

# Multi-dimensional Object Retrieval Using Object Hypergraph Structure and Spatial Structure

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## ABSTRACT:-

*Massive production in the industries is demanding an important of reproducing multidimensional engineering objects. This paper presently deals with representing a new retrieval approach for multidimensional object through a combination of hypergraph structure and spatial structure. This method obtained better results over the existing methods in the literature. In this paper we propose to jointly learning the object hypergraph structure and spatial structures (view-model) relevance among multidimensional objects for retrieval, in which the multidimensional objects are formulated in different graph structures. In this work collaboration of both view and model approaches are used for retrieval and multidimensional objects perception is performed based on various graph structures. Objects view information is implemented at initial stage to perceive the multidimensional objects in multiple views and object graph is constructed for model data obtaining the information about the relationship between different features of the object better performance and high efficiency of proposed work over the traditional state of art methods. The proposed method has been evaluated in three datasets. The experimental results and comparison with the state of art methods, demonstrate the effectiveness on retrieval accuracy of proposed multidimensional object retrieval method*

**Keywords:** - Multidimensional object, Hypergraph structure, Spatial structure, Jointly learning.

## I. INTRODUCTION

Rapid developments in the hardware of graphics, an importance of multidimensional objects have been observed in the application of computers, medical applications and animations. With the improvement of the Multi-dimensional

modelling tools and scanning devices, as well as the development of computer software and hardware technology, Multi-dimensional objects become a type of important multimedia data with many applications, whose amount increases at geometric series. Roughly, beginning by 2000, Multi-dimensional objects increasingly came into focus of multimedia retrieval research. Reusing the models by retrieving Multi-dimensional models in a large database becomes an important issue in the entertainment, CAD/CAM, game design and medical imaging. This has led to the research and development of Multi-dimensional shape retrieval methods. Obviously, the Multi-dimensional models [4] can't be easily and precisely described only by text, content-based Multi-dimensional model retrieval (below CBMDR) system was developed. These systems use the colour, texture and shape information. The shape information is represented by rotation, scaling-, translation-invariable feature descriptors based on topology, views and shape. Part matching uses local features.

There exist two major research problems concerning the design of content-based multimedia retrieval systems. In the first problem, one is concerned with finding robust representation schemes describing the content of multimedia objects in terms of compact surrogates. In the context of Multi-dimensional objects [13], content description is synonymous to Multi-dimensional shape description. Several effective and efficient description algorithms have been proposed in the last decade and promising performance results have been obtained on standard benchmarks. In the second

problem, one seeks computational similarity measures between descriptors that well approximate the semantic similarity between objects, based on the grounds of user requirements and perceptual judgments. This second issue constitutes the main focus of the present paper. Specifically, we propose novel similarity learning algorithms for Multi-dimensional object retrieval (MDOR) and test them against existing ones.

With the fast development of internet technology, computer hardware, and software, Multi-dimensional models have been widely used in many applications, such as computer graphics, computer vision, CAD[8] and medical imaging. Effectively and efficiently retrieve Multi-dimensional model retrieval has attracted much research attention these days. Multi-dimensional model retrieval methods can be divided into two categories: model-based methods and view-based methods. Early works are mainly model-based methods, in which low-level feature based methods (e.g. the geometric moment, surface distribution, volumetric descriptor and surface geometry or high-level structure-based methods are employed. Due to the requirement of Multi-dimensional models, these methods are limited in the practical applications.

It is noted that most of existing methods separate the model based methods and the view-based methods, and employ either model information or view feature for Multi-dimensional object retrieval. In this work, we propose to jointly employ both the model and the view information for Multi-dimensional object relevance estimation. In the view part, representative views are firstly selected for each object, and then the view-level distances are calculated. An object hypergraph[6] is constructed using the view star expansion. In the model part, the spatial structure circular descriptor is extracted and a simple graph is generated using the pair wise object distances. In this way, the view information and the model data can be formulated in two graph structures. Learning on the two graphs is conducted to estimate the relevance among Multi-dimensional objects, in which the graph weights can be also optimized.

