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Image matching using a local distribution based outlier detection technique

Haifeng Zhao [a,b], Bo Jiang [a], Jin Tang [a,c], Bin Luo [a,b,*]

[a] School of Computer and Technology, Anhui University, Hefei 230601, PR China
[b] Key Lab of Intelligent Computing and Signal Processing of MOE, China
[c] Key Lab of Industrial Image Processing &Analysis of Anhui Province, Hefei 230039, PR China

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ABSTRACT

In this paper, an efficient image matching algorithm for finding the consistent correspondences between two sets of image feature points has been presented. Correct assignments are usually compatible with each other, and thus likely to form a strong cluster. The main idea of the proposed algorithm is to detect this cluster using a local distribution based outlier detection technique. Based on neighbor similarity (or affinity), we first define an inlier score for each assignment in candidate assignment set. Then, we iteratively detect the correct assignments from the candidate assignment set by exploiting the inlier score. Experimental results on several real-world image matching tasks demonstrate the effectiveness and robustness of the proposed algorithm.

1. Introduction

Image registration is one of the fundamental problems in image processing and computer vision. It has a variety of applications including object recognition, content-based image retrieval, 3D reconstruction and target localization [1–3]. The main process of image registration usually contains the following two steps: (1) establishing the correct correspondences between images and (2) determining the transformation function for them. Generally, the aim of correspondences establishment is to determine one-to-one relationships between features in two images. If some correspondences are incorrect, they will generate an incorrect transformation function which leads to totally incorrect image registration results [2,4]. Therefore, establishing correct correspondences is important in image registration process. There are voluminous literatures on the methods of image feature matching [1–9]. Generally, due to the image noise or imperfect feature point detection step, outlying features usually exist. Therefore, a practical feature matching method should be robust to the outlying features.

One of the most popular methods to the robust feature matching is to use pairwise constraints [2,3,10–13]. These methods usually first define an affinity (or similarity) for the candidate pairwise assignments, and then establish correct assignments from the candidate set by finding a subset of pairwise compatible assignments that maximizes the total pairwise affinity. Although, this problem is a binary quadratic programming problem and thus NP-hard, these methods generally use some techniques to find approximate solutions. For instance, using graph vertex cover, Enqvist et al. [12] have proposed a graph method to solve the feature matching problem with pairwise constraints. Ng et al. [2] have presented a method which uses the spatial constraints and mean shift algorithm to produce robust matches from candidate assignments. Leordeanu and Hebert [11] have proposed a spectral technique (Spectral Matching, SM) to find the best correspondence cluster from the graph involving the pairwise affinities of candidate correspondences. The method first builds a graph whose nodes represent the potential candidate correspondences and the weights on the edges contain pairwise agreements (affinities) between them. Then, it iteratively finds the correct correspondences based on the principal eigenvector of the graph [11]. Cour et al. [10] have extended SM to Spectral Matching with Affine Constraint (SMAC) by incorporating affine constraints into the spectral relaxation. Comparing with SM, it further encodes the one-to-one matching constraints. Cho and Lee [17] have interpreted feature matching problem based on a random walk model, and provided a robust matching algorithm by simulating random walks with re-weighting jumps enforcing the mapping constraints on the associated graph. A survey and comparative study of image

* Corresponding author at: School of Computer and Technology, Anhui University, Hefei 230601, PR China. Tel./fax: +86 551 5108 455.
E-mail addresses: senith@163.com (H. Zhao), jiangboahu@gmail.com (B. Jiang), ahhftang@gmail.com (J. Tang), luobin@ahu.edu.cn (B. Luo).

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registration and matching can refer to the works [8,9,18]. In this paper, we propose a novel pairwise constraint based feature matching method by adopting an outlier detection technique.

In outlier detection, outlier is defined as an observation that deviates too much from other observations that it arouses suspicions that it was generated by a different mechanism from other observations [19–23]. Outlier detection is to explore these abnormal data patterns corresponding with a minority of samples in a given data set [20]. Many outlier detection methods have been proposed and widely used in several communities [19–23]. One of the most popular methods is to use distance (similarity) information, which aims to judge a point based on the distances (similarities) to its neighbors. These approaches usually first assign each object of database an *outlier score* (*inlier score*) based on the distances (similarities) to its neighbors, and then judge outliers by a given threshold. The higher outlier score (inlier score) is, the more likely that this object is an outlier (inlier). For instance, Ramaswamy et al. [23] have taken the distance to the kth-nearest neighbor as its outlier score. Angiulli and Pizzuti [14] have defined a kind of outlier score for an object by integrating the distances of this object to all its 1NN, 2NN …, kNN. Hautamaki et al. [19] have proposed an inlier scoring and detection method using *in-degree* number of the kNN graph.

