A Parametric Thoracic Spine Model Accounting for Geometric Variations by Age, Sex, Stature, and Body Mass Index

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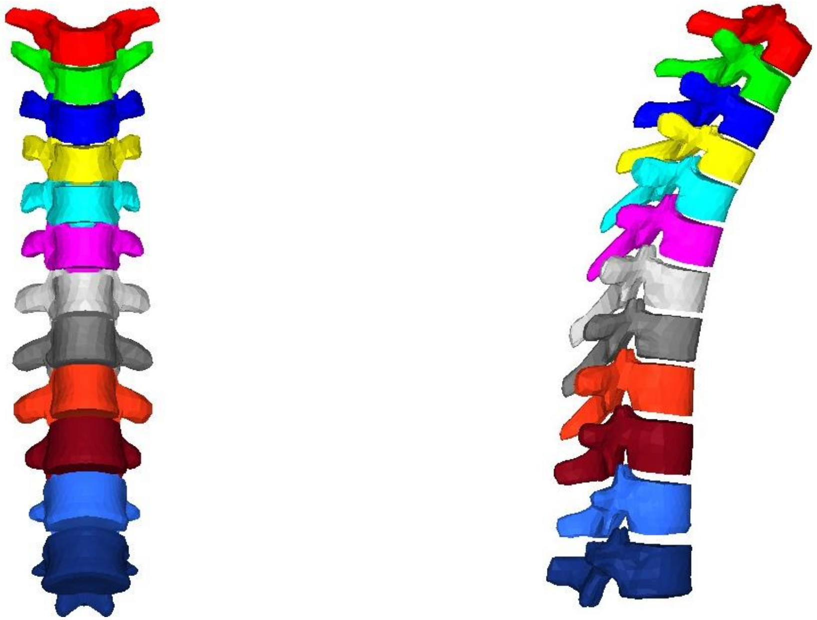
Introduction

- Thoracic spine (T-spine) injury prevention will become more challenging
  - Autonomous driving technology.
  - Reclined sitting position and seat back.
- Literature on T-spine geometry is very limited
  - No study on morphological variations of T-spine in the diverse population.
  - Three most important injury mechanisms: compression, distraction, and axial torque.

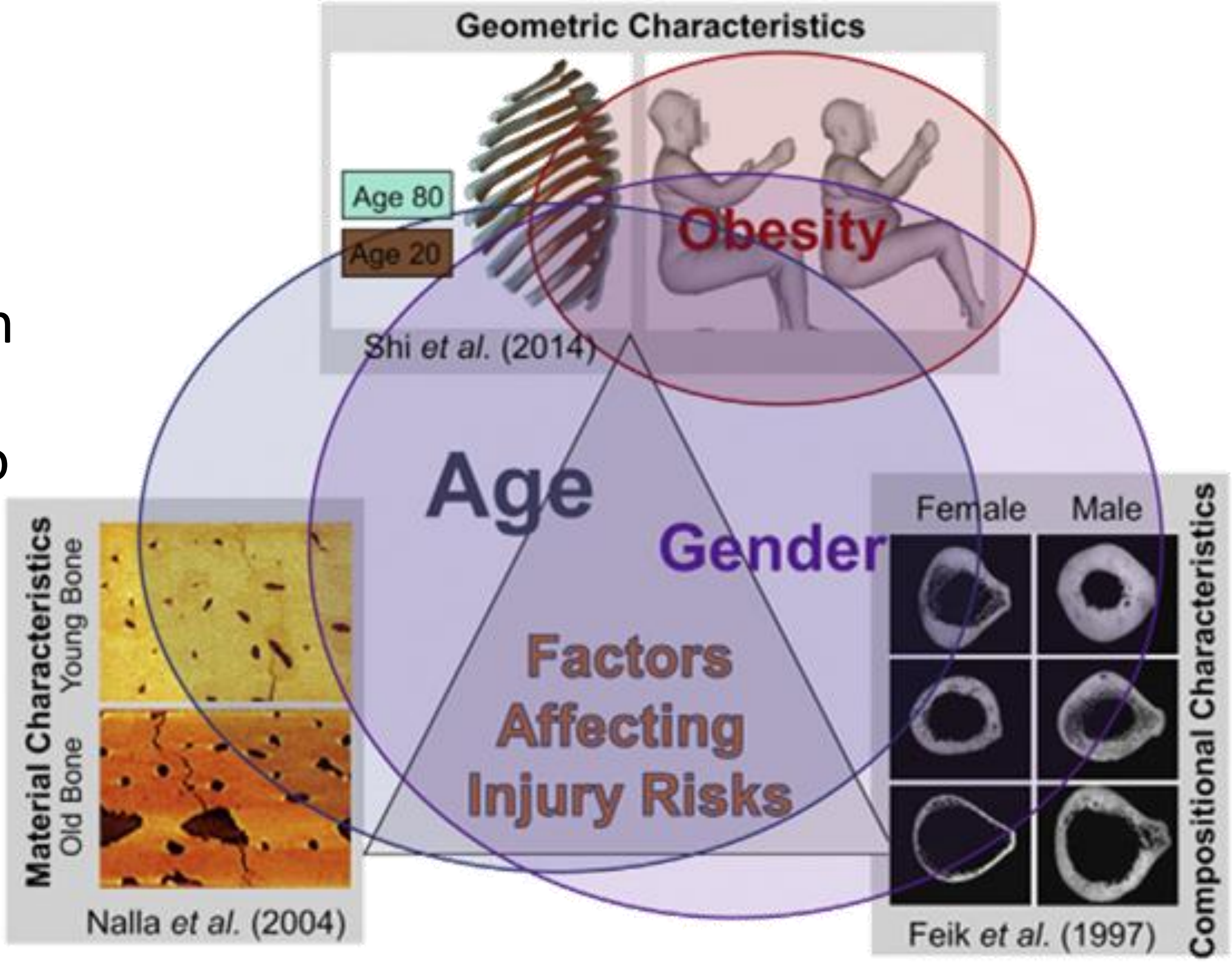


Source: Drive safely and conveniently from start to finish - https://www.hyundaimotorgroup.com/tech/1075

Introduction

Parametric human models are needed for safety equity

- Age, stature, BMI and sex are all important factors for risk of injuries.
- Small females, elderly, and people with obesity are more vulnerable in motor-vehicle crashes (MVCs) as compared to midsized, young males.



Source: Hu J (2018) "Parametric Human Modeling" *Basic Finite Element Method as Applied to Injury Biomechanics*, 417-445.

