



AIN SHAMS UNIVERSITY Faculty of Computer and Information Sciences Scientific Computing Department



3D Object Retrieval

Thesis submitted to the Department of Scientific Computing Faculty of Computer and Information Sciences Ain Shams University

In partial fulfillment of the requirements for the degree of Master of Computer and Information Sciences

By

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Cairo - 2014



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Acknowledgement

In the name of Allah, the Most Gracious, the Most Merciful. Alhamdulillah, all praise be to Allah for His blessings, and for the strength He gave me to complete this thesis.

> **"فخذ ما آتيتك وكن من الشاكرين"** [سورة الأعراف - آية 144] "So take what I have brought you, and be of the thankful" [Al-A'raf – 144]

It would not have been possible to complete this thesis without the help and support of the kind people around me, to only some of whom it is possible to give particular mention here.

First and foremost, I would like to express my deep gratitude and respect to Prof. Dr. Essam Khalifa for his continuous support in all stages of this thesis. He is a man of vision who deserves more than acknowledgment for his professional expertise and insightful discussions since the early stages of my undergraduate education. Simply, I am ever indebted to his believing in me and constantly pushing me to give the best of me.

My sincerest gratitude is for my supervisor, guide and friend, Dr.Safwat Hamad, who has supported me throughout my thesis with his patience and knowledge, whilst allowing me room to work my own way. He gave me the confidence to explore my research interests and the guidance to avoid getting lost in my exploration. I attribute my achievement to his unfailing encouragement and effort. Without him this thesis would not have been completed. One simply could not wish for a better or friendlier supervisor. Additionally, I wish to thank Dr.Amal Khalifa for her valuable comments that helped me structure the content of this thesis.

Last but not the least; I would like to express my appreciation to Dr.Howaida Abdelfattah, for her continuous care and understanding of the hardships I have encountered during my research.

Dedication

I dedicate this thesis to my great mother: words cannot express how grateful I am for your unconditional love, sympathy and support throughout my whole life. I could not have completed this thesis without you and I wish I could make you proud of me.

I also dedicate it to my supportive and encouraging husband, whose faithful support during the final stages of this thesis is so appreciated. He has shared most of the ups and downs of this thesis and his belief in what I have been doing has been stronger than my own on many occasions. Last but not the least; I dedicate this thesis to my little sweet angel Mariam: her innocent smile and her humorous soul give me the power to bypass all my difficulties through the long journey of accomplishing this thesis.

Thank you all my small family for your love, support, patience, and numerous sacrifices throughout my academic career. This thesis and the pursuit of my goals would not have been possible without you.

Abstract

The advent of the World Wide Web as well as the rapid evolution in graphics hardware and software development, has given the opportunity to experience applications using 3D models not only to specialized users of the scientific community and the industrial domain, but also to common users. The number of available 3D models in digital libraries as well as domain-specific databases has increased substantially. 3D models are currently being used in a wide variety of vital fields. For example, the medical industry uses detailed 3D models of organs, the science sector uses 3D models as highly detailed models of chemical compounds, the architecture industry demonstrates proposed buildings and landscapes through Software Architectural 3D Models in addition to the engineering community which uses 3D models to design new devices, vehicles and structures. In recent decades the earth science community has also started to construct 3D geological models as a standard practice.

Though the number of 3D models keeps on increasing, 3D models are time and effort consuming to build. A more convenient and profitable approach is the use of existing 3D models instead of creating 3D models from scratch. Therefore, the challenge has shifted from "How can we generate 3D models?" to "How can we search 3D models?"

3D model search and retrieval could be performed by using a textual description of the user's target which identifies the semantic meaning of the desired model or class of models. In this case, the user would explicitly describe the target, but such an approach is sensitive to the user's subjectivity factor which is not necessarily in agreement with the textual information which has been annotated to the target. Furthermore, this method is problematic as it requires individually annotating every model of a repository which is impractical due to the huge and continuously increasing number of existing 3D models.

Therefore, content-based 3D object retrieval methods are suited for search since they do not require any annotation while. They only require robust 3D shape feature extraction that can be applied automatically. In these methods, a shape descriptor is computed which represents the model and is consequently used at the matching stage. When 3D model comparison is performed, it is required that shape descriptors are compact in size, discriminative as well as invariant under geometrical transformations, deformations and possible perturbations. Thereafter, the discriminative power of these methods is highly affected by these aspects, while extraction and comparison time also affect the performance, especially for real-time applications.

Recently, a major effort of the research community has been devoted to the creation of accurate and efficient content based 3D object retrieval algorithms. Nevertheless, the problem remains challenging and it is far from being completely solved due to the lack of unique measure that defines shape similarity between 3D models. Work on shape representations and matching is based on a trade-off between conciseness and expensiveness of the chosen scheme.

In this thesis, we present a robust and efficient content-based 3D object retrieval technique after presenting a comprehensive survey of different methods proposed in literature. The key idea of the proposed technique is the synergy between Heat Kernel Signatures (HKS) (Sun et al., 2009) and Bag of Features (BoF) paradigm (Harris, 1954), such that the problem of matching different 3D models is reduced to simply matching their corresponding bags of features vectors which act as their representative shape descriptors. First, the HKS computation phase encodes each point in a given 3D model by a feature vector describing its local and global geometric properties at different time values. Next during the feature point detection and description phase, HKS critical points are captured in order to constitute an initial set of feature points. Then, an innovative filtering technique is applied on this initial set in order to carefully pick the most stable significant feature points, resulting in a compact set of points covering the whole surface of a given 3D model uniformly. This concise set of feature points constitutes the final feature space required for constructing the geometric vocabulary that holds the most distinct geometric words. It should be pointed out that, each point belonging to such descriptor space is associated with a compact and informative HKS-based feature descriptor vector. Afterwards through the BoF phase, each point from a given 3D model is associated to the nearest visual word in the given geometric vocabulary, which has been preliminary built using K-means clustering technique in the descriptor space. Then, the 3D model is represented by a BoF distribution representing a histogram of occurrences of the visual words all over the model. Eventually, the problem of matching 3D models is reduced to matching their corresponding significant BoF descriptors.

Through our extensive evaluation experiments, we conclude that the proposed technique is quite effective for the purpose of 3D Object Retrieval, showing very high

retrieval accuracy and descriptive power. It achieves state of the art results on SHREC 2011 dataset; a public well known benchmark of non-rigid 3D models. The proposed descriptor is not only invariant against different kinds of deformations and transformations, but also can handle 3D models under perturbations of noise. Moreover, it is significant that the proposed technique is computationally efficient.

Furthermore, we compare the proposed technique with other state of the art methods recently proposed in literature. The proposed technique clearly outperforms all other competitive methods, providing quite good results almost always better than other methods regarding different standard evaluation metrics.

In conclusion, the significant contributions of our work can be summarized in introducing a compact, easily computed and informative HKS-based feature vector for point feature description, applying a robust filtering technique for reducing time and space complexity of clustering descriptor space required for geometric vocabulary construction, encoding 3D models with a compact highly discriminative feature descriptor and finally attaining high retrieval results invariant against noise and different kinds of both deformations and transformations.

In the future, we look forward to exploring other applications in the area of 3D shape analysis. In addition to adapting our technique so that it can be applied in other 3D applications such as partial matching, segmentation, pose estimation and matching specific domain 3D models.

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