Landmark-free Mesh Morphing Method for Statistical and Subject-specific Modelling: A Geometric Deep Learning-based Solution

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I. INTRODUCTION

Considering variations in anthropometry across the population is of particular significance in future occupant and pedestrian safety. Recently, methods have been developed to morph a baseline model, e.g., THUMS and GHBMC into desirable shapes, based on manually selected homologous landmarks [1-2]. Selecting landmarks is time-consuming and error-prone. We propose a learning-based method that automatically computes the anatomical correspondences in a landmark-free manner. The proposed method will benefit downstream tasks like subject-specific modelling and statistical shape analysis, with a drastically improved accuracy and efficiency.

II. METHODS

Regarding the task of finding homologous landmarks, humans instinctively discriminate points based on local, e.g., curvatures, and global features, e.g., locations. Our idea is to instantiate this instinct or intuition with a computational model, which computes geometry-informed features from the shape. When applied to non-isometric shapes, points that are closer in feature space are geometrically correlated, i.e., homologous.

Self-supervised Learning in Feature Extraction

We propose a novel self-supervised method to learn geometry-informed features directly from a group of bone surfaces. A state-of-the-art model, *DiffusionNet* [3] with six blocks and 256 channels, is selected as the feature extractor. It outputs a 256-channel feature at each vertex from original 3D *xyz*-coordinates.

Eighty femurs were segmented from CT scans in previous work [2]. The *DiffusionNet* is trained to simultaneously align the shapes with themselves through the learned features. Technically, we build a Siamese architecture. In a single iteration, the model is jointly fed with a pair of randomly rotated copies of the input sample, and a third module is incorporated to minimise the distance between the learned features (Fig. 1).

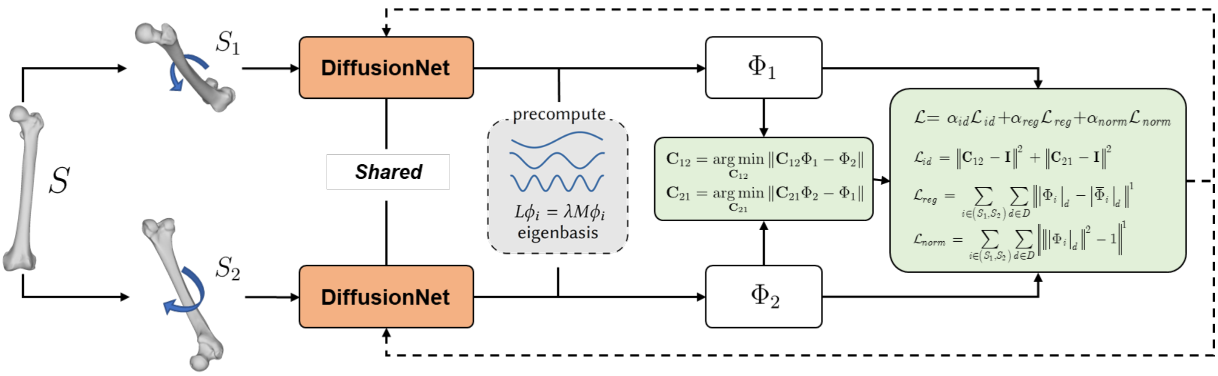

Fig. 1. Overview of our self-supervised method. F_1 and F_2 are the spectral representations, computed by doing inner product between eigenfunctions and the learned features. L is the weighted sum of the proposed losses.

In this work, we compute the alignment in spectral domain. The learned features are converted to spectral representations using eigenfunctions of the Laplace-Beltrami Operator, which can be viewed as an on-surface alternative of the well-known Fourier basis functions. The coefficients compose a *spectrum*, which documents components of the original feature over frequencies. A combination of identity loss L_{id}, regularisation loss L_{reg} and normalisation loss L_{norm} are applied to align the spectral representations while promoting an evenly as possible distribution inside the spectrum. See equations in Fig. 1 for details of the loss terms.

We implement our method in a deep learning framework, PyTorch [4]. The network is trained using the ADAM optimiser for 500 epochs and in a batch size of 4. The learning rate is initially set as 0.001 and decayed by a factor of 0.5 every 12000 iterations. Weights of the losses a_{id}, a_{reg} and a_{norm} are 1, 50 and 10, respectively.