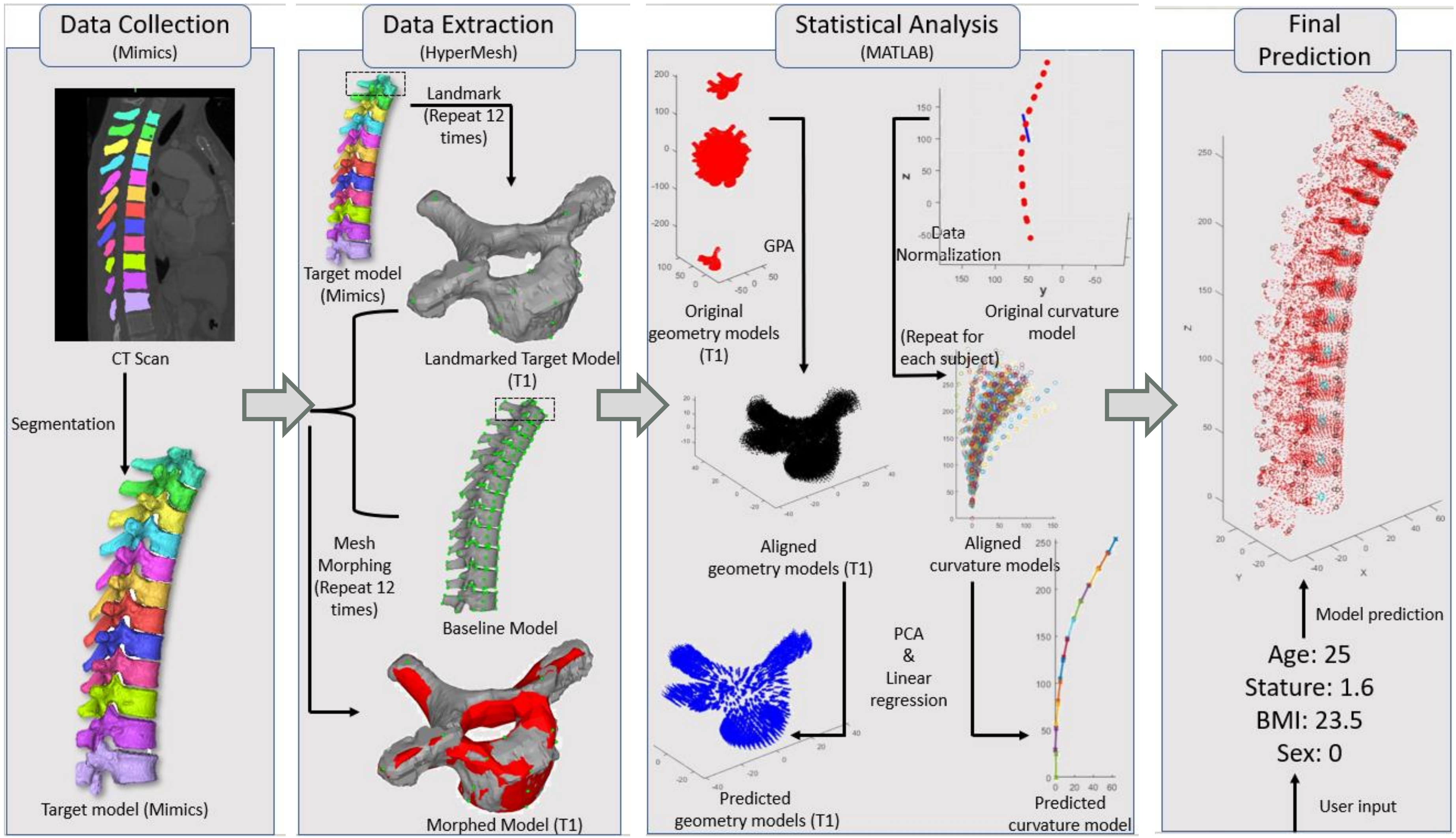
Objective

- Develop a statistical thoracic spine model accounting for morphological variations by age, sex, stature, and BMI, based on the data extracted from CT scans.
- To the best of our knowledge, this is the first study that a whole T-spine 3D model can accurately predicted for any given age, sex, stature, and BMI. Our study also revealed the statistical significance of each subject covariate.
- This model could serve as the geometric basis for parametric human modeling for better assessing T-spine injuries and other pathological analysis.

Source: Hu J (2018) "Parametric Human Modeling" *Basic Finite Element Method as Applied to Injury Biomechanics*, 417-445.

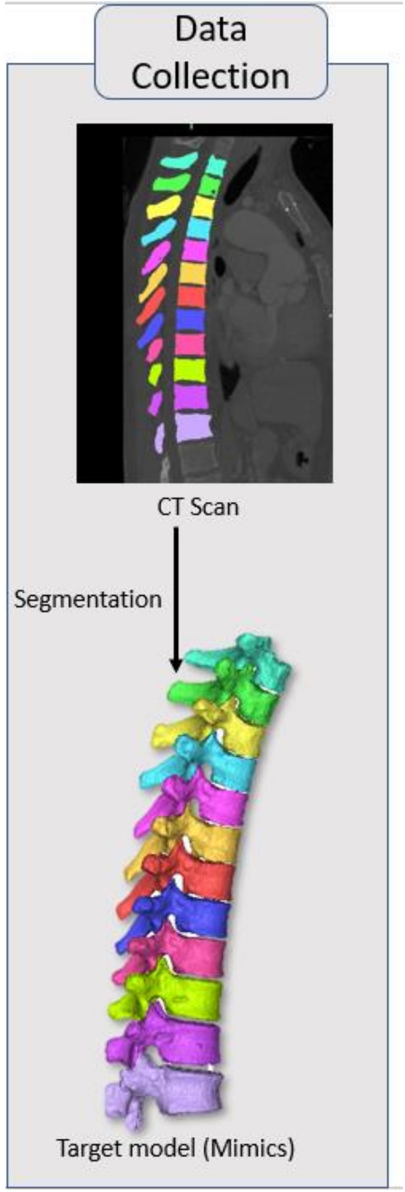
Methods : Overview

- Data collection
- Data extraction
- Statistical analysis
- Final prediction



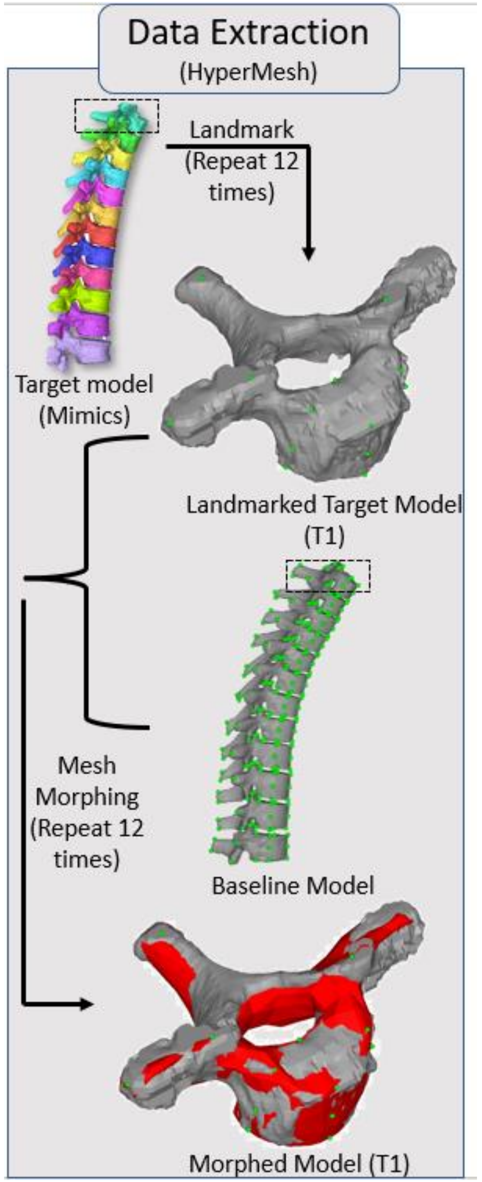
Methods : Data Collection

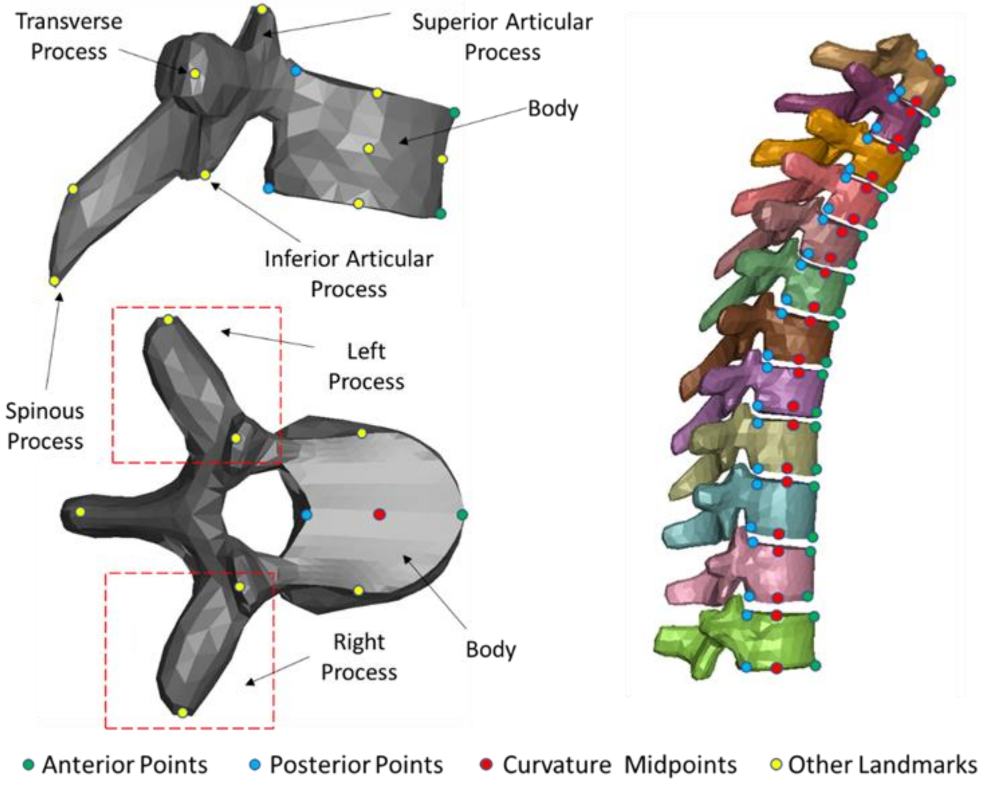
- Data collection
  - Total of 84 subjects & subject distribution.
  - Use Mimics to semi-automatically extract T-spine 3D geometry from CT scan and output STL files.
- Purpose
  - Provide non-standard raw data.
  - Output STL files are used to process in HyperMesh.



