A Hybrid 3DCNN and 3DC-LSTM Based Model for 4D Spatio-Temporal fMRI Data: An ABIDE Autism Classification Study

Binghao HE

12th Dec 2019

Abstract

This paper introduces an end-to-end algorithm to extract spatio-temporal features from the full 4-D data (3D space + 1D time)

- End-to-end
- Spatio-temporal features
- Full
- 4-D data

Introduction

Functional Magnetic Resonance Imaging (fMRI)

- Captures the temporal dynamics of neural activity as function of spatial location in brain.
- Can be represented as 4D-Dimensional (3D:space; 1D:time)
- spatio-temporal patterns in fMRI manifests as behavior and clinical symptoms.

Introduction

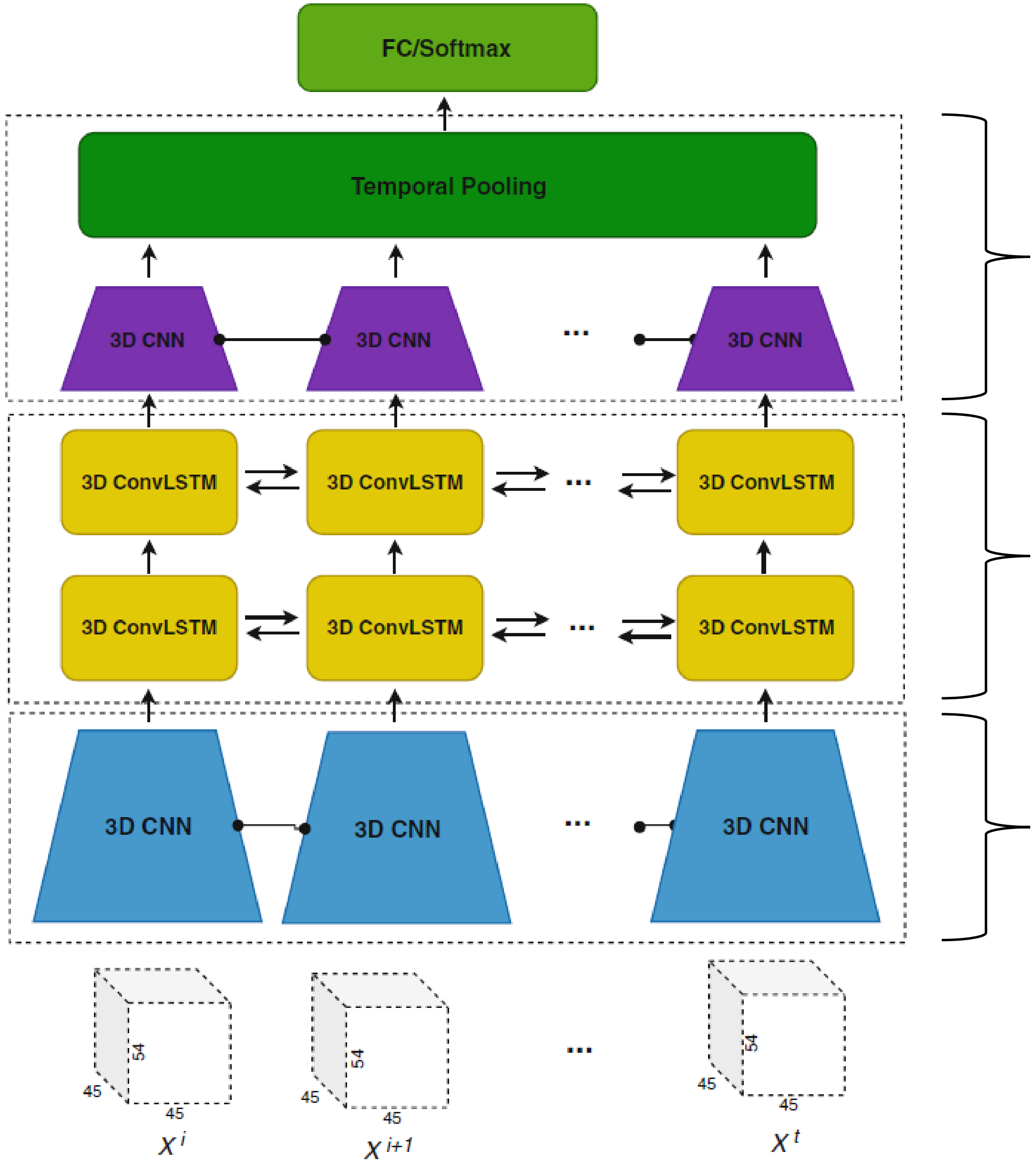
Challenges in Pattern Extraction in fMRI

- high dimensionality (~1 million)

Standard Approach

- Reduce the dimensionality of the data by either summarizing activation over time or space
- loss of information

