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Partial matching of 3D cultural heritage objects using panoramic views

Konstantinos Sfikas · Ioannis Pratikakis · Anestis Koutsoudis · Michalis Savelonas · Theoharis Theoharis

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Abstract In this paper, we present a method for partial matching and retrieval of 3D objects based on range image queries. The proposed methodology addresses the retrieval of complete 3D objects using range image queries that represent partial views. The core methodology relies upon Bag-of-Visual-Words modelling and enhanced Dense SIFT descriptor computed on panoramic views and range image queries. Performance evaluation builds upon standard measures and a challenging 3D pottery dataset originating from the Hampson Archaeological Museum collection.

Keywords 3D object retrieval · Partial matching · 3D pottery dataset · Cultural heritage

K. Sfikas · A. Koutsoudis · M. Savelonas (✉)
ATHENA Research and Innovation Center, Xanthi, Greece
e-mail: msavelonas@gmail.com

K. Sfikas
e-mail: ksfikas@di.uoa.gr

A. Koutsoudis
e-mail: akoutsou@ipet.gr

I. Pratikakis
Department of Electrical, Computer Engineering, Democritus University of Thrace, Xanthi, Greece
e-mail: ipratika@ee.duth.gr

T. Theoharis
IDI, NTNU, Trondheim, Norway
e-mail: theotheo@idi.ntnu.no;theotheo@di.uoa.gr

T. Theoharis
Department of Informatics and Telecommunications, University of Athens, Athens, Greece

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1 Introduction

Generic 3D object retrieval has considerably matured and a number of accurate and robust descriptors have been proposed in the literature [7, 16, 26, 28, 34]. However, there are still many challenges regarding the retrieval of 3D models that originate from specific domains and/or exhibit special characteristics. One such domain is Cultural Heritage (CH), which includes 3D models that usually deteriorate due to aging, whereas their shape is altered due to environmental factors and, in most cases, they have only been preserved in the form of incomplete artefacts.

The challenge with the partial data is that it is difficult to effectively match them against a full 3D model representation. The representation gap complicates the extraction of a signature that will be, at least partially, similar when presented with a complete 3D model and when presented with a partial query of a similar object.

We propose to bridge the representation gap by a common representation based on features at interest points in the panoramic views of the 3D dataset models and the range images of the partial queries, respectively. For the complete 3D models, we compute a number of panoramic views on axes, which are perpendicular to the faces of a dodecahedron. Then, we build a Bag-of-Visual-Words (BoVW) model, for the dataset of complete 3D objects, that relies upon an enhanced Dense SIFT (e-DSIFT) descriptor of the keypoints. Similarly, for the partial objects, we initially compute a range image representation used as the query model for which the e-DSIFT descriptor is computed.

The remainder of the paper is structured as follows. In Section 2, we discuss state-of-the-art research on 3D model retrieval based on range image queries. Section 3 details the proposed method and Section 4 presents experimental results achieved in the course of the method's evaluation. Finally, conclusions are drawn in Section 5.

2 Related work

Over the past few years, the number of works addressing the problem of partial 3D object retrieval has increased significantly. Although this task still remains non-trivial, very important steps have been made in the field.

Stavropoulos et al. [31] present a retrieval method based on the matching of salient features between the 3D models and query range images. Salient points are extracted from vertices that exhibit local maxima in terms of protrusion mapping for a specific window on the surface of the model. A hierarchical matching scheme is used for matching. The authors experimented on range images acquired from the SHape REtrieval Contest 2007 (SHREC'07) *Watertight Models* [13] and the Princeton Shape Benchmark (PSB) standard [30] datasets.

Chaouch and Verroust-Blondet [5] present a 2D/3D shape descriptor which is based on either silhouette or depth-buffer images. For each 3D model, six projections are calculated for both silhouette and depth-buffers. The 2D Fourier transform is then computed on the projection. The same authors propose, in [6], a method where a 3D model is projected on the faces of its bounding box, resulting in six depth buffers. Each depth buffer is then decomposed into a set of horizontal and vertical depth lines that are converted to state sequences which describe the change in depth at neighboring pixels. Experimentations were conducted on range images artificially acquired from the PSB dataset.

