International Master's Thesis

Modeling 3D Object Context

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Abstract

In this work we introduce a method and descriptor for object context in full 3D pointclouds of places. Among various applications for this we are suggesting it to be used for place categorization and semantic mapping. This work is unique regarding its use of full 3D pointcloud of scenes and also introducing this descriptor to be used to represent places.

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Contents

List of Figures

List of Tables

List of Algorithms

Chapter 1
Introduction

A stereotypical image of a robot is a humanoid in a servant costume which can do all the chores at home and perhaps even more. Assuming such goal, human behavior becomes a natural inspiration for the algorithms governing the behavior of a robot in the assigned tasks and situations. Imagining a simple but common task of find-and-fetch, in witch a mobile robot is asked to find an object and bring it to the user. The first solution that could be thought of, is to learn how exactly a human would perform the task. Then, how the procedure can be translated to an algorithm executable on a robotic system. Often such translation can not be direct due to the differences in embodiments and lack of complete understanding of underlying processes.

In case of the find-and-fetch task, if it is assigned to a human agent, he is likely to imagine what does the target object look like, where and in what situation it is often found. If the object is known, a natural behavior is to visit the most probable location for the object first. Only in the worst case scenario and without the knowledge of the object, one would perform a thorough search of the whole scene. In other words, the strategy depends on the amount of information about the target object.

A similar behavior could be implemented on a mobile robot. A valuable prior knowledge for an object detection/recognition problem could be semantic knowledge about places and possible context for the object, which not only can reduce the search time but also can increase the chance of success and correctness of the results.

Torralba et al. in [22] point to the fact that there are many experiments showing that the human visual system uses contextual information to facilitate search for objects. Moreover, he proposes the use of context for object detection in 2D images.

In this work, we focus on 3D information and therefore, consider surfaces surrounding the object as its context. This includes surfaces the object is located on or next to and also other objects which are usually beside the

Figure 1.1: A water tap as the object of interest and what we call its context. The context is surfaces within the green bounding box.

object of interest. For instance, if the object of interest is a $\mathtt{kitchen\ water\ tap}$, it's context ca be the $\mathtt{kitchen\ sink}$ and the wall behind it. (Figure 1.1)

1.1 Contributions

In this work, we propose a method to build models of 3D object context, which not only can be used as a prior to an object detector, but also as a useful knowledge in building 3D representation for places. Benefiting from this model, the area needed to be searched in an object detection task can be reduced to parts of the scene with high probability of being the context for the object of interest. It can also have a positive effect on number of true positive in prediction results. Combining the information encoded in this model with other features and structural information of different place categories can result in a representation for places.

To build Object context models we applied supervised learning methods on data extracted from manually annotated objects in point-clouds. Point-closed that we used as input are full 3D representations of a place such as an office, a kitchen, etc. The learning is done on features which are representing local geometry and spacial location of object context.

Most important points about this work ca be briefly mentioned as follows:

- Emphasizing on the role of context in object detection and it's related applications.

- The features and methodology suggested to model the Object Context.

- The input data used in this work are full point-clouds of places rather than single frames with depth information or 2D images.
- Suggesting the application of Context model in place classification.

Applications in place classification would be discussed later in chapter 4.

1.2 Related Work

In this Section, some related works focusing on using contextual information for object detection/recognition or place classification are briefly reviewed. Moreover, other works which contribute 3D features and descriptors for similar purposes are mentioned.

Object Context

In [21] Torralba et al. present a low dimensional global image representation capturing useful information for recognition of places and show how contextual information can provide priors for object recognition. As mentioned before, this work considers 2D images only.

In [23] Torralba uses the relationship between object and it's context properties from 2D images to build model that helps the focus of an object detector's attention and also for scale selection.

In [13] Perko and Leonardis extract and learn contextual information for objects from examples. Then they use this learned context to calculate a focus of attention, that represents a prior for object detection. Their work is also used 2D features extracted from images.

Aydemir et al. in [2] learn 3D context of objects to predict object locations in real world scenes. They used separate RGB and depth frames and used histograms of surface normals as a 3D geometrical feature to model object context.

In [19] Rusu et al. proposed Viewpoint Feature Histogram that encodes 3D geometry and pose. They suggested that this descriptor can be used for object recognition and pose estimation with high reliability. In this work we employ a descriptor, which contains their descriptor, for modeling context of objects.

Place classification

In [25], Vasudevan and Siegwart proposed a representation for space based on objects. The authors discuss several algorithms, some of which only uses object category presence and some are more sophisticated using both objects and their relationships and also spacial structure of places.

More researches are discussed later in Chapter 4 which is specifically devoted to this particular application.

1.3 Outline

The rest of this thesis is structured as follows: In Chapter 2, the problem definition and more about motivation, applications and challenges are presented. Chapter3, describes our method and details about implementation, experiments and evaluation. In Chapter4, applications of our model and descriptor in place classification is discussed and an analytical study is done for the results that could be expected for this application. Finally, we have a review while next steps that could be considered for this work, possible improvements and also future works are mentioned in Chapter 5.

Chapter 2
Modeling Object Context

2.1 Problem Statement

As discussed in the previous Chapter, in order to facilitate object detection and provide a means to classify places based on key objects for a place category, in this thesis we proposed a structure and a method to build models for object context.

Based on the definition stated in Chapter 1, by context of the object we are referring to the surfaces surrounding it. The problem that is addressed in this research, is how to define suitable features to represent those surfaces as the context of the object class. The trained model would be applied on pointclouds of new scenes to determine locations in the scene that are likely to contain the object. The expected result, is a prediction probability for all regions in a pointcloud that corresponds to the likelihood of object being present.

2.2 Motivation and Applications

The main motive for this work is achieving a complete and robust 3D descriptor for places based on object contexts rather than objects. When a human agent enters a room, intuitively he is able to decide about the category of the place based on a simple and shallow perception, with a good confidence. Even if the room is not furnished yet and there is not many objects in it to help the agent in determining its category. It gives us the inspiration that more than presence of some objects, possibility of their presence in a place helps us to determine the category of the place. For sure other information adds up to this knowledge to make a human able to distinguish between places, such as general shape and size of the place also its location regarding other places. A model for an object context can provide us with the possibility of object presence. In addition, this model is a useful prior for object detection which is discussed in applications.

Among the applications that is considerable for the model, most obvious ones are as follows:

Object Detection

Object detection is an expensive and complex task. Scale of the object is an issue here. Searching for context of an object is significantly easier than the object itself, particularly when the searched object is in a rather small scale. When the context is detected, then the search for the actual object is done in a reduced area, where is predicted as the context. Scale selection in object detection is another problem that detecting the context can diminish it.

In addition, false positives are avoided or at least reduced. When a table is detected as the context for a cup, a cup like object which is located on the floor is not predicted as a positive detection.

Place Classification

A very important piece of information that can help a robotic system to be able to distinguish between different place categories is knowing about the objects which are expected to be found in a specific category of a place.

If the robot is looking for a kitchen, it helps if it knows about some objects that are most probable to be found in it and perhaps not in other places. For instance a kitchen sink is such a discriminative object. If the robot can find such an object in a place, it can obtain a good confidence about that place to be a kitchen.

Viswanathan et al. in [26], also pointed to the fact that object detection is a good prior for place categorization. T. Southey and J. J. Little in [20] argued that, rooms are defined by their geometric properties, while definition of places is based on objects they contain and activities takes place in them.

On the other hand, the place classification system would be more robust if it is able to recognize the place, using object information, even when the actual object is not present in the place, but the presence is expected. Here is where the contextual model of object finds it's application. When the context is present, there is no need to detect the actual object for the purpose of classifying the place.

Object Placement

An intuitive application for the model of object context is finding a suitable location or surface to put an object. When a robot knows the context model of an object it can place it correctly by finding matches of that model in its surrounding. For instance, a robot that performs typical household chores, like cleaning or serving guests can benefit from it.