Model 3DCNN-CLSTM

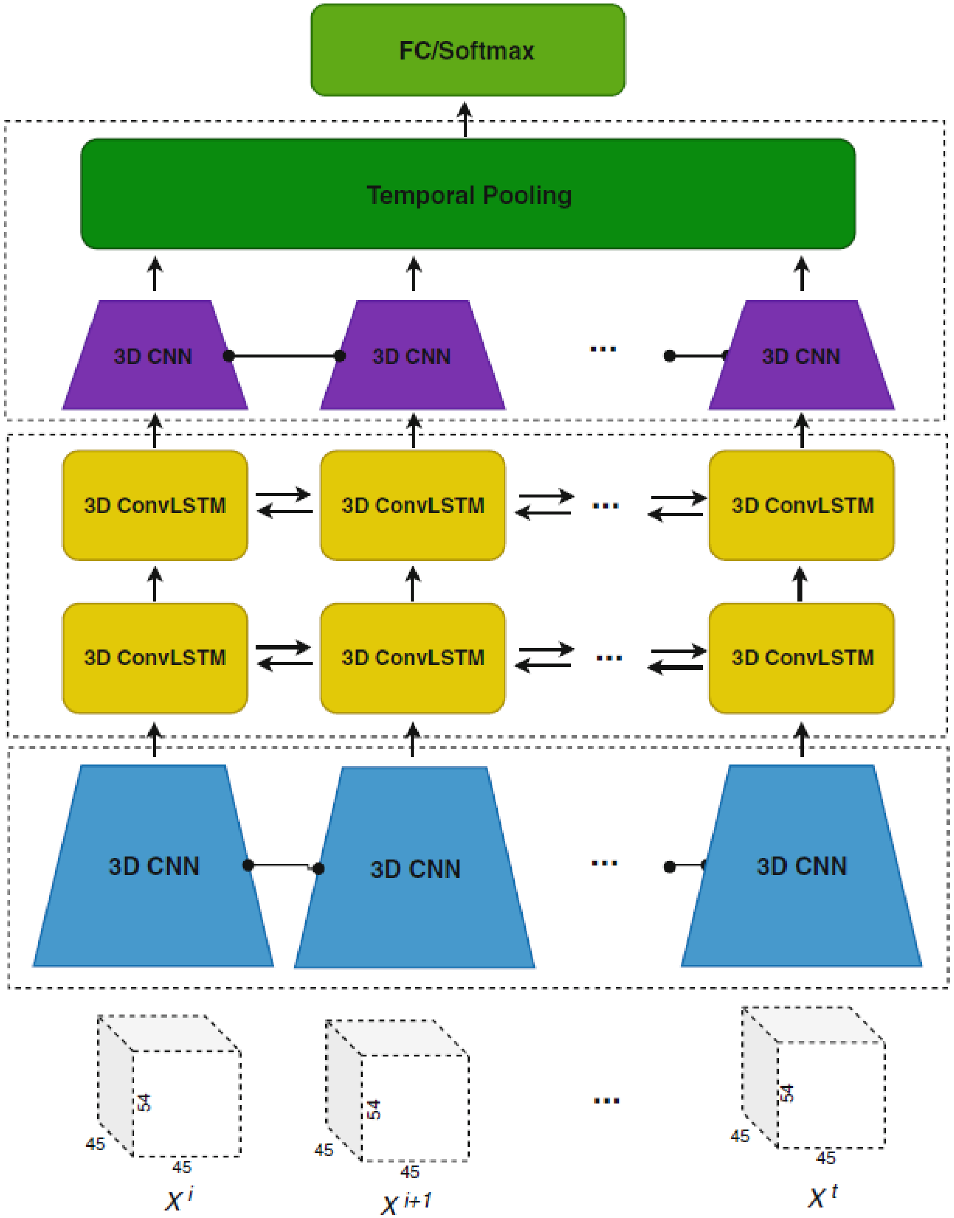


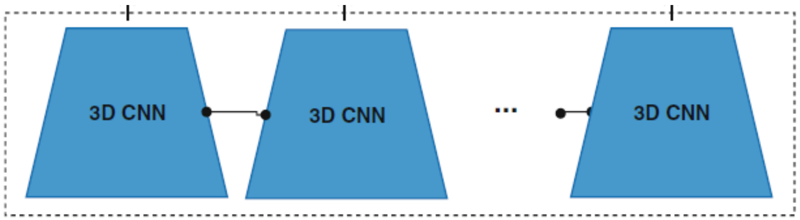
3D CNN
Higher level spatio-temporal feature learning

