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A Minor Project Report on

PARTIAL 3D OBJECT RETRIEVAL

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in

Computer Science and Engineering

By

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Under the guidance of

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CERTIFICATE

This is to certify that Minor Project entitled PARTIAL 3D OBJECT RETRIEVAL is a bonafide work carried out by the student *Ms.Apoorva Surendra Malemath - 01FE16BCS041*, in partial fulfillment of the award of Degree of Bachelor of Engineering in Computer science and Engineering during the year 2018 – 2019. The report has been approved as it satisfies the academic requirement with respect to the project work prescribed for the above said program.

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Apoorva Malemath

Abstract

In this project, we address the problem of partial 3D object retrieval for point cloud data. Due to increasing availability of 3D point cloud data, there is a surge of interest with respect to retrieval problems. In order to address this issue we propose a partial 3D object retrieval technique. We perform sampling, feature extraction, feature encoding, matching and performance evaluation. We use Poisson disk sampling, then we extract improved wave kernel signature (IWKS) feature. These feature descriptors are then encoded using Fisher vector(FV) and Bag-of-Features (BoF). And they are matched using l_1-norm, l_2-norm, cosine distance and earth mover distance (EMD). We then demonstrate the performance of the proposed technique.

Keywords: Partial 3D object retrieval, improved wave kernel signature, Fisher vector, bag-of-features, point cloud data

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Chapter 1

Introduction

In this project, we aim to solve the problem of partial 3D object retrieval. Many applications in recent times have been benefited from 3D models. The 3D models used are represented in the form of point cloud. A point cloud is a set of data points in space. They are produced by scanners, which measure a large number of points on the external surfaces of the objects and around them. The improvement in capture devices has led to generation of low-cost 3D objects, thus tasks involving 3D models are in active research. Numerous tasks such as cultural heritage, craniofacial research, archaeology, 3D protein retrieval and classification, 3D video sequences, 3D retrieval for museums, 3D face recognition, etc. depend on partial object retrieval.

We propose to solve the problem by first performing feature extraction using improved wave kernel signature feature (IWKS) [1]. We then encode the extracted features using Fisher vector and Bag of Feature, we then perform matching using various matching methods such as l_1-norm, l_2-norm, cosine and earth mover distance (EMD) distances.

In Section, in 1.1 we discuss the motivation for this project and in Section 1.2 we give the problem statement and in Section 1.3 we provide the objectives. In Section 2, we list the related works. In Section 3, we discuss the methodology. In Section 4, Results and discussions are given. Finally, in Section 5, We conclude.

1.1 Motivation

With rapid growth in technology, the dependence over machine is increasing. Few fields have witnessed such impressive advances of the application of computer technology. The recent introduction of consumer depth cameras has made 3D data acquisition easier and widely increased the interest in methods for the automatic classification and recognition of 3D shapes. Shape analysis of 3D surfaces is a classical problem in computer graphics. The main goals are to compute geometric properties of surfaces and to produce new representations from which important features can be inferred.

1.2 Problem Statement

To build a partial 3D object retrieval technique to solve the retrival of relevent objects given a partial query.

1.3 Objectives

1. To extract features from the given 3D objects.
2. To perform encoding of the extracted features.
3. To perform matching of the input query with the dataset.
4. To evaluate the performance of the proposed technique.

Chapter 2

Literature Survey

In [5], the authors construct a partial object retrieval method, applicable on both point cloud and structured data. It is based on shape matching scheme combining local shape descriptors with their fisher encodings. The proposed system is based on hybrid shape matching scheme so as to account for both global and local shape similarities. Differential fast point feature histogram is computed and global shape similarity is estimated by means of weighted distance of fisher vector.

In [3], the authors present a technique compute fast point feature histogram. It considers only the direct connections between current key point and its neighbours, removing additional links between the neighbours. For each query point single point feature histogram (SPFH) is computed. And for each point we re-determine its k-neighbours and use neighbouring SPFH value to weight the final one. Each direct neighbour is connected to its own neighbours and resulted histogram are weighted together with the histogram of the query to form fast point feature histogram (FPFH).

In [6], the authors introduced a retrieval system design where in they perform feature extraction methonds such as shape context features and spin image features, they further encode the features using Bag of Features and perform matching using l_1-norm distance.

