Computing Midcurve by Neural Networks
Yogesh Kulkarni
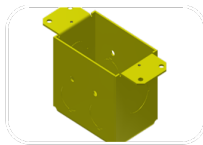
Introduction to Midcurve

MidcurveNN : Encoder-Decoder Neural Network for Computing Midcurve of a Thin Polygon
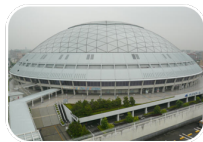
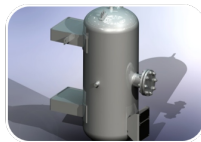## Introduction

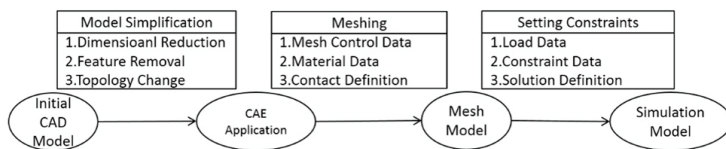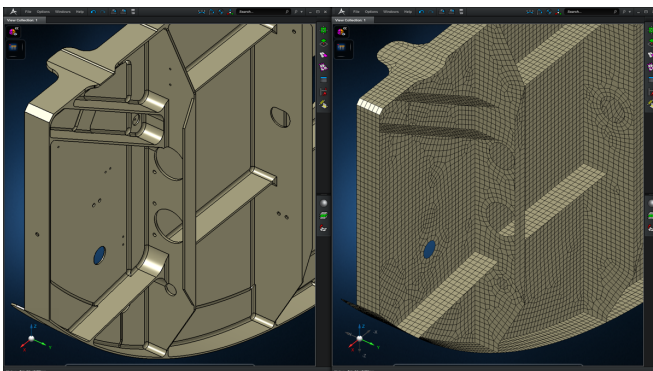Aerospace   Machinery   Consumer Products

Energy   Construction   Industrial equipment

Can we use shapes directly?

- CAD : Designing Shapes
- CAE : Engineering Analysis
- CAD→CAE: Simplification for quicker results.
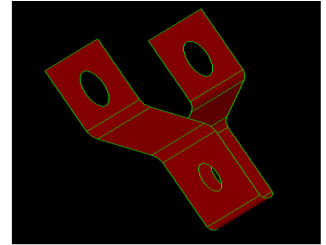

CAD-CAE

For Shapes like Sheet Metal . . .

	Solid mesh	Shell+Solid mesh	Difference (%)
Element number	344,330	143,063	-58%
Node Number	694,516	75,941	-89%
Total Degrees of freedom	2,083,548	455,646	-78%
Maximum Von. Mises Stress	418.4 MPa	430 MPa	+3%
Meshing + Solving time	Out of memory	22 mins	N/A (4G RAM)
Meshing + Solving time	30 mins	17 mins	-43% (12G RAM)

Half the computation time, but similar accuracy
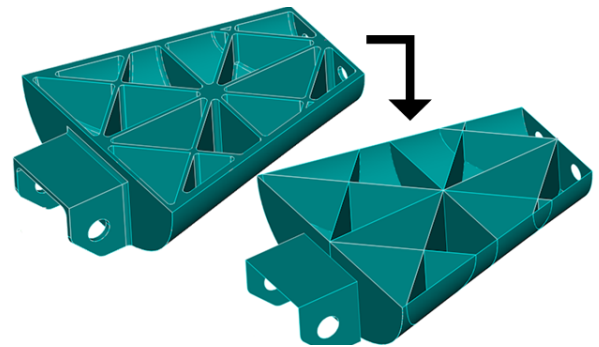
Midsurface is?
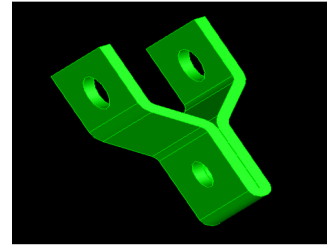
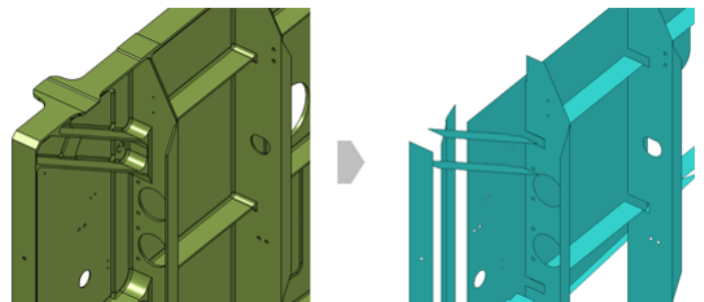Input: Solid   Output: Midsurface