3D C-LSTM
Spatio-temporal feature learning

3D CNN
Spatial feature learning

Model 3DCNN-CLSTM

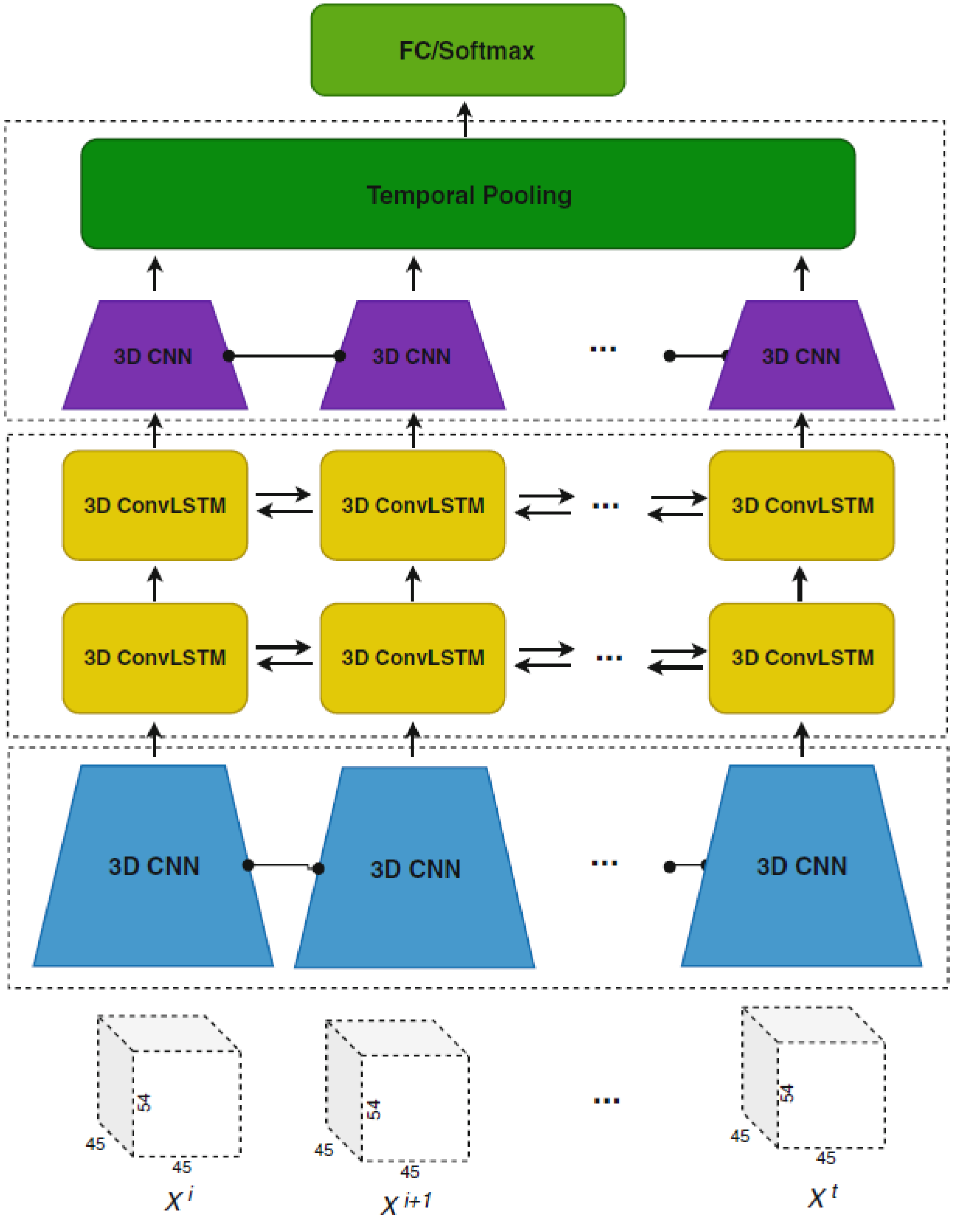


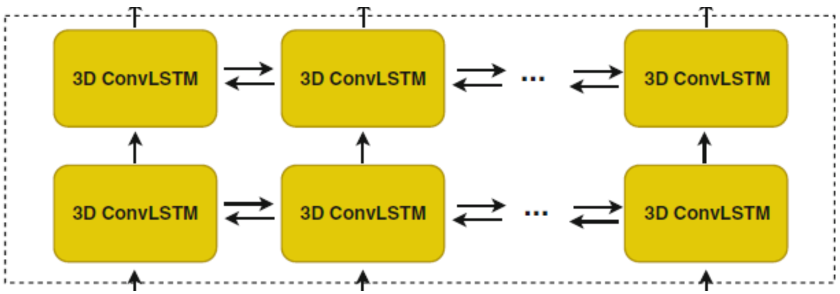


3D CNN with 4 convolutional layer

- Reduce the spatial dimension
- Extract lower level spatial feature maps

Model 3DCNN-CLSTM

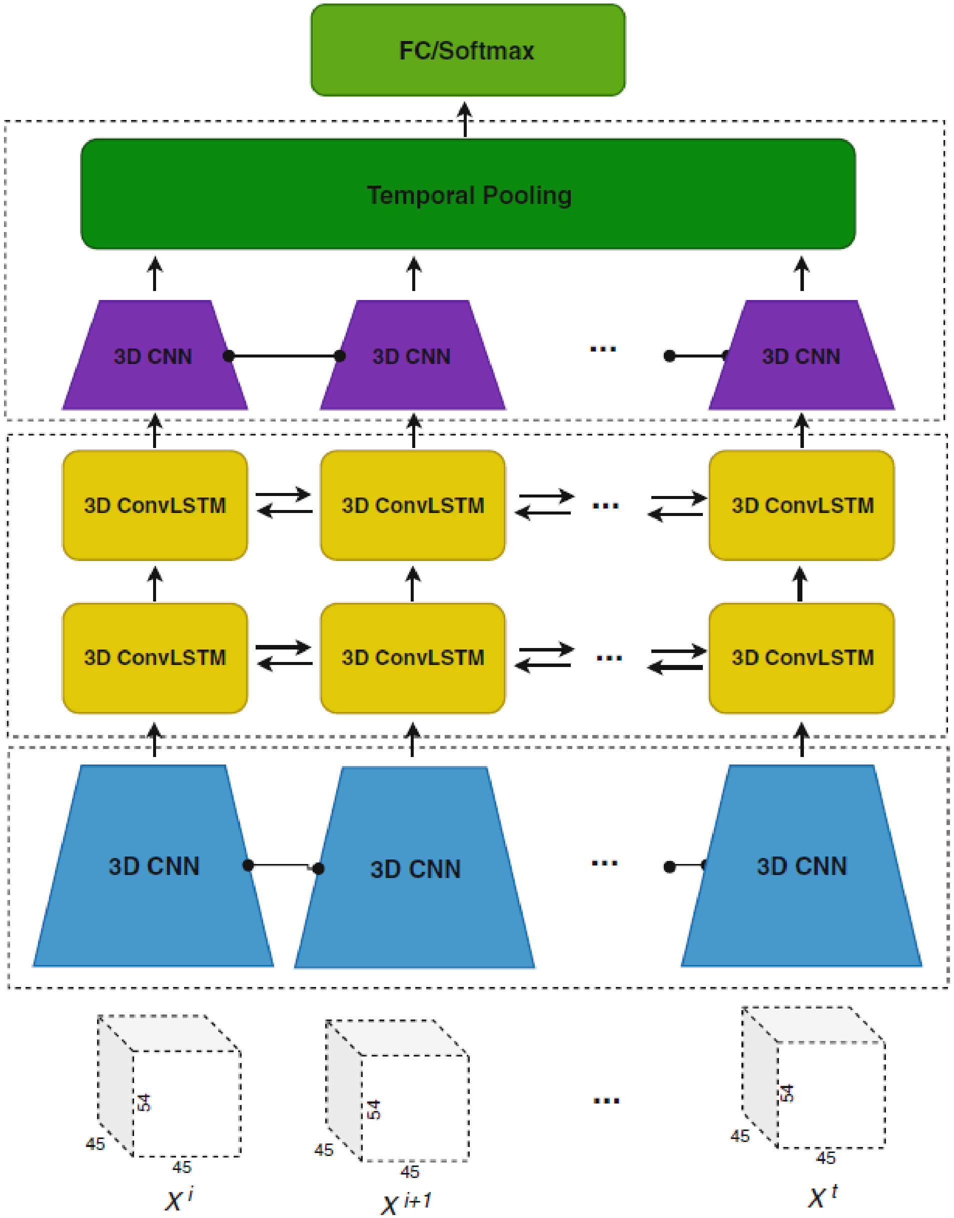


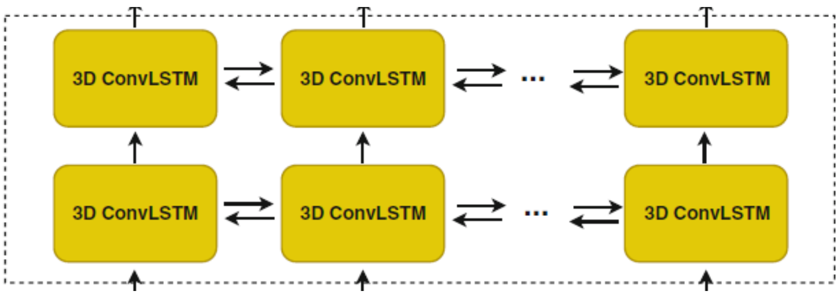


Traditional LSTM

- Input: sequence of vectors
- -> Flatten spatial dimension
- Fully connected transformations
- -> Very large weight matrices