As noted earlier, pairwise constraints based matching methods are robust to noise and outlying features. As one the most popular pairwise constraints based feature matching methods, Leordeanu and Hebert [11] have introduced a spectral technique to find the correspondences between two sets of image features. As discussed in this work [11], correct assignments are usually pairwise compatible and they are likely to form a strongly connected cluster, while incorrect assignments happen in an unstructured, random way and they are unlikely to belong to this strongly connected cluster. Based on this statistical observation, our aim in this paper is to obtain correct assignments by adopting outlier detection methods. We first present an inlier scoring method using neighbor similarities (Section 2). Then, we find the cluster of correct assignments based on inlier score and greedy algorithm. Similar to [11], this is done by first inspecting the inlier score for each assignment, and then keeping removing the assignments with low inlier score. The process is iteratively repeated until the constraints on the correspondence mapping are satisfied (Section 3). We call this algorithm as inlier scoring based feature point matching algorithm (ISPM). Experimental evaluations on real world image matching show that our method is robust to noise and outlying features (Section 4). In the following, we use the terms *assignment* and *correspondence* interchangeably.

2. Inlier scoring based on local distribution

In this section, a local distribution based inlier scoring method is introduced. Usually, this kind of inlier scoring is defined on the distances of point pairs [14,15,19,20,23,25,27]. In this paper, we redefine it from the similarity perspective to make it be consistent with the affinity introduced in the following sections. Let O denote the data set. Let $sim(p, q)$ and $N_{k,O}(p)$ denote the similarity between two points p and q and k nearest neighbors (kNN) of the point p, respectively. In the following, we first introduce two measurements, i.e., local-mean-similarity and local-min-similarity [14,15,19,20,23,25,27]. Then we propose an inlier scoring method based on these two measurements.

Definition 1. (Local-mean-similarity (MeanSIM) of an object p): given the local neighborhood $N_{k,O}(p)$ of object p, the MeanSIM of p is defined as the average similarities (or affinities) between p and its neighbors in $N_{k,O}(p)$, i.e., $\mathrm{MeanSIM}_{k,O}(p) = \frac{1}{k}\sum_{q \in N_{k,O}(p)} sim(p,q)$.

The local average similarity of an object p measures the closeness (or affinity) of p to its neighbors. Intuitively, inlier points are usually close to each other and thus form a cluster with high density. Therefore, the neighbors of an inlier object p are also inlier objects and thus close to object p, i.e., object p usually has high affinities with its neighbors. Outlier objects, in contrast, happen in unstructured, random way and they are usually far away from inlier objects. The neighbors of an outlier object q may contain both inlier and outlier objects and thus usually have low affinities with object q. Therefore, the above MeanSIM can be regarded as inlier score for inlier objects, i.e., the higher the MeanSIM (p), the more likely that this object is an inlier object. Similar to the local average similarity, we can also derive the following local minimum similarity measurement.

Definition 2. (Local-min-similarity (MinSIM) of an object p): Given the local neighborhood $N_{k,O}(p)$ of object p, the MinSIM of p is defined as the similarity between p and its kth neighbor, i.e., $\mathrm{MinSIM}_{k,O}(p) = \min_{q \in N_{k,O}(p)} sim(p,q)$.

The local minimum similarity of an object p measures the closeness (or affinity) of p to its kth neighbor. Similar to MeanSIM, MinSIM can also be regarded as a measurement for inlier object. Based on MeanSIM and MinSIM, we propose an inlier scoring method by integrating both MeanSIM and MinSIM simultaneously. We call the method as kNN distribution based inlier scoring (KDIS).

Definition 3. (KDIS of an object p): Given the local neighborhood $N_{k,O}(p)$ of object p, its kNN distribution based inlier scoring (KDIS) of p is defined as the weighted sum of the local-mean-similarity and local-min-similarity i.e.,

$$\mathrm{KDIS}_{k,O}(p) = \alpha \mathrm{MeanSIM}_{k,O}(p) + (1-\alpha)\mathrm{MinSIM}_{k,O}(p) \tag{1}$$

where $\alpha \in [0, 1]$.

It is noted that, if there exists a main cluster in data set O, then we can regard inlier score $\mathrm{KDIS}_{k,O}(p)$ as the *confidence* that p is a member of this cluster, i.e., the higher $\mathrm{KDIS}_{k,O}(p)$ is, the more likely it is that this object belongs to this cluster. Therefore, we can detect the cluster from data set O using KDIS. If the object p has a KDIS value of a predefined threshold T or larger, it is marked as a member of the cluster, otherwise it is marked as an outlier.

3. Feature matching with KDIS

Given two sets of features M, containing n_M model features and D, containing n_D data features, our aim is to detect the accurate one-to-one correspondences between the feature points in M and D. To do this, we first generate an initial (candidate) correspondence O between the feature points in M and D, allowing multiple correspondences for each feature point. Then, we design an inlier scoring based feature point matching algorithm (ISPM) to remove the erroneous correspondences from O and thus obtain the accurate one-to-one correspondences.

3.1. Initial correspondences and affinity

For image feature matching, there usually exist some highly discriminative feature descriptors such as SIFT or color histogram [4,16,18,24]. These descriptors can be used to compute an initial correspondence O between feature points in M and D. There are several ways to compute the initial correspondences O based on these feature descriptors. One simple way is firstly computing the distances between their respective descriptors and then matching each feature point in D to the closest point in M. In this case, the one-to-one mapping constraint that one data feature in D should

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