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Shape similarity assessment based on partial feature aggregation and ranking lists☆

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ABSTRACT

In this paper, we focus on the problem of similarity assessment of isometric 3D shapes, which is of great relevance in improving the effectiveness of retrieval tasks. We first present an effective shape representation technique by proposing a partial aggregation model based on the bag-of-words paradigm. This technique can effectively encode our multiscale local features and has a good discriminatory ability. We then develop a parameter-free distance mapping approach to re-evaluate the similarity results based on intrinsic analysis of a well organized reciprocal k-nearest neighborhood graph. Different from the existing methods which determine k manually and globally, the proposed method can automatically adjust k to a reliable local domain, which therefore ensures a more accurate similarity measurement. We fully study our shape representation technique and evaluate the performance of the proposed distance mapping approach on several popular public shape benchmarks. Experiment results have demonstrated the state-of-the-art performance of our approach.

1. Introduction

The research and development of 3D modeling has resulted in an increasing amount of 3D models in multiple fields including multimedia, graphics, entertainment, design, manufacturing, and so on. The content-based similarity assessment of 3D objects from different classes has been being used in a number of established and emerging fields. To distinguish inter-class shapes, a common feature of existing methods is to employ descriptors that capture the major characteristic of 3D objects.

The similarity assessment of isometric non-rigid 3D shapes is a challenging problem and it has attracted extensive attention from the researchers. This challenge usually becomes much harder when there exist intra-shape deformations caused by the factors such as shape scaling and noises [7,24,25]. In the past few years, there has been considerable research on global and local shape descriptors, such as the global distance feature [9,12,18,31], part-based feature [1,41,44] and the keypoint based feature [2,10,28,38,42].

The keypoint and part based shape descriptors have recently attracted more attention due to their flexibility for partial shape expression, such as depth image [26,42], manifold geometry [17,23,40], and so on. The well-known bags-of-word (BOW) framework [19,20,22,29,37,48], built on a collection of keypoint or patch based features, is usually employed to represent a shape. In particular, the BOW model with soft assignment strategy is more preferred and has demonstrated its advantages in many 2D and 3D shape retrieval tasks [4,7,48]. The spatial information is a critical issue in improving the effectiveness of local descriptors and many versions of the spatial BOW model (e.g. the Hybrid BOW [20]) have been proposed based on the standard BOW model. Lately, Li et al. [23] presented a multiscale shape context (MSC) feature combined with a scale sensitive BOW model for the shape retrieval. The BOW voting schemes in existing 3D shape retrieval methods usually weight all vocabulary words undiscriminatingly and evenly when encoding each local feature, which would accumulate noises from cross-class objects and lead to lower accuracy.

Recently, many context-sensitive methods have been proposed to re-evaluate the similarity ranking [15,45–47]. This is because the initial similarity measurement usually suffers from noise due to inappropriate features or distances (e.g. L_1 or L_2), which would leads to inaccurate ranking results. Kontschieder et al. [16] proposed to use a modified mutual-KNN (mKNN) graph for shape retrieval and

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0167-8655/

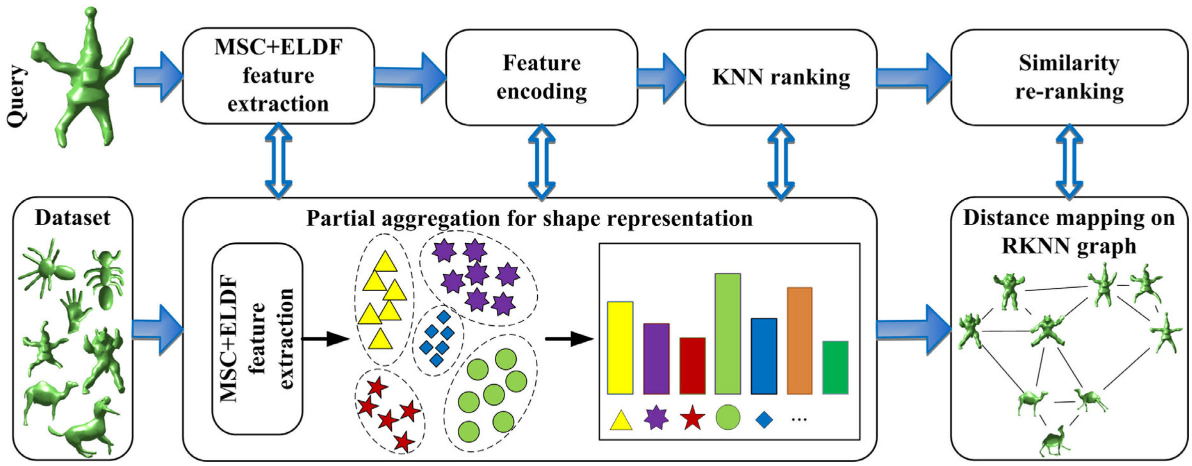

Fig. 1. The pipeline of this proposed approach. Our contribution mainly consist of two parts: (1) a shape representation framework built on improved partial aggregation model and MSC+ELDF feature, and (2) a distance mapping based similarity re-ranking algorithm.