## II. FROM 2D PHOTOGRAPHY TO MULTI-DIMENSIONAL OBJECT RETRIEVAL

Due to the compactness of global Multi-dimensional object descriptors, their performance in capturing inter/intra class variability's are known to be poor in practice. In contrast, local geometric descriptors, even though computationally expensive, achieve relatively good performance and captures inter/intra class variability's (including deformations) better than global ones. The framework presented in this paper is based on local features and also cares about computational issues while keeping advantages in terms of precision and robustness.

Our target is searching Multi-dimensional databases of objects using one or multiple 2D views; this scheme will be referred to as "2D-to-Multi-dimensional". We define our probe set as a collection of single or multiple views of the same scene or object while our gallery set corresponds to a large set of Multi-dimensional models. A query, in the probe set, will either be (i) multiple views of the same object, for instance stereo-pair, or (ii) a Multi-dimensional object model processed in order to extract several views; so ending with the "2D-to-Multi-dimensional" querying paradigm in both cases (iii). Gallery data are also processed in order to extract several views for each Multi-dimensional object

At least two reasons motivate the use of the 2D-to-Multi-dimensional querying paradigm:

- The difficulty of getting "Multi-dimensional query models" when only multiple views of an object of interest are available. This might happen when Multi-dimensional reconstruction techniques fail or when Multi-

dimensional acquisition systems are not available. 2D-to-Multi-dimensional approaches should then be applied instead.

- Multi-dimensional gallery models can be manipulated via different similarity and affine transformations, in order to generate multiple views which fit the 2D[7] probe data, so “2D-to-Multi-dimensional” recognition and retrieval paradigm can be achieved.

### III. LITERATURE SURVEY

Elad et al. [2001] have used moments (up to the 7th order) of surface points, exploiting the fact that, different from the case of 2D images, Multi-dimensional models computation of moments is not affected by self-occlusions. In Zhang [2001], a representation based on moment invariants and Fourier transform coefficients has been combined with active learning to take into account user relevance feedback and improve the effectiveness of retrieval. In Novotni [2003], a method has been presented to compute Multi-dimensional Zernike descriptors from voxelized models. Multi-dimensional Zernike descriptors capture object coherence in the radial direction and in the direction along a sphere. However, the effectiveness of the approach is strongly dependent on the quality of the voxelization process.

View-based descriptions use a set of 2D views of the model and appropriate descriptors of their content to represent the Multi-dimensional object shape. One problem with this approach is concerns the need for representations that are computationally tractable. In Mahmoudi [2002] and Ohbuchi [2003], a number of views of the Multi-dimensional object is taken and, for each view, the 2D profile is considered. Hence, PCA[10] has been used to reduce all object views to a limited set of representative views that are used to represent the whole Multi-dimensional object shape.

Shape descriptions based on statistical models consider the distribution of local features measured at the vertices of the Multi-dimensional object mesh. The simplest approach approximates a feature distribution with its histogram. Any metric can be used to compute the similarity between the distributions of two models[3]. In Vandeborre [2002], representation of Multi-dimensional objects is captured using histograms of the curvature of mesh vertices. In Osada et al. [2002], the authors have introduced shape functions as distributions of shape properties. Each distribution is approximated through the histogram of the values of the shape function