Model 3DCNN-CLSTM





3D C-LSTM

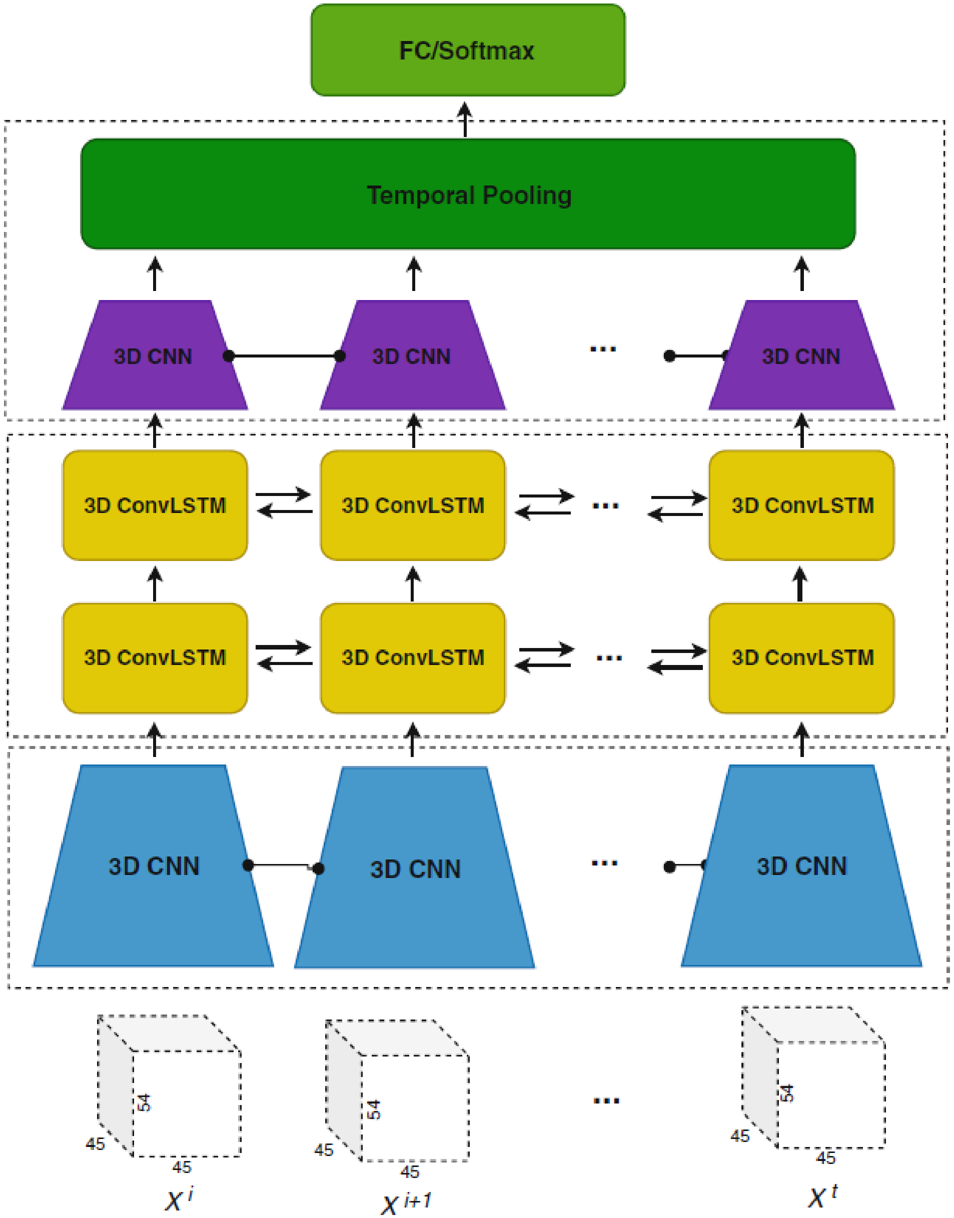
Replaces the fully connected vector-transformations by convolutions