Methods : Data Extraction

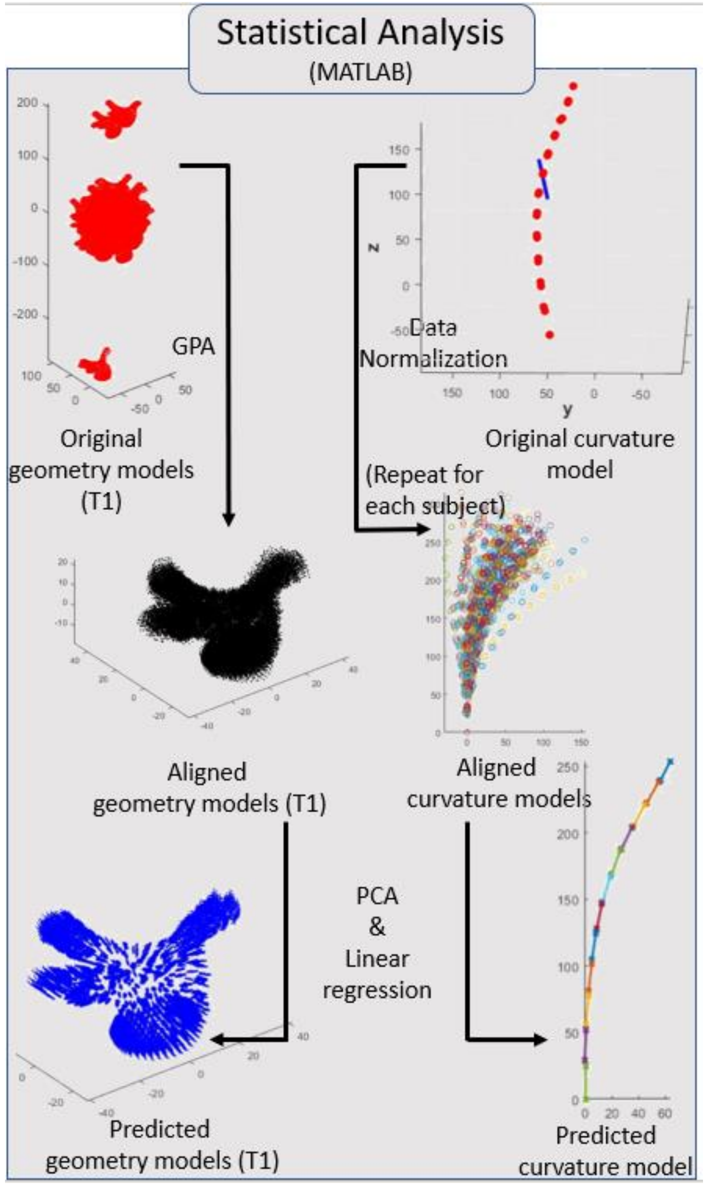
- Data extraction
  - Use a standard model as baseline and landmarked model as target.
  - Morph from baseline model to target model.
- Purpose
  - Make geometry of morphed model as close as possible to target model.
  - Standardize the data for statistical analysis.





Methods : Statistical Analysis

- Statistical analysis – geometry model for each vertebra (T1 to T12)
  - Generalized-Procrustes-analysis (GPA).
  - Principal Component analysis (PCA)
  - Linear regression.
- Statistical analysis – curvature model
  - Data normalization.
  - Principle Component analysis (PCA).
  - Linear regression.



Methods : PCA

of nodes

Nodal ID, x, y, z

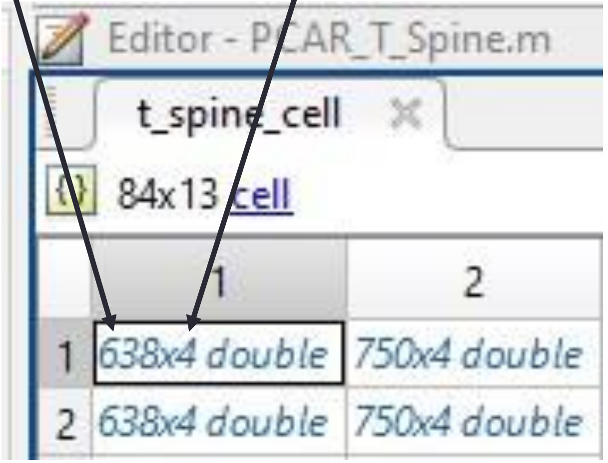


Illustration of PCA

- Decompose a large matrix into product of two smaller matrices:

$$A = U \times V^T$$

Where A is original matrix, U is score matrix and V is loading matrix (Principal Component)

- Matrices dimensionality for T1
  - 84 x 1914 nodal location matrix (A)
  - 84 x 83 Scores matrix (U)
  - 1914 x 83 loading matrix (V)

Can select at most 83 PCs (in this case of 84 subjects).

```
% perform PCA on training subjects; desired output matrices:
% coeff(M*(N-1)), score(N*(N-1)), mu(1*M)
[coeff,score,latent,tsqured,explained,mu] = ...
    pca(matrix,'Centered',true, 'NumComponents', k);
%% Regression
% perform regression; calculate C(coefficients for regression)
% and F(feature matrix containing training parameters)
stature_sex = [ input_feature(:,2) .* input_feature(:,4)];
F = [ones(length(input_feature),1) input_feature stature_sex];
C = F\score(:, 1:k);
```

Methods : Linear Regression

Illustration of linear regression

- Associate PC scores with input human characteristic parameters

$$U = F \times C$$

Where F is the feature matrix used for regression, C is regression coefficient matrix.

- Matrices dimensionality for T1
  - 84 x 83 Scores (U)
  - 84 x 6 feature matrix (F)
  - 6 x 83 regression coefficient (C)

	A	B	C	D	E
1	SubjectID	Age	Height	BMI	Gender
2	FG2S106	23.56	1.7	23.52941176	0
3	FG2S110	28.35	1.65	20.82644628	0
4	FG2S112	29.89	1.82	24.63470595	0
5	FG3S101	38.52	1.71	29.47915598	0
6	FG3S105	38.14	1.49	48.42124229	0
7	FG4S101	45.05	1.67	28.68514468	0
8	FG4S104	41.58	1.57	25.92397257	0

Add intersection for regression

Add due to correlation between two parameters

```
% perform PCA on training subjects; desired output matrices:
% coeff(M*(N-1)), score(N*(N-1)), mu(1*M)
[coeff,score,latent,tsqured,explained,mu] = ...
    pca(matrix,'Centered',true, 'NumComponents', k);
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stature_sex = [ input_feature(:,2) .* input_feature(:,4)];
F = [ones(length(input_feature),1) input_feature stature_sex];
C = F\score(:, 1:k);
```
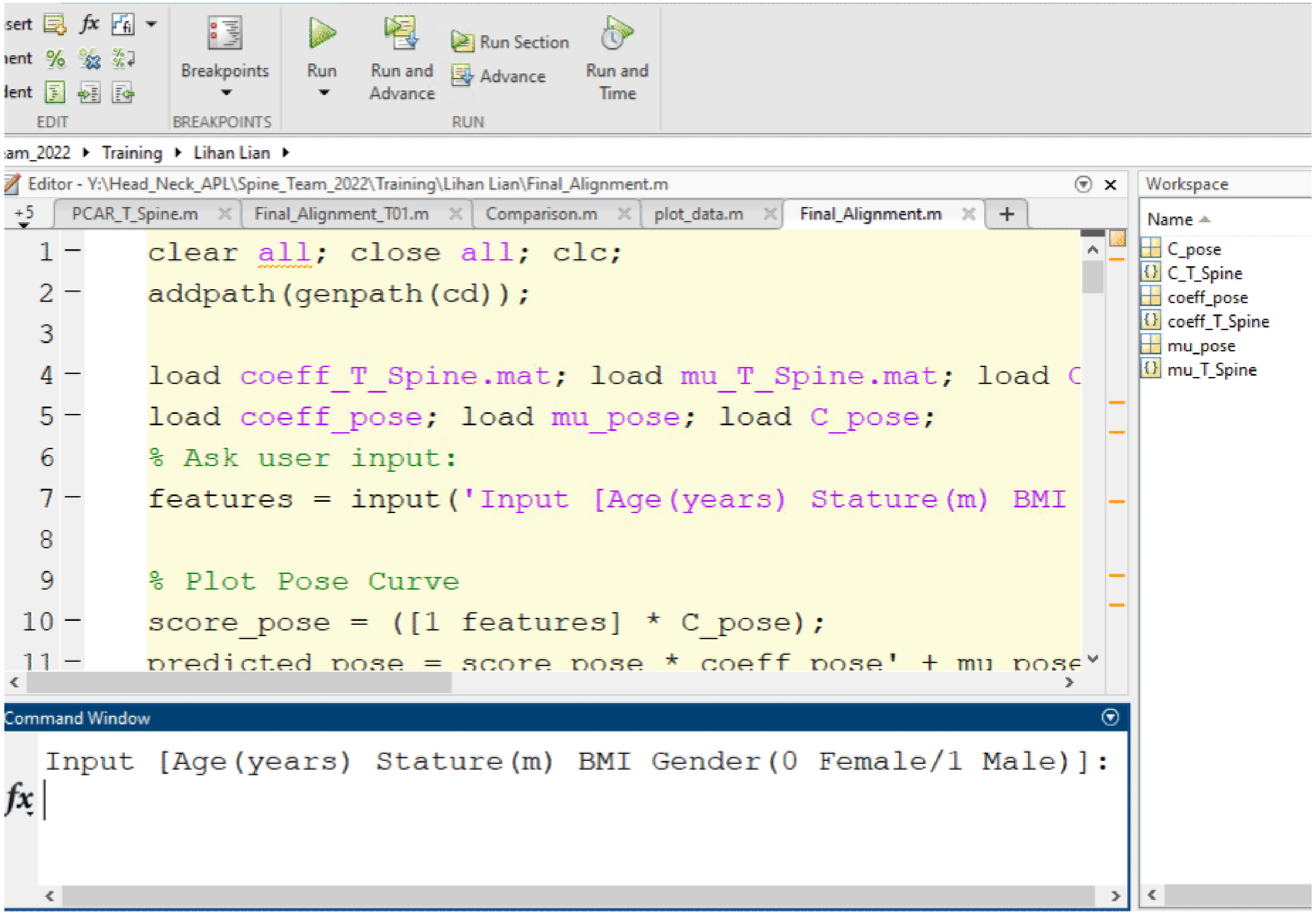