#### IV. PROPOSEDMETHOD

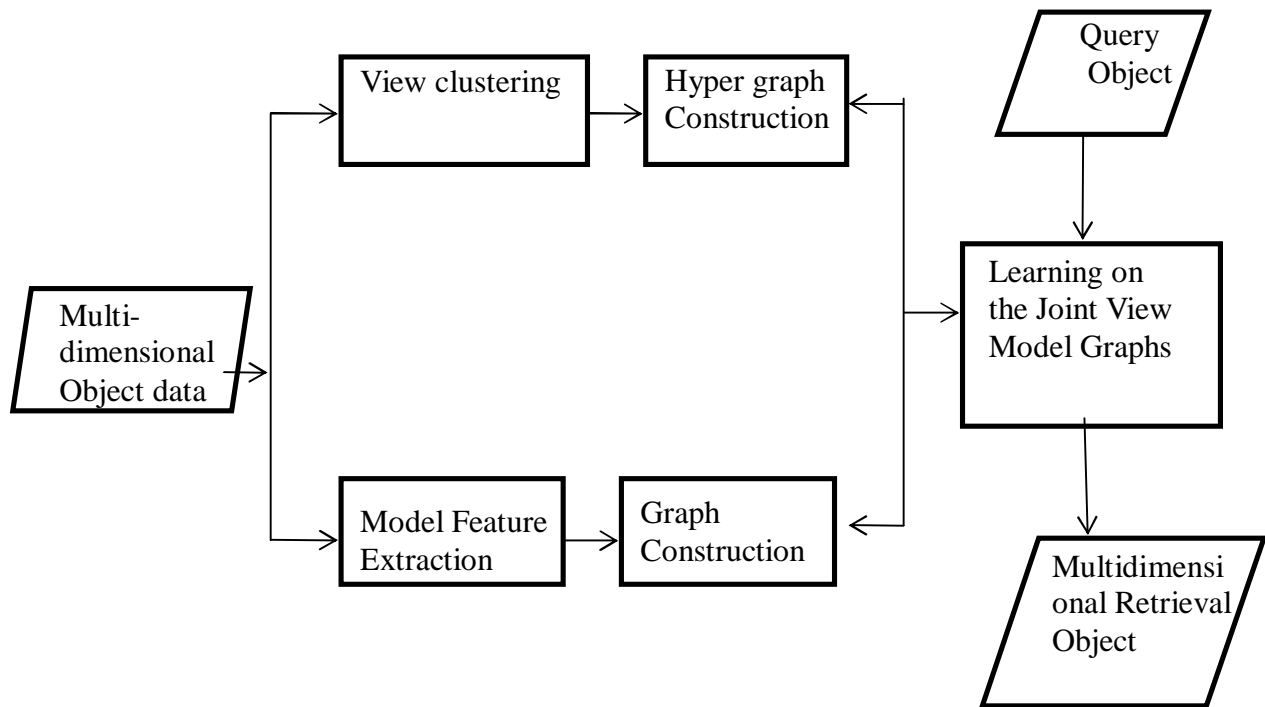


Fig1: The frame work of the proposed method

##### (A) Multi-dimensional object retrieval and recognition with hyper graph analysis

View based 3-D object retrieval and recognition has become popular in practice, e.g., in computer aided design. It is difficult to precisely estimate the distance between two objects represented by multiple views. Thus, current view-based Multi-dimensional[1] object retrieval and recognition methods may not perform well. In this paper, we propose a Hypergraph analysis approach to address this problem by

avoiding the estimation of the distance between objects: In particular, we construct multiple hyper graphs for a set Multi-dimensional objects based on their 2-D views. In these hyper graphs, each vertex is an object, and each edge is a cluster of views. Therefore, an edge connects multiple vertices. We define the weight of each edge based on the similarities between any two views within the cluster. Retrieval and recognition are performed based on the hyper graphs. Therefore, our method can explore the higher order relationship among objects and does not use the distance between objects.

### (B) Hyper graph generation from hyperstructure

Here the view-based hyper graph is generated following the method in [2] and briefly introduced as follows. Let  $O = \{O_1, \dots, O_n\}$  denote the Multi-dimensional objects in the data set, and  $V_i = \{v_{i1}, \dots, v_{in}\}$  denote the  $n_i$  views of the  $i^{\text{th}}$  Multi-dimensional object  $O_i$ . In this part, we aim to explore the relevance among Multi-dimensional object with multiple view information.

Generally, although multiple views can represent rich information of Multi-dimensional objects, they also bring in redundant data, which may cause much computational cost and even lead to false results. Here we first select representative views for each Multi-dimensional object, and only these representative views are employed in the Multi-dimensional object retrieval process.

Given then  $n_i$  views  $V_i = \{v_{i1}, \dots, v_{imi}\}$  of  $O_i$ , we conduct hierarchical agglomerative clustering (HAC) to group these views into view clusters. The HAC method is selected here due to that it can guarantee the intra cluster distance between each for  $O_i$ . In our experiments,  $m_i$  mostly ranges from 5 to 20.