Shih et al. [29] proposed the elevation descriptor where six depth buffers (elevations) are computed from the faces of the 3D model bounding box and each buffer is described by a set of concentric circular areas that give the sum of pixel values within the corresponding areas. The models being used were also derived from the standard PSB dataset.

Experimenting on the SHREC'09 *Querying with Partial Models* [9] dataset, Daras and Axenopoulos [8] presented a view-based approach for 3D model retrieval. According to their approach the 3D model is posed normalised and a set of binary (silhouette) and range images are extracted from predefined views on a 32-hedron. The set of features computed on the views are the Polar-Fourier transform, Zernike moments and Krawtchouk moments. Each query image is compared to all the extracted views of each model of the dataset.

Ohbuchi et al. [25] extract features from 2D range images of the model, viewed from uniformly sampled locations on a view sphere. For every range image, a set of multi-scale 2D visual features is computed using the Scale Invariant Feature Transform (SIFT) [23]. Finally, the features are integrated into a histogram using the Bag-of-Features approach [12]. The same authors enhanced their approach by pre-processing the range images, in order to minimize interference caused by any existing occlusions,as well as by refining the positioning of SIFT interest points, so that higher resolution images are favored [11, 24]. Their works have participated on both SHREC'09 *Querying with Partial Models* and SHREC'10 *Range Scan Retrieval* [10] contests.

Wahl et al. [35] propose a four-dimensional feature that parameterises the intrinsic geometrical relation of an oriented surface point pair (surflets). For a 3D model a set of surflet pairs is computed over a number of uniformly sampled viewing directions on the surrounding sphere. This work was one of the two contestants of the SHREC'10 *Range Scan Retrieval* track.

Koutsoudis et al. [18, 19] presented a set of 3D shape descriptors designed for content based retrieval of complete or nearly complete 3D vessels. Their performance evaluation experiments were performed on a dataset that included among others a subset of Virtual Hampson Museum 3D collection [17].

Bronstein et al. [4] introduced Shape Google, a 3D object retrieval method, which focuses on the retrieval of non-rigid objects. The method starts by calculating a feature detector and descriptor based on heat kernels of the Laplace-Beltrami operator. The descriptors derived are used to construct a BoVW vocabulary. The spatial relations between features are considered in an approach similar to commute graphs.

Lavoué [20] has presented an alternative 3D object retrieval method which combines standard BoVW and spatially-sensitive BoVW. Lavoué's method relies on a uniform sampling of feature points, based on Lloyds relaxation iterations. Each feature point is associated to a descriptor defined as the Fourier spectra of a local patch, which is computed by projecting the geometry onto the eigenvectors of the Laplace-Beltrami operator, so as to speed-up computations and enhance discriminative capability.

Li et al. [21] proposed a partial 3D object retrieval method which utilizes both geodesic distance-based global features and curvature-based local features, together with the BoVW framework, in order to develop a generic 3D shape retrieval algorithm that can be used for both non-rigid and partial 3D model retrieval. This framework can be extended to integrate different or more features, so as to develop other similar unified retrieval algorithms for both non-rigid and partial 3D model retrieval. This work also includes a rather extended review on the area.

Sfikas et al. [27] presented a methodology for 3D object partial matching and retrieval based on range image queries. The core methodology was based on Dense SIFT descriptor computed on panoramic views. This work was the first to address the partial retrieval of 3D pottery objects and still is the sole such application. In that respect, it provides a baseline to evaluate the improvements introduced here. In this paper, that preliminary work is extended in a two-folded fashion: first, enhancing the DSIFT descriptor with a histogram of depth values, computed in a neighborhood around each keypoint, resulting in the e-DSIFT descriptor. Second, using the e-DSIFT descriptor in a Bag-of-Visual-Words context.

3 Methodology

The main steps of the proposed methodology for partial 3D object retrieval via range image queries are: (i) 3D model panoramic view computation, (ii) shape descriptor extraction from each full 3D model of the dataset (off-line), (iii) range image computation for the partial query model, (iv) shape descriptor extraction from the range image (on-line) and (v) matching of the query descriptor against the descriptor of each 3D model of the dataset.

In the case of the complete 3D models, a number of panoramic views of each model are extracted on viewpoint axes that are defined by a dodecahedron, thus, extending the PANORAMA [26] method to multiple viewpoint axes.