- Widely used for CAE of Thin-Walled parts
- Computation is challenging and still unsolved

Getting Midsurface

- Going on for decades . . .
- Manually by offsetting and stitching, initially
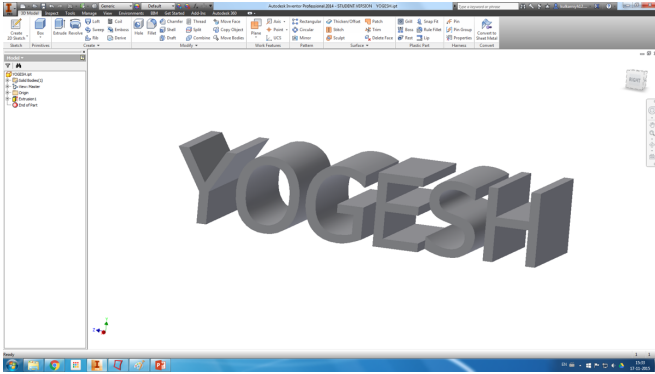- Many CAD-CAE packages give automatic option, but . . .
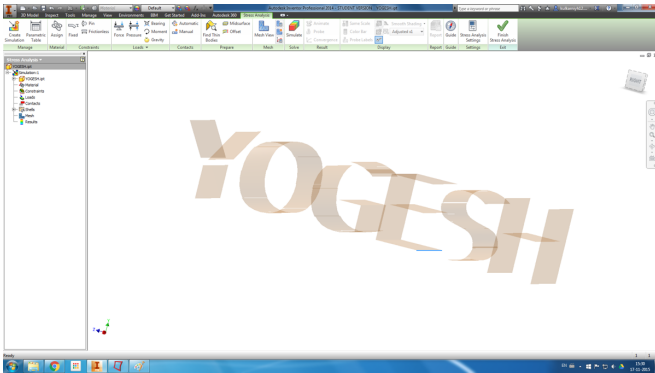

Look at the output

Can't tolerate gaps

- We have thickness sampling,
- To recreate-represent the original shape
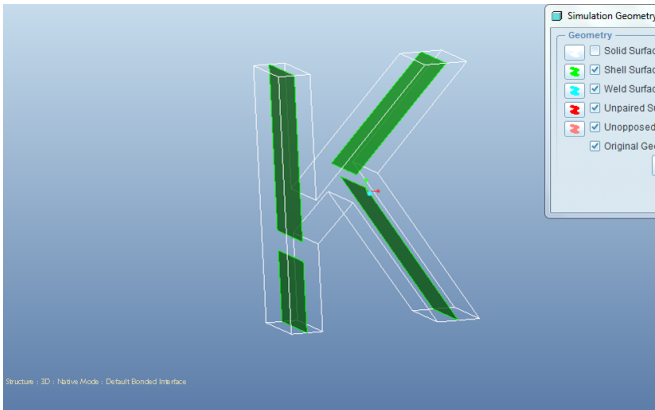- Input and output difference not desirable
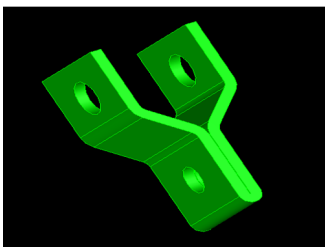
For a simple model like
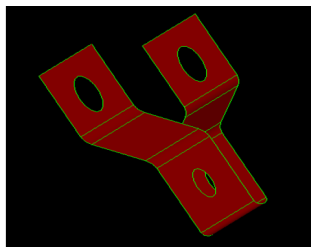

