BaRe-ESA: A Riemannian Framework for Unregistered Human Body Shapes

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In this paper we introduce a new pipeline that quantifies geometric differences between unregistered human body scans, i.e., that does not require prior point correspondences or consistent parametrization across the dataset. Furthermore, we are not only interested in a pure metric comparison of two individuals, but also in estimating plausible deformation processes from one human body to the other. To that end, we introduce a transformation model that allows to disentangle changes in the pose and in the shape of the human body so as to obtain realistic ways to interpolate from one scan to another, extrapolate a given motion or transpose it to a new individual and even to generate visually plausible random pose and shapes. It is important to highlight that, through the use of the varifold representation and kernel metrics, our approach does not require having a consistent mesh structure across the dataset and performs well on human body scans with different numbers of vertices and even under the presence of topological noise (e.g. holes in the scans). Furthermore, unlike current deep learning frameworks for human body analysis, the encoding component in our approach relies on pre-trained deformation bases for the shape and pose changes but is coupled with a non-Euclidean metric in the latent space. Thus the training of our model is notably simple and does not require large amount of training data. Moreover, as our results suggest, it leads to better properties when it comes to the interpretability of human body paths and the generalization to unseen data.