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Parallel relevance feedback for 3D model retrieval based on fast weighted-center particle swarm optimization

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ABSTRACT

In this study, we present a parallel approach to relevance feedback based on similarity field modification that simultaneously considers all factors affecting the similarity field for 3D model retrieval. First, we present a novel unified mathematical model which formalizes the problem as an optimization problem with multiple objectives and constraints. Secondly, our approach optimizes all the parameters synchronously by treating all the modification operations of the similarity field equally. Thirdly, we improved the standard particle swarm optimization in two different ways. Finally, we present several experiments that show the advantages of our method over existing serial ones.

1. Introduction

According to one estimate, nearly 80% design work of new product is based on reuse of existing examples and design knowledge [1]. Today, with the wide use of computer-aided design (CAD) systems and 3D digital scanning technologies, there are a tremendous number of 3D models in all kinds of libraries. Obviously, reusing rich digital design resources is extremely beneficial for designers, since modeling of 3D objects from scratch is still error-prone and time-consuming. To effectively take advantage of existing reusable design cases, the first task is to discover them quickly and exactly, which is a nontrivial problem. In recent years, various researchers have done a lot of work on this problem and proposed many different solutions [1]. Nevertheless, retrieval results often fall short of users' expectations, because of the wide semantic gap between user-interpretable high-level semantic features and machine-representable low-level values. To narrow the semantic gap, researchers have introduced relevance feedback (RF) to represent users' true intent in the retrieval system. RF has attracted much attention in content-based image retrieval (CBIR) in recent years, and some researchers have used it for 3D model retrieval as well [2–8]. However, it is still an open problem for 3D model retrieval.

In this paper, we propose a new RF approach based on parallel optimization of all the parameters affecting the similarity field of 3D model retrieval. Here, we formulate RF as a multiple-objective optimization problem in which all the parameters are optimized equally. Furthermore, to satisfy RF's requirements of fast response and robustness to limited feedback examples, we present an algorithm called "fast weighted-center particle swarm optimization" (FWCPSO). This algorithm solves RF effectively with self-adaptive particle velocity.

The rest of this paper is organized as follows. Section 2 provides an overview of related work. Section 3 analyzes the deficiencies of existing methods and gives motivation of our work. Section 4 describes our new mathematical model for similarity field modification (SFM)-based RF, which is solved with parallel optimization based on standard particle swarm optimization (PSO). Section 5 discusses how to reduce the dimension of the descriptor and the number of the parameters to be optimized. Section 6 provides two strategies to improve the performance of the typical PSO algorithm, and thus we propose FWCPSO for the specific requirements of RF. Section 7 gives the implementation of our methods and some experimental results with discussion. The last section concludes and discusses future work.

2. Related work

Some researchers have introduced RF technologies for 3D model retrieval to improve unsatisfied query results. These methods can be classified into the following categories:

Query optimization-based methods: Bang et al. presented a feature space wrapping approach [2]. In this approach, all the models in the database move to the relevant or irrelevant models

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in the feature space through interaction. The movement of each model is the compound effect of the models submitted by the user, and closer relevant models contribute more to movement than do further ones. Atmosukarto et al. adjusted the weights of features to improve the distance measurement of similarity [3]. Their method records models' ranks with multiple integer queues. With these queues, the similarity between the relevant models and the query models is always set to 1, ensuring that the number of relevant objects in the retrieval result increases monotonically with the number of feedback iterations. Papadakis et al. introduced pseudo-RF into 3D model retrieval [4]. This approach is based on the assumption that the m-most similar models are considered relevant and thus used as training data. Then, in the feature space, the feature vector of a model is moved to its cluster centroid. In the method of Biao et al. [5], both the relevant set and the weights of the descriptors are updated during interaction for RF, and the algorithm then optimizes the similarity to refine the retrieval result. This algorithm uses the strengths of different descriptors to enhance feedback result. A new method based on parallel optimization has been introduced into CAD model retrieval by Hu et al. and brought good feedback result in [6].

Classifier-based methods: Elad et al. [7] did the initial work on the application of RF technology to 3D model retrieval for VRML models with the kernel-based RF technique. Their approach trains a support vector machine (SVM)-based classifier on moment descriptors of relevant models and irrelevant models, which are marked by the user in the feedback interaction. This training maximizes the margin between descriptors of the relevant and irrelevant models. Then, the trained SVM classifier divides the models in the library into two subgroups: relevant and irrelevant. Leifman et al. did RF by combining linear discriminant analysis (LDA) with biased discriminant analysis (BDA) [8]. Their method builds a compound classifier with the goal of maximizing the distance between the different classes while simultaneously minimizing the distance within the same class. The compound classifier adaptively takes the form of LDA or BDA according to Fisher's linear discriminant (FLD) criterion.