2.3 Challenges

2.3.1 Challenges Related to Applications

Place Classification

Finding object classes which are discriminative for places is not easy for all place categories. In addition, context model for different object classes can be similar which decreases certainty of place classification.

Object Detection

Object detection can be challenging when the size of the object compared to the size of the scene is very small. Illumination conditions, occlusion and pose of the object can affect the time needed for the search and performance of the system.

Identifying potential locations for the object within the scene can drastically reduce the search space. Detecting a table as a context for cups is easier due to its scale and is less affected by illumination and occlusion. When the table is detected, recognizing objects on the table is facilitated regardless of the challenges mentioned above.

2.3.2 Challenges Related to Modeling the Object Context

There are challenges regarding modeling the object context that follows:

- Train set quality: Employing a train set without enough generalization. There could be situations and scenes which are completely different from what have been considered in train set to build the context model.

- Pointcloud quality: The quality of pointclouds is a critical issue. The amount of smoothness in the pointcloud and missing points have a significant effect on the extracted features, which are used to describe surfaces, and as a result, on the context model. When pointclouds are being captured, if due to the viewpoints of the sensor some parts of a surface are occluded, the resulting pointcloud might lack important points. The geometry that is extracted from such surfaces is not accurate and in some cases are wrong.

2.3.3 2D vs 3D context, benefits of 3D

Popularity of devices such as Microsoft Kinect, has made 3D data widely accessible. Therefore, many researchers and academics have shown great desire to use 3D information in their researches, which gives a lot more information about our surrounding compared to 2D data. Using 3D data has made it simple to capture geometrical information in addition to visual properties. From the output of this type of sensors, we can easily and directly have access to depth information and 3D coordinates of any points that are perceived.

Geometrical features, which are obtained from 3D information, enhances performance of systems significantly in tasks like feature based object detection compared to relying only on visual information. Particularly, in the problem we are dealing with, to build a model for object context, depending on features which only encode changes in intensity and color is not enough. The surfaces needed to be studied, 3D information facilitate and improves this study.

Chapter 3
3D Model of Object Context

3.1 An example Scenario

In this scenario, a situation is considered where a mobile robot wants to look around in a building and make a map including semantic information about the places that it meets in the map. The robot builds a 3D map of the building using, for instance, a SLAM application. Employing the context models, which has been trained for different key object classes, the robot can estimate which object classes are probable to be found in each place that is present in the map.

By key objects we are referring to distinctive objects for a place category. These specific object classes should be chosen based on a ground truth which is defined in advance for a place category. It is discussed in Chapter 4 in more detail.

Then using the results, showing which object classes are expected in a place and based on the ground truth, for key objects of each place category, the place is classified.

3.2 Methodology

In this Section, the procedure of building the context model and how it is applied, is described in detail. The input in this procedure is the pointcloud of a scene and the output is a list of probability values assigned to all regions in the scene. The probability value shows if the region is likely to be a context. The input cloud is first preprocessed and then get annotated with instances of the object class whose context model is being built. Feature extraction would be run on this annotated pointcloud and result in the train samples. Train samples would be combined from several different pointclouds for the same object class to make the Train Set. Then the Train Set is given to SVM classifier to make the Context Model. A block diagram in figure 3.1 shows the system overview.

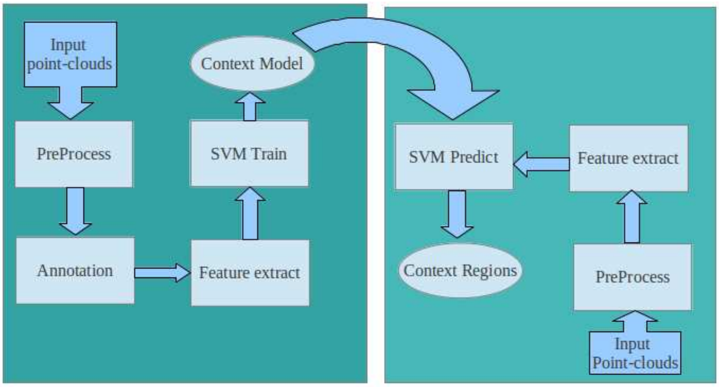


Figure 3.1: The overview of the system. Box on the left side shows the Train part of the system while the one on the right shows the prediction part.

In the following Subsection, we introduce the features used in this work and description of the modules of the system will come next.

We used PCL [18] for pointcloud processing. We used Microsoft Kinect with OpenNi driver to capture these pointclouds.

3.2.1 Object context descriptor

The feature descriptor we proposed in this work, consists of 2 parts which is discussed below.

The first part includes two fields : A field that captures a rough estimation of query surface orientation with respect to the vector of gravity. This feature is computed by estimating the angle between average normal of the surface and the gravity vector. We consider a unit vector along the z axis in the world coordinate system as the gravity vector.

Second field is the average height of the query surface from which the features are extracted with respect to the floor. The floor is assumed to have the lowest height or vertical position in the pointcloud.

And the rest of the fields are in second part of the feature vector which is a histogram. This histogram is called VFH which captures the geometry of the blob with respect to a specific view point. [19]

The Viewpoint Feature Histogram (VFH)

As it is described in PCL official website [17] and [19], VFH consists of two component as follows:

- First component is a histogram for viewpoints(128 bins)

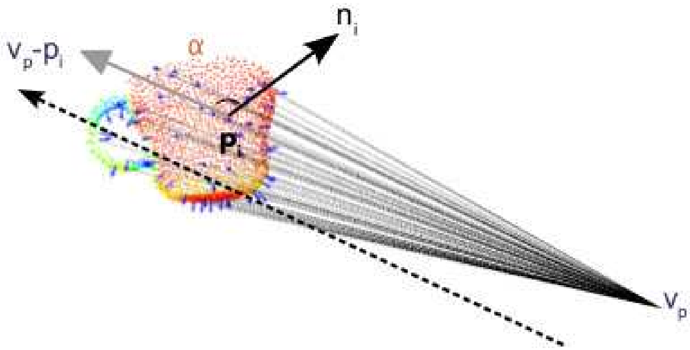


Figure 3.2: Viewpoint part of the feature vector.[17]

- Second component is extended Fast Point feature histogram(FPFH:4*45 bins)

The viewpoint component is computed as a histogram of the angles that direction of the viewpoint makes with each surface normals. It is important to notice that, this angle is between the central direction of the viewpoint and the normal, not the view angle of the normal which would have made it not scale invariant.

The second component measures the relative pan, tilt and yaw angles that are measured between direction of the viewpoint at the central point and each of the normals on the surface. So it consists of accumulated FPFH values for points in the query pointcloud. That is why it is referred here 3.4 as extended FPFH.

VFH is robust to different sampling densities or noise levels in the neighborhood of the query point. The descriptor is computed by estimating a histogram with concatenated 45 bins for four different elements. These elements consist of three angles and a distance.

Figure 3.3 shows the encoded elements and their relation in FPFH.

In VFH the resulting FPFH of points in the pointcloud are integrated to produce one of the two components(extended FPFH). The histogram in this component has 180 bins (4*45 bin). By adding the view point component (128 bin), it produces a 308 bin histogram. Unlike FPFH, as a result of adding the viewpoint component VFH is dependent to viewpoint which is the reason we chose it as a part of our descriptor. The viewpoint component is the element that makes distinction between features captured from a single query blob viewed from different directions. It is discussed in more detail in Section 3.2.2. In spite of its dependency to a viewpoint it still preserves the property of being scale invariant. Figure 3.4 shows a sample plot of VFH and its components.