Hypergraph has been used in many multimedia information retrieval tasks, such as image retrieval. Hypergraph has shown its

superior on high-order information representation. In our work, we propose to employ star expansion to construct an object hypergraph with views to formulate the relationship among Multi-dimensional objects. Here we denote the object hypergraph as  $G_H = (V_H, E_H, W_H)$ . For the  $n$  objects in pair of views cannot exceed a given threshold. Here the widely employed Zernike moments are used as the view features, which are robust to image rotation, scaling and translation and have been used in many Multi-dimensional object retrieval tasks. The 49-D Zernike moments are extracted from each view of Multi-dimensional objects. With the view clustering results, one representative view is selected from each view cluster. Here we let  $V_i = \{v_{i1}, \dots, v_{imi}\}$  denote the  $m_i$  representative views for  $O_i$ . In our experiments,  $m_i$  mostly ranges from 5 to 20.

Hypergraph has been used in many multimedia information retrieval tasks, such as image retrieval. Hypergraph has shown its superior on high-order[10] information representation. In our work, we propose to employ star expansion to construct an object hypergraph with views to formulate the relationship among Multi-dimensional objects.

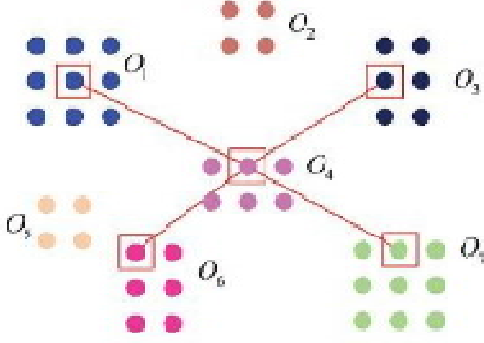


Fig.2: An illustration of hyper edge construction. In this figure, there are seven objects with representative views. Here one view from O4 is selected as the centra view, and its four closest views are located in the figure, which are from O1, O3, O6 and O7. Then the corresponding hyper edge connects O1, O3, O4, O6 and O7

The hyper edges are generated as follows. We assume there are totally  $n_r$  representative views for all  $n$  objects. We first calculate the Zernike moments- based distance between each two views, and the top  $K$  closest views can be generated for each representative view. For each representative view, one hyper edge is constructed, which connects the objects with views in the top  $K$  closest views. In our experiment,  $K$  is set as 10. Figure 2 shows an example of hyper edge generation. Generally,  $n_r$  hyper edges can be generated for  $G_H$ . The weight of one hyper edge  $e_H$  can be calculated by

$$w_H(e) = \frac{1}{k} \sum \exp\left(-\frac{d(v_x, v_c)^2}{\sigma_H^2}\right) \quad (1)$$

Where  $v_c$  is the centre view of the hyper edge,  $v_x$ , is one of the top  $K$  closest view to  $v_c$ ,  $d(v_x, v_c)$  is the distance between  $v_c$  and  $v_x$ , and  $\sigma_H$  is empirically set as the median of all view pair distances.

Given the object hyper graph  $G_H = \{V_H, H, W_H\}$ , the incidence matrix  $H$  can be generated by

$$h(v_H, e_H) = \begin{cases} 1 & \text{if } v_H \in e_H \\ 0 & \text{if } v_H \notin e_H \end{cases} \quad (2)$$

In the constructed hypergraph, when two Multi-dimensional objects share more similar views, they can be connected by more hyperedges with high weights, which can indicate the high correlation among these Multi-dimensional objects.

### (c) Spatial structure generation

Given the model data of Multi-dimensional objects, here we further explore the model-based object relationship. Here the spatial structure circular descriptor (SSCD) is employed as the model feature. SSCD aims to represent the depth information of the model surface on the projection minimal bounding box of the Multi-dimensional model. The depth histogram[11] is generated as the feature for the Multi-dimensional model. Following, the bipartite graph matching is conducted to measure the distance between each two Multi-dimensional models,  $d_{SSCD}$  i.e.,  $(O_i, O_j)$ . Here, the relationship among Multi-dimensional objects is formulated in a simple object graph structure  $G = (V, E, W)$ . Here each vertex in  $G$  represents one Multi-dimensional object, i.e., there are  $n$  vertices in  $G$ . The weight of an edge  $e(i, j)$  in  $G$  is calculated by using the similarity between two corresponding Multi-dimensional objects  $O_i$ , and  $O_j$  as

$$w(v_i, v_j) = \exp\left(-\frac{d_{SSCD}(v_i, v_j)^2}{\sigma_s^2}\right) \quad (3)$$

Where  $d_{SSCD}(v_i, v_j)$  is distance between  $O_i$ , and  $O_j$  and  $\sigma_s$  is set as the median of all modal pair distances.

