Learning Shape Manifolds using Diffusion Maps

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Abstract

Classical shape analysis [1] methods have traditionally used linear dimensionality reduction methods, such as principal component analysis (PCA), in order to find intrinsic dimensions of a given shape assuming that the shape manifolds [2] in the high-dimensional shape feature space are linear. It can be argued that while this assumption may hold true for shape manifolds comprising of rigid transformations of a single shape, the manifolds may be highly non-linear when multiple types of shapes or non-rigid transformations of a single shape are involved. Manifold learning, an active area of research in recent years [3], promises to infer the instrinsic dimensionality of shape manifolds while preserving the locality of the high-dimensional space, thus allowing us to effectively visualise the sub-manifolds corresponding to different shapes in a lower-dimensional space.

In this talk, we will present our recent work on learning the shape manifolds using diffusion maps [4, 5]. Diffusion maps define a Markov random walk on an adjacency graph whose nodes represent the shape feature vectors. The mapping from high-dimensional shape feature space to low-dimensional Euclidean space evolves as the Markov chain progresses, where time controls the speed of diffusion. We give two examples of the application of diffusion maps for learning the shape manifolds: one using a number of shapes from a medium-size shape database [6], and another one for separating two different kinds of nuclei in human prostate histology images [7]. We extend the frameworks proposed in [6, 7] such that classification of unseen shapes can also be performed using only the intrinsic dimensions learnt from the training data.

References

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