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Smooth point-set registration using neighboring constraints

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ABSTRACT

We present an approach for Maximum Likelihood estimation of correspondence and alignment parameters that benefits from the representational skills of graphs. We pose the problem as one of mixture modeling within the framework of the Expectation–Maximization algorithm. Our mixture model encompasses a Gaussian density to model the point-position errors and a Bernoulli density to model the structural errors. The Gaussian density components are parameterized by the alignment parameters which constrain their means to move according to a similarity transformation model. The Bernoulli density components are parameterized by the continuous correspondence indicators which are updated within an annealing procedure using Softassign. Outlier rejection is modeled as a gradual assignment to the null node. We highlight the analogies of our method to some existing methods.

We investigate the benefits of using structural and geometrical information by presenting results of the full rigid version of our method together with its pure geometrical and its pure structural versions. We compare our method to other point-set registration methods as well as to other graph matching methods which incorporate geometric information. We also present a non-rigid version of our method and compare to state-of-the-art non-rigid registration methods.

Results show that our method gets either the best performance or similar performance than state-of-the-art methods.

1. Introduction

Alignment of point-sets is frequently used in *pattern recognition* when objects are represented by sets of coordinate points. The idea behind is to be able to compare two objects regardless the effects of a given transformation model on their coordinate data. This is at the core of many object recognition applications where the objects are defined by coordinate data (e.g., medical image analysis, shape retrieval, ...), learning shape models (Dryden and Mardia, 1998; Cootes et al., 1995) or reconstructing a scene from various views (Hartley and Zisserman, 2000).

Given that the correspondences are known, there is an extensive work done towards the goal of finding the alignment parameters that minimize some error measure. To cite a few, Dryden and Mardia (1998) and Kendall (1984) deal with isometries and similarity transformations; Berge (2006), and Umeyama (1991) deals with Euclidean transformations (i.e. excluding reflections from isometries); Haralick et al. (1989) deal with similarity and projective transformations; and Hartley and Zisserman (2000) deal exclusively with projective transformations.

However, the point-set alignment problem is often found in the more realistic setting of unknown point-to-point correspondences. This problem becomes then a *registration problem*, this is, one of jointly estimating the alignment and correspondence parameters. Although non-iterative algorithms exist for specific types of transformation models (Ho and Yang, 2011), this problem is usually solved by means of non-linear iterative methods that, at each iteration, estimate correspondence and alignment parameters. Despite being more computationally demanding, iterative methods are more appealing to us than the direct ones due to its superior tolerance to noise and outliers.

We distinguish between two families of approaches at solving this problem. Ones are based on the *Expectation–Maximization* (EM) algorithm (Dempster et al., 1977), and the others use *Softassign* (Gold and Rangarajan, 1996; Gold et al., 1998; Rangarajan et al., 1997). The former ones have the advantage of offering statistical insights of such decoupled estimation processes while the latter ones benefit from the well-known robustness and convergence properties of the Softassign embedded within deterministic annealing procedures.

Myronenko and Song (2010) proposed *Coherent Point Drift* (CPD), a point-set registration method using the EM algorithm that is defined for rigid, affine and non-rigid transformations. Gold et al. (1998), Rangarajan et al. (1997) proposed *Robust Point Matching*

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