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Inference of Point-to-point Correspondences

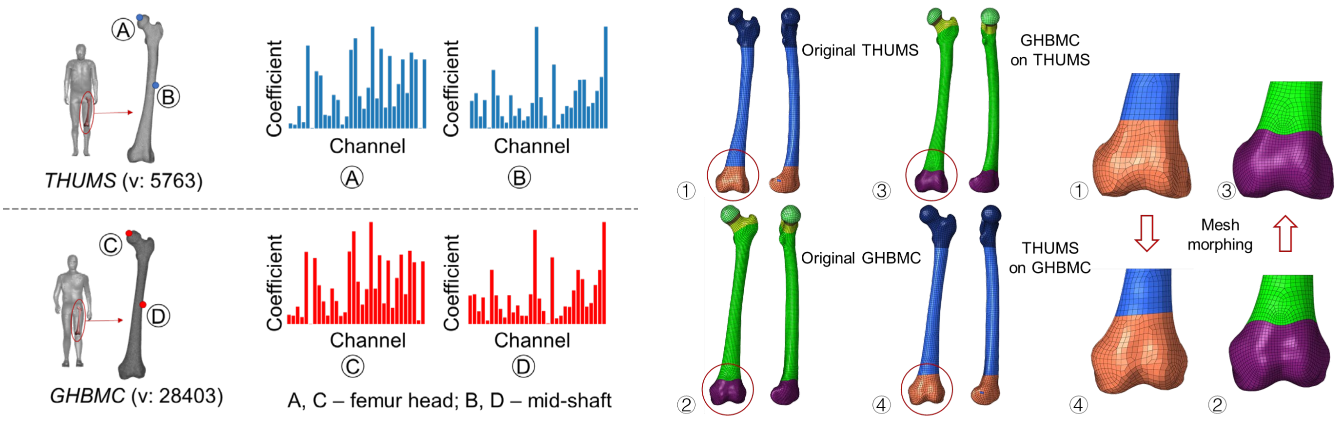
Intuitively correlating points through nearest-neighbour search within the learned features might be unstable, as it neglects connectivity across vertices. Instead, we compute a *functional map* [5], which compactly and robustly encodes the global correspondences, and then retrieves the point-to-point map from the computed functional map with a hybrid strategy combining deblurring and conformality-intended refinement.

Landmark-free Mesh Morphing Method

In practice, the source and target shapes are supposed to be triangle meshes (if not, triangulation and regularisation are needed). The meshes are fed into the DiffusionNet to get per-vertex features. The functional map is computed via the least-squares method and then high-accuracy point-to-point correspondences are retrieved [6]. Each vertex on the source mesh is mapped onto the target shape, forming a pair of homologous landmarks. Classical landmark-based mesh morphing method, e.g., thin plate spline, is consequently available.

III. INITIAL FINDINGS

We evaluated our method by registering the left femurs of THUMS and GHBMC models onto each other. The femurs were re-meshed in different densities. Fig. 2(a) visualises part of the feature channels at the femur head and mid-shaft sites. The features are similar for homologous points (A to C, B to D), while being apparently distinct otherwise (A against B, C against D). This explains why our method establishes an anatomically meaningful map as it discriminates points geometrically. THUMS and GHBMC femurs are successfully morphed into each other's shape (Fig. 2(b)). As shown by the zoomed-in views, our method not only correlates homologous landmarks, but also smoothly transfers the featured texture patterns and preserves mesh quality for subsequent statistical or computational analysis.



(a) per-vertex features (32 of 256) (b) the registered models

Fig. 2. Demonstration of registering the left femur of the THUMS and GHBMC models with our method.

IV. DISCUSSION

The proposed method is available for any given near-isometric shapes. It can serve as an essential part in all morphology-related tasks, and therefore benefits studies on, e.g., accident reconstruction and strategy of personalised protection. As a learning-based study, we eliminated the tedious and error-prone manual annotations with a self-supervised scheme, which significantly improves accuracy and efficiency. The method is not a trivial automation of existing approaches. It actually provides a deterministic solution, while humans cannot tell points apart at a very local scale. In future, we expect to incorporate a more informative feature extractor model, and other shapes from component to whole-body level are to be considered for completeness.

V. ACKNOWLEDGEMENTS

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VI. REFERENCES

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