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Gaussian field consensus: A robust nonparametric matching method for outlier rejection

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ABSTRACT

In this paper, we propose a robust method, called *Gaussian Field Consensus* (GFC), for outlier rejection from given putative point set matching correspondences. Finding correct correspondences (inliers) is a key component in many computer vision and pattern recognition tasks, and the goal of outlier (mismatch) rejection is to fit the transformation function that maps one feature point set to another. Our GFC starts by inputting a putative correspondence set which is contaminated by many outliers, and the main task of our GFC is to identify the underlying true correspondences from outliers. Then we formulate this challenging problem by Gaussian Field nonparametric matching model which bases on the exponential distance loss and kernel method in a reproducing kernel Hilbert space. Next, We introduce a local linear constraint based on the regularization theory to preserve the topological structure of the feature points. Moreover, the sparse approximation is used to reduce the search space, in this way, we can handle a large number of points easily. Finally, we test the GFC method on several real image datasets in the presence of outliers, where the experimental results show that our proposed method outperforms current state-of-the-art methods in most test scenarios.

1. Introduction

The problem of recovering the underlying correspondence (i.e., inliers) from two or more images of the same 3D scene is a critical component in many computer vision and pattern recognition tasks, and it is a prerequisite in multiple applications, including image stitching [1], tracking [2], registration [3], object retrieval [4], structure from motion (SFM) [5], and stereo matching [6]. However, outlier makes them be challenging problems. For example, in retinal image registration [7], in order to assist doctors to diagnose a pathology area in a large view, it is necessary to first remove outliers from the putative correspondences and then register images accurately. The putative matches contain many outliers, and the underlying correspondences are identified after rejecting the false matches. Where the image features are extracted by a certain feature detector such as the corner and represented by a local descriptor such as SIFT [8], SURF [9], and Shape Context [10], and the initial matching method is the Best Bin First (BBF) [11].

Practical outlier rejection method in computer vision should have the following properties: 1) establishing reliable point correspondences between two or more images with a certain constraint (e.g., descriptor similarity constraint where the putative correspondences are matched with similar descriptors, geometric constraint which requires that the initial matches satisfy rigid, affine, or even non-rigid transformation) which can regularize the ill-posed matching problem, 2) the ability to fit the underlying correspondences by modeling a desirable transformation that maps one feature point set to another, 3) robustness to false matches due to imperfect key-point detection and matching, especially when handling multi-view, wide-baseline, and deformation images and 4) with tractable computational complexity when facing a large number of feature points.

A well-known two-step strategy is widely used for feature matching problem, and common sense suggests that typical two-step methods like RANSAC [12] and MLESAC [13,14] are applicable for outlier rejection. In the first step, according to the degree of freedom (DoF) of the given parametric model, a minimum subset of outlier-free putative correspondences is extracted to estimate the model parameters, such as selecting 3 pairs of feature points for an affine model. The second step is designed to verify

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the above computed parametric model on whole sample set. This two-stage runs alternatively until meeting a given termination condition of the algorithm. These resample methods are easy to implement and popular in many applications, however, they also suffer from efficiency and robustness problems when facing nonparametric transformation models (with high DoF) and the number of false matches or outliers in the putative correspondences becomes large.

In this work, we present a robust nonparametric matching method: Gaussian Field Consensus (GFC), for outlier rejection to address the aforementioned limitations. The proposed GFC is based on the Gaussian fields criterion [15] where a Gaussian mixture-distance is used to measure the rigid and affine models from feature attributes (e.g., edge or shape), while GFC extends the Gaussian fields criterion to nonparametric model, and simplifies the Gaussian mixture-distance to a single Gaussian model like vector field learning with an exponential loss function. The motivation is that the Gaussian distance penalty can be approximately considered as a truncated form of the ℓ_2 loss penalty, in this way, the exponential loss model can handle a large number of outliers with paying low penalty [16]. More precisely, we first formulate the outlier rejection problem as data fitting using the modified Gaussian fields criterion. Inspired by Yuille and Grzywacz's motion field theory [17,18], the nonparametric transformation is modeled like a displacement function that drives the key-points of the frame one towards onto the frame two step by step. Fortunately, we can give the explicit expression (a linear combination of kernels) of the high DoF transformation by the Representer Theorem and kernel method in a reproducing kernel Hilbert space (RKHS). In order to avoid the overfitting problem and make matching well defined, inspired by the locally linear embedding in nonlinear dimensionality reduction [19], we introduce a locally linear constraint to preserve the topological structure of the local neighborhood area in a low-dimensional manifold. Moreover, we use a sparse approximation strategy to pursue a suboptimal solution of the nonparametric transformation function in an RKHS, in this way, it keeps the balance between efficiency and accuracy of the proposed method when handling a large number of putative correspondences. Extensive experiments on several 2D real image datasets illustrate that our proposed GFC is more robust to outliers, even the outlier ratio up to 70%, and outperforms several state-of-the-art outlier rejection methods in most test scenarios. In our related previous works, we use the graph-Laplacian regularized context-aware Gaussian fields criterion for non-rigid registration [20], here we simplify and extend the registration model to remove outliers. In addition, we also formulate the point matching problem as learning a corresponding coherent vector field using a mixture model of Gaussian and uniform distribution [21], where the manifold regularization is introduced to preserve the local neighborhood structure, then the optimal mapping function is obtained by solving a weighted Laplacian regularized least squares (LapRLS), while here we just use the simple Gaussian model and quasi-Newton method to solve the optimization problem.

