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Mode seeking on graphs for geometric model fitting via preference analysis☆

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ABSTRACT

In this paper, we propose a novel graph-based mode-seeking fitting method to fit and segment multiple-structure data. Mode-seeking is a simple and effective data analysis technique for clustering and filtering. However, conventional mode-seeking based fitting methods are very sensitive to the proportion of good/bad hypotheses, while most of sampling techniques may generate a large proportion of bad hypotheses. In this paper, we show that the proposed graph-based mode-seeking method has significant superiority for geometric model fitting. We intrinsically combine mode seeking with preference analysis. This enables mode seeking to be beneficial for reducing the influence of bad hypotheses since bad hypotheses usually have larger residual values than good ones. In addition, the proposed method exploits the global structure of graphs by random walks to alleviate the sensitivity to unbalanced data. Experimental results on both synthetic data and real images demonstrate that the proposed method outperforms several other competing fitting methods especially for complex data.

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1. Introduction

Geometric model fitting is a challenging problem for a variety of applications in computer vision, such as two-view homography estimation, optical flow calculation, and motion segmentation. In practice, data are unavoidably contaminated by noises and outliers. Numerous robust fitting methods have been proposed [10,19,22,27,34]. Random Sample Consensus (RANSAC) [10] is one of the most popular methods due to its efficiency and simplicity. However, RANSAC is very sensitive to the input inlier scale and it is originally designed to handle single-structure data. Many fitting methods have been proposed to improve the performance of RANSAC, such as, CC-RANSAC [11] and PROSAC [6]. In addition, some recently proposed robust methods, like KF [3], PEARL [14], and AKSWH [27], claim to be able to deal with multiple-structure data heavily corrupted with outliers. However, most of them are very sensitive to unbalanced data (i.e., the numbers of inliers belonging to different model instances in data are significantly different), which are quite common in practical applications.

Mode-seeking is a simple and powerful data analysis technique, and it has been widely applied to clustering and filtering, e.g., [1,5,7,17,24,25,28]. For example, mean-shift [7] and medoid-shifts [24] are two popular nonparametric mode-seeking methods. Traditional mode-seeking methods are restricted in a metric feature space. Recently, some methods such as [5,17,28] have been proposed to extend mode-seeking to the graph domains. For example, Cho and Lee [5] proposed a node-shifting scheme, called Authority-Ascent Shift (AAS), for clustering. AAS achieves better performance than other graph-based clustering methods, especially for complex data. In addition, there are also some mode-seeking based methods, such as Hough Transform (HT) [13] and Randomized Hough Transform (RHT) [33], proposed for robust model fitting. HT discretizes the parameter space into bins and enables data points to vote for the bins, and it assumes that the bins with higher votes are the estimated parameters of model instances in data. As an extension of HT, RHT uses random sampling to generate hypotheses instead of data points to vote for the bins in the parameter space. The above mode-seeking based fitting methods can fit model instances in the parameter space and estimate the number of model instances in data. However, these fitting methods may be seriously affected when the ratio of bad model hypotheses is high.

Note that preference analysis has attracted much attention in statistics [8,20], since it does not require any data-dependent information. Some preference analysis based methods (e.g., [3,4,31,32]) have been proposed for geometric model fitting problems. Chin et al. proposed to exploit the preferences of data to discover the correlation of data for fitting multi-structure data in KF [3] and

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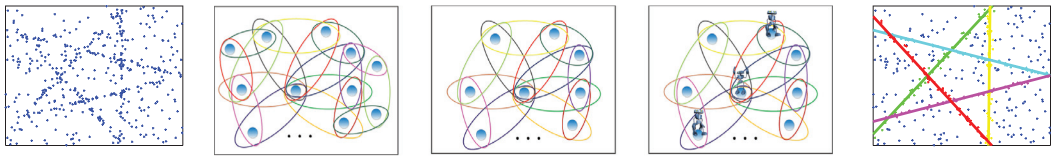

(a) Input data (b) Graph modelling (c) Graph pruning (d) Mode seeking (e) The final fitting result

Fig. 1. Overview of the proposed method for line fitting: (a) the original data with five model instances and a number of outliers, (b) graph modelling in which each vertex represents a model hypothesis and each edge denotes the similarity of model hypotheses, (c) graph pruning by selecting vertices corresponding to the "promising" model hypotheses, (d) mode-seeking on the graph via random walks, and (e) the final fitting result.

guided sampling in Multi-GS [4]. Wong et al. extended to exploit the preferences of model hypotheses to discover the correlation of model hypotheses for hypothesis generation in ModeSamp [31] and ITKSF [32].