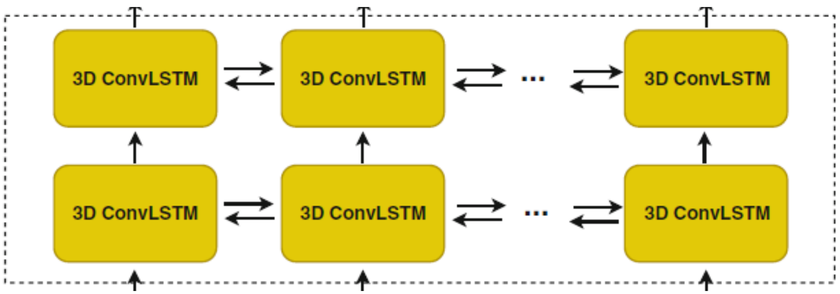
->

Model temporal information in a memory efficient way

Don't need to flatten the spatial dimensions

Model 3DCNN-CLSTM





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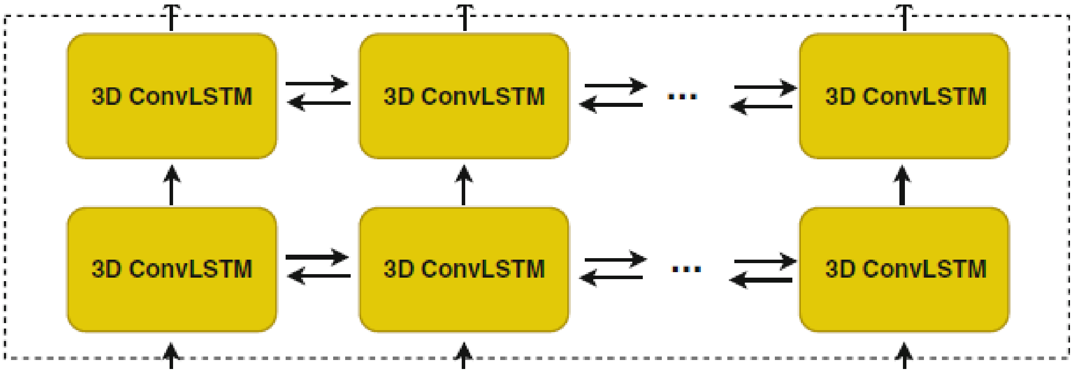
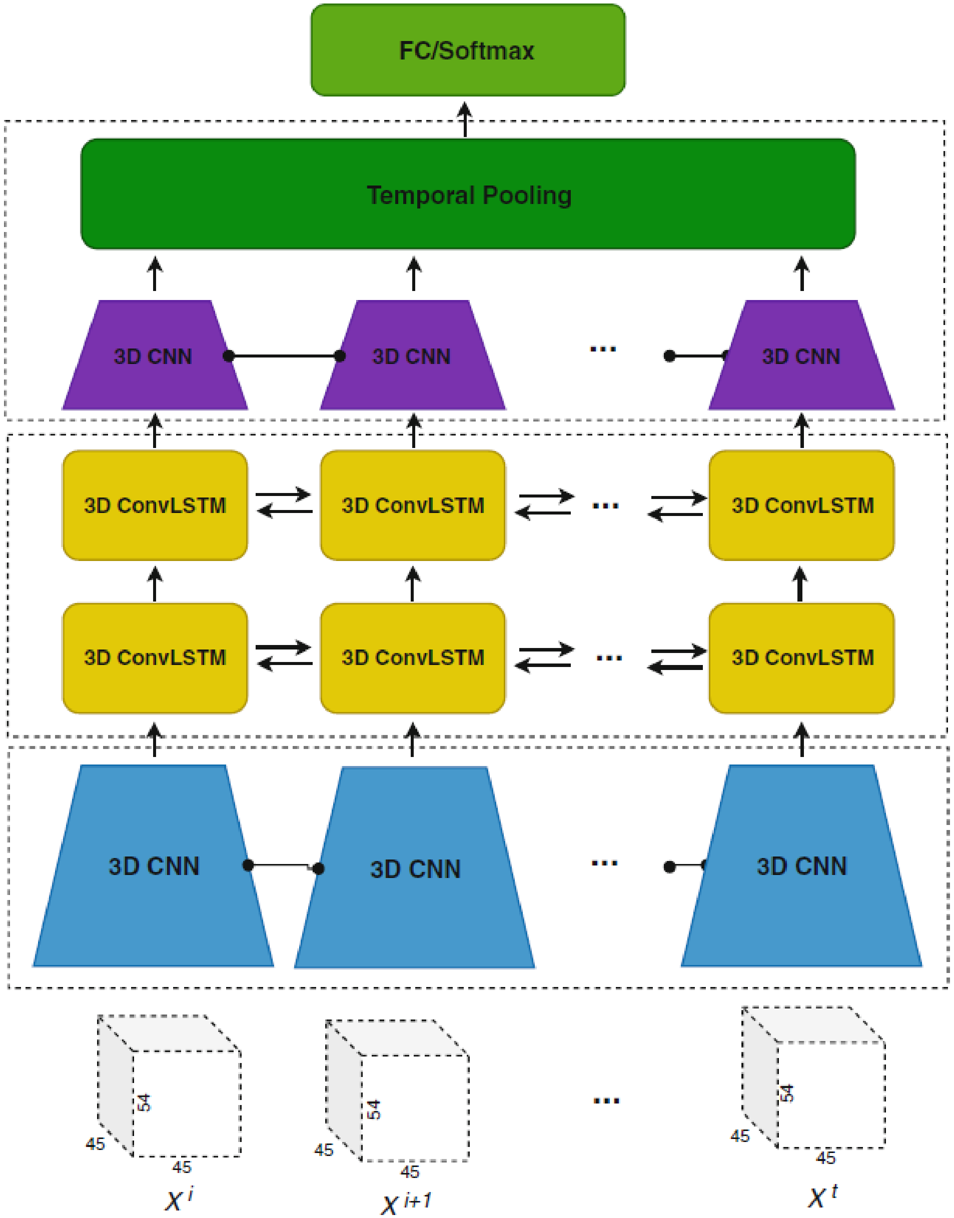


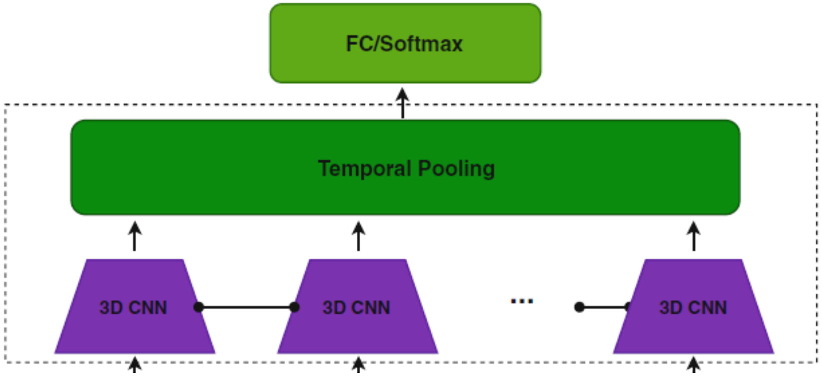
3D C-LSTM

The inputs $X_1, \ldots, X_t$, the cell states $C_1, \ldots, C_t$, the hidden states $H_1, \ldots, H_t$ and the gates i_t, f_t, o_t of C-LSTM are all 4D tensors. Let $*$ denote the convolution operator, and let $\otimes$ denote the Hadamard product. The C-LSTM can be formulated as:

$$
\begin{aligned}
i_t &= \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + b_i) \\
f_t &= \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + b_f) \\
o_t &= \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + b_o) \\
C_t &= f_t \otimes C_{t-1} + i_t \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c) \\
H_t &= o_t \otimes \tanh(C_t)
\end{aligned}
$$