The main contribution of this paper includes the following aspects. First, we simplify the context-aware Gaussian fields registration model for outlier rejection by modifying the mixture of Gaussian distances to a single Gaussian model. Second, the locally linear constraint that relates to the manifold regularization is introduced to preserve local neighborhood structures, then we just use it as a constraint term for the objective function. Third, in our previous work, we used low-rank approximation [20] to speed up the computation, here we introduce a sparse approximation to express the transformation, and then the computational complexity becomes linear approximately by reducing the search space.

The rest of the paper is organized as follows: In Section 2, we introduce the related work of outlier rejection methods. In Section 3, we present the proposed Gaussian field consensus. Section 4 details the algorithm implementation. Experimental setup, results, and comparative studies are reported in Section 5, followed by some concluding remarks in Section 6.

2. Related work

Many methods exist for outlier rejection in computer vision and pattern recognition, particularly in the field of image stitching [22,23], registration (retinal image [24,25], remote sensing image [26]). They aim to remove the false matches from the putative correspondences, i.e., recover the correct correspondence. Here, we briefly overview the outlier rejection methods according to the pipeline (as shown in Fig. 1).

Commonly, a robust feature matching framework consists of four parts: detecting key-points, representing local features, initial matching, and removing outliers. After initial matching, the putative correspondences are constructed by measuring local descriptors which are more efficient than assigning the intractable affinity matrix. There are several popular local feature descriptors, including SIFT [8], SURF [9], PIIFD [27] and shape context [10]. The initial matching algorithm BBF (Best Bin First) [11] is designed to efficiently find an approximate solution to the nearest neighbor search problem in high-dimensional spaces. In practice, putative correspondences are always contaminated by false matches or outliers due to the imperfect feature extraction. Then extensive outlier rejection methods are presented to solve this matching problem.

Least-Median of Squares (LMedS) [28] and M-estimator [29] are two robust regression methods in the statistics literature. The goal of these type of methods is to change the error loss criterion to reduce the undue influence of outliers. Although LMedS is robust and easy to handle outliers, it suffers from high computational complexity, especially when facing a large number of putative correspondences. While M-estimator estimates an indicator variable to indicate whether data is a false or a true correspondence.

The two-step strategy is well used in the resampling methods which are hypothesis-and-verify methods. The most popular algorithm in the field is RANSAC (RANdom SAmple Consensus) [12], its main idea is to generate a hypothetical model from a minimum subset of outlier-free putative correspondences repeatedly, and then verify each model on the whole set to select the best one. However, limitation occurs when facing nonparametric models. To overcome the limitation, many progressive RANSAC algorithms have been developed, such as maximum likelihood estimation sample consensus (MLESAC) [13] which uses likelihood to evaluate the potential hypotheses, progressive sample consensus (PROSAC) [30] whose samples are drawn from progressively larger sets of top-ranked correspondences, deformation RANSAC [31] which assumes that the distribution of true correspondences usually resembles a low-dimensional affine subspace. Moreover, Sunglok et al. [32] have reviewed and evaluated the performance of RANSAC algorithm family.

Moreover, Li and Hu [33] introduces a concept of correspondence function and a learning algorithm which uses the support vector machine regression method (SVR) to identify the underlying correspondences and reject outliers, although it outperforms RANSAC, the robustness becomes poor when facing a large number of outliers. Zhao et al. [34,35] presented a vector field consensus (VFC) method based on robust vector field learning, the learning problem is formulated as a mixture model. VFC can handle a large percentage of outliers, but the main shortcoming is its low computational efficiency. Subsequently, Ma et al. [36] use the sparse approximation strategy to overcome the limitation of VFC, then they presented the sparseVFC which can approximately reduce the computational complexity down to linear. Motion modeling method can get the feature correspondence robustly with bilateral functions [37] or grid-based motion statistics [38].