UNIVERSITÄT AUGSBURG
Universitätsbibliothek

OPEN ACCESS
OPUS AUGSBURG

Learning anatomical variability: statistical shape models for vertebral joint pose estimation

Elina Gastreich de Llanes, Melina Wördehoff, Lukas Förner, Josua A. Decker, Thomas Wendler

Angaben zur Veröffentlichung / Publication details:

Gastreich de Llanes, Elina, Melina Wördehoff, Lukas Förner, Josua A. Decker, and Thomas Wendler. 2026. "Learning anatomical variability: statistical shape models for vertebral joint pose estimation." *Current Directions in Biomedical Engineering* 12 (1): 155–58. https://doi.org/10.1515/cdbme-2026-0140.

Nutzungsbedingungen / Terms of use:

CC BY 4.0

Dieses Dokument wird unter folgenden Bedingungen zur Verfügung gestellt: / This document is made available under these conditions:
CC-BY 4.0: Creative Commons: Namensnennung
Weitere Informationen finden Sie unter: / For more information see:
https://creativecommons.org/licenses/by/4.0/deed.de

Elina Gastreich de Llanes*, Melina Wördehoff, Lukas Förner, Josua A. Decker, and Thomas Wendler

Learning Anatomical Variability: Statistical Shape Models for Vertebral Joint Pose Estimation

https://doi.org/10.1515/cdbme-2026-0140

Abstract: Medical image registration, encompassing both rigid and non-rigid transformations, plays a fundamental role in medical image analysis. Applications such as therapy planning, longitudinal disease analyses, and model-based segmentation benefit from the use of registration. While rigid registration suffices for applications like bone imaging, where motion is constrained by joints and bone stiffness, non-rigid registration becomes necessary to accommodate tissue deformation from interventions, temporal changes, and substantial anatomical variability across individuals. However, non-rigid registration comes at the cost of overfitting, implying the potential loss of anatomical plausibility.

This work presents a hybrid framework that combines Statistical Shape Models (SSM) and Active Shape Models (ASM) with kernel-based Principal Components Analysis (kPCA) to derive statistics of vertebral joint poses, setting a foundation to constrain joint pose changes in a registration setup. Using Computed Tomography (CT)-derived vertebral meshes, the pipeline generates mesh correspondence via Coherent Point Drift (CPD), shape variability using SSM and ASM, and estimates orientation through Principal Component Analysis (PCA)-based coordinate frames. The resulting model captures non-linear anatomical variation while maintaining geometric consistency across samples.

Experimental results demonstrate that the proposed approach can reconstruct vertebral shapes with mean reconstruction errors of 7.55 ± 2.25 mm, while robustly estimating intervertebral orientations and distances. The study highlights the feasibility of extracting anatomical priors with the possibility of integration into non-rigid registration frameworks to improve both accuracy and biomechanical realism.

Keywords: Statistical Shape Model, Vertebrae, Joint Pose Estimation

***Corresponding author: Elina Gastreich de Llanes,** Department of Diagnostic and Interventional Radiology and Neuroradiology, University Hospital Augsburg, Germany, e-mail: elina.gastreich-de-llanes@uk-augsburg.de

Melina Wördehoff, Lukas Förner, Josua A. Decker, Thomas Wendler, Department of Diagnostic and Interventional Radiology and Neuroradiology, University Hospital Augsburg, Germany

Melina Wördehoff, Lukas Förner, Thomas Wendler, Digital Medicine, University Hospital Augsburg, Augsburg, Germany

Lukas Förner, Thomas Wendler, Chair for Computer Aided Medical Procedures and Augmented Reality, Technical University of Munich, Germany

Melina Wördehoff, Thomas Wendler, Bavarian Center for Cancer Research (BZKF) Augsburg, Germany

Thomas Wendler, Center for Advanced Analytics and Predictive Sciences, University of Augsburg, Germany

1 Introduction

Medical image analysis has become an indispensable tool for modern medicine. It can support application cases, such as therapy planning, disease monitoring, combinations of data in preoperative and intra-operative imaging settings, or longitudinal image analysis [1]. For two images taken at different times, rigid registration can be useful when analyzing movement-constrained regions, such as bones. However, when soft tissue or joints should be analyzed, unconstrained, non-rigid registration is used at the cost of a possible overfit, risking unrealistic anatomical deformation of structures [1].

Standard intensity-based registration methods do not explicitly encode complex biomechanical constraints present in the spine. Tissue-differentiation approaches [2] and stiffness-regularization frameworks [3] partially address this, but rely on predefined physical priors that may not generalize across patients with pathological deformations. Learning-based deformation models offer flexibility but require large annotated datasets and offer limited interpretability of learned constraints. In contrast, SSMs offer a data-driven way to learn anatomical variability directly from CT-derived shapes, enforcing plausibility during reconstruction without requiring explicit physical priors. We propose a pipeline combining SSM and ASM with kPCA to estimate the relative pose between vertebrae, providing a principled, anatomy-aware foundation for joint-constrained spine registration.