### (D) Studying collective of hypergraph and spatial structures

Now we have two types of formulation of relationship among Multi-dimensional objects, i.e., view-based and model-based. Here these two formulations are jointly explored to estimate the relevance among Multi-dimensional objects. In this part, first we introduce the learning framework[12] when the view-based and model-based information are regarded with equal weight, and then we propose a jointly learning framework to learn the optimal combination weights for each modality.

#### 1. The fundamental study on framework:

Here we start from the learning framework which regards different modalities, i.e., model and view, as equal. The Multi-dimensional object retrieval[1] task can be formulated as the one-class classification work as shown. The main objective is to learn the optimal pair wise object relevance under both the graph and hyper graph structure.

Given the initial labeled data (the query object in our case), an empirical loss term can be added as a constraint for the learning process.

The transductive inference can be formulated as a regularization as

$$\arg \min_f \{ \Omega_V(f) + \Omega_M(f) + \mu R(f) \} \quad (4)$$

In this formulation,  $f$  is the to-be-learned relevance vector;  $\Omega_V(f)$  is the regularizes term on the view-based hypergraph structure,  $\Omega_M(f)$  is the regularizer term on the model-based graph structure,  $R(f)$  is the empirical loss.

This objective function aims to minimize the empirical loss and the regularizes on the model-based graph and the view-based

hyper graph simultaneously which can lead to the optimal relevance vector  $f$  for retrieval.

The two regularizes and the empirical loss terms are defined as follows.

The view-based hyper graph regularizes  $\Omega_V(f)$  is defined as

$$\Omega_V(f) = f^T \Delta_H f \quad (5)$$

The model-based graph regularizer  $\Omega_M(f)$  is defined as

$$\Omega_M(f) = f^T (I - \theta_S) f \quad (6)$$

where  $\theta_S = D^{-\frac{1}{2}} W D^{\frac{1}{2}}$ .

$$\Omega_M(f) = f^T \Delta_S f \quad (7)$$

We denote  $\Delta_S = I - \theta_S$

The empirical loss term  $R(f)$  is defined as

$$R(f) = \|f - y\|^2 \quad (8)$$

Where  $y$  is the initial label vector. In the retrieval process, it is defined as an  $n \times 1$  vector, in which only the query is set as 1 and all other components are set as 0.

Now the objective function can be rewritten as

$$\arg \min_f \left\{ f^T \Delta_H f + f^T \Delta_S f + \mu \|f - y\|^2 \right\} \quad (9)$$

can be solved by

$$f = \left( I + \frac{1}{\lambda} (\Delta_H + \Delta_S) \right)^{-1} y \quad (10)$$

$f$  is the relevance of all the objects in the dataset with respect to the query object. A large

relevance value indicates high similarity between the object and the query. The higher the corresponding relevance value is, the more similar the two objects are. With the generated object relevance  $f$ , all the objects in the dataset can be sorted in a descending order according to  $f$ .

## 2. Study of combination weights

Ultimately, the goal in Multi-dimensional similarity search is to design database systems that store Multi-dimensional objects and effectively and efficiently support similarity queries. In this section, we discuss the main problems posed by similarity search in Multi-dimensional object databases. 2.1. Descriptors for Multi-dimensional Similarity Search Multi-dimensional objects can represent complex information. The difficulties to overcome in defining similarity between spatial objects are comparable to those for the same task applied to 2D images. Geometric properties of Multi-dimensional objects can be given by a number of representation formats as outlined in the introduction. Depending on the format, surface and matter properties can be specified. The object's resolution can be arbitrarily set[14]. Given that there is no founded theory on a universally applicable description of Multi-dimensional shapes or how to use the models directly for similarity search, in a large class of methods for similarity ranking, the Multi-dimensional data is transformed in some way to obtain numeric descriptors for indexing and retrieval.