Methods : Final Prediction

MATLAB demonstration

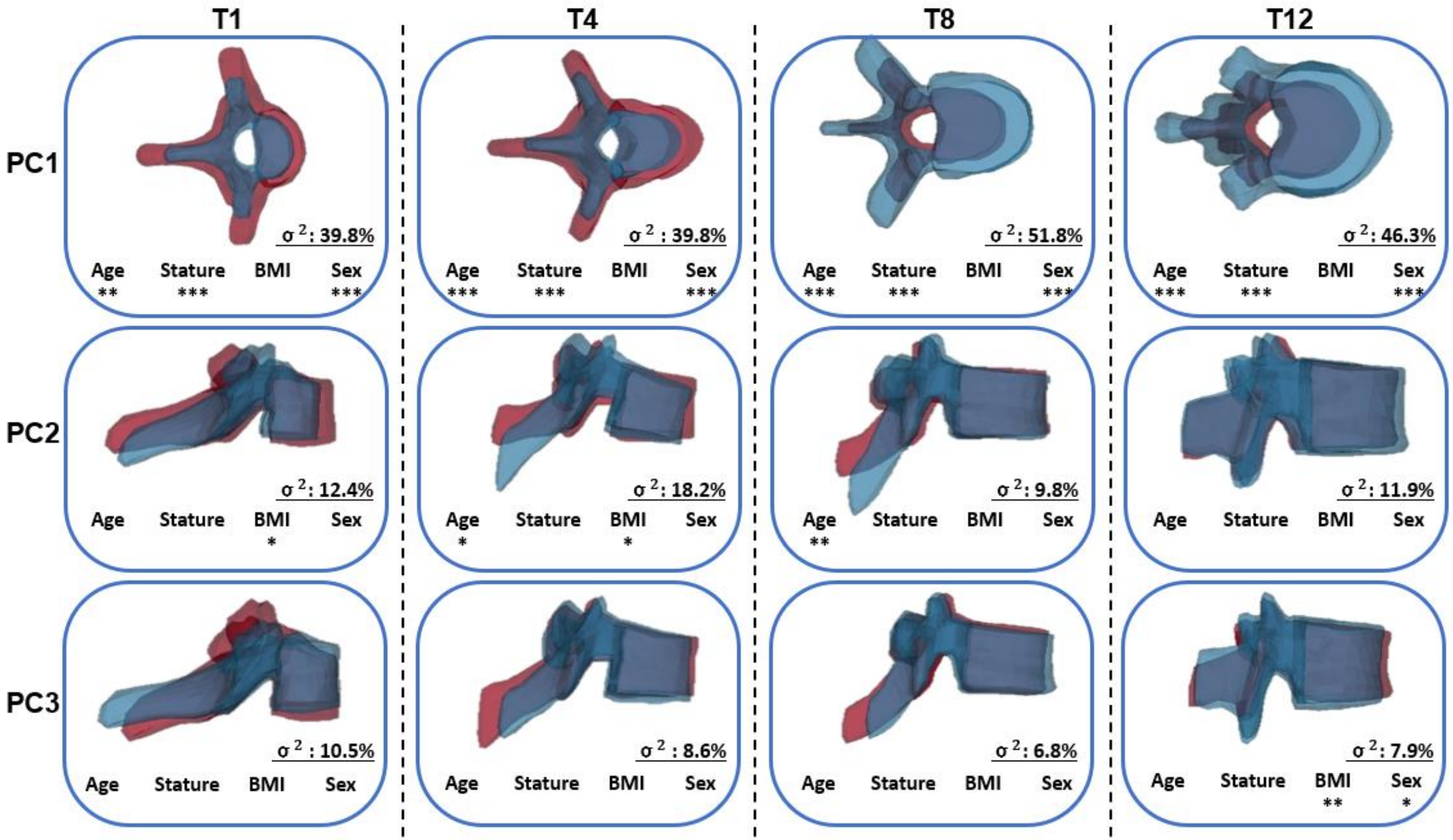
- Repeat 12 times and align each vertebra to their corresponding position.
- Can also see the necking effect in the predicted model.



Results : PC Variation

Statistical T-spine model

- PC1 accounts for the overall size variation.
- PC2 and PC3 accounts for the angle variation.

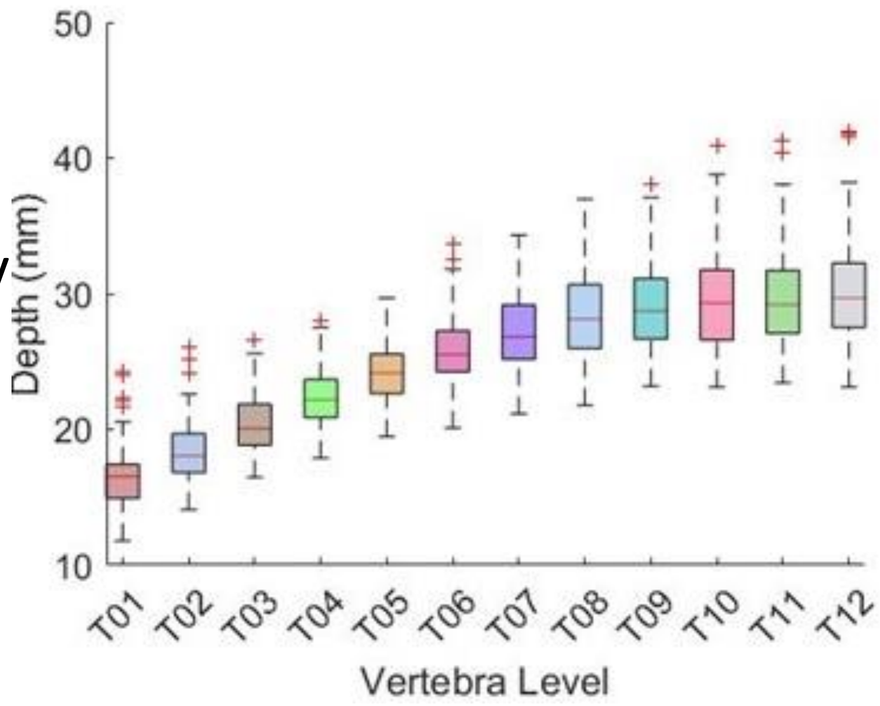


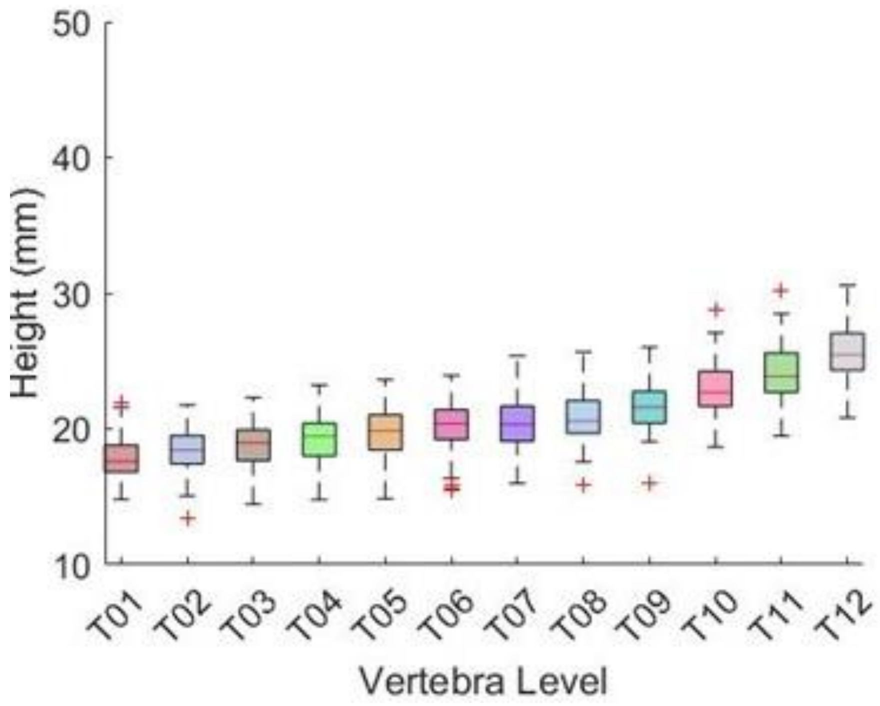
Note:***: < 0.001, **: < 0.01, *: < 0.05, Red: +2STD Blue: -2STD

Results : Vertebral Body Dimension

Vertebral body dimension variation trend

- Vertebral height and depth strictly increase from T1 to T12.