clustering. Yang and Bai et al. studied a flow of algorithms for similarity learning [5,49,50], including locally constraint diffusion process (LCDP), graph transduction (GT), and tensor product graph (TPG). Among these algorithms, TPG [50] integrates the relations of higher order than pairwise affinities into the diffusion process and obtain a good retrieval performance. However, it requires high computation and storage cost. In [13], the authors carried out a detailed comparison of the diffusion related similarity re-ranking methods and, on this basis, they proposed a new diffusion process (DP) to propagate affinity on a k-nearest neighborhood (KNN) graph. In [34] and [30], the authors developed a new re-ranking method (RLSim) by only using the rank list of each query and they achieved a promising performance in improving retrieval accuracy. Lately, Bai et al. [3] suggested employing the neighbor set similarity (NSS) for similarity re-ranking and Li et al.[23] presented a metric mapping method for the re-ranking task. Existing similarity re-ranking algorithms benefit from proper modeling and a well organized KNN graph. Although prior works have attained some promising results, they can be further improved since they use a predefined k in the KNN graph and therefore inevitably introduce noises into the KNN list which further limits their performance.

In this paper, we improve the problem of shape similarity assessment by two parts: an effective shape representation approach and a novel re-ranking technique. The flowchart of this paper is illustrated in Fig. 1. On the part of shape representation, we develop a partial aggregation (PA) model on the works of Li et al. [23] and Bronstein et al. [7]. Unlike previous encoding methods for 3D shape representation, our model aggregates local multiscale features by considering both the scale and position information, which has shown a great performance improvement in experiment. The novelty and advantage of PA is that it alleviates noise and enhances the spatial-sensitivity of local features. Moreover, we also extend MSC [23] and propose a new local descriptor that better fits the problem of shape similarity assessment.

On the part of re-ranking technique, we design a parameter-free distance mapping method to discover the intra-class shapes based on a reciprocal KNN graph. Specifically, our algorithm automatically decides a local graph parameter k and therefore reduces the effect from the noises, which has not been addressed by previous work. We have fully evaluated our methods on different benchmarks. The results show that our approach has achieved state-of-the-art performance.

The rest of this paper is organized as follows. Section 2 presents our feature extraction and partial aggregation model for shape representation. Section 3 describes our distance mapping method for re-ranking. Section 4 shows the results of our experiments, and lastly Section 5 draws conclusions.

2. Partial aggregation for shape representation

Following the flowchart in Fig. 1, we separate the proposed shape representation method into two components: local feature extraction and feature encoding. For the first component, we generate keypoints and multiscale shape context (MSC) domain following [23] and create a more effective local feature. For the second component, we present a distinguished partial aggregation model for feature encoding.

2.1. Local feature extraction

The multiscale property of MSC has enabled it to grasp different co-occurrence information in each keypoint domain, which makes the feature spatial sensitive and informative. Given shape X, a keypoint set $\mathcal{P} \subseteq X$ is detected and a MSC feature is defined for each keypoint $x \in \mathcal{P}$

$$\mathcal{MSC}(x) = (v^l(x), r^l)_{l=1}^{\tau} \tag{1}$$

where τ denotes the number of scales and a domain is assigned to scale l centered at x with radius r^l. $v^l(x)$ represents the feature vector at scale l, which is defined as the histogram frequency of the distances between x and the vertices in the ball domain. Then, the resulting local features are used to represent shape X

$$\mathcal{M}(X) = \{\mathcal{MSC}(x), x \in \mathcal{P}\}. \tag{2}$$

Although some promising results were presented in [23], the retrieval accuracy of MSC is still unsatisfactory due to the limited performance of the adopted local distribution feature (LDF). As an improvement, we propose an extended LDF (ELDF) feature to describe the information at each scale

$$\bar{v}^l(x) = (v^l(x), \xi^l(x)) \tag{3}$$

where $\xi^l(x)$ is defined as the distribution histogram of the heat diffusion function $\delta(x, \cdot)$ to compensate for the information loss of $v^l(x)$. We use B_1, B_2 and $B = B_1 + B_2$ to represent the length of $v^l(x)$, $\xi^l(x)$ and $\bar{v}^l(x)$, respectively.

In the recent years, heat diffusion exhibits promising results for shape deformation analysis [7,38,40] and the heat kernel [21] is quite popular used to define shape features

$$h(x, y, t) = \sum_i e^{-\lambda_i t}\phi_i(x)\phi_i(y), \qquad x, y \in X. \tag{4}$$

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