In [2], the authors introduced a retrieval system design based on extending standard global 3D descriptors with local description of the object. It is based on the idea to apply an existing global 3D descriptor on both whole models and model segments. Partial similarity search is performed by searching for local to local correspondences. The partial descriptors also improve global retrieval by including model information which is suppressed by certain descriptor extractors when they process whole models. Here model segmentation algorithm partitions each 3D object into a fixed number of segments. And 3D descriptors are extracted for each 3D model and for each model segments.

Chapter 3

Methodology

In this Chapter, we propose the partial 3D object retrieval technique. In 3.1 we provide a block diagram of our proposed system along with its description. In Section 3.2 we explain the feature extraction methods used. In Section 3.3 we dicuss the different encoding methods used. In Section 3.4 different matching techniques are employed and in Section 3.5 we define the evaluation metrics. In Section 3.6 we provide the software requirements and in Section 3.7 system models are explained.

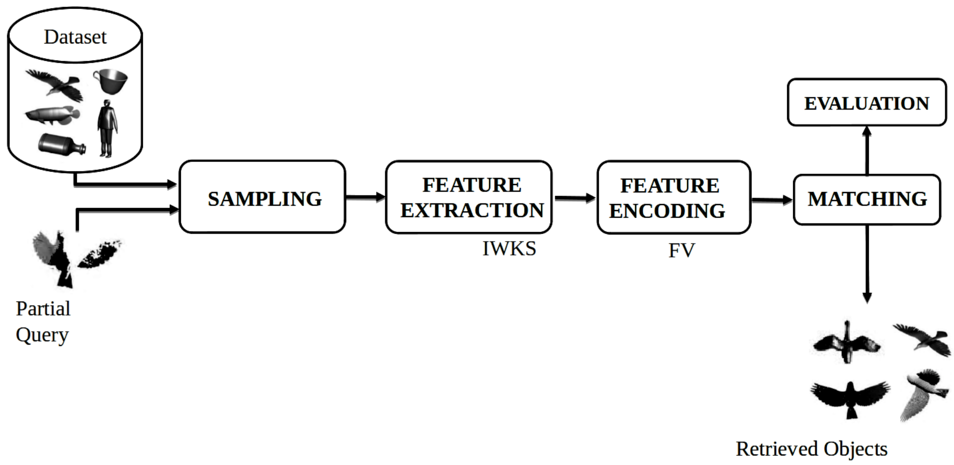

Figure 3.1: Partial 3D Object Retrieval

3.1 Partial 3D Object Retriveal Technique

The proposed partial object retrieval technique is shown in Figure 1. The data set consists of 50 classes with 20 objects each and a partial query is given as an input. We first sample the objects to obtain uniformly distributed points. Then we extract IWKS features and perform feature encoding using Fisher vector. The queries are matched against the encoded features using l_1-norm, l_2-norm, cosine and EMD distances and the performance is evaluated using nearest neighbors(NN),first tier(FT), second tier(ST) and discounted cumulative gain(DCG).

3.2 Feature Extraction

Feature extraction methods are applied on to the 3D point cloud in order to get feature vector.These features provide cues for retrieval.For each point in the point cloud we extract the following features.

3.2.1 Improved Wave kernel Signature

IWKS features [1] are invariant to isometric deformations, relatively stable against articulations. It uses the eigenvalues and eigenfunctions of the Laplace-Beltrami operator (LBO) to compute signatures, which capture local and global information of the shape.

The basic idea is to characterize a point $x \in X$ by the average probabilities of quantum particles of different energy levels to be meased in x.Energies of paarticles correspond to frequencies, thus information of all frequencies is captured and the influences from differnet frequencies are clearaly seperated.

In order to construct a signature, it is necessary to apply a filter to the eigen values of the LBO to create a feature vector for each point of the shape. Each element of the feature vector is a combination of different frequencies of eigen functions. These filters must be optimized to deal with noise deformations of the shape. Low frequencies of the band-pass filters used in wave kernel signature (WKS) are very narrow, thus they account for very specific part of the spectrum.

Hence, adaptive scaling is used in IWKS. It precisely accounts for the difference in eigen values when the shape is articulated.