You get

For a far simpler shape

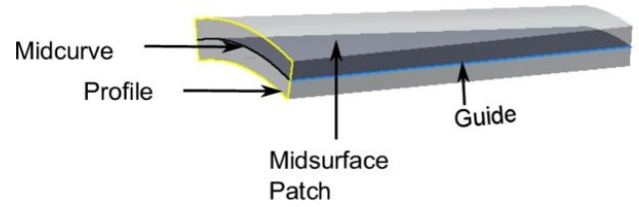## Current Quality

Input: Solid   Output: Midsurface

- Errors take weeks to correct for complex parts.
- But still preferred, due to vast savings time
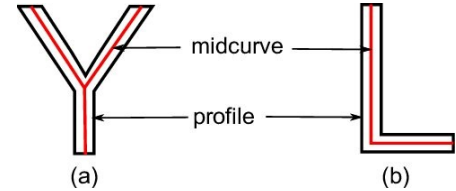- From Days to hours . . .

Midsurface Computation

- Midsurface of a Patch is Midcurve of its profile extruded.
- So, it boils down to computing 1D midcurve of a 2D profile

What is a Midcurve?

- Midsurface : From 3D thin Solid to 2D Surface
- Midcurve : From 2D Profile to 1D Curve

Many Approaches

- More than 6 decades of research. . .
- Most CAD-CAE packages. . .
- Rule-based!! Heuristic!! Case-by-case basis!!

When-What?

| 1967 Blum MAT | 1994 Dabke Features for Idealization | 1996 Armstrong MAT for CAE | 1996 Rezayat MA SDRC | 1999 Fischer Param Midcrv | 2002 Deng FBD Simplification | 2005 Stolt Pocket Pad Mids | 2007 Robinsn Sketch Mids | 2012 Russ FBD defeaturing | 2013 Woo Decomp, per feature mids |
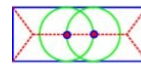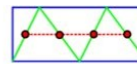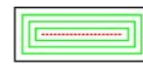
2017: My PhD Work: Rule-based

Limitations

- Fully rule-based
- Need to adjust for new shapes
- So, not scalable

Idea

Can Neural Networks "learn" the dimension reduction transformation?

How?

- Supply lots of training data of profiles and their corresponding midcurves and train.
- Then given an unseen profile, can Neural Network compute a midcurve, mimicking the original profile shape?