Model 3DCNN-CLSTM





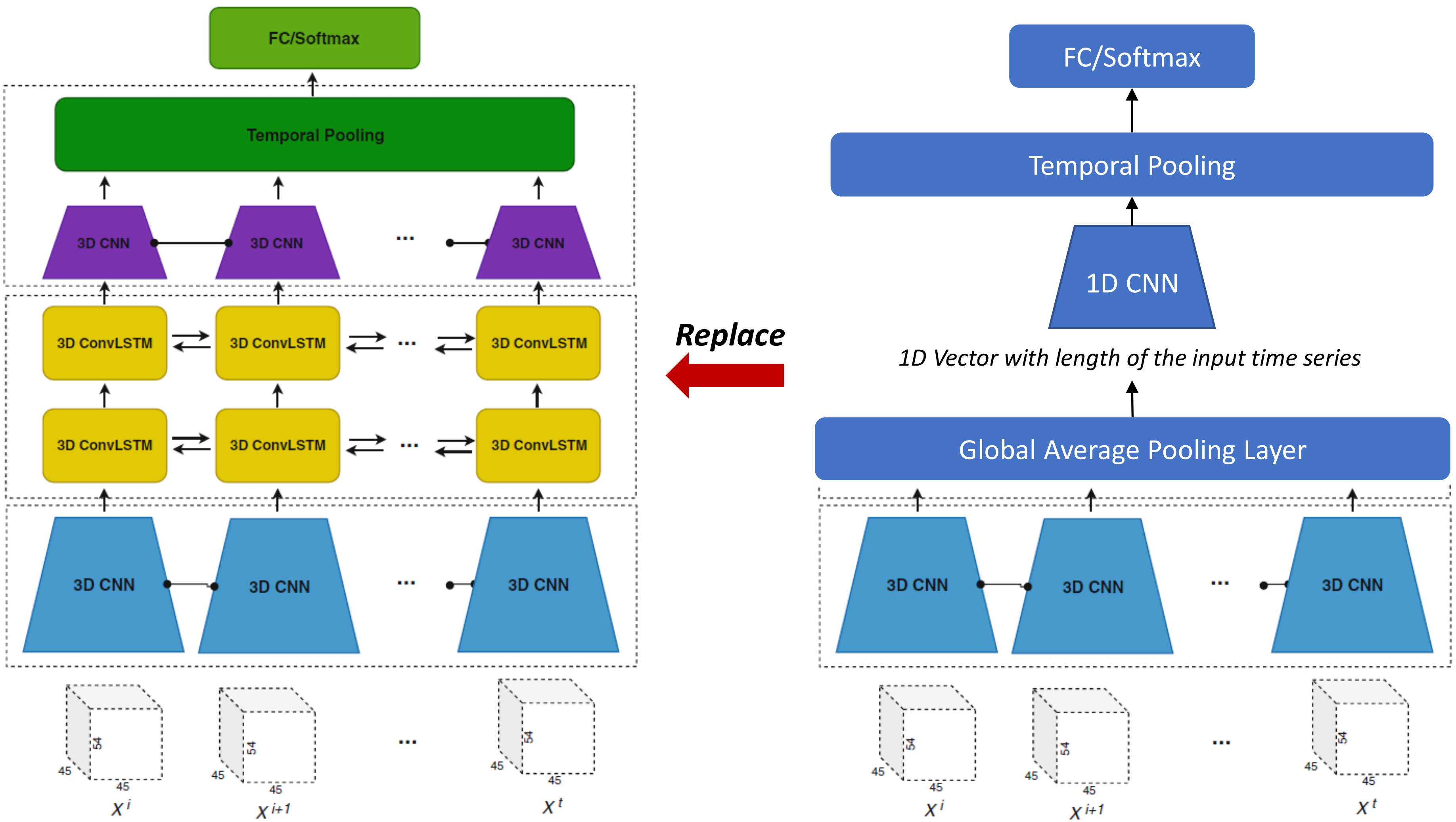
3D CNN

3D Spatio-temporal feature maps still have large spatial size

-> Dimensionality reduction is needed

Learn higher level spatio-temporal features

Model 3DCNN-CLSTM -> 3DCNN-1D-Conv [Alternative]



Experiment Results

Available ABIDE dataset is used to evaluate the proposed pipeline.

Autism Spectrum Disorder (ASD) classification

- Single site experiments: NYU and UM sites from ABIDE-I

  (184 and 110 subjects repsectively)

- Multi-site experiments: ABIDE-I with 19 sites and 1100 subjects

Experiment Results

Data	Model	Accuracy	F1-score
NYU	AE_MLP [8]	0.64 ± 0.1	0.67
	SVM [5]	0.6 ± 0.13	0.59
	1D_Conv [7]	0.64 ± 0.11	0.62
	CNN3D_TC* [3]	0.57	0.61
	CNN3D_MS* [3]	0.60	0.65
	convGRU-CNN3D* [3]	0.67	0.71
	CNN4D* [3]	0.60	0.68
	3DCNN_1D (ours)	0.59 ± 0.07	0.58
	3DCNN_C-LSTM (ours)	$\mathbf{0.77 \pm 0.05}$	**0.78**
UM	AE_MLP [8]	0.56 ± 0.11	0.59
	SVM [5]	0.54 ± 0.11	0.56
	1D_Conv [7]	0.63 ± 0.1	0.62
	3DCNN_1D (ours)	0.66 ± 0.09	0.58
	3DCNN_C-LSTM (ours)	$\mathbf{0.71 \pm 0.06}$	**0.70**
ABIDE-I	AE_MLP [8]	0.63 ± 0.02	0.64
	SVM [5]	0.58 ± 0.04	0.6
	1D_Conv [7]	$\mathbf{0.64 \pm 0.06}$	**0.64**
	3DCNN_1D (ours)	0.54 ± 0.02	0.50
	3DCNN_C-LSTM (ours)	0.58 ± 0.03	0.53

*Results as reported by Bengs et al. [3] on NYU data.

Conclusion

This paper introduces an end-to-end algorithm to extract spatio-temporal features from the full 4-D data (3D space + 1D time)

- End-to-end
- Spatio-temporal features
- Full
- 4-D data

Advanced Multi-objective Design Analysis to Identify Ideal Stent Design

Binghao HE

12th Dec 2019

Abstract

This paper provides a methodology for multi-objective design analysis for ideal stent design. With this methodology, "trade-off" curves between different objectives can be constructed.

Introduction

Coronary Stent (冠状动脉支架)

→ treating diseased coronary arteries(冠状动脉)

- Still high failure (2%-8%)
- Restenosis (再狭窄) and stent thrombosis (支架血栓)

Stent → blood flow disruption (hemodynamic (血液动力学) change)

Several hemodynamic measures ← → restenosis and thrombosis

Goal:

- minimize these adverse hemodynamic conditions (multi-objective)

Introduction

Limitations of Previous Studies

- Consider only 3-4 design variables
- Crucial variables are left out due to difficulty of constraining them such that designs remain physically feasible
- Use Newtonian model for blood flow (less accuracy compared to non-Newtonian)
- Conflicting conclusion (thicker stent → better or worse?)
- Pant et al. analyzed 3 design variables and 6 objectives, objectives too simple and utilized a Newtonian fluid model

Method: objectives selection

Some primary hemodynamic objective:

- Minimizing areas with **low Wall Shear Stress** (low WSS: <0.5Pa)
  - → Atherosclerotic plague (动脉粥样硬化病) formation
- Minimizing areas with low **Time Averaged WSS** (low TAWSS: <0.5Pa)
  - → Similar with low WSS
- Minimizing areas with **high WSS** (high WSS: >2.5Pa)
  - → Adverse vessel remodeling

