.org/10.1371/journal.pone.0224502
9. O. Brina, R. Ouared, O. Bonnefous, F. van Nijnatten, P. Bouillot, P. Bijlenga, K. Schaller, K.-O. Lovblad, T. Grünhagen, D. Ruijters, and V.M. Pereira, “Intra-Aneurysmal Flow Patterns: Illustrative Comparison among Digital Subtraction Angiography, Optical Flow, and Computational Fluid Dynamics”, AJNR American Journal of Neuroradiology, vol. 35(12):2348-2353, 2014. https://doi.org/10.3174/ajnr.A4063
10. Litjens, F. Ciompi, J.M. Wolterink, B.D. de Vos, T. Leiner, J. Teuwen, and I. Išgum, “State-of-the-art deep learning in cardiovascular image analysis”, JACC: Cardiovascular Imaging, vol. 12(8 Part 1), pp. 1549-1565, 2019. https://doi.org/10.1016/j.jcmg.2019.06.009
11. Gessert, M. Lutz, M. Heyder, S. Latus, D.M. Leistner, Y.S. Abdelwahed, and A. Schlaefer, “Automatic plaque detection in IVOCT pullbacks using convolutional neural networks”, IEEE transactions on medical imaging, vol. 38(2), pp. 426-434, 2018. https://doi.org/10.1109/TMI.2018.2865659

12. A. Garcia, S. Bhakta, J. Kay, K.-C. Chan, O. Wink, D. Ruijters, and J.D. Carroll, "On-line multi-slice computed tomography interactive overlay with conventional X-ray: A new and advanced imaging fusion concept", International Journal of Cardiology, vol. 133(3), pp. e101-e105, April 17, 2009. https://doi.org/10.1016/j.ijcard.2007.11.049
13. Balzer, T. Zeus, K. Hellhammer, V. Veulemans, S. Eschenhagen, E. Kehmeier, C. Meyer, T. Rassaf, and M. Kelm, „Initial clinical experience using the EchoNavigator-system during structural heart disease interventions", World journal of cardiology, vol. 7(9), pp. 562, 2015. https://dx.doi.org/10.4330%2Fwjc.v7.i9.562
14. Haskins, U. Kruger, and P. Yan, "Deep learning in medical image registration: a survey", Machine Vision and Applications, vol. 31(1), pp. 1-18, 2020. https://doi.org/10.1007/s00138-020-01060-x
15. D. de Vos, F.F. Berendsen, M.A. Viergever, H. Sokooti, M. Staring, and I. Išgum, "A deep learning framework for unsupervised affine and deformable image registration", Medical image analysis, vol. 52, pp. 128-143, 2019. https://doi.org/10.1016/j.media.2018.11.010
16. F. Mut, D. Ruijters, D. Babic, C. Bleise, P. Lylyk, and J.R. Cebral, "Effects of changing physiologic conditions on the in vivo quantification of hemodynamic variables in cerebral aneurysms treated with flow diverting devices", International Journal for Numerical Methods in Biomedical Engineering, vol. 30(1), pp. 135-142, January 2014. https://doi.org/10.1002/cnm.2594

Status:

SUBMITTED

Images

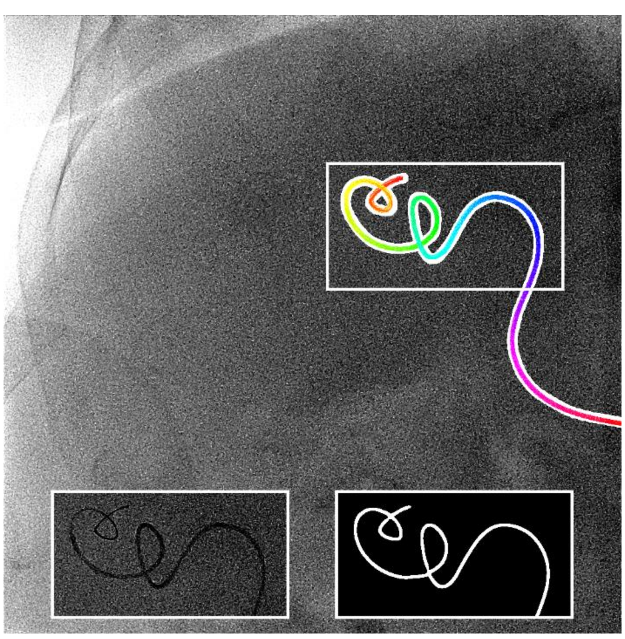

Fig 1: Automatic device detection, such as catheter segmentation and catheter tip extraction performed by machine learning [1].