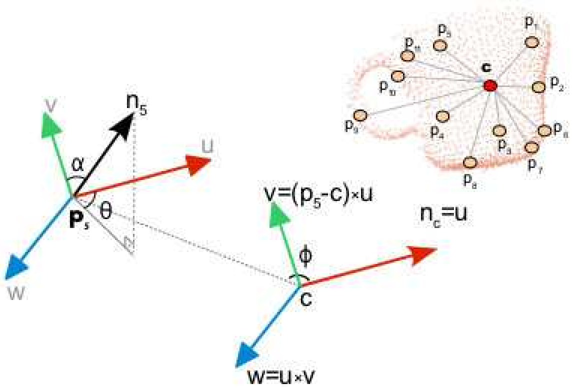


Figure 3.3: Three angles and a distance encoded in FPFH and the points considered.[17]

Table 3.1: Structure of object context descriptor.

Field number	1	2	3-310
Field content	Orientation	Height	VFH

The images and definitions are taken from Point Cloud official website.

The resulting object context descriptor is a vector with 310 elements that encodes a general orientation, height and geometrical properties of the query blob.

3.2.2 System Modules

As illustrated in figure 3.1, apart from libraries we used for SVM [5] and [9], there are three modules in the system:

- PreProcess
- Annotation
- FeatureExtract

PreProcess

In this module, the input pointclouds get prepared for annotation and feature extract. The processes for capturing these pointclouds is discussed in Section 3.3. First step in preparation of the input is transforming it. Based on the location and orientation of the sensor in time t_0 the resulting point cloud is

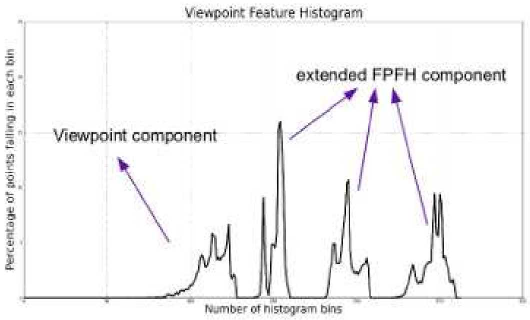


Figure 3.4: A sample plot of VFH and its components.[17]

transformed from sensor coordinate system to the world's coordinate system. The sensor is in a fixed orientation and vertical position in time the first frame is captured for all pointclouds used in experiments of this work.

As a different PCL point type, in which labels can be saved for each point, is used in the rest of the process, in this step a conversion of the transformed pointcloud into that type is also carried out.

The most important step, which is taken here is estimation of surface normals which is essential for feature extraction. The accuracy of the VFH feature is directly dependent to the accuracy of the normals. Here the normals for the whole pointcloud are estimated once and saved in a separate pcd file to be used in feature extract.

There is also one more product for this module, which is discussed more in 3.2.2. It is a generated cube-shaped pointcloud with length, width and height of the input cloud, filled with points. The density of these points is determined by a fixed radial distance between them. It is used as a source for picking viewpoints that are needed in feature extraction.

Therefore, the results of this module are as follows:

- Point-cloud's normals
- The transformed version of the input cloud
- Converted version
- TFP-cloud

Annotation

In this module the transformed and converted version of the pointcloud is loaded to get annotated. The objects needed to be annotated in the scene, are

Algorithm 1 A brief algorithmic description of PreProcess.

Require: Input Point-cloud(XYZRGB).
Require: Sensor Location and orientation.

1: Transfer the input cloud based on Sensor location and orientation from camera coordinate to world coordinate, and store the result.
2: Estimate Normals and store.
3: Convert the Pointcloud_Transfered to Point type XYZRGBL and store in Pointcloud_Converted.
4: Estimate 3DMINMAX of the Pointcloud_Converted.
5: Using result from previous step, generate TFP pointcloud.

Ensure: Pointcloud_Transfered.
Ensure: Pointcloud_Normals.
Ensure: Pointcloud_Converted(XYZRGBL).
Ensure: Pointcloud_Generated(TFP).

selected by clicking roughly on their center. The labels of the points belonging to them are assigned with a value representing object points. Objects from different classes could be labeled with different values (2).

Figure 3.5, shows a scene in an office at KTH. The object of interest here is the trash bin, which is marked by a green bounding box. This figure is an image of the scene whose pointcloud is available in our dataset and the annotation is done on the pointcloud. In figure 3.6 the annotated object could be seen in red within the scene's pointcloud. It can be seen that some part of the floor is also colored in red, which means that part of the floor is also annotated as the object. The reason is the object radius, that is given to annotation tool was not accurate enough or the center of the object was not picked accurately. But it does not harm the result and this much of accuracy is more than enough. Usually annotation is done using a bounding box which consider the box surrounding the object as the object. Here, we exactly separate the points of the object by benefiting from the 3D coordinates of the points in the pointcloud. As it is described in the algorithm 2, object segmentation is done automatically in a very simple way. Based on the picked object center, selecting points from the 3D neighborhood of it separates object points from the rest of the pointclouds.

This package is available with source to be used by other researchers and get improved by developers.[3]

FeatureExtract

First, we Introduce some terms used in this part. They are as follows:

Algorithm 2 A brief algorithmic description of Annotation.

Require: Pointcloud_Transfered(XYZRGB).
Require: Object radius(rough estimate).

1: Visualize input cloud.
2: for all objects to be annotated do
3: Run Point picking procedure.
4: Extract neighbor points indexes with respect to the input object radius.
5: Label points whose indexes are extracted in previous step.
6: end for
7: Store the pointcloud with the labels in output cloud.

Ensure: Pointcloud_Annotated(XYZRGBL).

- Blob: A sub set of the Point-cloud which includes a number of points in a neighborhood within a specific radius.
- Query Blob: The blob from which the features are being extracted.
- QPoint: The Query Point that is the center of the query blob. It is a point on the context of the object.
- OPoint: The Object point is the point in surrounding of the Qpoint which is an object point in a positive sample.

Instances of these elements are illustrated in Figure 3.7 for the example scene that we saw in Figure 3.5. The red point in the figure shows the `Query Point`, which is a point picked from the context of the object and the features are extracted from the sphere surrounding it. The sphere is also visible in the figure which is the `Query blob`. The yellow point is the `OPoint` or object point which is a point on the annotated object.

In this module, the converted and transformed pointcloud and its normals are loaded. To build the data set for train or test, Features are extracted for a number of keypoints from all over the pointcloud. Keypoint selection is described later in this Section.

The goal here is to get samples which are useful in building the context model for objects of interest. This is done in a way that for each key point, which is considered as a QPoint when it is selected for feature extract, we take a neighborhood of points and their corresponding point-normals to extract features from (Query Blob).

The important idea applied here is the view point used in VFH. For each QPoint and its corresponding Query blob, a number of points in a radius from the QPoint is considered as the view points (OPoints). A sample is extracted

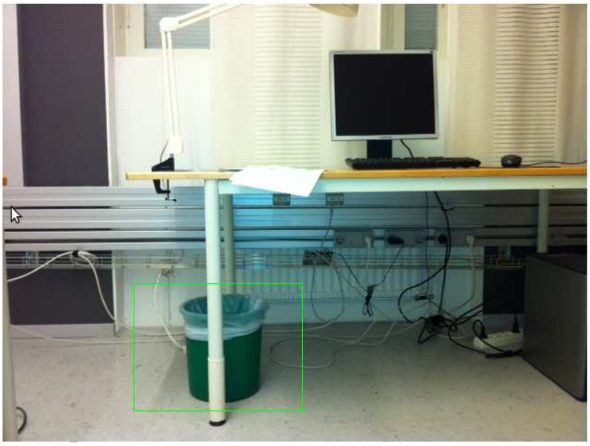


Figure 3.5: An example scene and a trash bin marked by a bounding box as the object which is being annotated (Best viewed in color).

for each pair of Qpoint and Opint_i. This way due to the difference in viewpoint, the features extracted for a single query point and its query blob would be slightly different. This will result in discrimination between same context viewed from different view point which is to our benefit.

As mentioned above, these viewpoints are candidates for being object points. In each sample if the OPoint in a pair of $(\mathsf{QPoint}, \mathsf{OPint})$, is actually an object point we want this sample to be labeled as a positive sample and if not, to be a negative one. The view point also helps to encode the most probable location of the object with respect to the positive context.