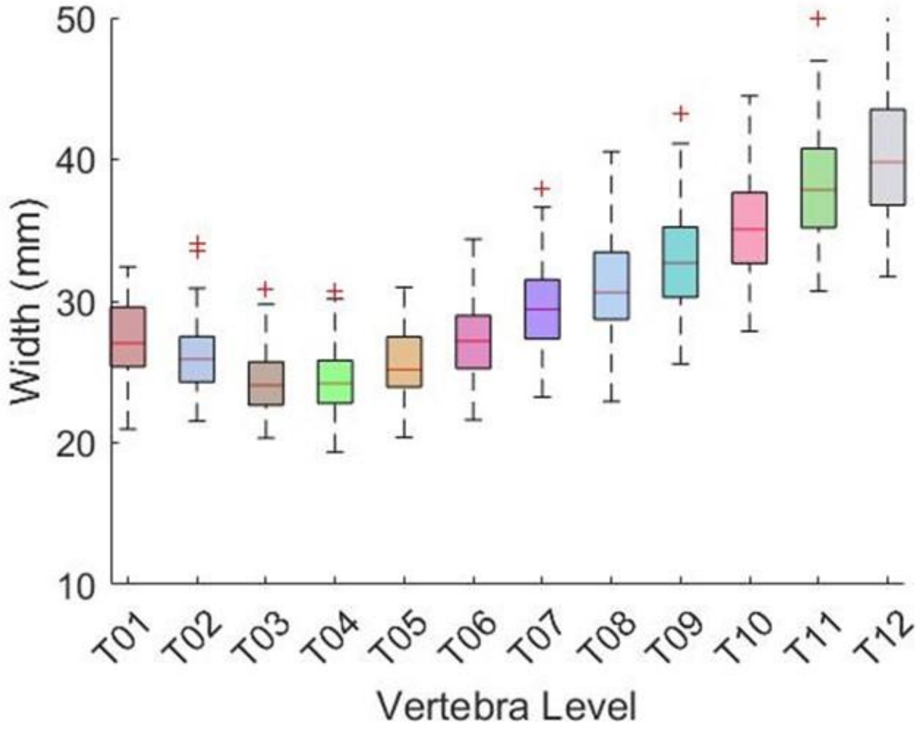


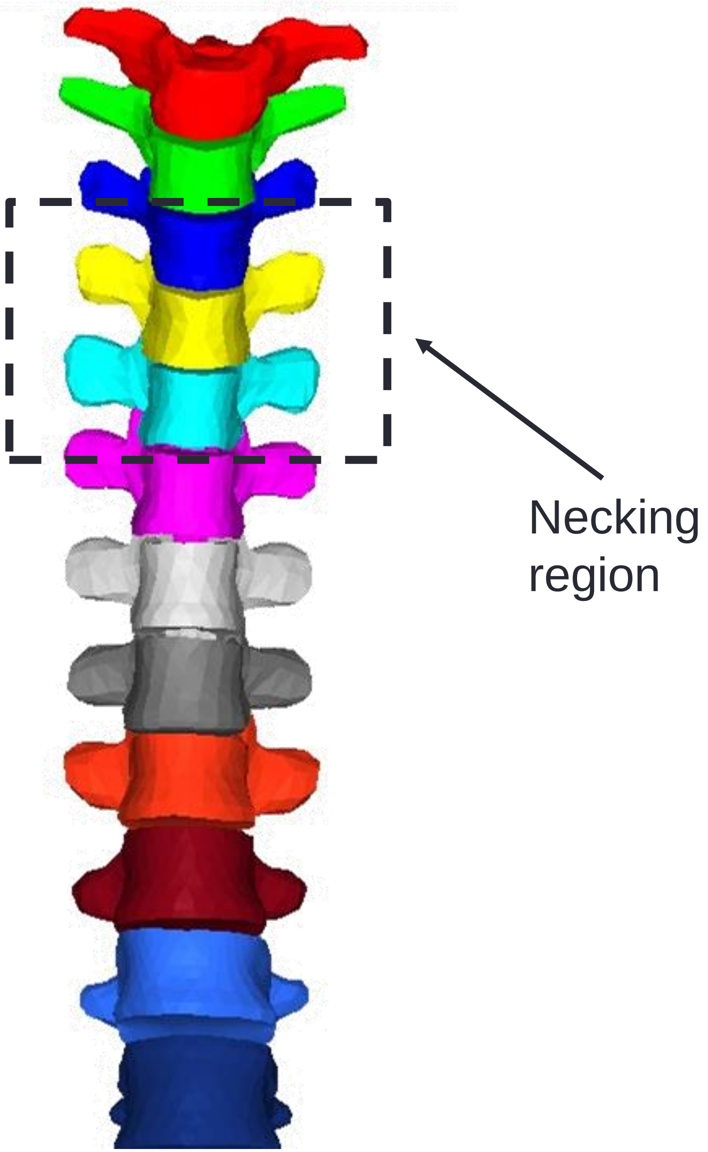


Results : Vertebral Body Dimension

Vertebral body dimension variation trend

- Width decreases from T1 to T3, and start increases from T4 to T12 (Necking effect)