Here we let  $m$  and  $n$  denote the combination weights for view-based and model-based information respectively, where  $m+n=1$ . After adding the  $l_2$ norm on the combination weights, the objective function can be further revised as

$$\arg \min_{f,m,n} \left\{ \begin{array}{l} mf^T \Delta_H f + n f^T \Delta_S f \\ + \mu \|f - y\|^2 + k(m^2 + n^2) \end{array} \right\} \quad (11)$$

Where  $m + n=1$

According to Eq. (10), it can be solved by

$$f = \left( I + \frac{1}{\lambda} (m\Delta_H + n\Delta_S) \right)^{-1} y \quad (12)$$

Then we optimize  $m/n$  with fixed  $f$ . Here we employ the Lagrangian method, and the objective function changes to

$$\arg \min_{m,n} \left\{ \begin{array}{l} mf^T \Delta_H f + n f^T \Delta_S f \\ + \eta (m^2 + n^2) + k(m + n - 1) \end{array} \right\} \quad (13)$$

Solving the above optimization problem, we can obtain

$$k = -\frac{f^T \Delta_H f + f^T \Delta_S f}{2} - \eta \quad (14)$$

$$m = \frac{1}{2} - \frac{f^T \Delta_H f - f^T \Delta_S f}{4\eta} \quad (15)$$

$$n = \frac{1}{2} - \frac{f^T \Delta_S f - f^T \Delta_H f}{4\eta} \quad (16)$$

The above alternative optimization can be processed under the optimal  $f$  value is achieved, which can be used for the Multi-dimensional object retrieval. With the learned combination weights, the model-based and view-based data[15] can be optimally explored simultaneously and the relevance vector  $f$  can be obtained. The main merit of the proposed method is that it jointly explores the view

information and the model data of Multi-dimensional objects in hyper graph/graph frameworks for Multi-dimensional object retrieval.

## V. RESULTS



Fig.3. Query image



Fig.4. Retrieved images

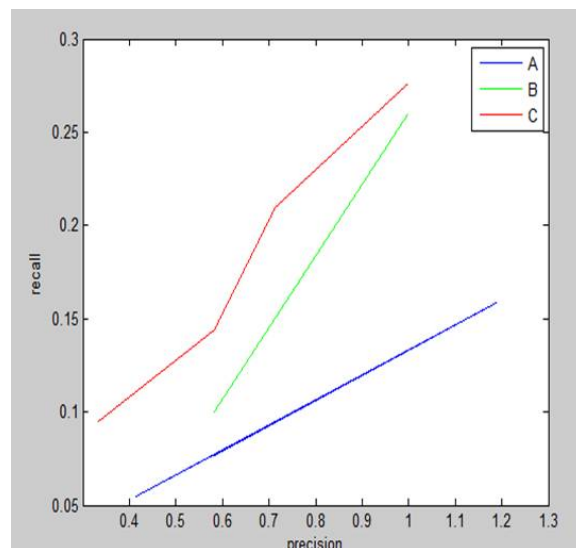


Fig.5. Difference between previous and present proposed method in accuracy

In fig5 :It is plot shown in efficient results of existing and proposed methods .The plot (A) shows hyper-structure analysis of view model.The graph drawn between precision and recall .The plots A and B are existing methods.The plot C is a proposed method which is better precision than the existing methods discussed in the literature.

## VI. CONCLUSION

In this paper, we proposed a hyper graph analysis method by integrating multiple hyper graphs for Multi-dimensional object retrieval and recognition. The proposed method groups the views of Multi-dimensional objects into clusters based on their visual descriptions[5]. Hyper graphs were then constructed, where each vertex was an object and an edge was a cluster of views. Therefore, an edge connects multiple objects in the hyper graphs. By varying the number of view clusters, we could generate multiple hyper graphs that captured the higher order relationship of the Multi-dimensional objects at different granularities. Retrieval and recognition were formulated as learning tasks

with different regularization frameworks on the hyper graphs.

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