Another important point here is that we want the model to be able to locate candidates for context in a test pointcloud where object may be not present at the moment but its context is. Therefor, we need the OPoints to be independent from actual points in the pointcloud.

This is where TFP-cloud finds it role. This is a pointcloud generated in accordance to the input pointcloud which includes points with fixed structure to be used as candidate OPoints in feature extract. Using these points as OPoints, we have fixed viewpoints to sample the context for. To have the same structure in train and test data, we use the same OPoints in feature extract for train set as well. The only difference in feature extract for train and test is that in train it is checked if the OPoint is on the object, using labels from annotated cloud. Then, if the answer is positive, the extracted sample would be a positive one. If not, it would be a negative sample. But in feature extract for test, we just do not do this check.

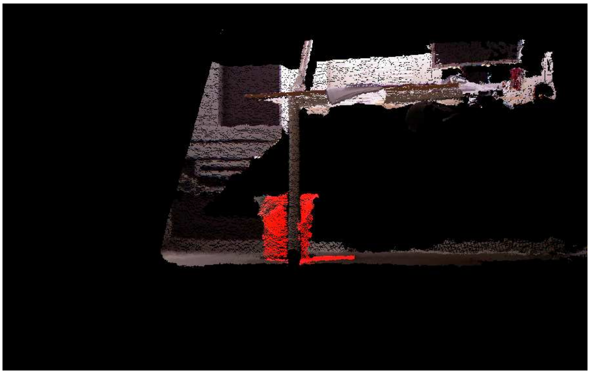


Figure 3.6: An example of annotation result on the pointcloud, red points assumed to belong to the object(Best viewed in color).

QPoints would be selected in a loop on key points in the pointcloud. The key points are all points in a down sampled version of the input cloud with a radius that is dependent to the size of the object of interest. This way, we have a uniformly distributed key points in the input pointcloud which will make the sampling more informative. For each of these QPoints, a blob around them is considered from the input cloud with point normals(Query blob). Therefore, Qpoints come from the down sampled cloud while query blob is from the original cloud.

In another loop, the OPoints are assigned as the view point in feature extraction of each sample. Feature vector would be extracted for this blob and the OPoint. Figure 3.8 shows these points and their related parameters. The values mentioned in the figure is for an example object class.

Learning

After Feature extraction, the resulting data set for train is made in a way that it includes samples from several pointclouds for the same object class. In first experiments we used a single Gaussian kernel for the whole feature vector whose fields are of two different types. As mentioned before part one is two float numbers and part two is a histogram. Later we separated these two parts to apply independent kernels on each.

Another important issue here is the distribution of samples in each of positive and negative classes. From the data we extracted, in average, about one percent of the samples were positive and the rest were negative. This is because the annotated object is a small part of the pointcloud and positive samples are the samples extracted from its surrounding. This significant difference in num-

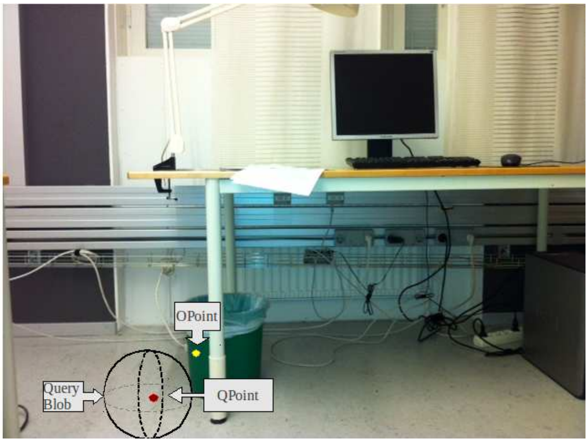


Figure 3.7: Structure used in Feature extraction; The red point is the QPoint; The sphere surrounding it, is the Query Blob; The yellow point is the OPoint (Best viewed in color).

ber of samples in positive and negative classes makes the classifier to prefer classifying test samples into the class with more train data.

In addition, this issue has some other effects that make the classier confused. The features extracted from blobs in object's neighborhood may be so similar to some feature extracted from a blob far from the object, while the first one would be a positive sample in train data and the second one would be a negative sample. For instance, features extracted for a cup context, which can be a table's surface, will get positive label when it is extracted from a blob close to where the annotated cup is located. But features from the same surface which is extracted from a region far from the annotated object gets a negative label. Because there was no annotation nearby to make it positive.

In order to solve the mentioned issue and both of its effects, or at least improve the result toward our goal, we needed to do an unbalanced weighting for our samples. We decided to assign different weights for misclassification cost in SVM binary classifier. It should be in a way that not only compensates the lower amount of positive samples, but also emphasizes the importance of positive samples compared to negative ones. It can be inferred that there should be a big weight for positive class and rather small value for negative class. In Section 3.3 a parameter selection procedure used to find suitable values for them is discussed.

The way datasets and experimental environment is created is discussed in Section 3.3.

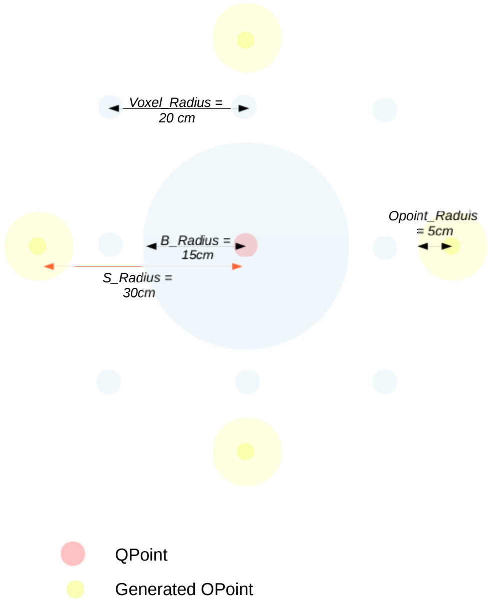


Figure 3.8: QPoint and generated OPoints and their spacial relations.

3.2.3 Parameters

Feature extract parameters: As mentioned before and depicted in figure 3.8 there are some parameters that play great role in achieving good results. These parameters are:

- B-Radius : Radius of the query blob (from which features are extracted) of points from the pointcloud with original density.
- Voxel-Radius : Radius used for voxel down-sampling.
- S-Radius = : Radius of the sphere to search object point in. It depends on the object class.
- OPoint-Radius : This is the radius of the neighborhood of the generated point to look for actual Object point.

Algorithm 3 A brief algorithmic description of Feature Extract.

```
Require: Pointcloud_annotated or Pointcloud_converted(Depending train or
    test).
Require: Pointcloud_Normals.
Require: Pointcloud_Generated.
Require: S_Radius
Require: OPoint_Radius

Key-point selection.
for all Key-points do
    Extract Query blob.
    Extract indexes of generated points within S_Radius from the key-point.

    for all extracted generated points do
        Assign generated point to OPoint.
        Extract features for the OPoint and the Query blob
        if Features are for train then
            if There is an object point within OPoint_Radius of the OPoint
            then
                Label the sample as positive
            else
                Label the sample as negative
            end if
        end if
    end for
    Store the sample
end for

Ensure: Pointcloud_Extracted samples.
```

These parameters directly or indirectly are dependent to the average size of the object class that we are making the context model for. This dependency is not so tight, it means that the object size does not need to be very accurate. As long as these values does not cause the object to be missed, they are acceptable. The object can be missed if the down sampling radius, which depends on the object size, is too large. On the other hands, small values causes the complexity to increase and computation time to get too long. As a result, we reduced the number of dependencies to a single parameter which a rough estimate of the object size.

Learning parameters:

- w_i: Weight for class labeled (i)
- c: Sets the cost value for misclassification. w_i acts as a coefficient for c, so the combination of their values will set the cost value for each class.

