Non-rigid Shape Correspondence and Description Using Geodesic Field Estimate Distribution

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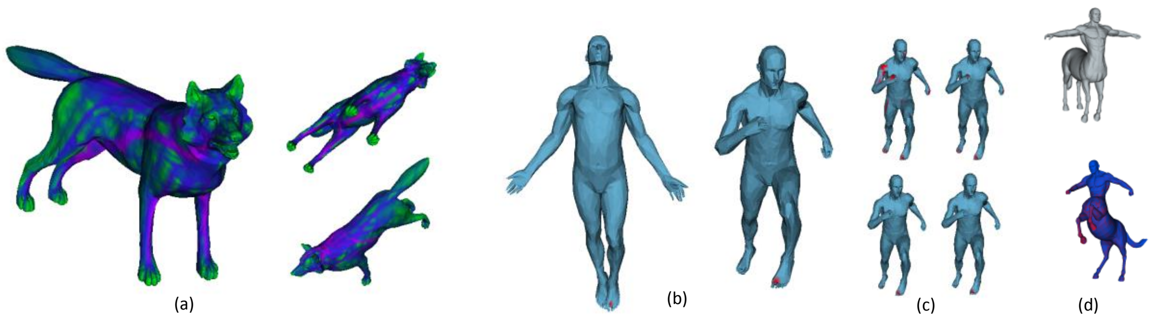

Figure 1: Illustrates the (a) GFE distribution over the surface (purple) along with the relative distribution of higher (blue) and lower (green) values; (b) isometry invariant point correspondence (red) at toes, (c) highest ranked correspondence candidates from coarser to finer level and (d) point correspondence error of the upper centaur into the lower centaur showing exact matches (blue) and relative errors (maximum is shown in red).

1 Introduction: Non-rigid shape description and analysis is an unsolved problem in computer graphics. Shape analysis is a fast evolving research field due to the wide availability of 3D shape databases. Widely studied methods for this family of problems include the Gromov Hausdorff distance [1], Bag-of-Features [2] and diffusion geometry [3]. The limitations of the Euclidian distance measure in the context of isometric deformation have made *geodesic distance* a de-facto standard for describing a metric space for non-rigid shape analysis. In this work, we propose a novel geodesic field space-based approach to describe and analyze non-rigid shapes from a point correspondence perspective. A novel estimate of the geodesic field around a point is proposed as follows:

Definition: For any point f on the surface $\mathbf{S}$, the *Geodesic Field Estimate* (*GFE*) at f is the probability that the geodesic between points x and y will pass through point f. More formally, $GFE(f) = \mathrm{P}\,(f \in Geod(x,y))$ where, $Geod(x,y)$ is the geodesic between points x and y and points $f, x, y \in \mathbf{S}$. For a given point, the GFE distribution of a local subsurface containing the point is computed as shown in Figure 1(a) and compared to the GFE distribution at other points using the Bhattacharyya coefficient measure [4]. The computation and comparison of the GFE distribution is performed starting from a coarser scale and proceeding to a finer scale (where the scale is defined by the area of the subsurface patch) to narrow down the search for corresponding points.

2 Methodology: The proposed method seeks to establish correspondence between surface features in a scale-, rotation-, and isometry-invariant manner. By definition the GFE is an isometry-invariant valuation of surface vertices, but this valuation must be generalized to achieve scale and rotation invariance. Scale invariance is achieved by normalizing the Geodesic length by the longest surface geodesic whereas rotation invariance is achieved by taking a sub-surface ring and representing it as a GFE distribution. This generalized valuation, resulting from replacing a vertex by the GFE distribution, may then be used as a basis for comparing vertices using the Bhattacharya coefficient measure. The search for correspondence was based on the refinement of candidates. A starting scale (0.05 of the longest surface geodesic) is picked, incremented (0.05 of the longest surface geodesic) and Bhattacharya coefficient is compared until the highest ranked candidate is found.

3 Conclusion and Future Work: Geodesic distance - the most common metric for non-rigid shape description, is used to generate a *Geodesic Field Estimate* (*GFE*) for surface points. The GFE distribution around each surface point is used to obtain a sparse point correspondence via the Bhattacharyya coefficient measure. The work is performed on TOSCA dataset [5]. As shown in Figure 1 (c) and (d), the results are promising with very high accuracy without considering symmetry (which would increase accuracy of hands and legs). In future, we propose to formalize the notion of geodesic scale space in the context of shape description which could then be used to establish partial shape correspondence, detect symmetry and search a large database of 3D shapes.

4 References

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