3.1 Panoramic views extraction

In order to acquire a panoramic view of a dataset model, we project the model on the lateral surface of a cylinder of radius R and height $H = 2R$, centered at the origin with its axis parallel to one of the viewpoint axes (in this example the principal axis z, see Fig. 1a). We set the value of R to $2d_{max}$ where d_{max} is the maximum distance of the model's surface from its centroid.

In the following, we parameterise the lateral surface of the cylinder using a set of points $s(\phi, y)$ where $\phi \in [0, 2\pi]$ is the angle in the XY plane, $y \in [0, H]$ and we sample the ϕ and y coordinates at rates $2B$ and B, respectively (we set $B = 128$). We perform sampling of the

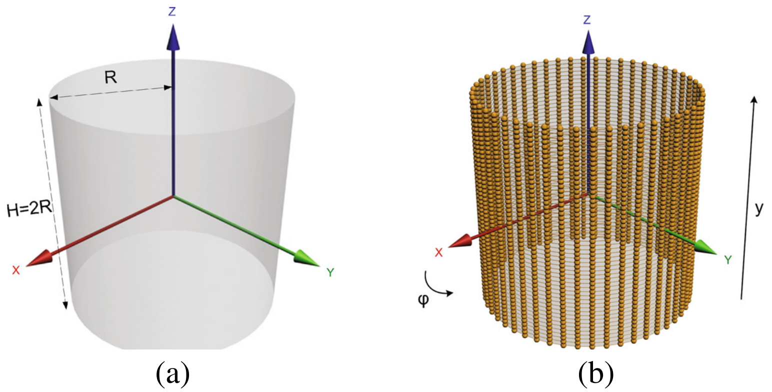


Fig. 1 **a** A projection cylinder for the acquisition of a 3D model's panoramic view and **b** the corresponding discretization of its lateral surface to the set of points $s(\phi_u, y_v)$

ϕ dimension at a sampling rate which is twice the rate of the y dimension. This is required to take into account the difference in length between the perimeter of the cylinder's lateral surface and its height. Thus, we obtain the set of points $s(\phi_u, y_v)$ where $\phi_u = u * 2\pi/(2B)$, $y_v = v * H/B$, $u \in [0, 2B-1]$ and $v \in [0, B-1]$. These points are shown in Fig. 1b.

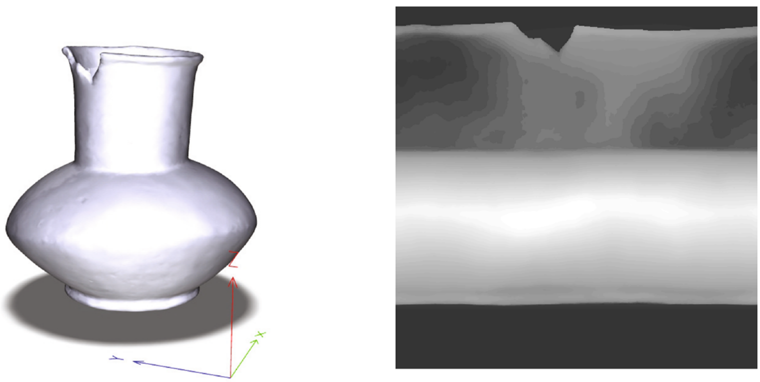
The next step is to determine the value at each point $s(\phi_u, y_v)$ of the panoramic view. The computation is carried out iteratively for $v = 0, 1, \ldots, B-1$, each time considering the set of coplanar $s(\phi_u, y_v)$ points, i.e. a cross section of the cylinder at height y_v and for each cross section we cast rays from its center c_v in the ϕ_u directions. In order to capture the position of the model surface, for each cross section at height y_v we compute the distances from c_v to the intersections of the model's surface with the rays at each direction ϕ_u.

Let $pos(\phi_u, y_v)$ denote the distance of the furthest from c_v point of intersection between the ray emanating from c_v in the ϕ_u direction and the model's surface; then $s(\phi_u, y_v) = pos(\phi_u, y_v)$. Thus the value of a point $s(\phi_u, y_v)$ lies in the range $[0, R]$, where R denotes the radius of the cylinder.

A cylindrical projection can be viewed as a 2D gray-scale image where pixels correspond to the $s(\phi_u, y_v)$ intersection points in a manner reminiscent of cylindrical texture mapping [32] and their values are mapped to the [0,1] space. In Fig. 2a, we show an example 3D model, aligned with the z axis, and in Fig. 2b the unfolded visual representation (panoramic view) of its corresponding cylindrical projection $s(\phi_u, y_v)$.