The log normal distribution assumes the eigen values of same class shape to vary according to log normal distribution i.e, majority of the absolute differences are close to zero or few are larger than zero. And the real data is not log normally distributed, thus we employ cube root scaling, it precisely accounts for difference of eigen values when the shape is articulated.

To decrease the difference of the eigen values from shapes belonging to the same class curvature aggregation is performed. By reducing the influence of shape joints in the descriptor there is increasse in the retrieval performance of the IWKS. To reduce this influence we need to down weight the joint regions so that they do not influence the final descriptor.

3.3 Feature Encoding

To assess the global similarity between the partial query object and each target object from the daataset, we employ the following feature encodings:

3.3.1 Fisher Vector(FV)

To assess the similarity between the partial query and each object from the repository. A Gaussian mixture model (GMM) [5] is estimated from local shape descriptors using an expecation maximization algorithm.The resulting GMM is used as the visual code book.

We consider a set of descriptors $x_1, x_2 ... x_n \in R^D$. GMM p(x| θ) is the probability density on R^D given by

$$p(x|\theta) = \sum_{k=1}^{K} p(x|\mu_k, \textstyle\sum_k)\pi_k \tag{3.1}$$

$$p(x|\mu_k, \textstyle\sum_k) = \frac{1}{\sqrt{(2\pi)^D \det \sum_k}} e^{-\frac{1}{2}(x-\mu_k)^T \sum_k^{-1}(x-\mu_k)} \tag{3.2}$$

where K is the number of Gaussian components used, θ is the vector of parameters (π_1,μ_1,$\sum_1$,...,π_K,μ_K,$\sum_K$), including the prior probability values $\mu_k \in R^D$, and covariance matrices $\sum_k \in R^{D \times D}$ of each Gaussian component.

Fishser encoding captures the average first and second order differences between the local descriptors and the centers of a GMM. It is considered as the visiual codedbook. For k^{th} GMM, we define:

$$u_k = \frac{1}{N\sqrt{\pi_k}} \sum_{i=1}^{N} q_{ik} \sum_{k}^{-1/2} (x_i - \mu_k) \tag{3.3}$$

$$v_k = \frac{1}{N\sqrt{2\pi_k}} \sum_{i=1}^{N} q_{ik} [(x_i - \mu_k) \sum_{k}^{-1} (x_i - \mu_k) - 1] \tag{3.4}$$

Fisher Encoding of feature vector is given by concatination of u_k and u_k for all K components, and gives an encoding of size 2DK.

$$f = [u_1^T, v_1^T, ..., u_k^T, u_k^T] \tag{3.5}$$

3.3.2 Bag of Features(BoFs)

Each object has a set of feature descriptors, we convert these descriptors to codewords [4], from which we construct the codebook. Codewords are generated using K-means clustering over all the descriptors to form cluster. The centers of these clusters are defined as codewords. The number of clusters determine the number of codewords. And histograms are further computed with respect to these code words.

3.4 Matching

Matching is applied between the encoded features obtained of the target objects and the query objects to form a distance matrix. Distance is measured between the query and each object in the dataset. The following distances are computed between the encoded features:

3.4.1 Manhattan distance (l_1-norm)

The Manhattan distance between two vectors a and b is defined as:

$$d = \sum_{i=1}^{N} |a_i - b_i| \tag{3.6}$$

3.4.2 Euclidean distance (l_2-norm)

The Euclidean distance between two vectors a and b is defined as root of square differences between coordinates of a pair of objects:

$$d = \sqrt{\sum_{i=1}^{N}(a_i - b_i)^2} \tag{3.7}$$

3.4.3 Cosine distance

The cosine distance between two vectors is defined as:

$$d = \frac{\sum_{i=1}^{N}(x_i y_i)}{\sqrt{\sum_{i=1}^{N} x_i^2}\sqrt{\sum_{i=1}^{N} y_i^2}} \tag{3.8}$$

3.4.4 Earth mover distance (EMD)

The EMD is a measure of the distance between two probability distributions over a region D, also known as the Wasserstein metric.

$$d = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} f_{i,j} d_{i,j}}{\sum_{i=1}^{M} x_i^2 \sum_{j=1}^{N} f_{i,j}} \tag{3.9}$$

where $f_{i,j}$ is the flow between p_i and q_j, which minizes the over all cost.