Midcurve by Neural network

Midcurve : The Problem

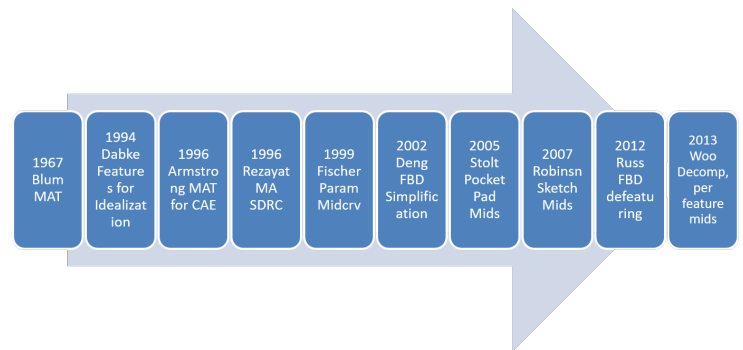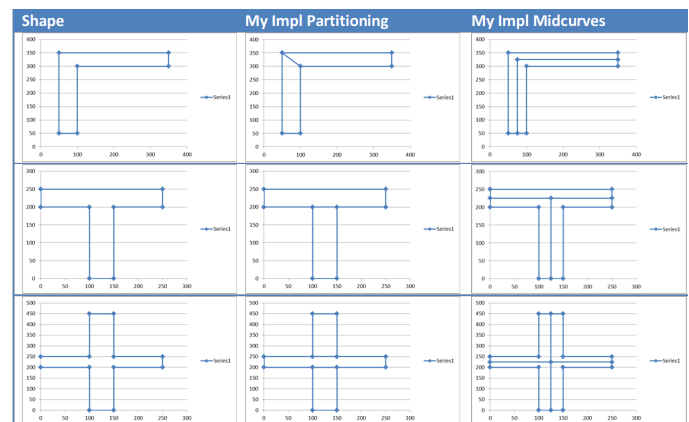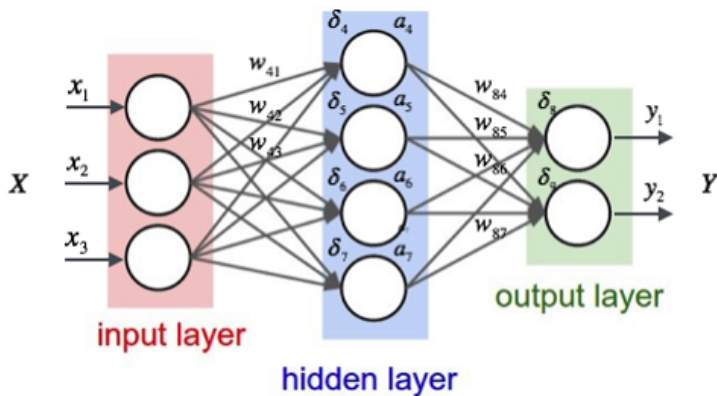- **Goal**: Given a 2D closed shape (closed polygon) find its midcurve (polyline, closed or open)
- **Input**: set of points or set of connected lines, non-intersecting, simple, convex, closed polygon
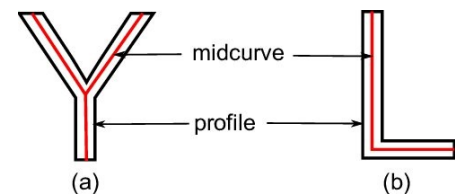- **Output**: another set of points or set of connected lines, open/branched polygons possible

Midcurve == Dimension Reduction

- Like PCA (Principal Component Analysis), wish to find Principal curve
- That 'represents' the original profile shape
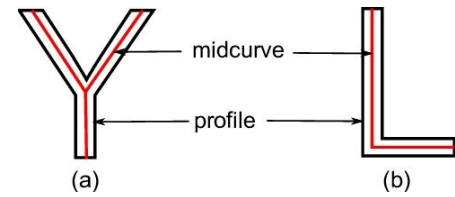
Midcurve == Translation

- Left side (input): 2D Sketch Profile
- Right Side (output): 1D Midcurve
- Sequence 2 Sequence problem

Midcurve ! = Auto-Encoder Decoder

- Its not Auto-Encoder as Input and Output are different
- Its not fixed size i/o as Input and Output sizes are different
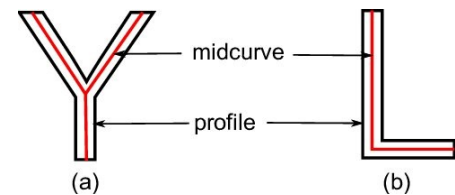
Variable Size Encoder Decoder

- Batches need fixed lengths
- Made fixed size by Padding.
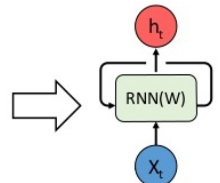
Variable Size Encoder Decoder

- OK for NLP, say Machine Translations, where padding values like "-1" can be added along with other words (vectors or indices)
- But in Geometry, its not OK.
- Because any value can represent a Valid Input, even though we don't want it to be the input.

A Twist to the problem

- Till we get good variable size encoder decoder network for geometry. . .
- Decided to convert this Sequence 2 Sequence problem as Image 2 Image problem.

A Twist to the problem

- Input: Black & White Image of 2D profile
- Output: Black & White Image of 1D midcurve

Solves . . .

