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Conceptual space based model fitting for multi-structure data

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A B S T R A C T

In this paper, we propose a novel fitting method, called the Conceptual Space based Model Fitting (CSMF), to fit and segment multi-structure data contaminated with a large number of outliers. CSMF includes two main parts: an outlier removal algorithm and a model selection algorithm. Specifically, we firstly construct a novel conceptual space to measure data points by only considering the good model hypotheses. Then we analyze the conceptual space to effectively remove the gross outliers. Based on the results of outlier removal, we propose to search center points (representing the estimated model instances) in the conceptual space for model selection. CSMF is able to efficiently and effectively remove gross outliers in data, and simultaneously estimate the number and the parameters of model instances without using prior information. Experimental results on both synthetic data and real images demonstrate the advantages of the proposed method over several state-of-the-art fitting methods.

1. Introduction

As a fundamental problem in computer vision, geometric model fitting has been applied to numerous applications, including fundamental matrix estimation [1,2], motion segmentation [3,4], moving object detection [5], etc. The geometric model fitting is a challenging problem since the real-world data are usually contaminated with some noises and outliers. Moreover, when multiple model instances (also called "structures") exist in data, the problem becomes more complicated, since the model fitting method is required to simultaneously deal with both gross outliers and pseudo-outliers (the latter refers to the data points which are the inliers belonging to one structure but the outliers to the other structures) [6].

RANdom SAmpling Consensus (RANSAC) [7] is one of the most popular model fitting methods. The main steps of RANSAC and its variants [8–12] can be described as follows: (1) Generate a number of model hypotheses by sampling some minimal subsets; (2) Select a model hypothesis from the generated model hypotheses based on the criterion of consensus set maximization. Here, a minimal subset denotes the minimal number of data points required to generate a model hypothesis (e.g., 3 for circle fitting and 8 for fundamental matrix estimation). These methods have achieved significant success in computer vision and other fields, and they are originally designed to deal with single-structure data. However, multi-structure data often exist in real-world applications. Hence, many fitting methods (such as AKSWH [13], gpbM [4] and MSH [14]) have been proposed to improve the fitting performance over RANSAC and its variants, but they also have a common drawback. That is, their fitting performance heavily relies on the quality of the generated model hypotheses. Therefore, if no any "clean" minimal set (i.e., all data points in the minimal set are inliers of a model instance) is sampled during the model hypothesis generation step, it is hard for these methods to obtain desirable fitting performance.

In recent years, another category of fitting methods (such as RHA [15], J-linkage [16], KF [17] and T-linkage [18]) is proposed from a different point of view for solving the geometric model fitting problem. Instead of relying on the consensus information as in RANSAC, these methods analyze the preference information, i.e., the distribution of the residual values derived from the generated model hypotheses to a data point. For example, RHA [15] estimates model instances by finding multiple modes according to the distribution of the residual values of each data point. For KF [17], each data point is represented by a permutation that arranges the generated model hypotheses in ascending order of the corresponding residual values, and each data point is projected into a Reproducing Kernel Hilbert Space by using a Mercer kernel. Both J-linkage [16] and T-linkage [18] map the data points to a conceptual space by using the preference vectors [19], and then estimate model instances in data by using an agglomerative clustering algorithm.

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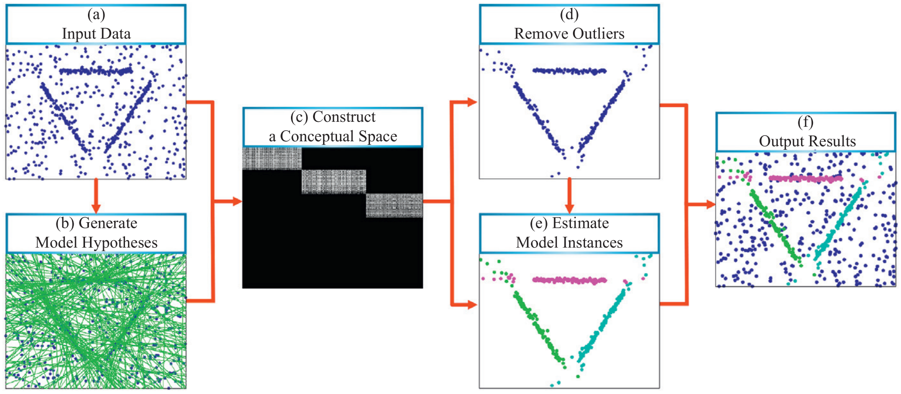

Fig. 1. Overview of the proposed method for line fitting.

