Early-stage new technology
Machine Learning:

Predicting the architecture of 3D textile fabrics

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Fabrics weaving

- Weaving is one of the most common techniques for manufacturing of textile preforms.

- Determining the mechanical properties of woven preforms is performed experimentally.

- It is important to be able to predict the mechanical properties of the woven fabric based on its initial geometry and architecture.
Multi filament simulation

SimTex is a kinematic multi-filament solver used for the prediction of the internal architecture. Weaving simulations are performed within a number of consecutive intermediate timesteps.

Multi filament simulation

The obtained compacted kinematic model can be further translated into FE model

• The model is converted into a structured mesh grid (voxelised model)
• Voxelised model is converted into FE model
• This procedure can be applied to any intermediate state of the solution, not only to final geometry
Voxel model

The density of a voxel model does not depend on the kinematic solution and can be adjusted

Red voxels – matrix; Blue voxels - fibres
Challenges. Problem statement

Challenges:

- Computational time for complex architectures can reach hours and days
- Design and optimisation of textiles requires to solve many different woven architectures

Problem statement

Capture the features of the fabric’s deformation process by learning yarns behaviour from a variety of training exercises.
Generating training set. Case studies

Several weaving architectures with different yarn paths were considered.

- Unit cell size is fixed
- Same number of timesteps within each case study (to keep the timestep constant)
- Areal weight of the fabric recalculated
- Periodicity condition

Total 4000 weaving architectures with different yarn paths were generated for further neural network training.
Each case study is solved throughout 15 timesteps
Training data

The outcomes of all case studies are joined in one database for further postprocessing.
Learning features.

3D Convolutional Network Layer

- Similar to 3D image analysis
- Facilitates the extraction of relevant features from the deformed yarns geometry
- Analyses voxel point cloud at every time step
- Input features:
  - Fibre volume fraction
  - Fibre orientation
Learning deformation evolution

Recurrent Networks (Long Short-Term Memory)

- A powerful tool for modeling sequential data
- Passes relevant information down the chain to make predictions
- Network selectively remembers or forgets information from previous time steps
Input/Output for the training

• Resulting set of solution timeframes is split into input and output sequences.

• Output sequence is defined by shifting forward input sequence by one timeframe
ConvLSTM3D approach

Input/output: 6-dimensional tensor
[case_study,
timeframe,
x_dim,
y_dim,
z_dim,
[fibre_vol, angle_1, angle_2]]

Advantages:
• Simplicity
• No intermediate steps
• Reliability

Disadvantages:
• High demand for computational resources
Encoder-Decoder approach

Step 1: Train encoder-decoder network

Step 2: encode training data

[case_study, timeframe, x_dim, y_dim, z_dim, fibre_vol, angle_1, angle_2]

Step 3: train new network

Advantages:
- Flexibility
- Lower computational requirements

Disadvantages:
- Additional error during encoding-decoding
- Complexity of architecture
Data preprocessing

Data preparation

- Checking for outliers, bad case studies
- Normalisation, the network output is $[0, 1]$
- Data reshaping into 6D tensors

Ideal representation
Prediction. 3D representation

- **Kinematic model initial architecture**
- **Compacted model, ground truth**
- **Compacted model, ConvLSTM3D**
- **Compacted model, Encoder-decoder**

**Case study 1**

**Case study 2**

**Case study 3**
Kinematic model

Ground truth

Prediction
Results. Features distribution
Results. Average properties

Averaging properties for the voxelised volume

\[
\mathbf{Q}^x = \begin{bmatrix}
Q_{xxxx} & Q_{xyyy} & Q_{xzxx} & Q_{xyzz} \\
Q_{yyyy} & Q_{yyyy} & Q_{yxxy} & Q_{yyzz} \\
Q_{zzzz} & Q_{zzzy} & Q_{xxyy} & Q_{zzzy} \\
\text{Sym} & & & \end{bmatrix}
\]

Comparison ground truth/prediction

Stiffness comparison

- Ground Truth
- ConvLSTM3D
- Encoder-Decoder

Stiffness matrix diagonal components:
- Q_{xxxx}
- Q_{yyyy}
- Q_{zzzz}
- Q_{xyxx}
- Q_{xyz}
- Q_{yzy}

Graph showing comparison between ground truth and predictions.
Conclusions

• Deep learning approach to predicting 3D woven geometry is confirmed
• Computational time required for prediction is insignificant
• Different network architectures are suitable for the considered problem
• Encoder-decoder approach requires more tuning to output a reliable prediction
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