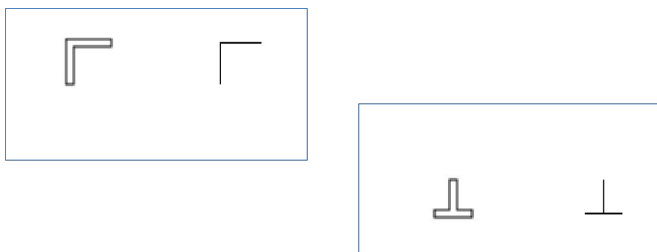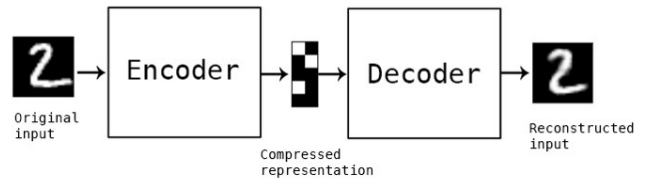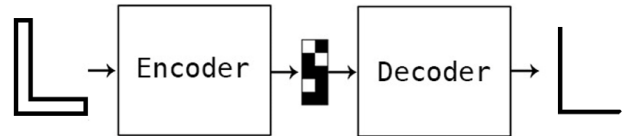Problems of Geometric sequences

- Variable input/output sizes
- Loops need to be crossed
- Branches

Reuse Image Encoder Decoder

For Dimension Reduction

For Deep Learning

- Need lots of data
- Had just few input output image pairs
- How to augment/populate large variations . . .

Data Preparation

Data

Original input and output are in the form of polylines, meaning a list of points, each having x,y coordinates

Profile Data		Profile Picture	Midcurve Data		Midcurve Picture
5.0	5.0		7.5	5.0	
10.0	5.0		7.5	32.5	
10.0	30.0		35.0	32.5	
35.0	30.0		7.5	32.5	
35.0	35.0				
5.0	35.0				

Data

Profile Data		Profile Picture	Midcurve Data		Midcurve Picture
0	25.0		12.5	0	
25.0	25.0		12.5	22.5	
25.0	20.0		25.0	22.5	
15.0	20.0		0	22.5	
15.0	0				
10.0	0				
10.0	20.0				
0	20.0				

- For each shape, we have this pair of input and output. That's it.
- We need to start with these few samples only

Augmentation

- Such few profile shapes, are just not enough for Neural Networks to train.
- Need more with as much diversity as possible.
- Will need to artificially augment data with transformations, like pan, rotate, mirror, etc.
- All needs to be automatically, programmatically

Geometry to Image

- Raw input data is in the Vector format
- Converted it to fixed size (100x100) image by rasterization of drawSVG library.

Variations

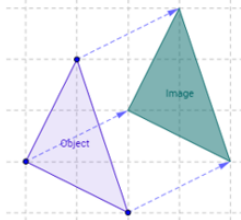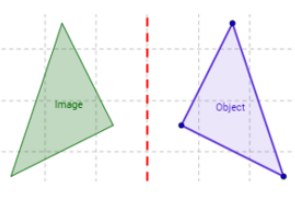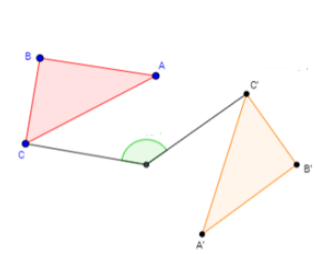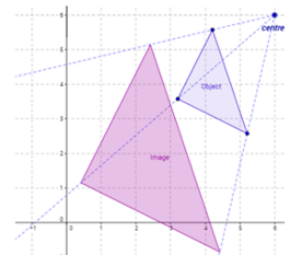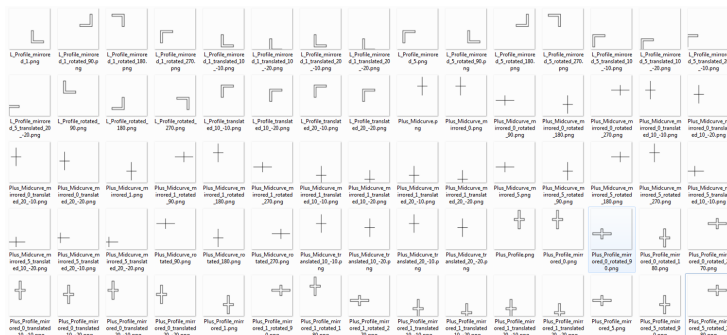- Inputs: I, L, Plus, T
- Operations:
  - Translated
  - Rotated
  - Mirrored
  - Mirrored Translated
  - Mirrored Rotated
- Total: 896 images (still less, but not bad)
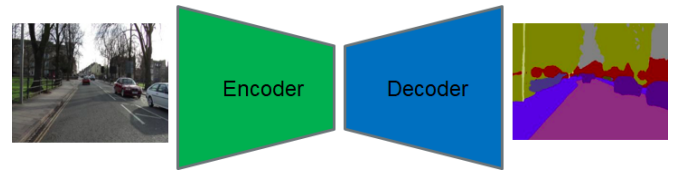
Training Data Samples

