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A novel robust model fitting approach towards multiple-structure data segmentation

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ABSTRACT

We propose a novel and effective robust model fitting approach based on the Structure Decision Graph (SDG) to segment multiple-structure data in the presence of outliers. The proposed approach is motivated by the observations that each structure can be characterized by one representative hypothesis, called as the Structure Prototype (SP), and the SPs have relatively large distances among them. In this paper, instead of analyzing each hypothesis individually, the residuals over all the hypotheses are used to explicitly construct an SDG, where a sorted weight score set and a minimum arrived distance set are respectively computed. Based on the SDG, the SPs corresponding to different structures can be easily determined. Compared with conventional robust model fitting approaches, one distinguishing characteristic of our approach is that the clustering procedure is not required. Therefore, the proposed approach is less disturbed by noises and outliers, and is relatively easy to implement. Experimental results on synthetic data and real-world image datasets demonstrate the superiority of the proposed approach over the state-of-the-art robust model fitting approaches for multiple-structure data segmentation.

1. Introduction

In many real-world applications, the observable data usually consist of inliers (refer to the data points whose distribution can be well explained by one or more parametric models) and outliers (refer to the data points that do not fit the models). The task of robust model fitting aims to segment multiple-structure data into inliers and outliers (i.e., multiple-structure data segmentation), and effectively extract multiple model instances from the inliers. Therefore, robust model fitting needs to not only exactly determine the number of structures (model instances) in data, but also recover the parameters of each structure with high precision and reliability.

A simple example of robust model fitting is multiple-line fitting. Given the input data with multiple lines (characterized by the line model $y = kx + b$) contaminated by outliers, multiple-line fitting aims to estimate the number of lines and the respective model parameters (i.e., k and b) for each line in the presence of outliers. Therefore, the multiple-structure in this case refers to multiple-line. Generally speaking, the structure can be any parametric model, such as a line, a circle, a homography matrix and a fundamental matrix. Note that the distribution of the model parameters in the multiple-structure data segmentation problem is multi-modal. Therefore, the multiple structures (e.g., the lines in the multiple-line fitting problem) usually correspond to multi-modality in the parameter space.

Robust model fitting plays an important role in a variety of applications in computer vision, such as motion segmentation [1–3], homography/fundamental matrix estimation [4–6], optical flow calculation [7,8] and range image segmentation [9–11].

Conventional robust model fitting techniques can be roughly divided into the preference analysis based approaches (e.g., J-Linkage [12]) and the consensus analysis based approaches (e.g., AKSWH [13]). The preference analysis based approaches analyze the distribution of residuals for individual hypotheses with respect to the data point, while the consensus analysis based approaches exploit the distribution of residuals for each hypothesis.

The above robust model fitting approaches have shown promising fitting performance, where the strategy of “filtering-and-clustering” is adopted. Specifically, all the hypotheses or data points are first scored based on their supports; and then a filtering step is employed to filter out insignificant hypotheses or outliers; finally the selected significant hypotheses or inliers are partitioned into clusters, from which multiple model instances are fitted. However, one potential problem of such a strategy is that the filtering step can discard the structure with minor

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inliers. Furthermore, some approaches involve the clustering step, which either requires to specify a reasonable clustering criterion (e.g., J-Linkage [12] requires to manually specify a fixed value for clustering) or needs extra procedures to deal with the clustering results (e.g., RCG [14] needs a step to eliminate duplicate clusters), thus greatly affecting the final model fitting performance.

In this paper, we propose a novel robust model fitting approach based on the Structure Decision Graph (SDG) to segment multiple-structure data in the presence of outliers. SDG is based on the observations that (1) for multiple-structure data, each structure is often characterized by one representative hypothesis, which we call as the Structure Prototype (SP); and (2) these SPs are usually at a relatively large distance from each other. These observations motivate us to introduce the concept of SDG to model fitting, through which the multiple-structure data segmentation problem can be easily solved, where no iteration is required.

Fig. 1 illustrates the overview of the proposed approach on the application of multi-homography detection. The original image pair is shown in Fig. 1(a) and (b). Firstly, a number of hypotheses are randomly generated from the feature points in the image pair and each hypothesis is assigned with a weight score based on the degree of the hypothesis importance (see Fig. 1(c)). Then, the Minimum Arrived Distance (MinAD) of each hypothesis, which computes the shortest distance between one hypothesis and the other hypotheses with higher weight scores, is obtained. After that, a Structure Decision Graph (SDG) is constructed based on a sorted weight score set and a MinAD set, where the dominant points corresponding to the different SPs can be easily identified, as illustrated in Fig. 1(d). Fig. 1(e) shows the feature points belonging to the two SPs in the input (left) image. Finally, the fitting results are shown in Fig. 1(f).