3.2 Enhanced DSIFT (e-DSIFT) descriptor computation

Once the panoramic views have been extracted, the enhanced DSIFT descriptor is calculated on them. The first step of the e-DSIFT computation, is the extraction of a number of keypoints, for which the DSIFT descriptors are calculated. The original implementation by Lowe [23] calculates interest points through the Difference of Gaussians (DoG) method, which is geared towards enhancing the edges and other details present in the image. It has been experimentally found that the calculation of the SIFT descriptors over the complete image for a large number of randomly selected keypoints (frequently defined as Dense SIFT/ DSIFT, in the literature), instead of selecting a limited number of interest points, yields better results in terms of retrieval accuracy [2, 3, 11].



(a) (b)

Fig. 2 **a** An example 3D model and **b** its corresponding cylindrical projection on the z-axis (panoramic view)

At each keypoint, an image descriptor is computed. The SIFT descriptor is defined as a position-dependent histogram of local gradient directions around the keypoint. To achieve scale invariance, the size of this local neighbourhood is normalised in a scale-invariant manner. To achieve rotational invariance of the descriptor, the dominant orientation of the neighbourhood is determined from the orientations of the gradient vectors in this neighbourhood and is used for orienting the grid over which the position-dependent histogram is computed.

A second feature calculated on the depth images is the histogram of depth values found in an n-ring neighborhood around a keypoint [1]. At each keypoint, a histogram accumulates the values of its adjacent pixels, with respect to their distance from the keypoint itself (Fig. 3). The total number of histogram bins corresponds to the number of cocentric shell sectors (selected neighborhood size). We have experimentally found that using a relatively small neighborhood n for the computation of the histograms, i.e. 5 pixels, yields better results than using a larger one. The keypoints selected for the computation of the histograms are the same keypoints, where the DSIFT descriptor is calculated. To compensate for the difference between the size of the depth values and DSIFT histograms, the first is resized so that its number of bins becomes equal to the size of the DSIFT histogram (128 bins). The intermediate values are determined via linear interpolation. The values stored in the bins of each histogram correspond to the image intensity values of the depth image. The bins are normalized by the total number of pixels added to the histogram.

3.3 Bag-of-Visual-Words modelling

Once the panoramic views extraction and the e-DSIFT descriptor calculation steps are complete, the Bag-of-Visual-Words (BoVW) model for the dataset is built. In visual information retrieval, the BoVW model defines that each image contains a number of local *visual features*. Since, in the general case a collection of visual features appears with different frequencies on different images, matching the visual frequencies on each image enables correspondence. In our case, the SIFT descriptors are defined as the BoVW features.

The basic step in the process of building the BoVW model for the 3D model dataset is the generation of a *codebook* (or a vocabulary), a collection of visual features that appear

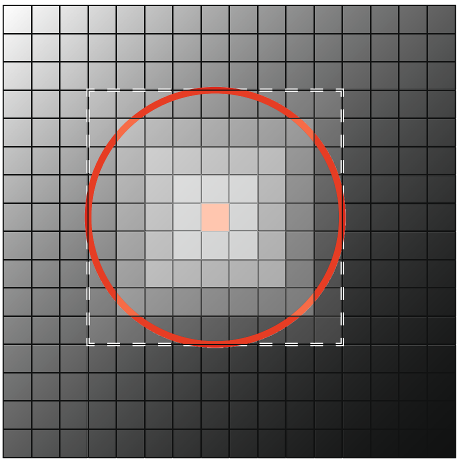


Fig. 3 Sample image detail with feature keypoint and n-ring neighborhood indicated

on each panoramic view image. The codebook is generated by considering the visual features of a representative number of dataset models. To achieve greater flexibility, rather than generating the codebook by selecting individual visual features of the models, the corresponding panoramic views are clustered into several similar patches, the *codewords*. One simple method is performing *k-means* clustering [22] over all the visual features. Codewords are then defined as the centers of the learned clusters. The number of the clusters is the codebook size. Thus, each patch in a panoramic image is mapped to a certain codeword through the clustering process and the panoramic image can be represented by the histogram of the codewords. In the proposed methodology, we have set the number of codewords to 80. Furthermore, the codebook of the BoVW model is built on 10 % of the complete 3D model dataset, selected in proportion to the population of the classes.

