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3D shape retrieval using Kernels on Extended Reeb Graphs

Vincent Barra[a,b,*], Silvia Biasotti[c]

[a] Clermont-Université, Université Blaise Pascal, LIMOS, BP 10448, F-63000 Clermont-Ferrand, France
[b] CNRS, UMR 6158, LIMOS, F-63173 Aubiere, France
[c] Istituto di Matematica Applicata e Tecnologie Informatiche Consiglio Nazionale delle Ricerche, 16149 Genova, Italy

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ABSTRACT

3D shape retrieval is becoming an acute issue for numerous applications that span from CAD to serious games to biomedicine and all contexts where it is fundamental to automatically retrieve geometric information from a collection of 3D models. This paper addresses 3D shape retrieval in terms of a graph-based description and the definition of a corresponding similarity measure. For this purpose, 3D models are represented as bags of shortest paths defined over well chosen Extended Reeb Graphs, while the similarity between pairs of Extended Reeb Graphs is addressed through kernels adapted to these descriptions. Results are comparable with the best results of the literature, and the modularity and evolutivity of the method ensure its applicability to other problems, from partial shape matching to classification.

1. Introduction

Technological advancements caused a remarkable increase of the volume of 3D models available in digital form and profoundly influenced the approach to science in many fields. Organizing these 3D models is becoming an acute issue for numerous applications, including CAD, medical imaging, molecular biology, architecture, virtual reality or game design. In this scenario, one fundamental problem is how to enable or improve 3D retrieval using content-based methods. Content-based methods are necessary when text annotations are nonexistent or incomplete. Furthermore, content-based methods improve retrieval accuracy even when text annotations are present by giving additional insight into the data collections [51].

Similarly to content-based image and multimedia retrieval, searching for 3D content requires several pre-processing steps to yield descriptions relevant for querying [29] and to interpret the information relevant to the user's query. 3D shape retrieval is generally decomposed into a four step pipeline.

First, descriptive features are computed from the 3D models, allowing a feature space to be defined and models to be projected onto this space. Besides the use of statistics that can be approximately correlated to the content features, the research on 3D content retrieval is gradually shifting to the automatic or semi-automatic selection of semantic features that are expected to be closer to the user's personal space. To this aim, the existing 3D shape descriptors can be roughly classified into graph-based, transform-based, statistics-based and view-based [25].

Second a similarity measure is introduced in this feature space to assess the proximity between models. Global or partial matching (in the sense of sub-part or part-in-whole correspondence) can be seen as different aspects of the same problem, depending on the globality or locality of the description and the similarity measure adopted.

Third, given a query, even represented by a sketch [33] or a partial description [50], the similarity degrees between this query and each target model are sorted so that models having the highest similarity are ranked first.

Finally, 3D model retrieval engines are implemented for their practical use.

To deal with a semantic representation able to couple global and local features, we adopt a shape description that combines the overall shape structure (coded in a topological graph) with a local geometric description (the spherical harmonic indices of subparts). Then, the 3D shape retrieval problem is addressed as a search in a space of attributed graphs encoding different shape characteristics through a similarity measure able to handle both the graph structure and the geometric attributes associated to its nodes and edges.

3D models are represented by bags of shortest paths defined over well chosen Extended Reeb Graphs, and to compute the similarity between pairs of Extended Reeb Graphs using a so called kernel, implicitly defining the similarity between models. This kernel acts on bag of shortest paths defined from graphs, and defines the similarity between two graphs by comparing their respective bag of paths. An aggregation scheme managing all the Extended Reeb Graphs allows a 3D model retrieval to be processed. In addition, our approach provides an automatic way to

* Corresponding author at: Clermont-Université, Université Blaise Pascal, LIMOS, BP 10448, F-63000 Clermont-Ferrand, France. Tel.: +33 473407492.
E-mail addresses: vincent.barra@isima.fr, vincent.barra@univ-bpclermont.fr (V. Barra).