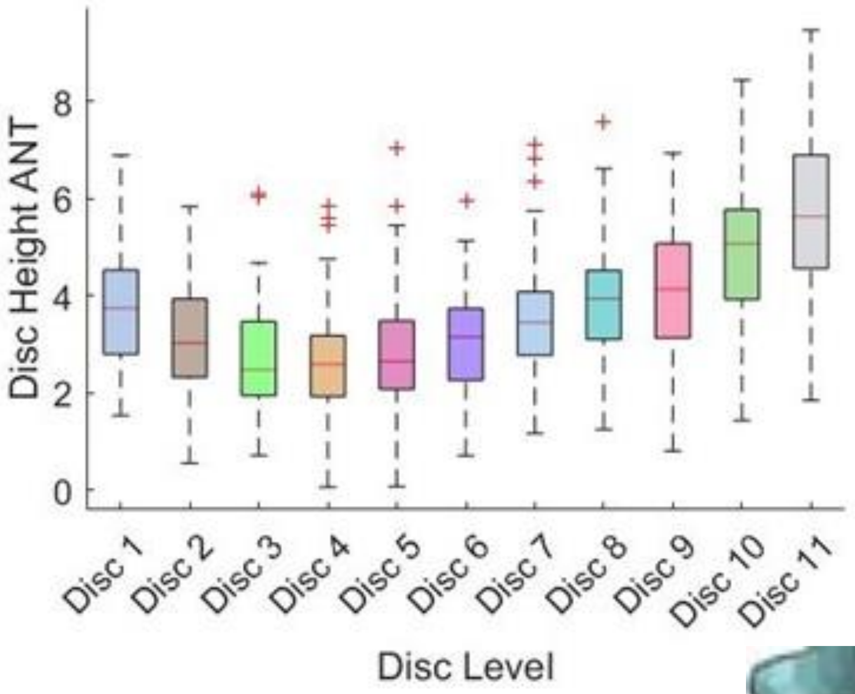


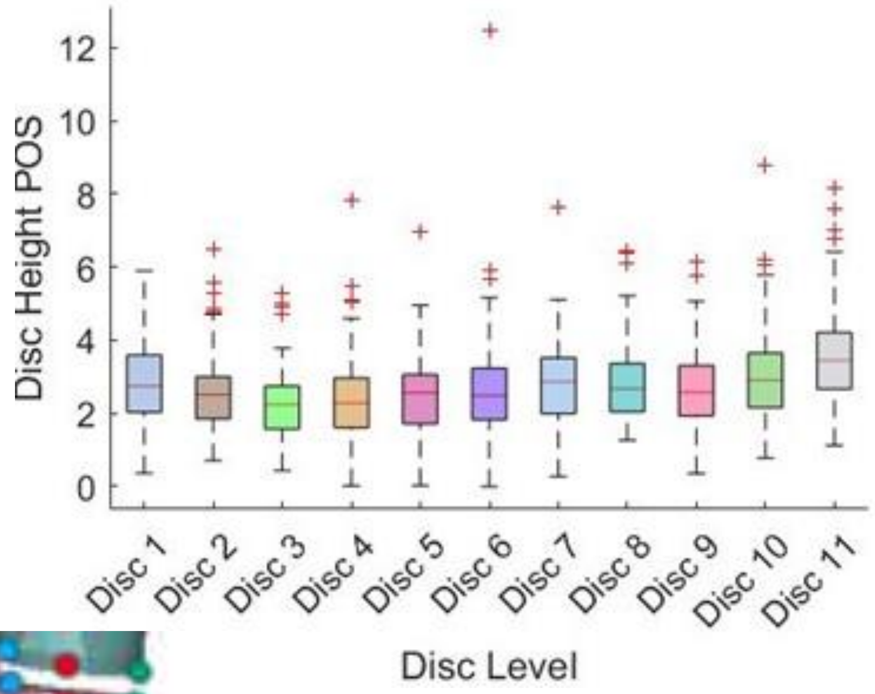


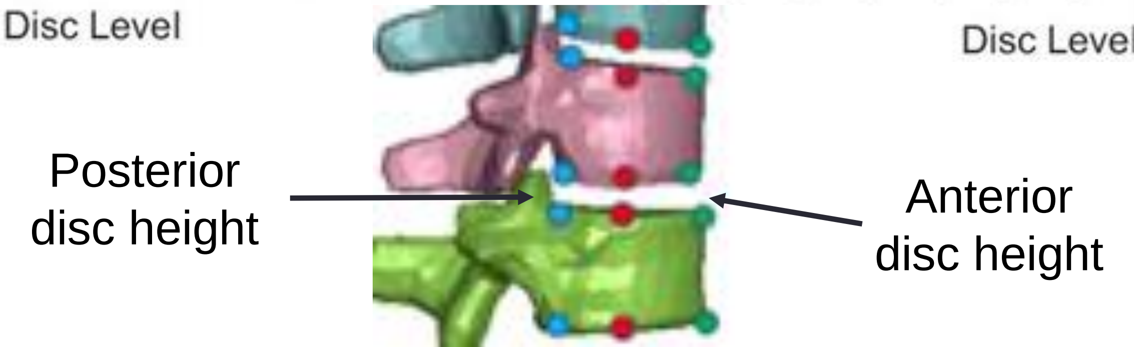
Results : Vertebral Body Dimension

Disc Height

- Disc height is the gap between the two level of vertebra
- Anterior disc height is bigger than posterior disc height



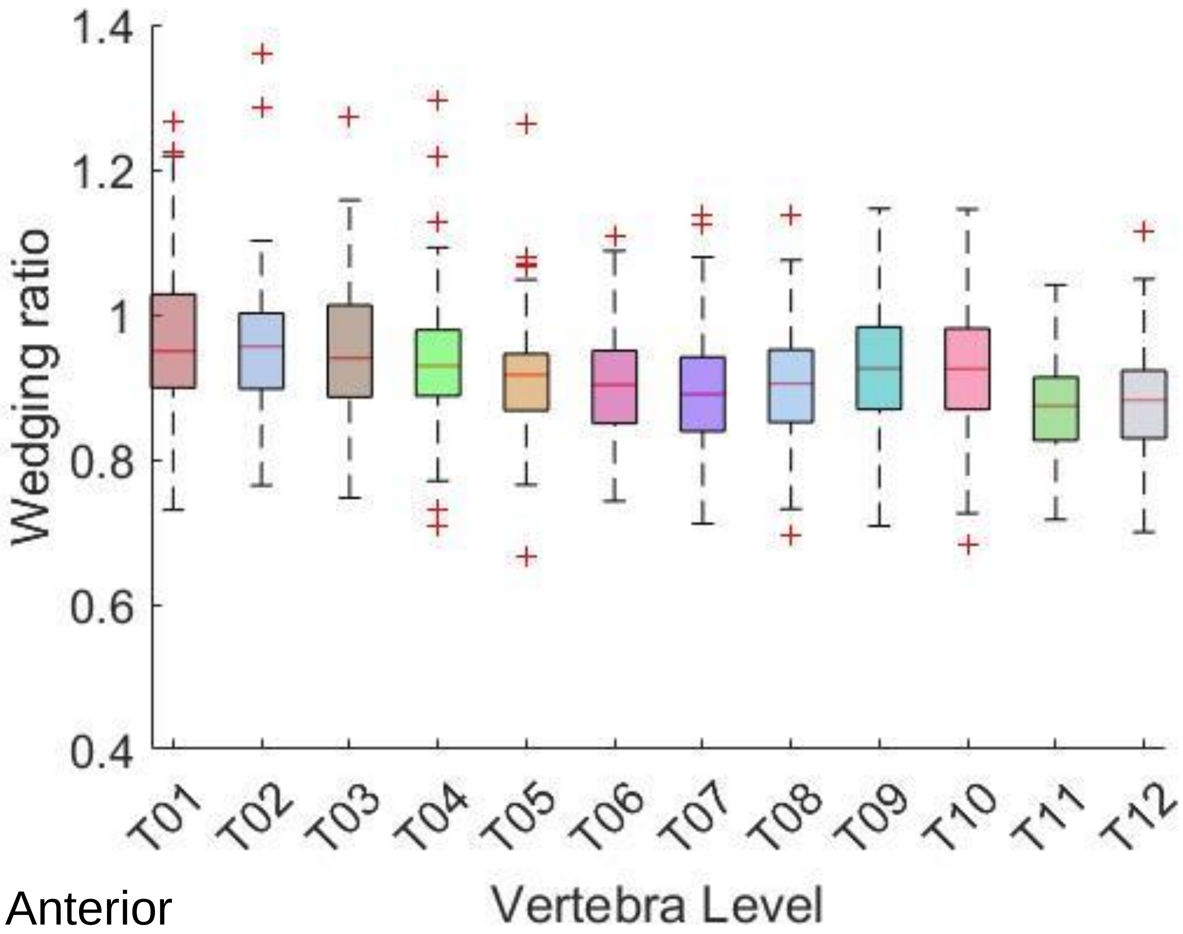


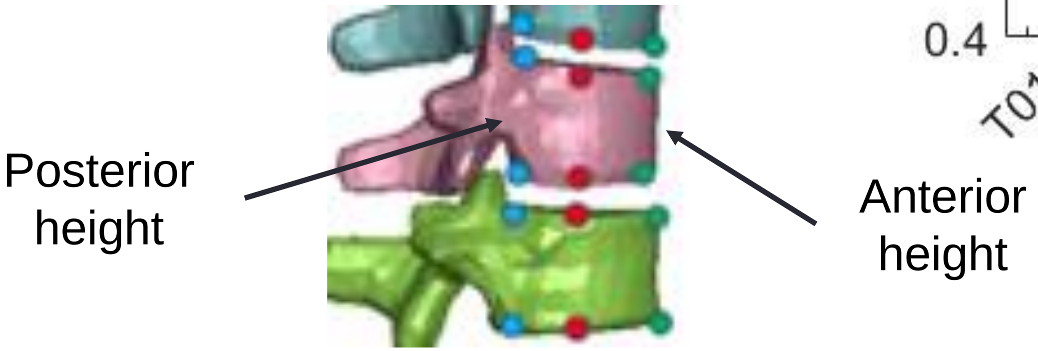


Results : Vertebral Body Dimension

Wedging Ratio

- Defined by anterior height divided by posterior height

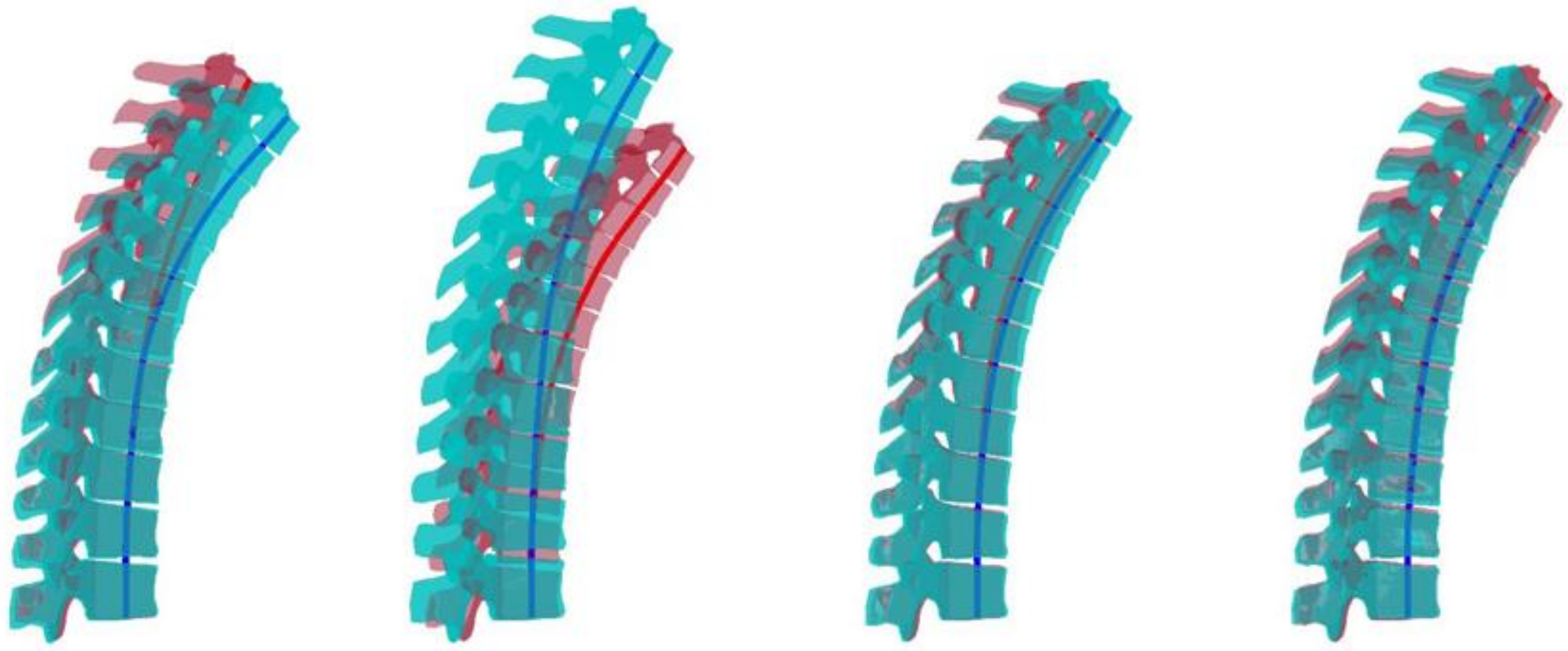




Results : Subject Covariate Effects

Effect of different parameters

- Age has big impact on curvature
- Stature has big impact on length
- Male has larger vertebral size than female
- BMI has relatively small impact