Method: variables selection

Stent Geometry (Primary determinant of hemodynamic changes)

- Struct width (60~120 μm)
- Struct thickness (60~120 μm)
- Struct angle (25°~50°)
- Cell height (CH, distance between strut rings) (0.86~2 mm)
- Struct alignment (0°, 180°)
- Connector type (straight, spline, semicircular)

* Parameterized in a CAD model to automatically generate new stent design

Method: variables selection

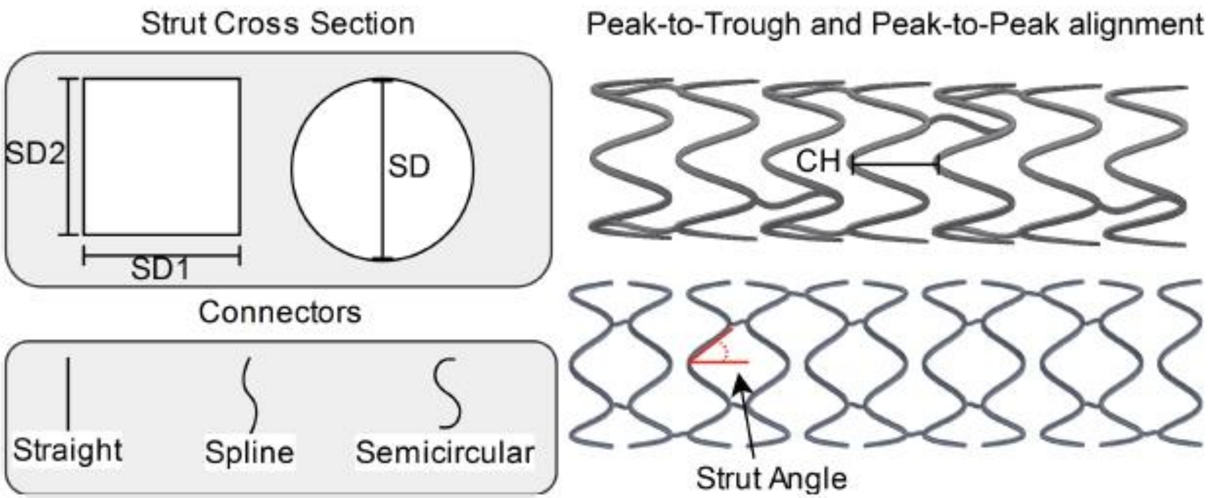


Fig. 1. Design variables used for this study.

Method: variables selection

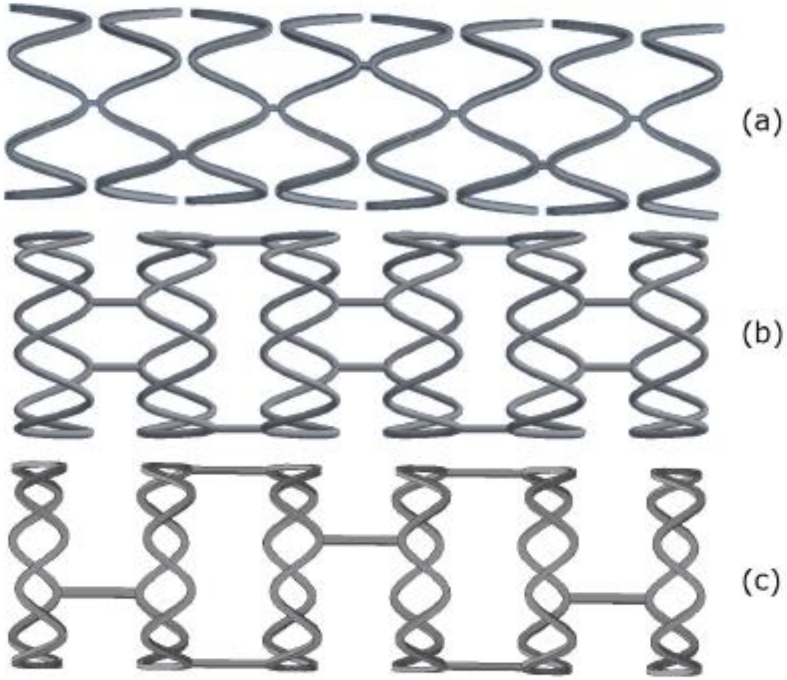


Fig. 2. Connector arrangements (a) one connector per strut ring, alternating location between rings; (b) two connectors per strut placed 180° apart, alternating between rings; (c) Alternating 1-2-1 number of connectors per strut ring.

Method: Computational Modeling (?)

Boundary Conditions

Conditions for blood flow

Mesh Generation

ANSYS 19.1 (有限元分析软件) is used to generate a patch-conforming unstructured tetrahedral mesh

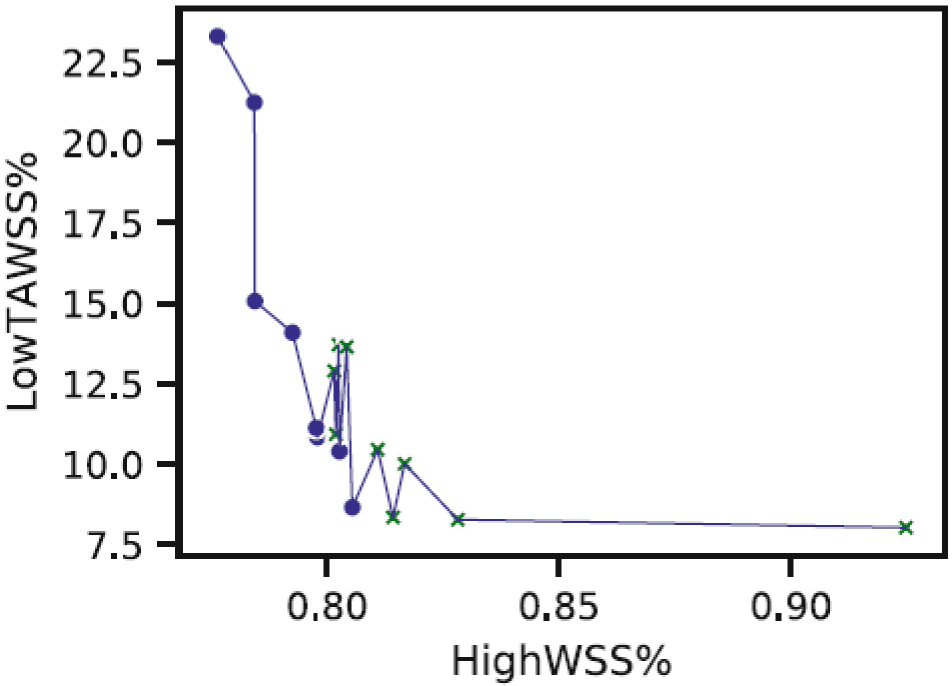
Simulation

ABSYS CFX 19.1 is used to solve the transient simulation.