Once the codebook generation is complete, the encoding/description of the 3D models in the dataset is performed using the corresponding codewords. In a similar manner, for each panoramic view of the 3D model set, the visual features are computed and matched to their closest codewords, by comparing them to the corresponding clusters, generated in the previous step. Again, the *k-means* algorithm is used for matching. The set of histograms describing the frequency of occurrence of the generated codewords, for each 3D model's panoramic views, is stored as the corresponding signature of the 3D model.

3.4 Query matching

In the case of query models, range images are computed from the depth buffer. The selected size of sampling is $B \times B$ pixels. In a strategy similar to the histogram computation for the panoramic views of the dataset 3D models, the queries are compared to the models of the dataset. The e-DSIFT descriptor is extracted from the range image and based on the generated BoVW model, a histogram describing the codebook frequencies of occurrence is computed as the query's descriptor.

Following feature extraction, the descriptor histogram for each query range image must be matched against the corresponding descriptor histograms of each complete dataset 3D model. To this end, the descriptor histogram of the range image is compared against every descriptor histogram of a 3D model's set of panoramic views, using as a metric the L_2 distance. The minimum of these distances is the final distance between the query and the target model.

4 Evaluation

For the experimental evaluation we have used a dataset related to the cultural heritage domain which is a 3D pottery dataset originating from the Hampson Archaeological Museum collection.

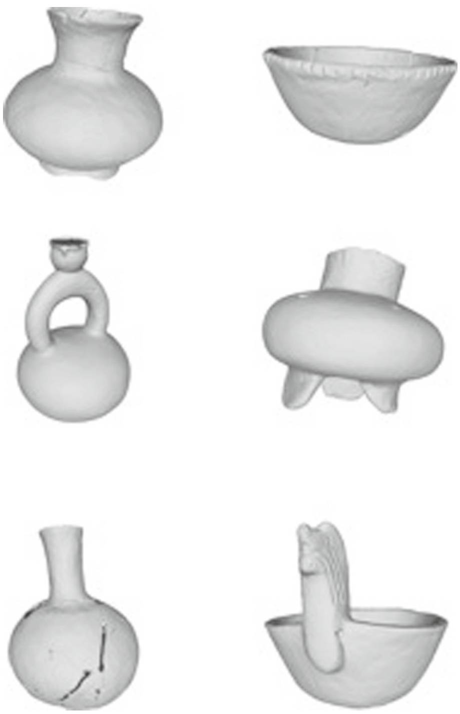
The Hampson Archaeological Museum collection is a major source of information on the lives and history of pre-Columbian people of the Mississippi river valley [14]. The Centre of Advanced Spatial Technologies - University of Arkansas worked on the digitisation of numerous artefacts from the Hampson museum collection using a Konica-Minolta Vivid 9i short-range 3D laser scanner. The digitisation was performed at a precision close to 0.2 mm. The 3D digital replicas are covered by the creative common 3.0 license and are offered for online browsing or downloading in both high (>1M facets) and low (<=25K facets) resolutions [15].

We have used 384 models of low resolution, that were downloaded from the website of the museum along with associated metadata information, as a testbed for content based retrieval and partial matching experiments. Initially the models were classified, based on semantics, into 6 classes (Bottle, Bowl, Jar, Effigy, Lithics and Others). As this classification did not ensure similarities based on shape within a given class, we performed an extended shape-oriented classification. We initially organised the models into thirteen classes of different populations (Bottles, Bowls 1 - 4, Figurines, Masks, Pipes, Tools, Tripod-Base Vessels, Conjoined Vessels, Twin Piped Vessels and Others). In the sequel five of these classes (all Bottles and Bowls classes) were further divided into 15 subclasses resulting in a total of 23 distinct classes.

It should be pointed out that this is the maximum amount of image examples that can be derived from the Hampson museum collection. Similar pottery datasets are not publicly available, a fact that could be the main reason for the lack of past research in retrieval methods of such objects. However, several state-of-the-art retrieval methods have been experimentally validated on datasets of comparable sizes (e.g. Tierny et al. [33], Stavropoulos et al. [31], Lavoué [20] have been applied on a dataset of 400 objects). Figure 4 illustrates example 3D models of the pottery dataset used, indicative of its diversity.