Age:
20 (Red)
80 (Blue)
Stature:1.75m
BMI:25
Sex: Male

Age:45
Stature:
1.55 (Red)
1.95 (Blue)m
BMI:25
Sex: Male

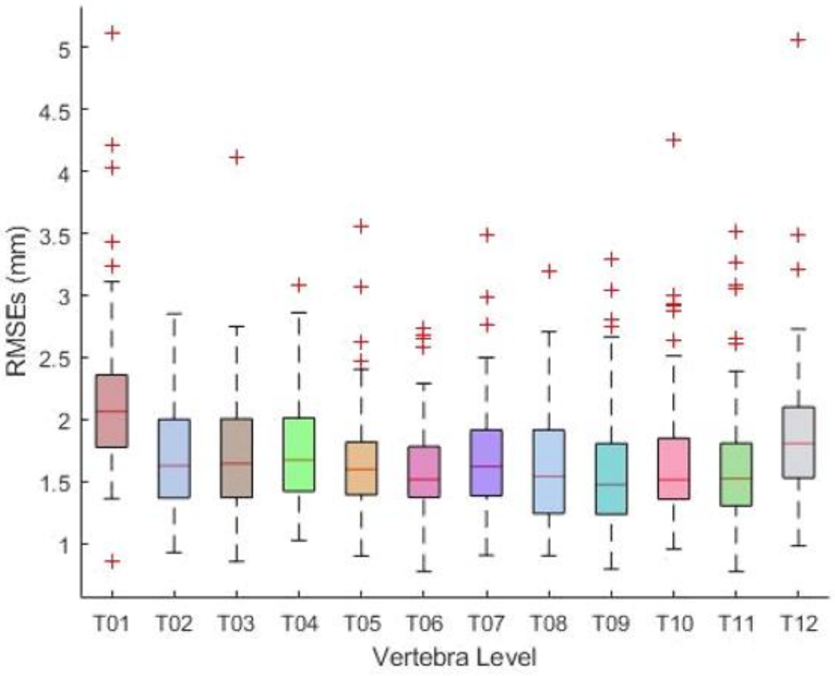
Age:45
Stature:1.7m
BMI:25
Sex:
Female (Red)
Male (Blue)

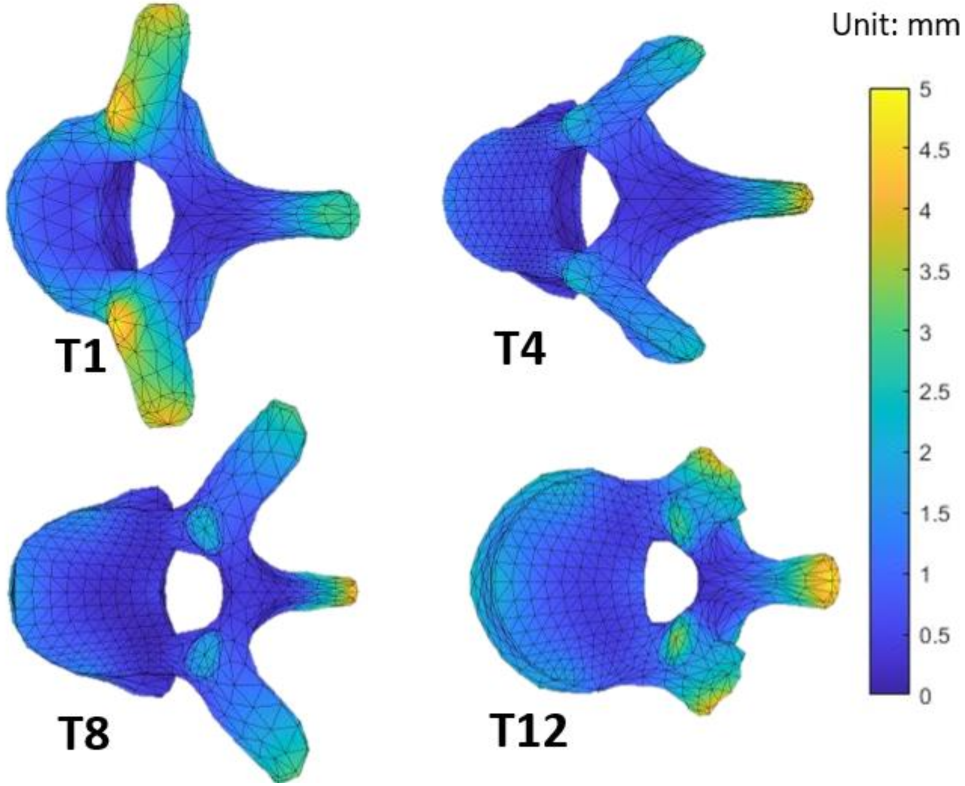
Age:45
Stature:1.75m
BMI:
20(Red)
40(Blue)
Sex: Male

Results : Model Validation

Model error analysis

- Leave one out cross validation
- Nodal location error
- Accurate & Robust





Discussion

- Develop a statistical model that can accurately predict a full T-spine model given a set of characteristic parameters.
- Analyze the variation trend of width, height, and depth from T1 to T12 and find the necking effect.
- Demonstrate the effect of different parameters through comparison.
- In this study, all CT scans were collected while subjects were in a supine position. Therefore, the curvature model developed in this study may not be appropriate for representing other postures. The landmarking process was finished by a single person manually and followed by another person checking the landmarking quality. This may potentially introduce errors related to landmark positioning and subsequently impact the morphing results.

Conclusion

- Develop a statistical model that can accurately predict a full T-spine model given a set of characteristic parameters.
- Analyze the variation trend of width, height, and depth from T1 to T12 and find the necking effect.
- Demonstrate the effect of different parameters through comparison.
- We plan to turn this study into a peer-reviewed journal publication this summer.

Acknowledgement

- The authors would like to thank Anne Bonifas from UMTRI for her support on CT acquisition and segmentation.
- The authors would also like to thank the students from the Multidisciplinary Design Program (MDP) at the University of Michigan for their support of the study.

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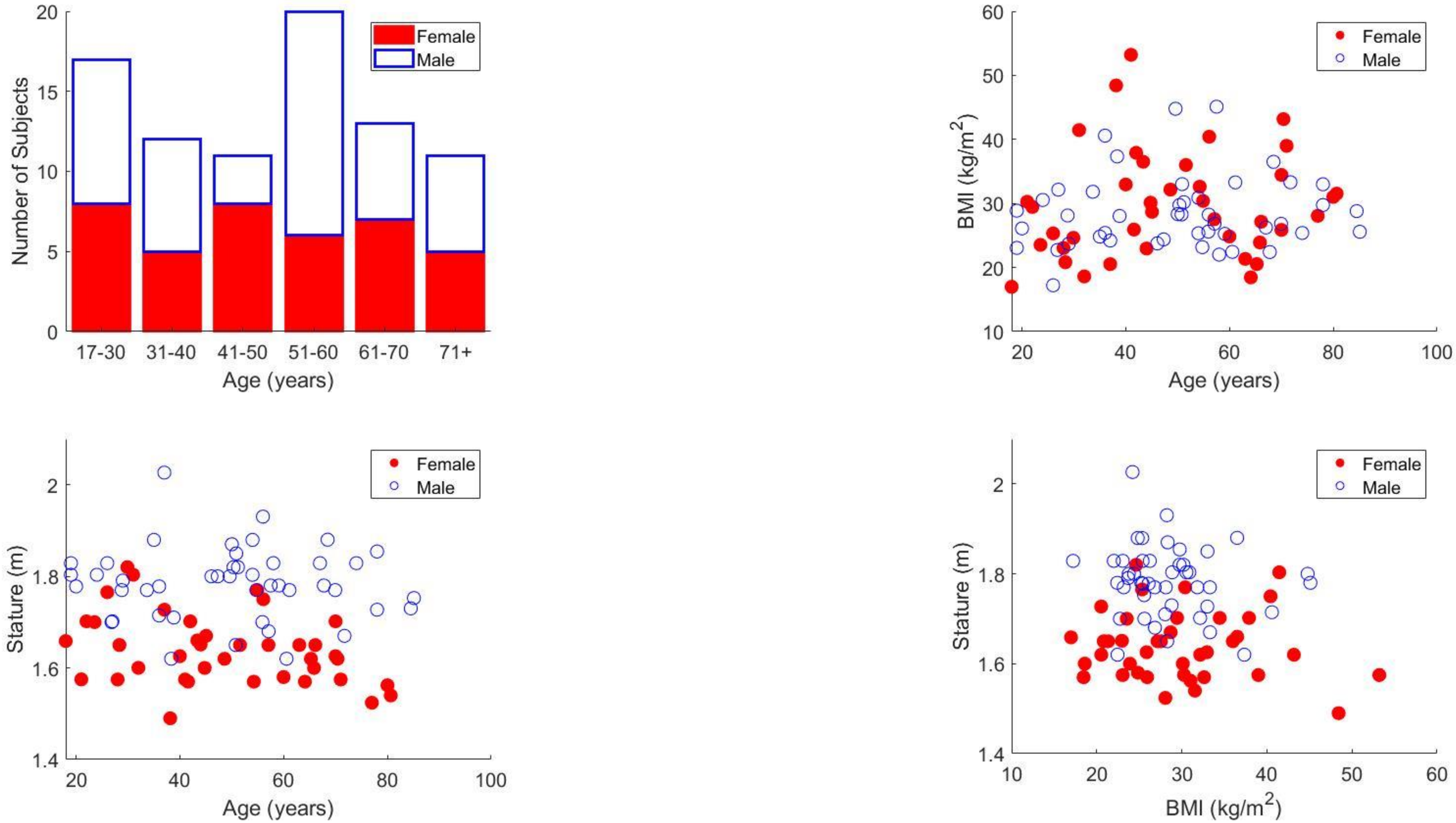
Thank you !