- g: Sets the value of gamma in Gaussian or chi-square kernels, which is clearly a very important factor for the result we can expect from the classifier.
- kernel type
- weight for kernels in multi kernel setup

3.3 Experimental Setup

In order to do an evaluation on our method and the model, some experiments are carried out. To prepare a data-set for our experiments we needed to capture several pointclouds from different scenes and places which include different object classes.

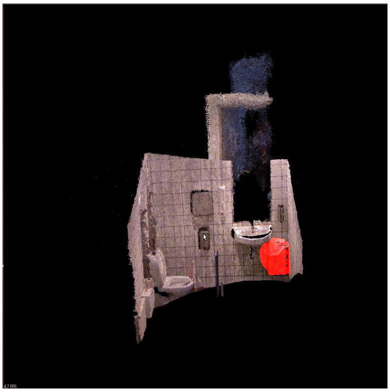
To capture pointclouds we used different tools: RGBDSLAM [6] is an open source package available in ROS. Using this package and kinect sensor with OpenNi driver a 3D model of a scene can be captured. The results are saved as a pcd file. Point-clouds were captured from different types of places from KTH campus like offices, Kitchens and bathrooms including different types of object that can be found in those places.

There is also a project in CVAP at KTH called KINECT@HOME [1] which is a web based application uses kinect out puts to build 3D mesh model of objects and places. A very good property of this system is that people from any part of the world capture their own video with kinect from different places and scenes and post the videos to a server where the 3D reconstruction happens. Through this means a good dataset can be prepared to train and test models. Of course, not all of the resulting pointclouds from this database are useful for our purpose due to the content and quality, but still there are applicable ones.

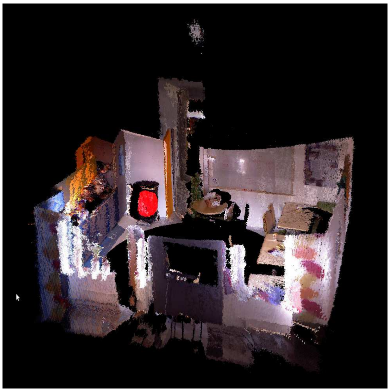
All resulting pointclouds were saved and based on the content a name was assigned to them. They were divided into two subsets of train and validation. Although, samples from the same pointcloud could be divided into train and validation sets, but we preferred to make them separate even from pointcloud level to be sure of having reliable results. Figure 3.9 shows full pointclouds with different type of trash bins annotated in them. These are the pointclouds used in experiments.

Table 3.2 includes names of four different object classes used in experiments and the number of train samples extracted for each of them. It also shows what fraction of those samples were positive samples that are actually samples captured from context point blobs.

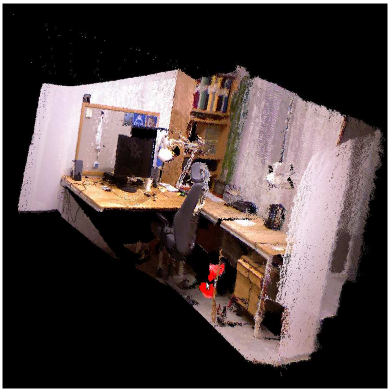
In experiments with four different object categories mentioned in table 3.2 few different scenes are considered to capture train pointclouds from. For each scene, a number of different location settings for objects are captured in different point cloud (figures 3.10(a) and 3.10(b)). Therefore, in the resulting train set each object has a number of instances in different scenes.



(a) A partial view of a bathroom.



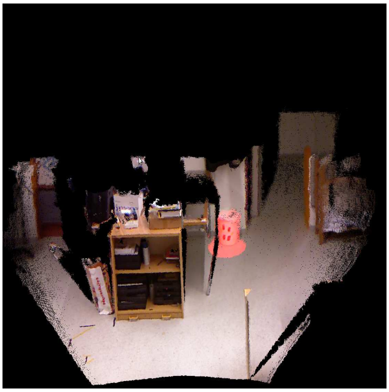
(b) Full pointcloud of a kitchen.



(c) A partial view of a office.

(d) A full pointcloud of an office.

(e) A full pointcloud of another kitchen in the same building.



(f) A partial view of an office with lots of missing points.

Figure 3.9: Point cloud used for extracting train samples with trash bin annotations. Bins are in different types and locations.(best viewed in color)

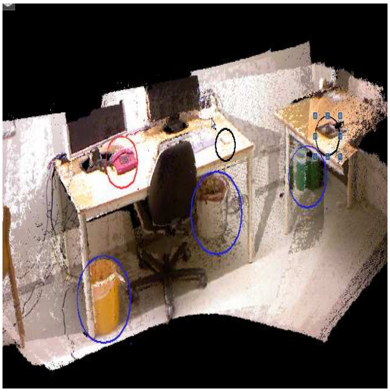
Table 3.2: Object classes used in experiments with number of samples extracted for each of them for training and ratio of positive samples in them.

Object		#Train samples	#Positive Train samples	Ratio
1	Trash Bin	142150	2493	1.7
2	Telephone	119725	554	0.4
3	Mouse	286825	1541	0.5
4	Wiper	170025	3086	1.8

(a) Partial cloud including telephone, mouse and trash bin.

(b) The same scene with different location of the objects.

(c) Partial cloud including white board wipers.



(d) A partial cloud including several instances of 3 object categories.

Figure 3.10: Partial pointclouds including four object categories: trash bin(marked with blue circles), mouse(back circles), telephone(red circles) and wiper(green circles) in different location settings used in training.(best viewed in color)

After acquiring the pointclouds, some python scripts were used that picks the pointcloud from the input dataset and load them into PreProcess module and saves the results of each pointcloud separately in a useful way into the automatically generated environment. Then the annotation tool were used to annotate objects of interest in the pointclouds. All pointclouds were annotated with present objects of interest, regardless of them being in the train set or validation to make evaluation possible on ones used for test as well. Although in validation we would not be using labels from annotation until the end of classification, this information is needed for evaluation which would be described later in next Section 3.4.

In the next step, another script picks annotated clouds and their normals (estimated in PreProcess) into Feature extract and resulting feature vectors are saved in a folder for the corresponding object class under train or validation set, regarding which set their source pointcloud belong to. Then, a subset is randomly selected from the train samples in a way that includes all the positive samples and sevral times more of negative samples to make the train set. In first experiments for Trash bin we have used train sets with 10 percent positive and 90 percent negative samples. In later experiments and for other objects train sets are generated with all extracted positive samples and two times more of negative samples. In these experiments positive sample have a 33% share in the train set.

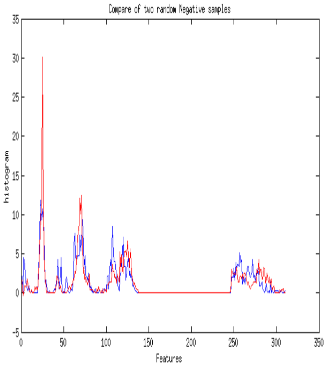
At this point, all data sets are scaled with the same parameters, then the scaled train set is given to SVM train to make the models for each of the object class's context. During training, different values for the parameters are considered, and each resulting model is applied on samples from validation set. Classification results with different examined values of these parameters are compared and best models are selected. The results and evaluation procedure are discussed in Section 3.4.

3.4 Results

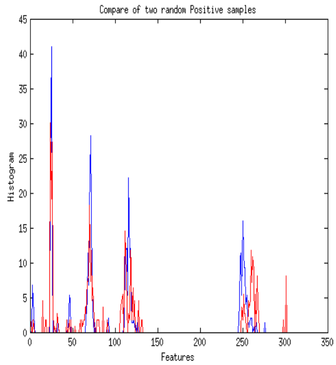
In this Section, we take a look at some results and analyze and evaluate them to see how good our method performs. It can help if we first check some plots showing how does the feature vector look like and how discriminative it can be. Figures 3.11(a) and 3.11(b) show the plot of two random negative and two random positive samples.