Since this dataset does not contain any partial 3D object that can be used as query, we artificially created a set of 20 partial queries by slicing and cap filling a number of complete 3D objects, originating from those classes that are densely populated. The partial queries comprise objects with a reduced surface compared to the original 3D object by a factor which ranges from 40 % to 25 % with a step of 5 %.

Fig. 4 Example 3D models of the pottery dataset used



As an update to the benchmark dataset, we have created a new categorization which takes more into consideration the shape characteristics of the 3D models and thus being more suitable for 3D object retrieval purposes. This new classification is composed of 16 classes. Table 1 shows the newly defined classes along with their cardinalities.

Our experimental evaluation is based on Precision-Recall (P-R) plots and five quantitative measures: Nearest Neighbor (NN), First Tier (FT), Second Tier (ST), E-measure (E) and Discounted Cumulative Gain (DCG) [30] for the classes of the corresponding datasets. For every query model that belongs to a class C, recall denotes the percentage of models of class C that are retrieved and precision denotes the proportion of retrieved models that belong to class C over the total number of retrieved models. The maximum score is 100 % for both quantities. Nearest Neighbor (NN) indicates the percentage of queries where the closest match belongs to the query class. First Tier (FT) and Second Tier (ST) statistics, measure the recall value for the $(D-1)$ and $2(D-1)$ closest matches respectively, where D is the cardinality of the query class. E-measure combines precision and recall metrics into a single number and the DCG statistic weights correct results near the front of the list more than correct results later in the ranked list under the assumption that a user is less likely to consider elements near the end of the list [30].

In Fig. 5 we illustrate the average P-R scores for the presented 3D model retrieval method using the artificially created partial queries of the complete pottery dataset (for both categorizations). The proposed method is compared to the previously presented approach in [27]. Results are presented for various amounts of partiality. Figure 6 illustrates query examples and the corresponding list of the retrieved 3D models for the proposed method, as well as for the method of [27].

Table 2 shows the results obtained in terms of the five quantitative measures by the baseline method of [27] (first part) and the proposed method (second and third part). The latter is applied on the initial version of the dataset (second part), in order to allow comparisons

Table 1 Categorization of the updated dataset

No	Class name	Cardinality
1	Appendages	19
2	Ball-like-short-neck	11
3	Bottles-wide-body-long-neck	12
4	Bottles-wide-prism-body-long-neck	30
5	Bottles-wide-body-medium-neck	39
6	Bottles-wide-body-short-neck	55
7	Ducks	20
8	flat-long	6
9	Open	87
10	Open-Curved	9
11	Other	44
12	pipes	2
13	Sphere-like_long_neck	11
14	Tooth	33
15	Tripod Base	4
16	Twins	2