3.5 Evaluation

3.5.1 Nearest Neighbor (NN)

Given a query, it is the precision on the first retrieved object in the ranked list i.e. we check the ratio of objects in the query's class that are present in the top N matches. N=1 is considered.

3.5.2 First Tier (FT)

Given a query, it is the precision when C objects have been retrieved, where C is the number of relevant objects. K=$|C| - 1$ is considered for first tier

3.5.3 Second Tier (ST)

Given a query, it is the precision when 2*C objects have been retrieved, where C is the number of relevant objects in the 3D dataset.$K = 2 * (|C| - 1)$ for the second tier.

3.5.4 E-measure

The idea is to combine precision and recall into a single number to evaluate the system performance. First we introduce the F-measure, which is the weighted harmonic mean of precision and recall. F-measure is defined as:

$$F = \frac{(1+\alpha) \times precision \times recall}{\alpha \times precision + recall} \tag{3.10}$$

Where α is the weight. Let $\alpha = 1$ then,

$$F = \frac{2 \times precision \times recall}{\alpha \times precision + recall} \tag{3.11}$$

The E-measure is defined as

$$E = 1 - F \tag{3.12}$$

$$E = 1 - \frac{1}{\frac{1}{precision} + \frac{1}{recall}} \tag{3.13}$$

3.5.5 Discount cumulative gain DCG

DCG evalustes the effectiveness of the retrieved objects based on object position in result list. the greater the position of the retrieved object that is relevant, the less useful it is for the user. Thus, DCG penalizes the objects wheich are relevent and appear lower in the result list. Thus, DCG of an object at a ranked position r is given as,

$$DCG_r = relevant_1 + \sum_{i=2}^{r} \frac{relevent_i}{log_2(i+1)} \tag{3.14}$$

3.6 Software Requirement Specification

In this section, we talk about the system requirements, it captures complete description about how the system is expected to perform.

3.6.1 Functional Requirements

1. The system shall extract the differential fast point features for the
2. given dataset and the partial query.
3. The system shall perform feature encoding using fisher vector on the obtained feature descriptors.
4. The system shall match the query object with the dataset.
5. The system shall evaluate the performance of the proposed technique.

3.6.2 Non-Functional Requirements

1. In building the system, PCL libraries need to be used on Linux platform.
2. The values of performance metrics such as NN, FT and ST shall be above 0.05

3.6.3 Software and Hardware Requirements

1. The system shall be built on Linux platform using PCL library and programming languages such as C++, python and Matlab.
2. The system shall require hardware configuration of 8 GB RAM, i7 processor, 10GB HDD.

3.7 System Design

In this section, we give an insight of the system design for our proposed system. In 5.1 we give the architecture of the system and, in , the level 0 DFD. In section 5.3 and 5.4 we provide the detailed DFD and Activity diagram respectively. 4.1

3.7.1 Architecture of the system

For our system, we consider pipe and filter architecture as shown in Figure 3.2, since the data flows from input to output from one functional process to another.

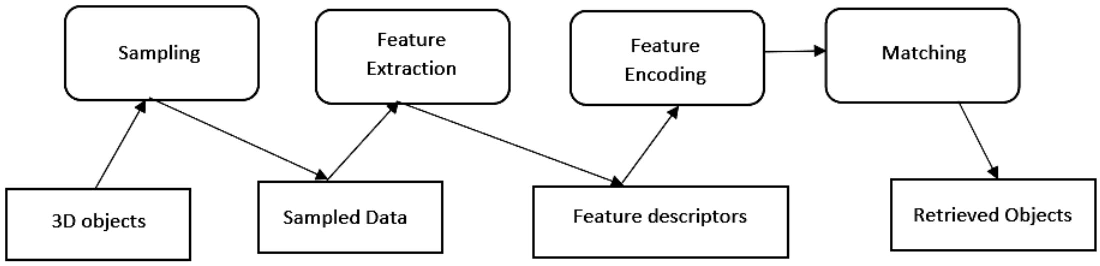

Figure 3.2: Architecture Diagram of the proposed Partial 3D Object Retrieval

3.7.2 Data Flow Diagram(DFD)

Figure 3.4 shows shows the level 0 DFD diagram and Figure 3.3 shows the detailed DFD. DS 1 stores the 3D objects, these are sampled using Posisson disc sampling and are stored in DS 2. The features extraction is performed on this sampled data and is stored in DS 3. These feature descriptors are futher encoded and matching is performed on it using L1 norm and L2 norm and the obtained results are stored in DS 5. Further performance is evaluated over the distance matrix.

