Machine Learning in the Cathlab

Daniel Ruijters

Abstract

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.

Introduction

Purpose

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.

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.

Results

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 2D-3D and 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],
- functional parametrization (e.g. blood flow quantification [9]),
- etc.

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.

References

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Figures

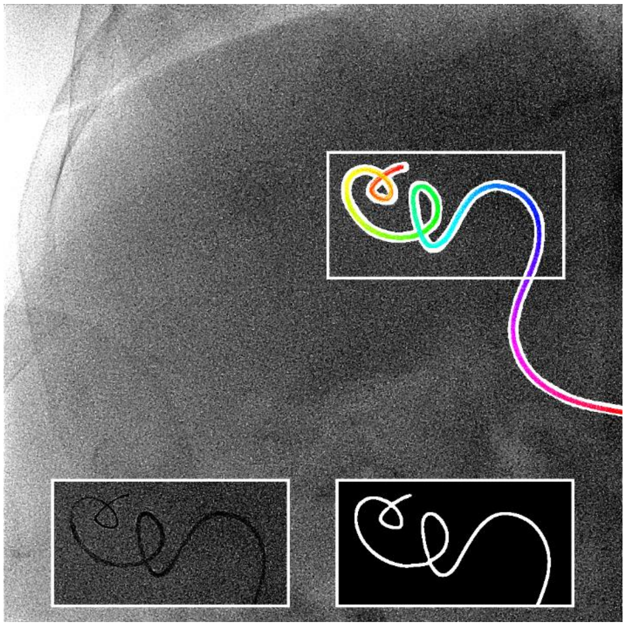

Figure 1: Automatic device detection, such as catheter segmentation and catheter tip extraction performed by machine learning [1].

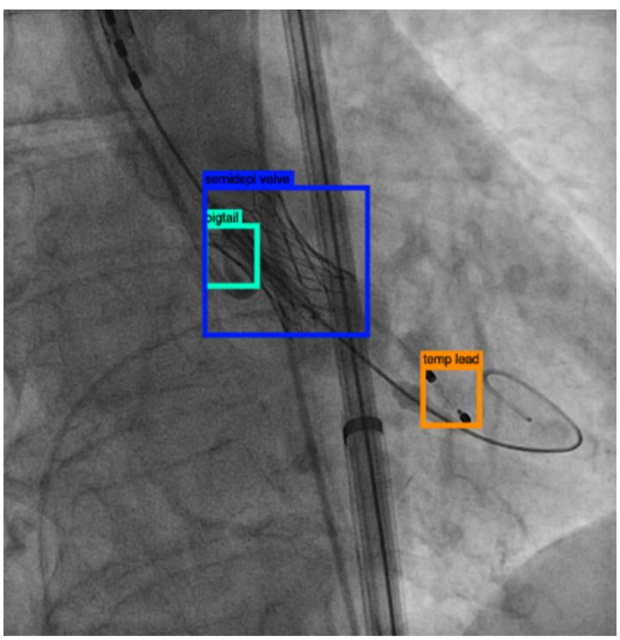

Figure 2: Device recognition (valve, pigtail, temp lead), including deployment status. Machine learning can also handle overlapping devices.

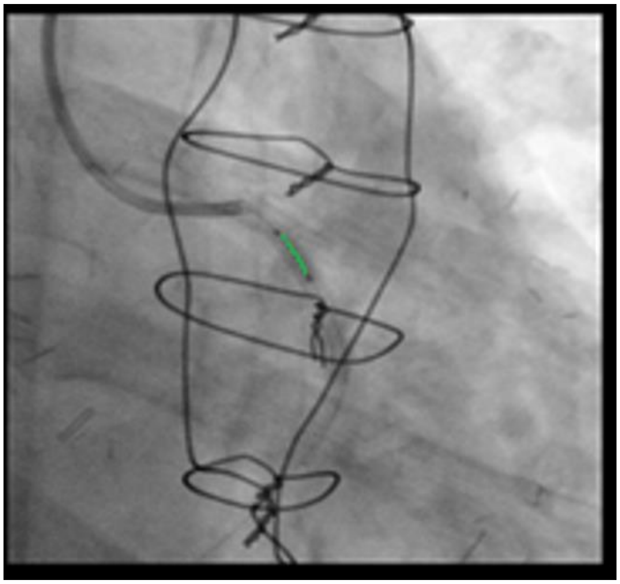

Figure 3: The presence of stitches does not prohibit the machine learning driven stent detection to find the stent.

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