Midcurve By Neural Network

Options For Architectures

- Simple Encoder Decoder (one layer each)
- Dense Encoder Decoder
- Convolutional Encoder Decoder
- Pix2Pix
- …

Simple Encoder Decoder

Simple Encoder Decoder

## Keras Implementation

```
input_img = Input(shape=(input_dim,))

encoded = Dense(encoding_dim,
    activation='relu',activity_regularizer=regularizers.l1(10e-5))(
decoded = Dense(input_dim, activation='sigmoid')(encoded)

autoencoder = Model(input_img, decoded)

encoder = Model(input_img, encoded)
encoded_input = Input(shape=(encoding_dim,))
decoder_layer = autoencoder.layers[-1]
decoder = Model(encoded_input, decoder_layer(encoded_input))

autoencoder.compile(optimizer='adadelta',
    loss='binary_crossentropy')
```

Results
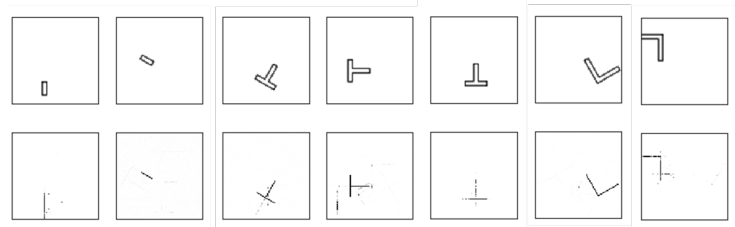
Results

- Not very perfect but encouraging
- NN is correct with
  - The location (bounding box)
  - Dimension Reduction is seen
- But, still some stray points and misses

What can be done?

- For the noise, use bounding boxes
- Feedback into error term: differencing with the known output expected
- Classify single pixel image as the skeleton, and rest as noise.

What Next?

- Add denoiser network after the current one
- More Network Architectures
- Sequence-to-Sequence based approaches, taking closed thin polygon as input and polyline as output
- Extending to 3D, ie Midsurface

End Notes

Summary

- Various applications need lower dimensional representation of shapes.
- Midcurve is one-dimensional(1D) representation of a two-dimensional (2D) planar shape.
- Used in animation, shape matching, retrieval, finite element analysis, etc.

Summary

- Approaches: Thinning, Medial Axis Transform (MAT), Chordal Axis Transform (CAT), Straight Skeletons, etc., all of which are rule-based.

- Proposing a novel method called MidcurveNN which uses Encoder-Decoder neural network for computing midcurve from images of 2D thin polygons in supervised learning manner.

Summary

- This dimension reduction transformation from input 2D thin polygon image to output 1D midcurve image is learnt by the neural network,
- Which can then be used to compute midcurve of an unseen 2D thin polygonal shape.

The End
References

- xxx