The main contributions in this paper can be summarized as follows:

1. We develop a novel and effective robust model fitting approach based on the proposed SDG. Compared with the state-of-the-art approaches, the proposed approach does not require the filtering/clustering procedure. Therefore, our approach is very robust to noises and outliers, and is easy to identify and fit multiple structures in data.
2. We extend the conventional Binary Consensus Set (BCS) to the Continuous Consensus Set (CCS) to more accurately characterize the consensus information of a hypothesis. Based on CCS, we propose to use the Pearson product-moment correlation coefficient to measure the similarity between two hypotheses, which is less sensitive to both location and scale variations than other similarity measures.
3. The effectiveness of the proposed approach is evaluated on synthetic data and three challenging multiple-structure data segmentation tasks including multi-homography detection, two-view motion segmentation and planar surface reconstruction. Experimental results demonstrate that the performance of the proposed approach is consistently better than the state-of-the-art robust model fitting approaches.

The remainder of the paper is organized as follows: related work is given in Section 2 and the detailed description of the proposed approach is presented in Section 3. Experimental comparisons with the state-of-the-art approaches are presented in Section 4. Finally, we draw conclusions and future work in Section 5.

2. Related work

A number of robust model fitting approaches have been developed to address multiple-structure data segmentation in the computer vision community, which can be roughly classified into the preference analysis based approaches [12,15,16] and the consensus analysis based approaches [13,17–20].

The preference analysis based approaches usually use the preference sets of data points to segment the multiple-structure data by optimizing a fitting criterion. For instance, Zhang and Kosecka [15] show that the multiple structures can be revealed via a nonparametric mode seeking approach. However, when the data include severe outliers or the bandwidth used in the density estimation is incorrectly estimated, this approach may fail. Building upon [15], J-Linkage [12] is presented to estimate both the number of model instances and the corresponding parameters. However, it dichotomizes inliers/outliers by using a user-specified inlier scale, which usually requires to carry out manual tuning. T-Linkage [12] extends the J-Linkage algorithm based on the continuous generalization of the binary preference analysis used in J-Linkage. Similar to T-Linkage, a user-specified threshold is required to filter out the insignificant clusters for determining the number of structures. Chin et al. [16] propose the Kernel Fitting (KF) method, which fits multiple model instances based on the assumption that the data points from the same structure concentrate at a location in the Reproducing Kernel Hilbert Space (RKHS). KF can effectively remove gross outliers in data and find multiple structures. Generally speaking, due to the clustering step adopted in these preference analysis based approaches, these methods usually have difficulties in dealing with intersecting structures.

The consensus analysis based approaches aim to find the representative hypotheses that can best depict the multiple structures in data according to the consensus sets of hypotheses. For instance, based on the steps of weighting, filtering, clustering, and fusing of hypotheses, AKSWH [13] simultaneously estimates not only the number of model instances, but also the parameters and the inlier scale of each model instance. PEARL [17] achieves the improved fitting performance by optimizing a global energy function, which balances geometric errors and regularity of inlier clusters, to perform multiple-structure data segmentation. RCG [14] provides an efficient way to handle multiple-structure data segmentation from the hypergraph point of view. Recently, Wang et al. [18] propose a robust model fitting method called MSH, which formulates robust model fitting as a mode seeking problem on a hypergraph. SDF [19] can efficiently and deterministically estimate the parameters of model instance based on the superpixel. Magri and Fusiello [20] cast the multiple-structure data segmentation problem in terms of set coverage, which generalizes RANSAC to handle the multiple-structure data. Note that our proposed approach also belongs to the consensus analysis based approach. However, in this paper, the conventional binary consensus set is extended to the continuous consensus set, which can describe the consensus information of a hypothesis more accurately.

3. Methodology

In Section 3.1, each hypothesis is assigned with a weight score to measure the importance of a hypothesis. In Section 3.2, the MinAD of a hypothesis is developed to compute the distance between one hypothesis and the other hypotheses. The construction of an SDG is given in Section 3.3. The complete algorithm is shown in Section 3.4. Finally, we discuss several important issues about the proposed approach in Section 3.5.

3.1. Hypotheses scoring

Our proposed approach is based on random sampling, where we assume that at least one clean hypothesis (fitted by an all-inlier minimal subset) is generated for each structure. In model fitting, it is critical to measure the reliability of a hypothesis quantitatively. A “good” hypothesis sampled from inliers should be given a high