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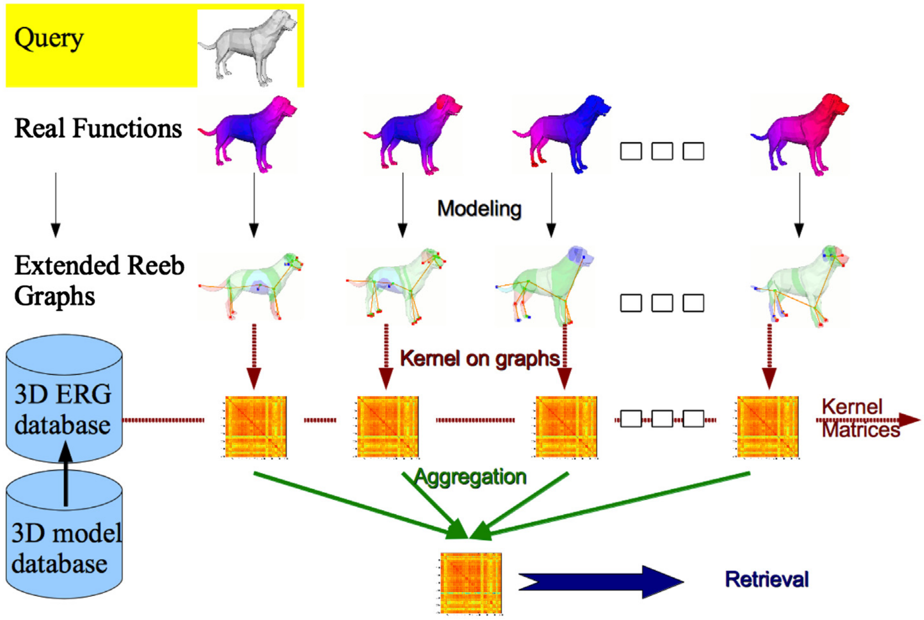

Fig. 1. A synoptic view of the algorithm.

correlate kernels with respect to the classes of a database. In fact, if we think to each kernel as an user's filter of the features of a dataset, the selection of the kernels that better hold retrieval implicitly defines the class complexity and the invariants that characterize it.

Fig. 1 proposes a synoptic view of the algorithm that will be detailed in this paper.

The paper is organized as follows. Section 2 reviews 3D shape retrieval methods, viewed form a graph similarity point of view. Section 3 introduces the elements of our method, *i.e.* Extended Reeb Graphs and kernel on graphs, and then proposes the 3D retrieval algorithm. Section 4 presents and analyses results on three benchmark databases, the SHREC'07 benchmark on watertight models, the SHREC'11 dataset of non-rigid objects and the SHREC'08 stability on watertight models benchmark, and compares the retrieval results with the state-of-the-art.

2. State of the art

As previously mentioned, 3D shape retrieval is usually decomposed into four phases. Numerous works have focused on one or several of these steps in the last few years and several reviews have already been proposed in this domain [19,25,45,76,67]. We address in this paper the first three steps, by introducing both a 3D model representation allowing for a suitable representation of 3D models, and a dedicated similarity measure based on kernels. We thus more particularly focus on these two parts in the following.

2.1. Model description using Reeb graphs

From the mathematical point of view, the global information of a 3D object is captured by the topology while the local one is expressed by the geometry. We propose to carry out both if this information using Extended Reeb Graphs, valued with proper features on their nodes and edges, and allowing the description of the 3D models to be both structural and feature-based.

Reeb graphs have already been proposed for several shape analysis problems, including mesh decomposition [10], mesh segmentation [68], feature selection [21] and classification [44] and also global or partial shape retrieval. The first attempt was performed by Hilaga et al. [44], where the authors proposed a multi-resolution Reeb graph construction allowing shape similarity computation through graph matching techniques. Similar techniques have also been used in [11,70]. Biasotti et al. [18] presented an efficient method based on Reeb graphs and Spherical Harmonics to address the problem of partial shape-matching. Chen et al. [27] proposed a 3D model retrieval method based on Reeb graph, associated to a preprocessing allowing the graph-matching step to be accelerated. Berretti et al. [9] proposed the use of Reeb graphs to extract structural and topological information of a mesh surface and to drive 3D object retrieval based on objects parts. Tierny et al. [68] represented shapes by Reeb graphs, then segmented them into a set of charts of controlled topology, and associated to each chart a geometrical signature composed of its unfolding signature. Areevijit and Kanongchaiyos [3] represented models with both structure and geometry information: structure property was coded by a Reeb graph which used an integral geodesic distance as a Morse function, whereas geometric property was represented by a pose invariant shape signature. Li et al. [52] captured the shape topology of 3D models using a multiresolution Reeb graph and proposed a 3D model retrieval algorithm combining this topological information with view-based features extracted from images rendered at each of the topological points.

2.2. Measuring graph similarity

Defining such a representation for the 3D model description totally impacts the way models have to be compared in the feature space. The definition of the similarity measure is now equivalent to the definition of a distance between two labeled graphs. Several methods are available to measure the similarity between two such graphs. Most of them are derived from graph matching techniques [69]. Matching can be exact, and based on the graph isomorphism property [24], or inexact, allowing graphs with different topology to be compared [26]. For an exact matching, even on subgraphs, the problem is known to be NP-complete, and is thus untractable for problems involving graphs with hundreds of nodes and edges.

Finding polynomial-time similarity measures then seems to be an important issue, and several methods were proposed for this. Graph edit distances [38] count and quantify operations that are