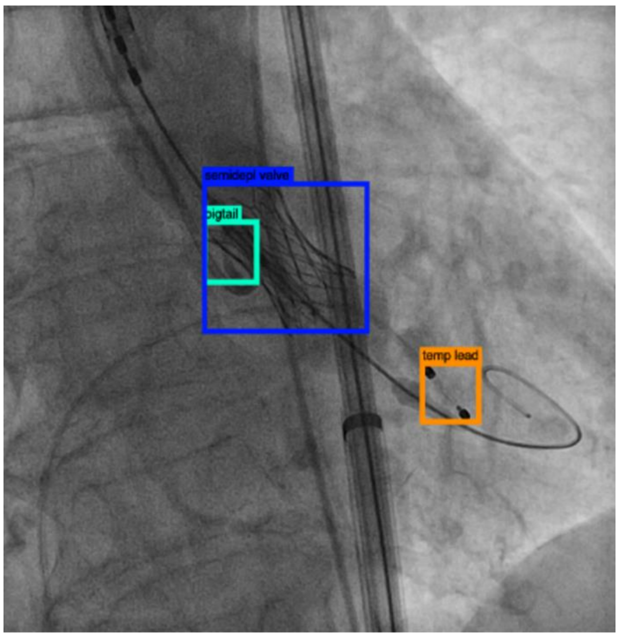

Fig 2: Device recognition (valve, pigtail, temp lead), including deployment status. Machine learning can also handle overlapping devices.

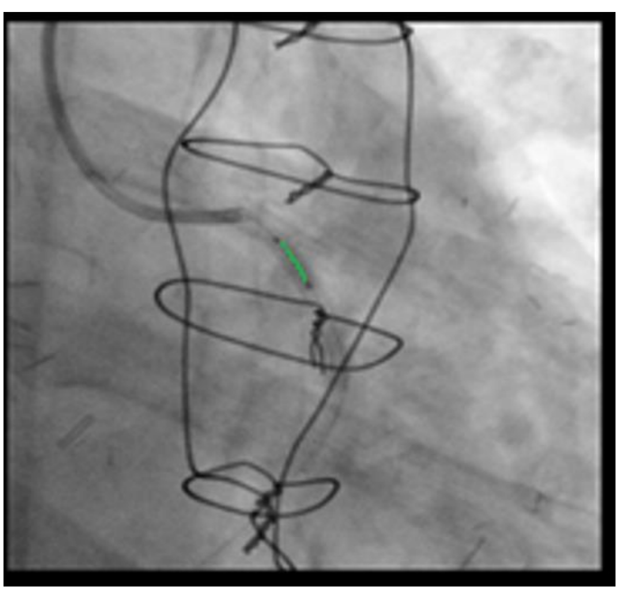

Fig 3: The presence of stitches does not prohibit the machine learning driven stent detection to find the stent.

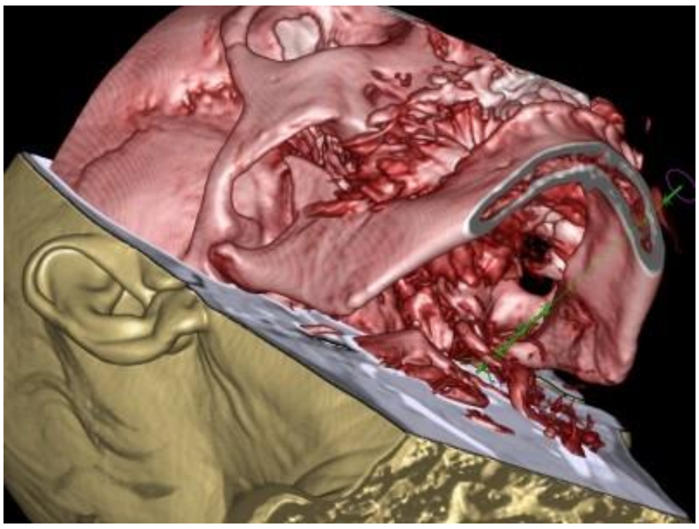

Fig 4: Example of spatially registered multi-modal datasets, used for percutaneous needle path planning and navigation.

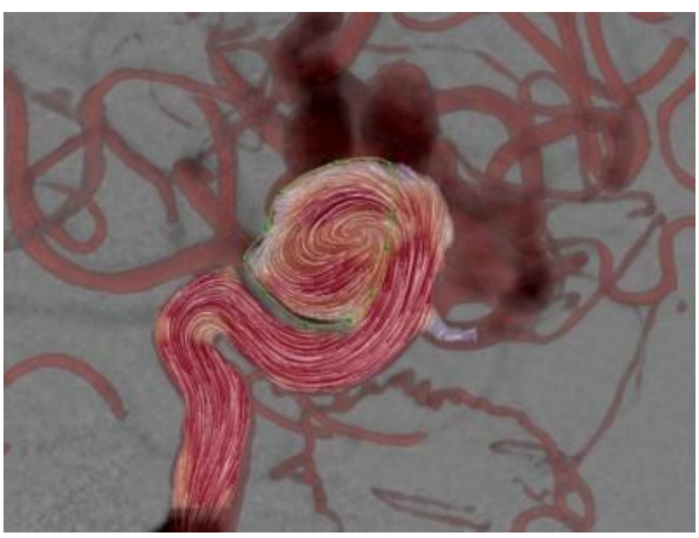

Fig 5: Example of intra-vascular flow imaging using digitally subtracted angiography imaging.