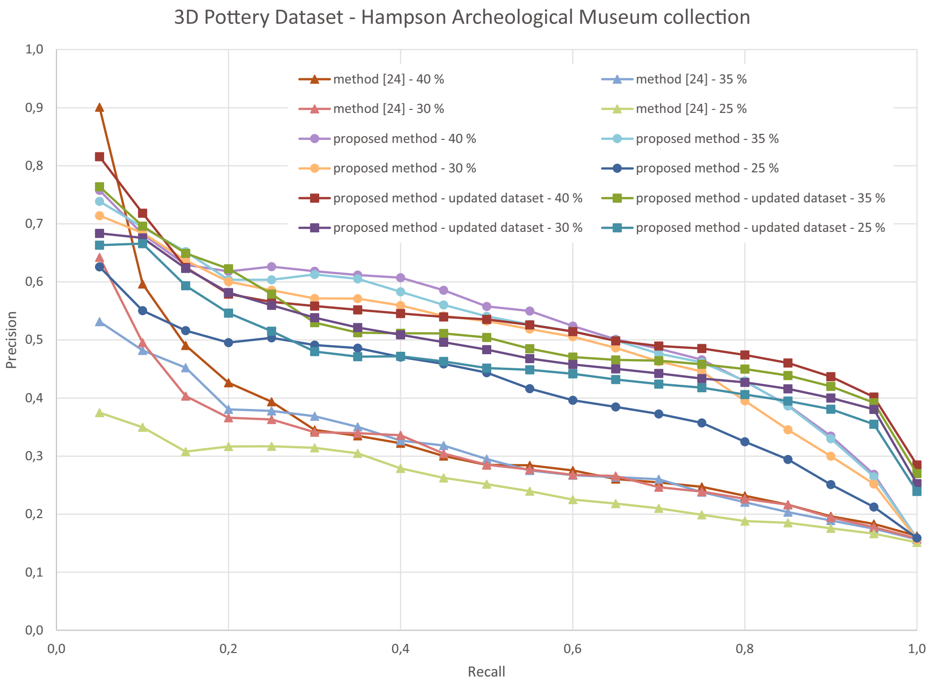


Fig. 5 Average P-R scores for the pottery dataset originating from the Hampson Archaeological Museum collection. Illustrated is the performance of the proposed method, as well as the previous method [27], obtained using queries with increasing available surface (25–40 %) with respect to the surface of the original complete 3D models

with the baseline method of [27], as well as on the updated version of the dataset (third part), in order to reflect more accurately the actual retrieval performance obtained. The results are apposed for four different levels of partiality (25–40 %). In the case of the baseline method, it can be observed that the retrieval performance is rather low for 25 % partiality. Moreover, the performance obtained is not consistently increasing with the relative size of the

Fig. 6 Example retrieval results from the pottery dataset. At each row, a partial query (column 1) and a ranked list of the retrieved 3D objects (columns 2–8) are shown

Table 2 Five quantitative measures for the presented 3D object retrieval methodology, using partial queries on the pottery dataset. All measures are normalized

Partiality	NN	FT	ST	E	DCG
Method [27]					
25 %	0.23	0.227	0.388	0.185	0.587
30 %	0.428	0.289	0.495	0.228	0.655
35 %	0.619	0.372	0.536	0.327	0.713
40 %	0.857	0.288	0.508	0.237	0.683
Proposed Method					
25 %	0.619	0.416	0.626	0.309	0.721
30 %	0.619	0.494	0.639	0.363	0.760
35 %	0.666	0.510	0.671	0.385	0.773
40 %	0.666	0.518	0.673	0.387	0.774
Proposed Method - Updated Dataset					
25 %	0.605	0.516	0.640	0.360	**0.743**
30 %	0.625	**0.524**	0.649	**0.368**	0.755
35 %	0.722	0.525	0.653	0.387	**0.780**
40 %	0.722	0.575	0.699	0.418	0.805

query. On the other hand, it can be derived that the proposed method is able to satisfactorily handle the problem of partial matching. Even when only one quarter of the surface of original model is available in the query, the results are acceptable. The addition of the depth values histogram, as well as the Bag-of-Visual-Words modelling has significantly increased the performance of the proposed method by an average of 13 % over all measures. Furthermore, it is clear that the numeric results exhibit a more coherent variation with respect to the partiality level of the 3D models. Finally, the retrieval performance obtained when using the updated version of the dataset is improved, since the classification of this version is shape-oriented.

The proposed method was tested on a Core2Quad 2.5 GHz system, with 6 GB of RAM, running Matlab R2012b. The system was developed in a hybrid Matlab/C++/OpenGL architecture. The average computational time for the creation of the Bag-of-Visual-Words model (for the complete dataset) is approximately 3 min (7 min including panoramic views extraction), however this constitutes an offline procedure. The average computational time for computing the retrieval list of a single query (including range image extraction) is approximately 2 seconds.

5 Conclusions

We have presented a method for partial matching based on Bag-of-Visual-Words modelling using enhanced DSIFT computed on panoramic views and range images queries. This method is able to encode the continuous characteristics of the partial 3D models into a 2D representation, thus preserving model structure. The performance of the method is evaluated on a pottery dataset originating from the Hampson Archaeological Museum collection of historical artefacts. We have shown that using the proposed methodology, we can attain retrieval results which are not severely affected by the reduction in 3D model surface.