Method: Multi-objective Design Optimization

Pareto Trade-off Curve

- Boundary formed by plotting the non-dominated solutions found
- Can be used to find the optimal design criteria depending on the desired trade-offs between the multiple objective functions



Method: Multi-objective Design Optimization

Finding Pareto Trade-off Curve

- **Create a single objective function incorporating all objective functions considered [x]**

  Difficult to account for non-convex objective and non-continuous variables

- **Response Surface Model (RSM) [√]**

Method: Multi-objective Design Optimization

Finding Pareto Trade-off Curve

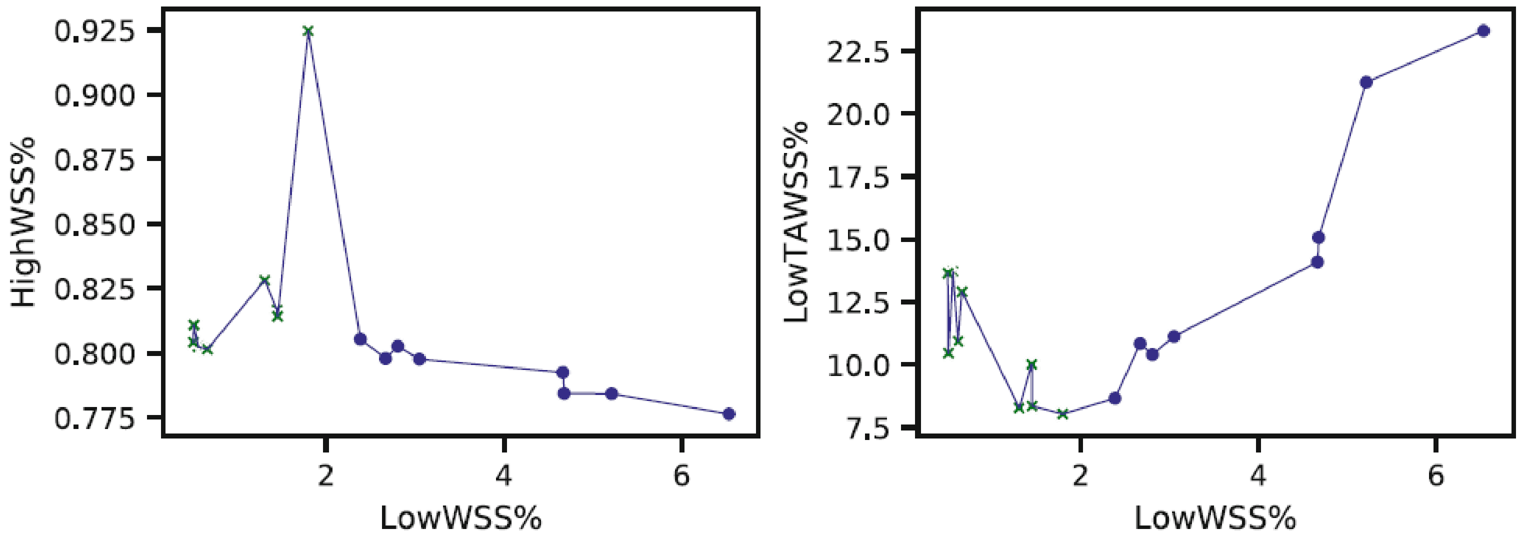
- **Response Surface Models (RSM) [√]**

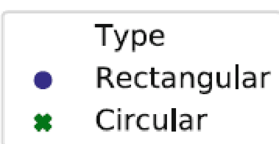
  Used to model the relationship between input space (variables) and output space (objectives), acts as an estimator of the real response

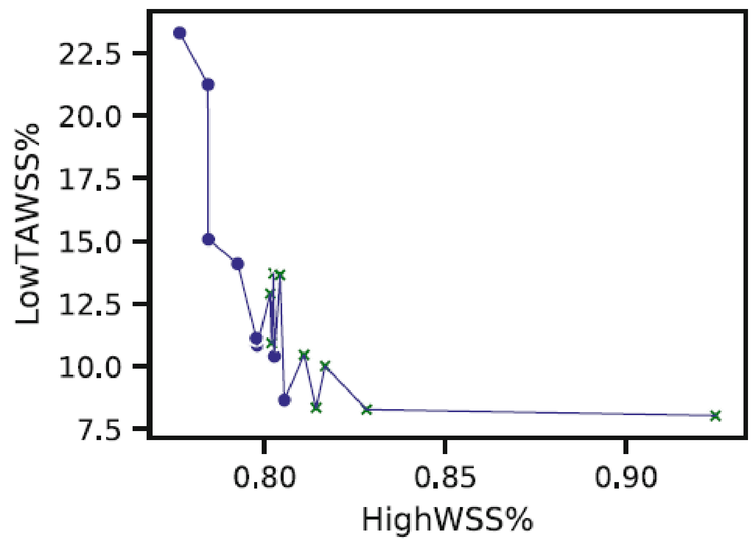
  After construction of RSMs for variables being studied, new data points are generated and their performance is tested to refine the predictions of the model.

  - **Gaussian process regression**: a commonly used RSM
  - **Non-dominated genetic sorting algorithm (NGSA II):** multiple objective RSM optimization.
  - **Expected hypervolume improvement (EHVI):** another multiple objective RSM optimization.

Experiments Results







An optimal stent design can be picked based on **the importance of each objective** and the need to **balance** these adverse flow conditions.

Trying to **optimize a single objective** often results in **large increase in other** objective functions. So, pick stent solutions from the central regions.

Conclusion

This study provide an effective methodology to investigate influence of a large number of design variables on hemodynamic measures.

This study gives a way for more “smart” design for stent.

This study has a potential to result in novel stent designs which take flow disruption caused by the stent and its potential adverse effects into acount