Open Access. © 2026 The Author(s), published by De Gruyter. This work is licensed under the Creative Commons Attribution 4.0 License.

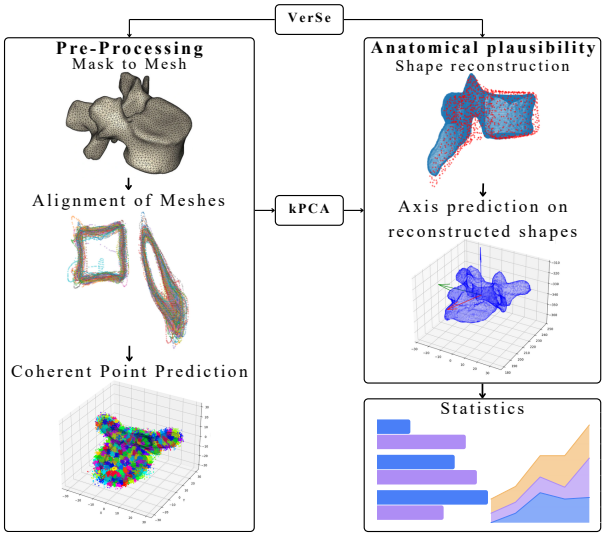


Fig. 1: Workflow chart describing the process of anatomical variability in the spine.

2 Methods

The following chapter proposes a workflow for constraining non-rigid registration based on anatomical variability as presented in Figure 1.

2.1 Dataset and Preprocessing

In this work, the VerSe dataset [4] is used. Its high-quality semi-manually annotated vertebrae segmentations ensure better model performance in later reconstruction steps. We incorporated a total of 2,627 vertebrae from 234 patients, randomly splitting all vertebrae into 80 % training data and 20 % test data. In the next step, the segmentation masks were converted into polyhedral data including a Laplacian smoothing step over 10 iterations correcting implausible surface shapes caused by the low resolution of the CT.

2.2 Alignment and Landmarking

The meshes were prepared for the SSM by normalizing the scale and position, followed by Iterative Closest Point (ICP) registration between the extracted mesh and a reference mesh used as atlas per vertebra group (C1, C2, ..., L5), and sampling of corresponding points for each group.

The position of all meshes' vertices was normalized, computing the mean position of all vertices and translating all the shapes to a mean point. We then defined the scale of the meshes as the mean Euclidean distance of each vertex to its centroid and correspondingly rescaled them to a scale of one.

Lastly, 500 corresponding points were predicted per mesh, using one uniformly sampled mesh as a reference and applying CPD as described by Myronenko et al. [5]. Each vertebral group has their own set of corresponding points. CPD was selected over alternative non-rigid point-set methods due to its probabilistic formulation, which provides robustness to noise and outliers without requiring manually defined landmarks — properties critical given CT segmentation artifacts.

2.3 Statistical Shape Modeling and Shape Reconstruction

With the aligned shapes and corresponding points, firstly, a mean shape can be modeled using Generalized Procrustes Analysis (GPA), calculating the mean position for each point group [6, 7]. The mean shape helps us in later shape reconstruction steps. Reconstruction is meant as the process of mapping the shape of a vertebra using ASM compared to the surface of the annotated label map. Due to the complex surface structure of the vertebra, we applied kPCA with a Radial Basis Function (RBF) kernel, which has been shown to better capture the non-linear variation of the vertebrae surface than the linear PCA [8], allowing the modeling of the non-linear variation in the data.

Alternative approaches, such as mesh-based variational autoencoders have demonstrated superior non-linear modeling capacity but require training sets an order of magnitude larger than the 2,627 vertebrae available here [9].

New shapes are reconstructed by projecting into the kPCA space and inverting the learned transformation, followed by reapplication of the saved rigid registration and scaling.

2.4 Estimation of Orientation

For each vertebra, a local coordinate frame was established based on its principal axes of variation. The centroid of the vertebra surface points was computed as the mean of all vertex coordinates, and the corresponding covariance matrix was derived from the centered points. The eigenvalue-decomposition of this covariance matrix yielded three orthonormal eigenvectors representing the major, intermediate, and minor anatomical axes of the vertebra. These vectors were ordered by descending eigenvalues to define the $x-$, $y-$, and $z-$axes of the vertebral principal component frame.