In order to have a more clear idea about differences between samples, we can also look at the distances between random samples in the same class and compare them to the distance of samples from different classes. Figure 3.11(c) shows the distance in two random negative samples. It should be noticed that the first part of the plot reflects the view point component of the feature vector.

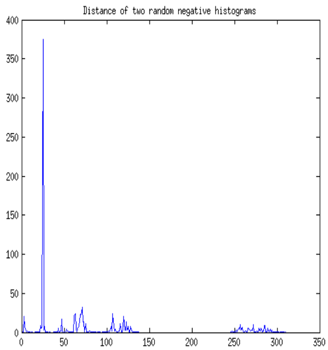
And figure 3.11(d) is the same plot for positive samples. Features extracted for each class can have big differences as well, which was predictable. Considering different surfaces captured as context by these features that can belong



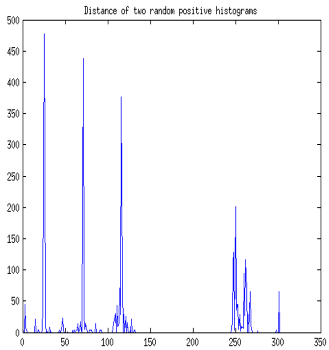
(a) Compare two random negative samples.



(b) Compare two random Positive samples.



(c) Distance between random negative samples.



(d) Distance between random Positive samples.

Figure 3.11: Plots of feature vectors of random positive and negative samples and the euclidean distances between them. This comparison shows the challenge in training a classifier for these samples.

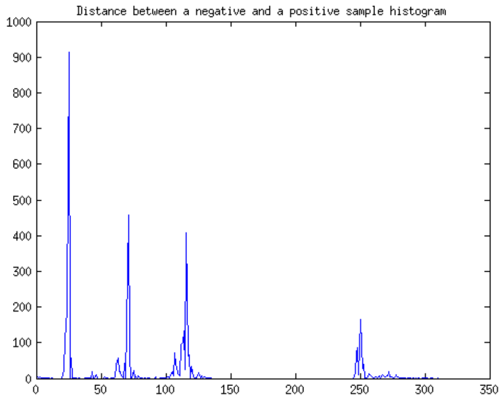


Figure 3.12: Distance between random positive and negative samples.

to a class causes the differences. A positive sample can be representing, for instance, the surface of a table or a wall or the meeting region of these two surfaces. This comparison gives us an idea about how challenging it is to train a classifier for such data. As mentioned before, it is also important that more attention to be put on learning the positive samples rather than negative ones.

Figure 3.12 is showing the distance between random positive and negative samples.

3.4.1 Evaluation

Here we define a metric and an evaluation method that we considered in this work. Metrics such as accuracy of prediction is not something that can show the performance of our system. Accuracy is measuring number of samples that are correctly classified with respect to the total number of samples. Here we do not have direct access to the number of correct classification.

Based on the problem definition, we are looking for possible context of an object, which regards to locations that an object is expected to be found, not just location that an object is present. Intuitively, set of points that belong to an actual object (if there is an actual object in the scene) is a subset of all possible object points in that scene. Therefore, actual object points (Lp) are a subset of predicted positive points (Pp) if the model and classifier perform well (equation 3.1).

$$\mathsf{Lp} \subset \mathsf{Pp} \tag{3.1}$$

In other words, from a good result, we expect any random point sampling which is an actual object point to be within predicted positive points. With this definition there would be a problem: if all points get predicted as positive then actual object points would definitely be a subset of it, while our classification has failed. As a result, we define a good result as predicted set of locations that reduces our search space for the object as much as possible while it preserves the high probability of finding the object.

Equation 3.2 shows the evaluation metric, where $E(\tau)$ is the the value of the metric with respect to a probability threshold τ. This threshold sets the boundary for the lowest probability value that the prediction should have, so that the sample can be considered as positive. This threshold is assigned with a value in a loop that as a result in each iteration a top fraction of the samples are being picked and analyzed. For instance we will pick top five percent of the samples and measure how much would be the probability of having the object in this fraction.

The threshold is computed based on an increasing value of the number of samples that are considered. Pp_τ is Predicted positive sample with respect to the value if the threshold and $n(x)$ is the number of members in the set x as in $n(Lp)$ it is number of points belonging to Lp. Lp is the Labeled positive points in the data-set or in other word the annotated object.

$$E(\tau) = \frac{n(Pp_\tau \cap Lp)}{n(Lp)} \tag{3.2}$$

This value is between zero and one, and a value closer to one, while the threshold is high enough, shows a better result. This metric is also used in experiments to find the best models and parameters. Here we also translate the sample base results into point base which means the result is assigned to the point for which the sample is taken. Therefore, the prediction directly shows if a candidate OPoint is a possible object point or not.

Figure 3.13 shows the value of E for top ten percent of the points with respect to their prediction probability in experiments with 80 different configuration of weights and gamma. As it can be seen the results look pretty good.

Considering best models, it can be inferred from the curves that for instance, top five percent of the points contains twenty percent of the object which is a very good result. In other words, reducing the the search space to only 5 percent we still have four time chance of finding the object.

Figure 3.14 shows this evaluation for seven experiments with different weights for class -1. The value is depicted with respect to the fraction of points considered.

Figure 3.15 shows the prediction of trash bin context on a full pointcloud of an office. The marked region shows the points with highest probability values(top 1%). It is noticeable that the context reaches the trash bin which

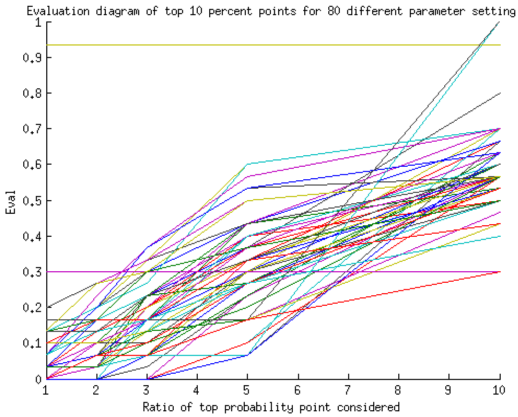


Figure 3.13: Top 10 percent of positive predictions in experiments with 80 different configurations for parameters.

is present in the scene when the probability threshold reaches top 5%. The interesting point is that this trained model is suggesting that corner is the best location to find a trash bin or put one.

In later experiments that we used multi kernel of type chi-square there was a significant improvement on the results. As the first two fields of our feature vector are two float values and the rest is histogram, they are to be treaded in different ways. So we separated the kernels applied on each of these parts. The visualized results of predictions using these kernels with equal weights are shown in figure 3.16 for the four object we used in these experiments.

In figure 3.16, the predicted contexts of four object used in experiments are projected on the pointcloud of an office. It should be noticed that the regions shown in cyan, are blobs with a key point in the center which is predicted as context.

The corresponding evaluation values for results shown in figure 3.16 are depicted in figure 3.17. A simple comparison between curves in this figure and figure 3.14 shows the improvement of the results.

To compare the performance of the system regarding each of these four object class, the values of E in a certain ratio of selected points with respect to all points in the pointcloud is considered for each of these object classes. Table 3.3 contains these values for the ratio of top 5%.

As it can be seen in table 3.3, the best performance of the system is for Telephone and after that for Mouse. These objects are often found in a similar context which can be a good reason for these results. The context for trash bin, at least based on our train set, can have wider variety compared to mouse

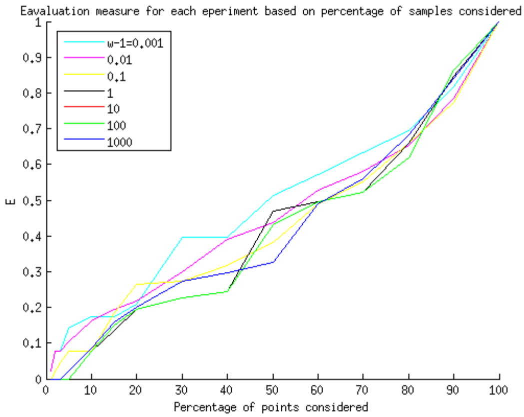


Figure 3.14: Evaluation diagram(1)

Table 3.3: Performance of the system for four object classes.