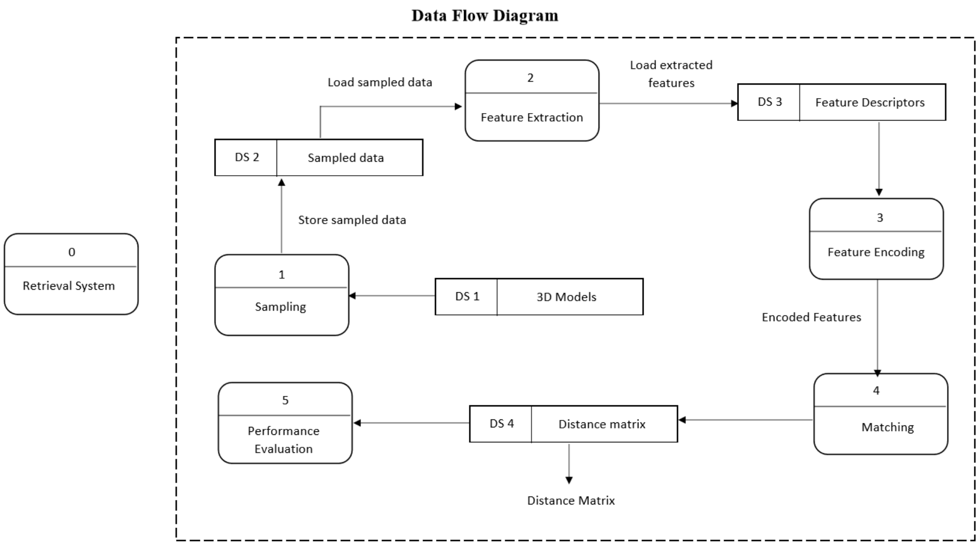

Figure 3.3: Detailed DFD Diagram of the proposed Partial 3D Object Retrieval

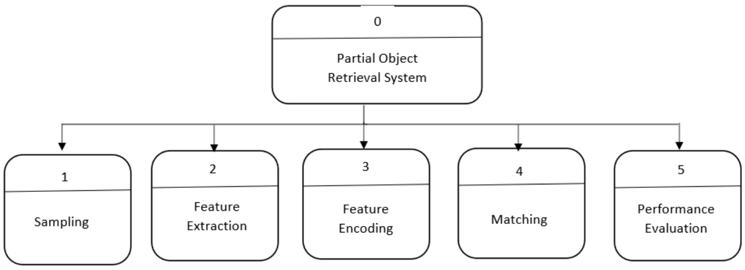

Figure 3.4: Level 0 DFD Diagram of the proposed Partial 3D Object Retrieval

3.7.3 State Diagran

The state diagram of the proposed technique is a diagram used to describe the behavior of a system considering all the possible states of an object when an event occurs. This behavior is represented and analyzed in a series of events that occur in one or more possible states. The control flow is drawn from one operation to another is shown in Figure 3.5.