To ensure consistent axis orientation and ordering across all vertebrae, a frame alignment procedure was applied. Using the first vertebra as a reference, each subsequent vertebra's lo-

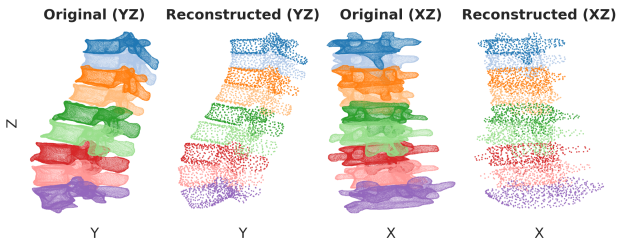


Fig. 2: Comparison of the lumbar section of the reference spine (left in each pair) and the reconstructed spine (right in each pair) visualized in the sagittal plane (first pair) and coronal plane (second pair). Solid surfaces represent the ground-truth vertebrae, while point clouds indicate the reconstructed shapes obtained from the SSM. The figure demonstrates that the reconstruction preserves vertebral orientation, ordering and global geometry while maintaining the original Neuroimaging Informatics Technology Initiative (NIfTI), world-space coordinate system.

cal coordinate system was compared through all possible permutations of its axes. The permutation maximizing the alignment score, computed as the sum of absolute dot products between corresponding axes, was selected. Sign inversions were corrected to maintain consistent axis directionality, and the determinant of each transformation matrix was verified to preserve a right-handed coordinate system. This process ensured globally consistent PCA-based coordinate frames for all vertebrae, allowing coherent orientation analysis across the spine model.

2.5 Intervertebral Statistics

Distance measures for registration and reconstruction error and intervertebral distances were calculated as Euclidean distance. Rotation between two angles was calculated returning the rotation as Euler angle for all three axes.

3 Results

3.1 Alignment

To quantitatively confirm the benefit of scale normalization, an ablation analysis of variance was performed using the non-parametric Wilcoxon signed-rank test. This test was chosen, due to the non-parametric distribution of the data. The mean improvement was 0.83 ± 1.75 mm, and all vertebral groups demonstrated statistically significant difference (p<0.05).

3.2 Sampling

Achieving consistent point correspondence across all vertebral meshes forms the foundation for reliable statistical shape modeling. Following Dupej et al. [10], each vertebra was registered to its reference shape using the CPD algorithm. Subsequently, for each point on the reference mesh, the closest point on the registered target mesh was identified, establishing a one-to-one point correspondence. Each mesh was then uniformly resampled to 500 points, balancing computational cost and geometric fidelity, compared to sampling to 250 and 1000 landmarks.

Comparing reconstruction results across 250-, 500-, and 1000-point sampling, a consistent improvement was observed in nearly all vertebrae with increasing point density. Quantitative analysis demonstrated a significant improvement (mean ($p < 0.05$)), with the mean Mean Absolute Error (MAE) decreasing from 8.50 mm (250 points) to 7.75 mm (500 points) and further to 6.93 mm (1000 points). This corresponds to an overall improvement of about 1.57 mm from 250 to 1000 points, with an average standard deviation of 0.11–0.14 mm across all configurations.

This procedure ensures that corresponding vertices represent homologous anatomical locations across subjects, which is critical for valid covariance estimation in PCA and its nonlinear extensions. Although in highly deformed vertebrae some local deviations remained, quantitative and qualitative analysis confirmed overall coherence of correspondences, providing a robust basis for subsequent shape analysis.

3.3 Reconstruction

Reconstruction of the vertebral shape using ASM provided anatomically consistent result that were robust to local segmentation artifacts, calcification and structural deformations. Quantitative analysis revealed that the mean reconstruction error varied between 4.82 mm (vertebra T2) and 17.51 mm (vertebra L5) over all used subjects. The weighted global mean reconstruction error on the test-set was 7.55 ± 2.25 mm, indicating overall stability.

3.4 Orientation

While the vertebral orientation can be extracted directly from the mesh, we demonstrate that reconstructing the mesh has a minimal but significant impact on the results. Comparing the angles extracted from the mesh against those from the reconstructed model using a Wilcoxon signed-rank test, significant differences were found for the x-axis (mean difference $1.52°\pm9.21°$, $p < 0.001$) and y-axis ($1.16°\pm11.20°$,

$p = 0.008$), but not for the z-axis ($-0.13° \pm 10.71°$, $p = 0.404$). The centroid angle showed a small but significant difference of $-0.79° \pm 12.77°$ ($p < 0.001$), consistent with centroids being robust to reconstruction. The variation of orientation amounts to $6.767° \pm 7.943°$ in the x-axis, $7.884° \pm 9.207°$ for the y-axis, and $7.381° \pm 11.161°$ for the z-axis.