Object	E in top 5% of points	The ratio that E reaches to 1
Mouse	0.6667	15
Telephone	1	5
Trash Bin	0.3333	40
Wiper	0.42	60

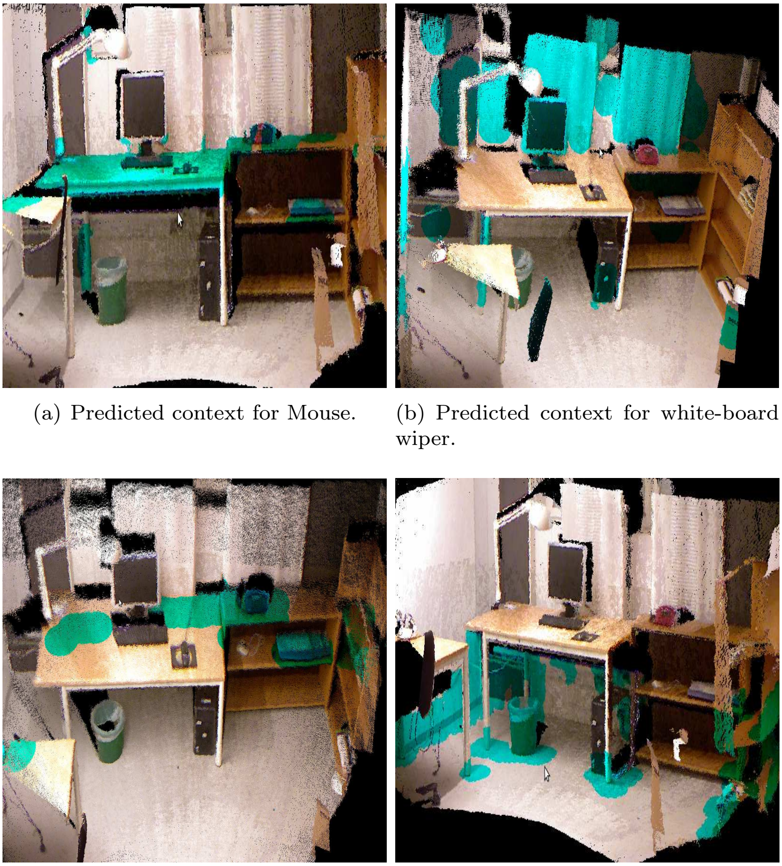
and telephone. That is why its performance value is the lowest. But for wiper, as the context is usually similar it can not be a good explanation. In the wiper case, the reason for its low performance should be the wide range of heights this object can be located in. We consider the height as an important feature in building our models which makes it very effective. The effectiveness of height seems to be not so useful in the case of wiper. A solution can be using smaller weights for the height feature in modeling these object classes.

Figure 3.18 shows the predicted contexts of these four object class on the pointcloud of an office where no instance of Mouse, wiper or telephone is present.

(a) A test pointcloud for trash bin model, marked region with red circle is the predicted context.

(b) Focused to predicted region.

Figure 3.15: Prediction of Trash bin context on a full pointcloud of an office. The marked region shows the points with highest probability values(top 1%).(best viewed in color)



(a) Predicted context for Mouse.

(b) Predicted context for white-board wiper.

(c) Predicted context for Telephone.

(d) Predicted context for Trash Bin.

Figure 3.16: Visualization of context model prediction on sample cloud 1 as a validation cloud, for four objects. The key point predicted as positive and the blob around it is projected on the pointcloud in cyan color.(best viewed in color)

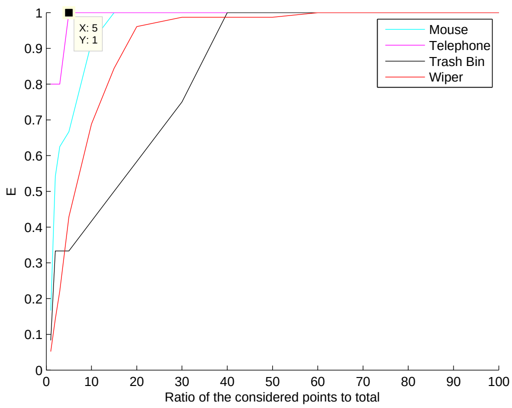
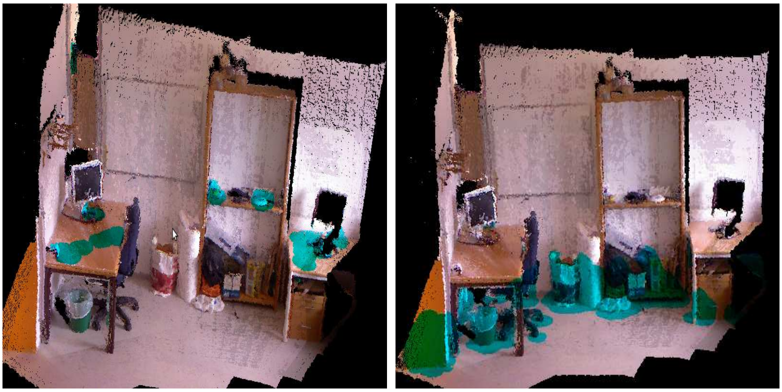


Figure 3.17: Evaluation results of context prediction for four objects Mouse, Telephone, Trash Bin and wiper. These results are from experiments using chi-square multi kernel.

(a) Predicted context for Mouse. (b) Predicted context for white-board wiper.



(c) Predicted context for Telephone. (d) Predicted context for Trash Bin.

Figure 3.18: Visualization of context model prediction on sample cloud 2 as a test cloud for four objects. This pointcloud does not include these objects except trash bin.(best viewed in color)

Chapter 4
Using Object Context for Place Classification

In this Chapter, we discuss the proposed idea of using `object context` in classification of places. Place classification in here, mainly mean to determine the category of a visited place so that some resulting semantics can be added to and understood by the system.

Adding semantic information to maps, to be used by mobile robots, enhances human-robot interaction. It helps robot localization and object detection. Obviously, the ability of a robot to understand semantics of space and associate spatial locations with semantic terms such as `kitchen` or `corridor`, provides a more clear idea of its location than a pure topological or metric position [14].

Regarding Object detection, having semantic information of a place in association with a ground truth about the objects expected to be present in that place, makes the search for an object faster and more successful. It helps robotic systems to communicate with humans and interpret environments built by and for them.

Concepts such as `office` or `kitchen` are different categories for a room based on its functionality. Other features categorized based on its spatial properties such as its shape, size or general appearance.

Figure 4.1 shows an overview of a semantic mapping system proposed by Pronobis in [14]. As it is illustrated in this picture, inputs to this system are models of objects, shape, size and appearance in the company of a commonsense knowledge database. It is considered as a future work for this thesis that 3D `context models` replace `object models` in this system and with some improvements a more robust and complete representation for places would be achieved.