Any questions ?

Checkout appendix for more detailed explanation

Appendix

Distribution of subjects that used for the study.



Appendix

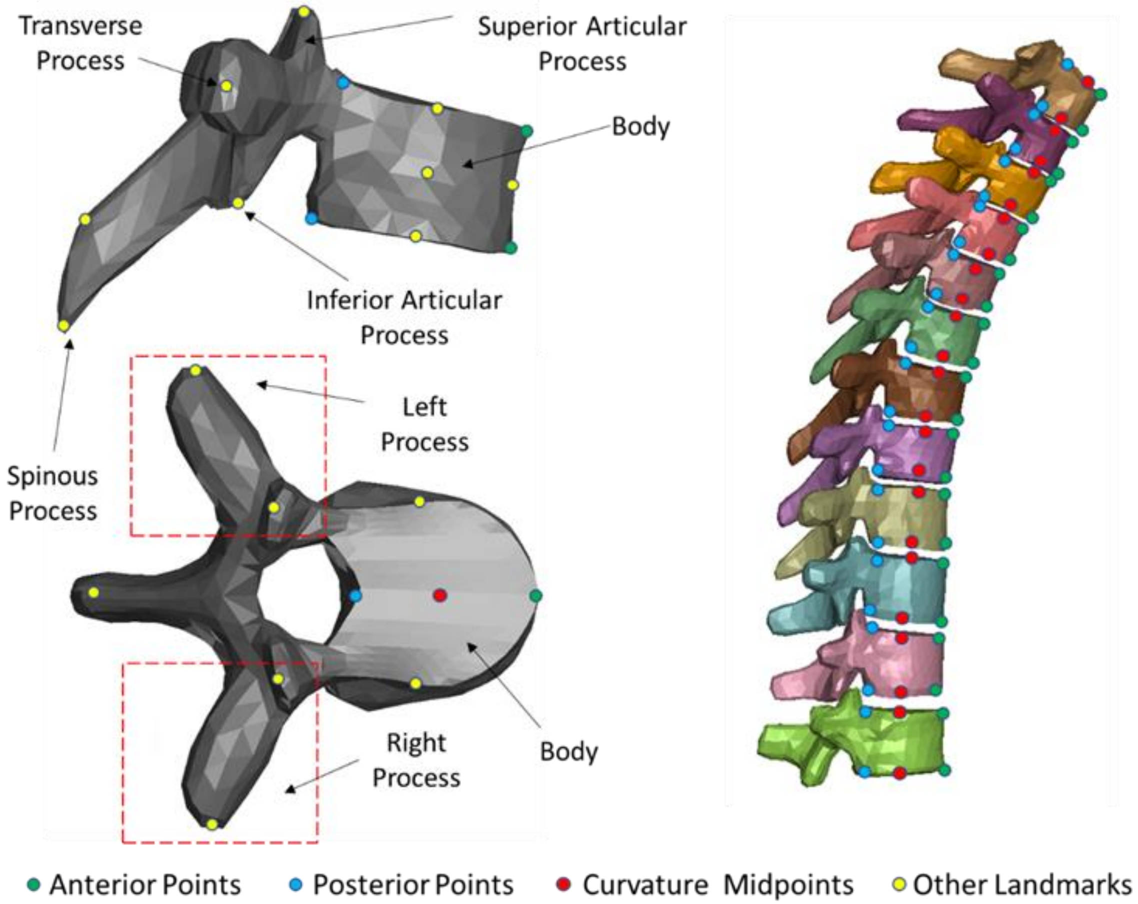
Landmark and curvature model definition.

- Landmark definition

Each vertebra has 19 landmarks.

- Curvature definition

Use midpoints (color in red) for curvature model, each vertebra has two midpoints



Appendix

Walkthrough of T1 prediction process

- Receive input from user: [Age, Stature, BMI, Sex]

Convert to $F_{input} = [1\ 25\ 1.6\ 23.5\ 0\ 0]$ (1 x 6)

- Use C and V obtained previously to get predicted scores and feature columns.

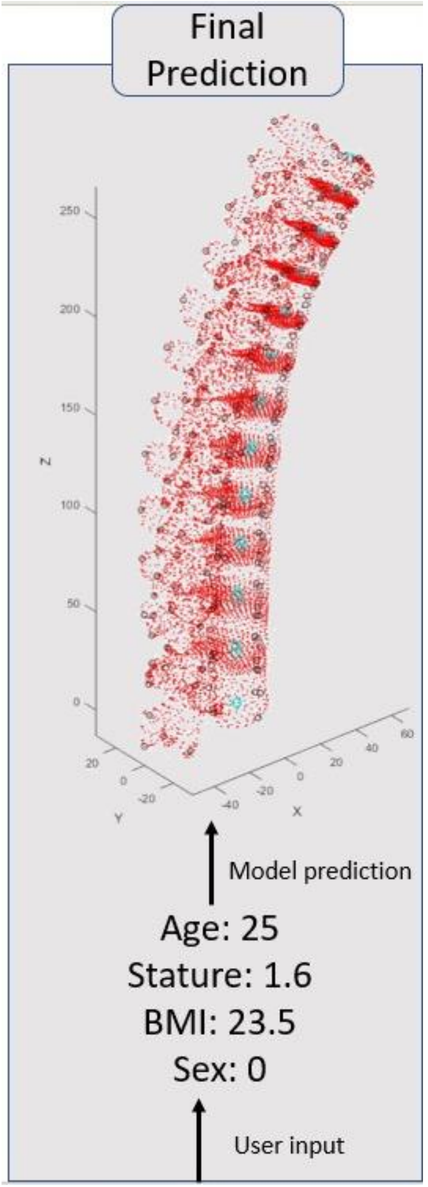
$U_{predict}$ = F_{input} x C

Where C is 6 x 83 and U_{input} (Scores) is 1 x 83

$A_{predict}$ = $U_{predict}$ x V^T

Where V is 1914 x 83, A is 1 x 1914

- Reshape $A_{predict}$ and plot predicted nodes



Appendix

Content inside nodal location matrix that used for statistical analysis

Editor - PCAR_T_Spine.m | Variables - t_spine_cell

t_spine_cell

84x13 cell

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	638x4 double	750x4 double	912x4 double	779x4 double	803x4 double	837x4 double	855x4 double	835x4 double	753x4 double	863x4 double	836x4 double	857x4 double	'FG2S106'
2	638x4 double	750x4 double	912x4 double	779x4 double	803x4 double	837x4 double	855x4 double	835x4 double	753x4 double	863x4 double	836x4 double	857x4 double	'FG2S110'
3	638x4 double	750x4 double	912x4 double	779x4 double	803x4 double	837x4 double	855x4 double	835x4 double	753x4 double	863x4 double	836x4 double	857x4 double	'FG2S112'

Editor - PCAR_T_Spine.m

t_spine_cell | t_spine_cell{1, 1}

t_spine_cell{1, 1}

	1	2	3	4	5
1	300596	-6.9024	78.5452	175.7676	
2	300597	-6.6523	80.3846	178.3122	
3	300598	-5.8968	78.2736	176.0006	
4	300599	-5.2170	78.1390	176.2391	
5	300600	-5.5886	79.6667	178.3699	
6	300601	-4.7320	78.9304	178.3732	