In this paper, we propose a novel Graph-based Mode-Seeking Fitting method (GMSF) to fit and segment multiple-structure data in the parameter space. GMSF formulates the geometric model fitting problem as a mode-seeking problem on a graph, where each vertex represents a model hypothesis and each edge denotes the similarity of model hypotheses. The similarity is effectively derived from residual sorting information. To solve the problem of mode-seeking on a graph, we present a modified AAS* based on the Authority Ascent Shift (AAS) [5]. AAS* exploits the global structure of the graph by random walks to alleviate the sensitivity to unbalanced data, and it also uses the residual information to compute the probability that a vertex is visited by random walkers. The main steps of the proposed method for line fitting are shown in Fig. 1.

The main contributions of the proposed method can be summarized as follows: (1) GMSF solves geometric model fitting problems based on the graph theory, where the global structure of graphs is exploited by random walks to alleviate the sensitivity to unbalanced data. (2) GMSF effectively expresses the complex relationships among vertices according to the information derived from the preferences of model hypotheses, which enables mode seeking to be beneficial for reducing the influence of bad hypotheses. (3) GMSF introduces a modified authority-ascent shifting scheme, instead of using a voting procedure (such as HT and RHT), to seek modes on graphs, by which model instances in data can be effectively estimated from putative model hypotheses. Overall, GMSF can effectively estimate the number and the parameters of model instances in multi-structure data that are heavily corrupted with outliers. Experimental results show that GMSF has achieved superior performance over several state-of-the-art fitting methods on both synthetic data and real images.

The rest of the paper is organized as follows: In Section 2, we describe the graph modelling in which the complex relationships among vertices are derived from the preferences of putative model hypotheses. We propose the graph-based mode-seeking method for geometric model fitting in Section 3. In Section 4, we present the experimental results on both synthetic and real data. We draw conclusions in Section 5.

2. Graph modelling

A graph $G = (\mathcal{V}, \mathcal{E}, \mathcal{W})$ consists of a vertex set $\mathcal{V}$, an edge set $\mathcal{E}$, and weight $\mathcal{W}$. In this paper, we deal with geometric model fitting problems in the parameter space. Then, each model hypothesis corresponds to a vertex in G. Each edge $e(i, j) \in \mathcal{E}$ from vertex v_i to vertex v_j is assigned a weight $w(i, j) \in \mathcal{W}$.

2.1. Weighting edges

In this paper, we use the theory of random walks [29] to analyze the structures of graphs. In the random walk framework, random walkers on a vertex travel to another vertex with a probability proportional to the edge weight. Ideally, if two model hypotheses show high similarity (e.g., sharing a large number of common inliers), the weight of the corresponding edge should be as high as possible. At the same time, the weight of the other edges should be as low as possible. Then random walkers can effectively seek modes on the graphs if the edge weights are properly given.

We propose to analyze the preference of model hypotheses to weigh edges in G. Let $X = \{x_i\}_{i=1}^N$ be a set of N data points and $\Theta = \{\theta_j\}_{j=1}^M$ a set of M model hypotheses. For each model hypothesis θ_j, we compute its absolute residuals for N data points to form a residual vector

$$\mathbf{r}_j = [r_j^1, r_j^2, \ldots, r_j^N], \tag{1}$$

where $r_j^i = |\mathbf{F}(x_i, \theta_j)|$, and $\mathbf{F}(\cdot)$ is a function computing the residual of a data point x_i to a model hypothesis θ_j.

To distinguish inliers from outliers, we sort the elements in $\mathbf{r}_j$ in a non-descending order to obtain the permutation

$$\mathbf{b}_j = [b_j^1, b_j^2, \ldots, b_j^N], \tag{2}$$

where $r_j^{b_j^1} \le r_j^{b_j^2} \le \cdots \le r_j^{b_j^N}$. Note that the higher a data point x_i is ranked, the more likely x_i is an inlier of θ_j.

Similar to [4] (where the "intersection" is defined between two data points), the "intersection" between two model hypotheses θ_p and θ_q is defined as

$$f(\theta_p, \theta_q) = \frac{1}{h}\left|\mathbf{b}_p^{1:h} \cap \mathbf{b}_q^{1:h}\right|, \tag{3}$$

where $|\mathbf{b}_p^{1:h} \cap \mathbf{b}_q^{1:h}|$ denotes the number of the common elements between $\mathbf{b}_p^{1:h}$ and $\mathbf{b}_q^{1:h}$, and h $(1 \le h \le N)$ is the number of data points to be taken into account.

Intuitively, two model hypotheses θ_p and θ_q should achieve a high value of "intersection" (i.e., they share many common data points at the top of their preference lists $\mathbf{b}_p$ and $\mathbf{b}_q$) if they show high similarity. Therefore, for a graph G, the weight $w(i, j)$ of edge $e(i, j)$ is assigned to the "intersection" between the two corresponding model hypotheses, i.e., $w(i, j) = f(\theta_i, \theta_j)$.

2.2. Graph pruning

Recall that each vertex denotes a model hypothesis in graph G, and most of sampling techniques may generate a large proportion of bad model hypotheses. Thus, we propose to prune the graph by selecting "promising" model hypotheses.

Firstly, we assign each model hypothesis a score based on the non-parametric kernel density estimate technique [26]. The score

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