3D object recognition based on shape embedding with the heat-kernel

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The problem of object recognition is a central one in computer vision with many potential applications. Recently, object recognition has been mainly addressed in the framework of 2D image and video analysis. The most successful methods are based on statistical machine learning theory. Images and videos are represented by bag-of-features (a data structure that has been previously used in document classification and data mining). The most successful recognition methods are based on kernel methods and on support-vector machines, which fall in the supervised learning family of techniques.

3D objects are generally described by meshes that correspond to uniform/dense samplings of surfaces of objects – 2D compact and continuous Riemannian manifolds. The latter representation has been thoroughly studied in the recent past and efficient mesh-processing algorithms were developed. There are many practical situations where the input data are gathered using a variety of sensors such as multi-sensor cameras, time-of-flight cameras, or structured-light laser range-finders. These observed data are less structured, they are not uniformly distributed and they are corrupted by noise and by outliers. The temporal coherence of the data is even more problematic in practice: an articulated shape that is observed from different viewpoints or gathered at different time instances may yield completely different sampling and spatial distributions.

In this project we propose to investigate the problem of how to represent 3D shapes for the tasks of shape learning and shape recognition. One promising approach is to construct a family of kernels based on the diffusion equation on Riemannian manifolds. Hence, the problem of recognition can be addressed within the framework of learning/classification using kernel-based methods. Nevertheless, this setting corresponds to the discretization of heat-diffusion on manifolds and of spectral geometry in the continuous setting. Therefore, shapes can be represented, analyzed, learnt and recognized in both frameworks, i.e. machine learning and metric geometry. In particular we propose to study semi-supervised (or weakly) learning algorithms based on the diffusion kernel. The following tasks will be investigated: Representation of discrete manifold data (point clouds or meshes) using eigenvalues and eigenvectors of the diffusion-kernel matrix, statistical characterization, construction of local and global shape descriptors, segmentation and registration of shapes, etc.