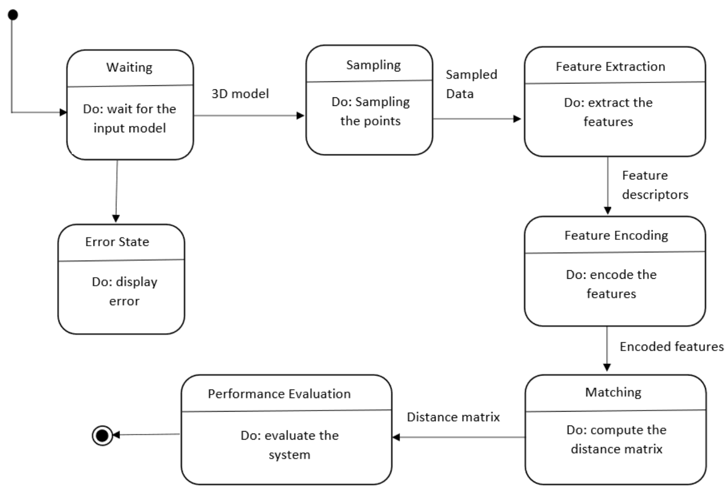

Figure 3.5: Detailed DFD Diagram of the proposed Partial 3D Object Retrieval

Chapter 4

Results

In this Section, we discuss the dataset used and the results obtained. The experimental analysis is performed with IWKS feature extraction method and two encoding techniques, namely, FV and BoF. In IWKS we compute 100 feature descriptors for each pointr in 3D object by considering 300 eigen values of Laplacian. For FV encoding we used cluster sizes from 5 to -. And for BoF we employ k-means clustering with cluster sizes ranging from 10 to 1000. We construct feature vocabulary using GMM for FV and k-means clustering for BoF.

4.0.1 Dataset

Figure 4.1: SHREC 2011 Range Scan Dataset

We employed data from the SHREC'11 shape benchmark constructed at NIST for all of our tests. It contains 1000 complete 3D models, which are categorized into 50 classes. In each class there are 18 models. And Query set consists of 150 partial 3D objects.

4.0.2 SHREC'11

The results obtained for proposed retrieval technique for SHREC'11 dataset consisting of 50 classes and 150 partial queries are shown. In table 4.1 matching is performed using L1 norm distance, in Table 4.2 matching is performed using L2 norm distance and in Table 4.3 matching is performed using cosine distance.

From Table 4.1 $l_1 - norm$ distance we observe that the best results obtained are using K=1000 for BoF and K=50 for FV. From Table 4.2 Considering $l_2 - norm$ distance we observe that the best results obtained are using K=1000 for BoF and K=50 for FV.From Table 4.3 Considering cosine distance we observe that the best results obtained are using K=1000 for BoF and K=50 for FV. From Table 4.4 Considering cosine distance we observe that the best results obtained are using K=1000 for BoF and K=5 for FV.

Thus we can infer that BoF works best with larger cluster sizes, as the number of clusters determine the size of the codebook. The larger the codebook is formed, the better it performs. And FV works better with lower cluster sizes.

4.0.3 Comparision with state-of-the art work

In this Section, we compare our technique with state-of-the-art techniques for partial 3D object retrieval SHREC'09. The dataset contains 50 classes with 18 object each, and 20 queries. We observe that that they have employed rectangular spin image feature (RSI), polar spin image feature (PSI), shape context feature (SC) and fast point feature histogram feature (FPFH). Table 4.5 shows the state-of-the-art technique and its performance.

From Table 4.6 it can be observed that FV performs better with cluster size K=50 using l_1-norm and BoF performs well with K=1000 and using l_1-norm.

Table 4.1: Performance metircs obainted using l_1-Norm for matching

Encoding	K	NN	FT	ST	E	DCG
	5	0.0133	0.0193	0.0417	0.0246	0.3144
FV	10	0.0333	0.0243	0.0490	0.0305	0.3211
	50	**0.0600**	**0.0600**	**0.0507**	**0.0507**	**0.3322**
	10	0.0000	0.0143	0.0243	0.0164	0.3056
BoF	50	0.0200	0.0217	0.0417	0.0246	0.3170
	100	0.0000	0.0140	0.0317	0.0182	0.3104
	150	0.0200	0.0177	0.0327	0.0205	0.3128
	200	0.0267	0.0257	0.0430	0.0285	0.3209
	300	0.0400	0.0257	0.0437	0.0282	0.3218
	500	0.0533	0.0240	0.0443	0.0290	0.3219
	1000	**0.0600**	**0.0527**	**0.0527**	**0.0333**	**0.3222**