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Konstantinos Sfikas is currently a Ph.D. candidate at the department of Informatics and Telecommunications, National & Kapodistrian University of Athens. He received his B.Sc. with honors, in Informatics from the Technological Educational Institute of Athens in 2006 and his M.Sc. with honors, in Advanced Informatics Systems from the National and Kapodistrian University of Athens in 2008. He has received various scholarships and awards for his performance during his B.Sc. and M.Sc. studies. In addition, for his M.Sc. and Ph.D. studies he received a scholarship by the Greek National Scholarship Foundation (I.K.Y.). He has been actively involved in various research projects since 2004. He is a reviewer in prestigious international journals and conferences. His main research interests are in the field of computer graphics, with special focus on both rigid and non-rigid 3D object retrieval.

Ioannis Pratikakis is currently an Assistant Professor at the Department of Electrical and Computer Engineering, Democritus University of Thrace, Xanthi, Greece. He received the Ph.D. degree in Applied Sciences from the Department of Electronics Engineering and Informatics at Vrije Universiteit Brussel, Belgium, in January 1999. From March 1999 to March 2000, he was at IRISA, Rennes, France as an INRIA postdoctoral fellow. Since 2003, he was working as Research Scientist at the Institute of Informatics and Telecommunications in the National Centre for Scientific Research “Demokritos”, Athens, Greece. His research interests include 2D & 3D image processing and analysis, 2D & 3D image sequence analysis, document image analysis and recognition, 3D computer vision, graphics and multimedia search and retrieval with a particular focus on visual modalities. He has published more than 100 papers in journals, book chapters and conference proceedings in the above areas. He has participated in more than 15 national and international R&D projects. He has served as a co-organiser of the Eurographics Workshop on 3D object retrieval (3DOR) in 2008 and 2009 as well as Guest Editor for the Special issue on 3D object retrieval at the International Journal of Computer Vision. He is member of the IEEE Signal Processing Society and the European Association for Computer Graphics (Eurographics). He is member of the Board of the Hellenic Artificial Intelligence Society (EETN).

Anestis Koutsoudis received his BSc (Hons) Computer Studies (Visualisation) from the University of Derby, UK and his MSc in Multimedia Technology from the Computer Science Department of the University of Bath, UK. He received his PhD degree from the Electrical and Computer Engineering Department of Democritus University of Thrace, Greece. He was worked as the head of computer administration and computer graphics department in Channel 6 RadioTelevision S.A. Xanthi, Greece. He currently holds an Associate Research Fellow (grade B’) position in the Institute for Language and Speech Processing of the Athena research centre. He has participated in several research and development projects that were focused on cultural heritage dissemination, 3D digitisation, multimedia and 3D graphics software development. His research interests involve 3D objects content based retrieval, virtual reality multimedia technologies, real time 3D graphics, 3D digitisation, 3D scene annotation and software engineering. He is a member of the IEEE Computer Society and a member of the Hellenic Informatics Union.

Michalis A. Savelonas received the B.Sc. degree in Physics in 1998, the M.Sc. degree in Cybernetics in 2000 with honors, and the Ph.D. degree in the area of Image Analysis in 2008 with honors, all from the University of Athens, Greece. For his Ph.D. research he received a scholarship by the Greek General Secretariat of Research and Technology (25 %) and the European Social Fund (75 %). He is currently a research fellow in Athena Research and Innovation Center, branch of Xanthi, as well as in the Dept. of Electrical and Computer Engineering in the Democritus University of Thrace. In addition, he is a regular research associate of the Dept. of Informatics and Telecommunications of the University of Athens, Greece, as well as of the Center for Technological Research of Central Greece. In the past, he has served in various academic positions in the University of Athens, University of Houston, TX, USA, Hellenic Air Force Academy and Technological Educational Institute of Lamia. In 2002–2004 he has been working in software industry for the development of real-time systems within the context of various projects. Dr. Savelonas has co-authored more than 50 research articles in peer-reviewed international journals, conferences and book chapters, whereas he has been actively involved in several EU, US and Greek R&D projects. He is a reviewer in prestigious international journals including Pattern Recognition and IEEE Trans. Image Processing. His research interests include image analysis, pattern recognition, 3D retrieval and biomedical applications.

Theoharis Theoharis received his doctorate from the University of Oxford in Computer Graphics and Parallel Processing in 1988. His research interests lie in graphics, visualization and vision and more specifically in biometrics, 3D object retrieval, medical and archaeological visualization, geometric algorithms and 3D reconstruction. He is an author of the textbook Graphics & Visualization: principles and algorithms, AK Peters, 2008, http://graphics.cs.aueb.gr/cgvizbook/index.html.