Recently, some articles have surveyed RF for 3D model retrieval. Novotni [9] compared existing algorithms on the Princeton Shape Benchmark (PSB) [10]. His experiments contain some useful and interesting conclusions: for example, the kernel-based RF approach in [7] outperformed the others.

3. Problems and motivation

For clarity of description, this section begins by defining some basic concepts. We discuss some open problems that often cause RF to fail and, accordingly motivate our RF approach to 3D model retrieval.

3.1. Basic concepts

Definition 1. *A feature vector* is a set of parameters that represents a model. Often, it is denoted by a 1D array $[x_1, x_2, \ldots, x_n]$. Furthermore, each feature vector can be regarded as a point in N dimensional space (U), which is called as *a feature point*.

Definition 2. *Feature similarity*: If the distance D between two feature points is satisfied with the condition $D \le \varepsilon$, where ε is a given threshold, their corresponding models are feature similar. The distance is used to represent the degree of feature similarity. The set of all feature-similar models is called a feature-similar set and written as S_f, as shown in Fig. 1.

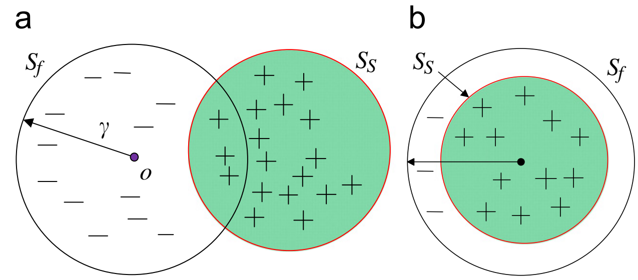

Fig. 1. Illustration of feature-similar set S_s and semantically similar set S_f: (a) normal state of S_f and S_s and (b) ideal state of S_s and S_f.

Definition 3. *Semantic similarity*: If two models are similar according to the user's perception, then they are semantically similar. The set of all semantically similar models is called a semantically similar set and written as S_s, as shown in Fig. 1.

Definition 4. *The similarity field* is the neighborhood of query points in the feature space. Given that q_0 is the query point and p_i is the point of the ith relevant model in space U, then $q_0 = q_0(q_{01}, q_{02}, \ldots, q_{0N})$, and $p_i = p_i(p_{i1}, p_{i2}, \ldots, p_{iN})$. Let vector $v(p_i, q_0) = [(p_{i1} - q_{01}), \ldots, (p_{iM} - q_{0M})]$. Then the feature similarity for the ith model to the query model is $d_i = \| v(p_i, q_0) \|$, where $\| \cdot \|$ is the 2-norm. Suppose that γ ($\gamma > 0$) is given a threshold. If $d_i < \gamma$, then p_i is in the γ-similarity field of q_0.

Essentially, computers determine whether models are similar by feature similarity. However, users make their determination by semantic similarity. Generally, the results are different. As shown in Fig. 1, users expect retrieval results to be S_s containing only relevant models. However, what they really get is S_f containing both positive examples (PEs) and negative examples (NEs). For different users, the degrees of difference of feature similarity and semantic similarity are also different. The reason is that different users have different ideas of likeness. It is this difference that leads to unsatisfied retrieval results for 3D models.

Intuitively, if point O is moved to a new position as shown in Fig. 1b, S_f changes consequently to a new state containing more PEs and fewer NEs. The task of RF is to adjust the position, shape and orientation of S_f to maximize the intersection of S_f and S_s as in Fig. 1b. We call this adjustment "similarity field modification" (SFM).

3.2. Problems

3.2.1. Minimization of the distance sum

Rui and Huang set up a model that minimized the sum of the distances between each feature point and query point and drew the conclusion that the optimal center was exactly the arithmetical average of PEs [11]. For convenience, the average distance from PEs to their arithmetic mean is called as average center distance (DA) and denoted by D_c. However, the average arithmetic center is not always the optimal point that maximizes the intersection of S_f and S_s. To demonstrate the conclusion simply, we give a 2D example as in Fig. 2. We give three PEs, represented by A, B and C. Here, the goal is to find a point that minimizes the average distance to points A, B and C. From Napoleon's theorem, we know that the point is exactly *Fermat* point—the red point F in Fig. 2, which is generated by constructing equilateral triangles externally on each side of ΔABC [12]. Here the average distance from PEs to the *Fermat* point is called the "*Fermat* average distance" (FAD) and written as D_f. Usually, the arithmetic mean center point O is different from the *Fermat* point F as shown in Fig. 2.