In general, these preference-based methods include three main steps for model selection: (1) Compute an affinity matrix based on a similarity measure; (2) Group data points by using a clustering method; (3) Remove gross outliers from the input data points and label the remaining data points to different structures. Although these preference-based fitting methods alleviate the above problem for the consensus-based methods (e.g., [4,13,14]), the strategies of outlier removal used by these preference-based methods are still far from satisfaction for real-world problems. Such as, KF removes outliers after the step of computing the affinity matrix, and it requires to calculate similarities between outliers as well as between outliers and inliers, which is very time-consuming. J-linkage usually takes more expensive computational cost than KF, since it not only calculates similarities between outliers as KF but also clusters outliers during the clustering step.

In this paper, we propose a fast and effective model fitting method, called CSMF (i.e., Conceptual Space based Model Fitting), to fit and segment multi-structure data containing a large number of outliers. We show the overview of CSMF in Fig. 1. To be specific, we firstly construct the conceptual space based on the input data and the generated model hypotheses. The conceptual space contains the powerful relationship information between data points. Then we exploit the information included in the conceptual space to remove gross outliers. After that, we further analyze the space based on the remaining data points to estimate the number and the parameters of model instances in data. The proposed outlier removal and model selection algorithms are jointly combined to achieve the excellent fitting performance. Overall, the proposed CMSF method is able to effectively deal with the problems of both outlier removal and model selection. The experimental results also demonstrate the superiority of the proposed method over several state-of-the-art fitting methods on both synthetic data and real images.

This paper has three main contributions: First, we construct a new conceptual space to effectively measure data points, in which gross outliers and inliers are well-separated. Second, we propose to remove gross outliers before the step of computing the affinity matrix, which makes the proposed CSMF method more robust and efficient. Third, we propose an effective model selection algorithm, which is able to automatically estimate the number and the parameters of model instances in data.

This paper is an extension of our previous work in [20]. We have made several significant improvements, including a novel model selection algorithm to further analyze the constructed conceptual space for model fitting (see Section 4), more related work about model fitting (see Section 2), more competing methods and experimental justification for model selection (see Section 6.2). We also have tested the performance of all competing methods for outlier removal in circle fitting (see Section 6.1.3).

The rest of the paper is organized as follows: In Section 2, we discuss recent progress in geometric model fitting. We propose the conceptual space based gross outlier removal algorithm in Section 3 and the novel model selection algorithm in Section 4. In Section 5, we show the complete CSMF method, and discuss the parameter setting and the time complexity of the proposed CSMF method. In Section 6, we show the experimental results obtained by the proposed CSMF and several state-of-the-art fitting methods on both synthetic data and real images. We draw the conclusions in Section 7.

2. Related work

In this section, we briefly review some fitting methods related to our work, including outlier removal algorithms and model selection algorithms.

2.1. Outlier removal algorithms

Outlier removal is able to effectively improve the performance of a fitting method, and it has wide applications [21–28]. Compared to robust model fitting, outlier removal is relatively less studied. KF [17] and J-linkage [16] are the two popular outlier removal algorithms. KF introduces statistical learning concepts into geometric model fitting and designs a novel Mercer kernel to measure the similarity between two data points. KF can effectively remove gross outliers in multi-structure data. However, as mentioned above, KF is very time-consuming. The reason is that it removes outliers after the step of computing affinity matrix, requiring to calculate the outlier-outlier and inlier-outlier similarities. J-linkage suffers from the same problem as KF. In contrast, the proposed method removes outliers before the step of computing affinity matrix, making it very fast.

2.2. Model selection algorithms

Model selection is a key step of model fitting, and the model selection algorithms can be coarsely classified into energy-based fitting methods [29–31], clustering-based fitting methods [13,14,16,18,32], and other related fitting methods [2,3,33–36].

The energy-based fitting methods (e.g. [29–31]) formulate the geometric model fitting problem as the optimal labeling problem, and provide fitting solutions by optimizing a global energy function balancing fitting errors and regularity of inlier clusters. These methods provide a general energy-based framework for geometric model fitting. However, the performance of these methods is sensitive to the parameters of the used energy function.

The clustering-based fitting methods (e.g., [13,14,16,18,32]) formulate the geometric model fitting problem as the clustering

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