Table 4.2: Performance metircs obainted using l_2-Norm for matching

Encoding	K	NN	FT	ST	E	DCG
	5	0.0067	0.0403	0.0690	**0.0446**	**0.3362**
FV	10	0.0133	0.0207	0.0390	0.0226	0.3184
	50	**0.0533**	**0.0343**	**0.0697**	0.0421	0.3338
	10	0.0067	0.0403	0.0690	0.0446	0.3362
BoF	50	0.0200	0.0200	0.0387	0.0226	0.3171
	100	0.0000	0.0160	0.0407	0.0218	0.3119
	150	0.0067	0.0203	0.0383	0.0231	0.3114
	200	0.0333	0.0247	0.0460	0.0285	0.3187
	300	0.0400	0.0190	0.0450	0.0295	0.3198
	500	0.0333	0.0267	0.0503	0.0313	0.3212
	1000	**0.0533**	**0.0267**	**0.0527**	**0.0333**	**0.3222**

Table 4.3: Performance metircs obainted using Cosine Distance for matching

Encoding	K	NN	FT	ST	E	DCG
	5	0.0000	0.0183	**0.0480**	**0.0292**	**0.3224**
FV	10	0.0067	0.0130	0.0253	0.0138	0.3039
	50	**0.0200**	**0.0153**	0.0337	0.0200	0.3129
	10	0.0067	0.0493	0.0907	0.0569	0.3436
BoF	50	0.0200	0.0243	0.0467	0.0277	0.3243
	100	0.0000	0.0217	0.0397	0.0249	0.3177
	150	0.0000	0.0140	0.0287	0.0172	0.3073
	200	0.0133	0.0273	0.0520	0.0338	0.3239
	300	0.0400	0.0247	0.0447	0.0292	0.3247
	500	0.0267	0.0247	0.0440	0.0277	0.3262
	1000	**0.0400**	**0.0290**	**0.0497**	**0.0292**	**0.0292**

Table 4.4: Performance metircs obainted using EMD Distance for matching

Encoding	K	NN	FT	ST	E	DCG
	5	**0.0200**	**0.0140**	0.0243	0.0164	0.3056
FV	10	0.0133	0.0137	**0.0283**	**0.0182**	0.3062
	50	0.0000	0.0110	0.0280	0.0159	**0.3076**
	10	0.0067	0.0167	0.0417	0.0246	0.3136
BoF	50	0.0000	0.0197	0.0397	0.0244	0.3187
	100	**0.0667**	0.0317	0.0633	**0.0418**	0.**3354**
	150	0.0600	**0.0323**	0.0630	0.0390	0.3338
	200	0.0200	0.0153	0.0370	0.0226	0.3134
	300	0.0067	0.0180	0.0347	0.0218	0.3102
	500	0.0067	0.0157	0.0370	0.0215	0.3160
	1000	0.0000	0.0187	**0.0420**	0.02625	0.3144

Table 4.5: State-of-the-art partial 3D object retrieval

Feature	NN	FT	ST
RSI	0.0892	0.0734	0.0713
PSI	0.0933	0.0812	0.0770
SC	0.0861	0.0825	0.0771
FPFH	0.1167	0.0799	0.074

Table 4.6: Proposed partial 3D object retrieval

Encoding	Distance	K	NN	FT	ST
FV	l_1-norm	50	**0.0600**	**0.0600**	0.0507
	l_2-norm	50	0.0533	0.0343	**0.0697**
	Cosine	50	0.0200	0.0153	0.0337
	EMD	5	0.0200	0.0140	0.0243
BoF	l_1-norm	1000	0.0600	**0.0527**	**0.0527**
	l_2-norm	1000	0.0533	0.0267	0.0527
	Cosine	1000	0.0400	0.0290	0.0497
	EMD	100	**0.0667**	0.0317	0.0633

Chapter 5

Conclusions and Future Work

In this project, we have addressed the problem of partial 3D object retrieval. In the proposed technique we perform sampling, feature extraction, feature encoding, matching and performance evaluation. We demonstarted the performance of the proposed partial 3D object retrieval system on SHREC'11. We sampled the data the using Poisson disk sampling. We extract IWKS feature descriptors, and encode the descriptors using FV, IWKS, which are then matched using l_1-norm , l_2-norm, cosine distance and EMD distance. We demonstrate the performance of the proposed technique on SHREC'11. As future work the proposed technique can be extended by using other feature extraction methods and matching techniques.

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