4 Discussion

This work presented a data-driven framework that combines SSM and ASM to learn plausible vertebral morphology from CT data. The preprocessing pipeline successfully generated consistent meshes, established dense point correspondences, and produced stable non-linear kPCA-based models for each vertebra. Reconstruction experiments showed that the ASM approach preserved global shape characteristics with a weighted mean error of 7.55 ± 2.25 mm. The per-vertebra range (4.82 mm at T2 to 17.51 mm at L5) reflects the increasing geometric complexity of lower lumbar vertebrae, where larger transverse processes and more variable morphology reduce reconstruction fidelity, suggesting the model is more reliable as a pose prior for thoracic than lower lumbar levels. While this error magnitude is higher than reported by Clogenson et al. [11] or Day et al. [12], the ASM prioritizes landmark prediction constrained by anatomical variability, making it robust to segmentation errors, pathological deformations, and other surface artifacts.

Orientation estimation using PCA-based coordinate frames showed axis-dependent reconstruction impact, as detailed in 2.4. Given the reported inter-observer variability of Cobb angle measurement is typically on the order of (3–5°), this level of error may be acceptable for spinal curve analysis [13]. However, the large standard deviations across all axes indicate that the spread reflects inherent anatomical variability in the dataset rather than reconstruction error. For downstream joint-constrained registration, x- and y-axis estimates should be interpreted with awareness of this variability, and supplemented by additional anatomical constraints where precision is critical. The approach provides a foundation for reducing deformation overfitting and improving the biological interpretability of longitudinal CT registration.

Author Statement

Research funding: This research was partially funded by the Bavarian Center for Cancer Research as part of the Lighthouse “Local Therapies”, as well as by the Bavarian Ministry of Economic Affairs, Regional Development and Energy (StMWi) under grant number DIK-2310-0004//DIK0556/02. **Conflict of interest**: Authors state no conflict of interest. **Informed consent**: A publicly available dataset was used, where informed consent information is not given. **Ethical approval**: A publicly available dataset was used, where ethics approval by the responsible institutional review board is claimed by the authors of the respective study that created the data.

References

[1] Keszei AP, Berkels B, Deserno TM. Survey of Non-Rigid Registration Tools in Medicine. Journal of Digital Imaging. 2017 Feb;30(1):102-16.

[2] Greene WH, Chelikani S, Purushothaman K, Knisely JPS, Chen Z, Papademetris X, et al. Constrained Non-Rigid Registration for Use in Image-Guided Adaptive Radiotherapy. Medical image analysis. 2009 Oct;13(5):809-17.

[3] Volker Gerhard Daum. Model-Constrained Non-Rigid Registration in Medicine - ProQuest; 2012.

[4] Sekuboyina A, Husseini ME, Bayat A, Löffler M, Liebl H, Li H, et al. VerSe: A Vertebrae Labelling and Segmentation Benchmark for Multi-detector CT Images. Medical Image Analysis. 2021 Oct;73:102166.

[5] Myronenko A, Song X, Carreira-Perpiñán M. Non-Rigid Point Set Registration: Coherent Point Drift. In: Advances in Neural Information Processing Systems. vol. 19. MIT Press; 2006. .

[6] Dijksterhuis GB, Gower JC. The Interpretation of Generalized Procrustes Analysis and Allied Methods. Food Quality and Preference. 1991 Jan;3(2):67-87.

[7] Goodall C. Procrustes Methods in the Statistical Analysis of Shape. Journal of the Royal Statistical Society: Series B (Methodological). 1991 Jan;53(2):285-321.

[8] Twining CJ, Taylor CJ. Kernel Principal Component Analysis and the Construction of Non-Linear Active Shape Models. In: Procedings of the British Machine Vision Conference 2001. Manchester: British Machine Vision Association; 2001. p. 4.1-4.10.

[9] Litany O, Bronstein A, Bronstein M, Makadia A. Deformable Shape Completion with Graph Convolutional Autoencoders. In: 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2018. p. 1886-95.

[10] Dupej J, Krajíček V, Velemínská J, Pelikán J. Statistical Mesh Shape Analysis with Nonlandmark Nonrigid Registration. 2014.

[11] Clogenson M, Duff JM, Luethi M, Levivier M, Meuli R, Baur C, et al. A Statistical Shape Model of the Human Second Cervical Vertebra. International Journal of Computer Assisted Radiology and Surgery. 2015 Jul;10(7):1097-107.

[12] Day GA, Jones AC, Wilcox RK. Using Statistical Shape and Appearance Modelling to Characterise the 3D Shape and Material Properties of Human Lumbar Vertebrae: A Proof of Concept Study. Journal of the Mechanical Behavior of Biomedical Materials. 2022 Feb;126:105047.

[13] Horng MH, Kuok CP, Fu MJ, Lin CJ, Sun YN. Cobb Angle Measurement of Spine from X-Ray Images Using Convolutional Neural Network. Computational and Mathematical Methods in Medicine. 2019;2019(1):6357171.