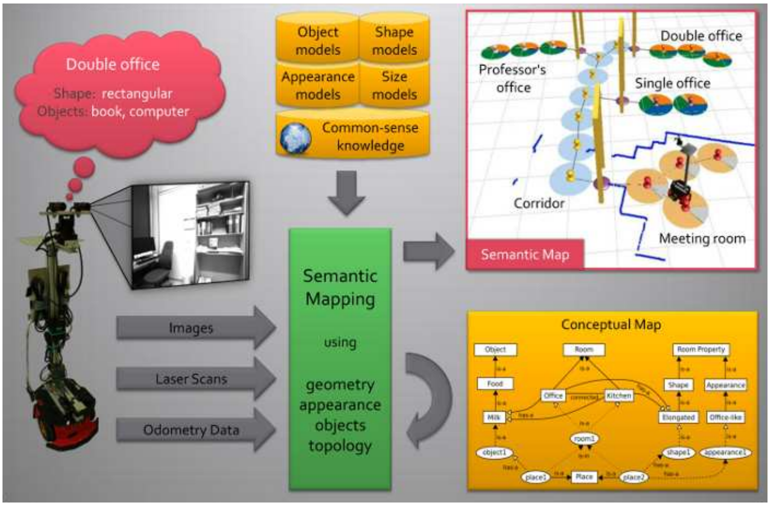


Figure 4.1: Overview of a semantic mapping system by Pronobis in [14](best viewed in color).

4.1 Brief overview of approaches to place classification

Place categorization based on vision in its first stages was focused on classifying single 2D images of an indoor or outdoor scene. Data achieved from laser range sensors are also popular due to their robustness to environmental variations and faster process time .[14] Several researchers in computer vision community addressed the problem of place classification, some examples are reviewed here.

Li and Perona in [8] represented images of scenes as a collection of local regions called codewords achieved from unsupervised learning. Similarly, Lazebnik et al. in [7] extended a bag-of-words approach in a computationally efficient way by introducing a spacial pyramid which contains approximate global geometric correspondences between local features.

Olivia and Torralba proposed a scene representation called gist of the scene in [12] which is used by Torralba et al. in [23] and [21] for place categorization. They used 2D object context information as mentioned in previous Chapters in their work. Later Quattoni and Torralba in [15] combined the gist of the scene with local features and reported significant improvement in their results.

Also in robotics, researchers worked through capturing some semantics mostly using laser range data. Buschka and Saffiotti classified different parts of grid maps into two categories: rooms and corridors in [4].

There are approaches that mostly rely on object information for place categorization. Usually a more fine grained description of a place based on its functionality needs association of some key objects for each place category.

As mentioned in Chapter 1, rooms are usually classified into categories like `Office kitchen` based on their functionality which is tightly dependent to the objects found within them.

In [24], Vasudevan et al. suggest a hierarchical probabilistic representation of space using object information. They use SIFT features to detect and recognize objects then create a local probabilistic object graph for the place. They also detect doorways to separate rooms from each other in their map. Using object graphs for each visited place they make a global topological representation of an environment.

[16] and [26] also used object based approaches using models trained in advance in a supervised manner. In [16], Ranganathan and Dellaert train object models using visual features capturing their shape and appearance from roughly segmented and labeled images. They also added 3D locations of the objects using stereo range data.

Pronobis in [14] integrated multiple visual cues with geometric information from laser range data. Object detection in association of a common-sense knowledge database completes the information needed to determine the category of places in his semantic mapping system.

4.2 Ground Truth

As mentioned before, a ground truth is needed to make the relation between the class of a place and object contexts present in it. This knowledge can be achieved by analyzing available common-sense knowledge databases like Open Mind [11], popular search engines such as Google Image Search, image repositories like Flicker or directly from a human user inputs.

Viswanathan et al. in [26], have performed an automated learning of object-place relations on an on-line annotated database such as `Label me`. Then object detectors are trained on some of the most frequently occurring objects. In our case instead of objects we train their context detectors.

Based on the dependencies between place category and its objects also between different object categories we can make probabilistic models that represent these relations and dependencies. Some objects are more discriminative for a place category which should have a more significant role in deciding the category of the place. For instance, a water tap in the kitchen or its sink as its context are quite discriminative for this place category.

$$w_i = p(R_c \mid O_i) \tag{4.1}$$

Equation 4.1 shows the dependency between a room category (R_c) and each object category (O_i). Sometime, the dependency lies on a combination of objects. A combination of shelves and books can be discriminative for an office, while shelves and dishes are good for kitchen.

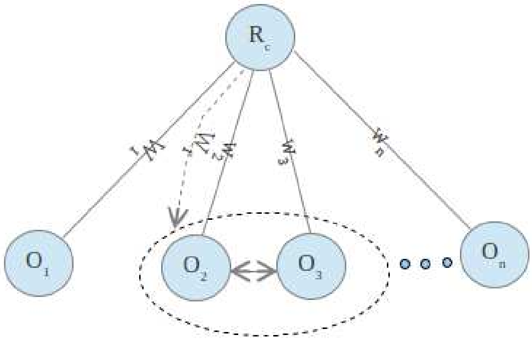


Figure 4.2: This figure shows dependencies between a room category and key object classes, dashed lines shows dependency to a combination of object categories.

$$w_{i'} = p(R_c \mid O_j, O_k) \tag{4.2}$$

Dependency of the room category to a combination of object categories is shown in equation 4.2. A probabilistic graphical model can be achieved like the one depicted in figure 4.2 in which singular dependencies are shown by continuous lines and combinational dependency is illustrated by dashed line. A normalized weight can be computed based on this analysis for each object category.

4.3 Benefits of Object Context for Place Classification

Some of the benefits of employing context models in place classification can be briefly mentioned as follows:

- It provides a simple way to include human annotations from common-sense knowledge bases into place representation.
- It is a way of including spatial relations into place representation.
- It is a way to make place models more universal.
- It brings in object information while no fine grained object detection is needed.

4.4 Place classification

A method is proposed here to compute a score for each place category based on the amount of objects possible to be found in a place. In each place category based on its ground truth learned from a lot of examples we compute a weighted sum of the scores of each key object class. The score for place categories should represent the followings:

- Probability of presence of an object class in a place.
- Weight or ratio for this presence.
- Based on a ground truth a probability of being an specific place category.

Applying context models on the point-cloud of a room, we get a subset of points with highest probability of being the context. In other words, we can estimate the amount of points belonging to a context category in that point-cloud. An average probability for context points belonging to each context category can be computed and assigned to that category. Using the ratio of points in each category and the value of the average probability a score is estimated for each context category (Equation 4.3).

$$Sc_i = Avg(p(c_i)) * \frac{points \in c_i}{points} \tag{4.3}$$

Sc_i is the score for object category i, $Avg(x)$ computes average and the last element of the equation shows the ratio of points in context category i with respect to all points in the point-cloud. Employing weights resulted from ground truth analysis (4.2) a score for each place category can be estimated.

$$Spc_j = w_1 * Sc_1 + w_2 * Sc_2 \ldots + w_k * Sc_k \tag{4.4}$$

In equation 4.4, Spc_j is the score for place category j, k is the number of key object categories. The corresponding weight for each object category is shown by w_k. Both scores should be normalized to a range between zero and one to be comparable for different place categories. Here we used object category and context category as equivalents.

Chapter 5
Conclusion and future work

In this thesis, we proposed an idea and a method to build 3D model of object context using geometrical features extracted from point-clouds of a scene or room. Point-clouds are produced using data from kinect sensor. A set of point-clouds is gathered from different place categories including different objects to be used for experiments.

A metric for evaluation of the results is proposed in a way that it can assess the results as they are expected to be. The context prediction of the system are expected to be a `superset` of positive samples in train set. In spite of the few number of point-clouds and instances of the objects used in experiments the results are acceptable.

In addition a method for employing the object context model in place categorization is proposed and analytically discussed. This work is unique regarding the suggestion of using 3D context model of objects in building a descriptor for places and also the use of full point-clouds of a place. These full point-clouds can be extended to a 3D map of an environment.

5.1 Future work

There are some suggestions for improvements and some potential future works which are mentioned here.

- The quality of the point-clouds are an important factor, so using better means and methods to capture and build point-clouds with higher quality makes an improvement in results. Doing some pre-process like smoothing and removing noise is even a more practical improvement.
- Larger train set with more variety of places and object instances is essential. Gathering data in a smart way for the train set which considers several possible situations can be more efficient than just increasing the number of samples.

- Some more features can be added to make the model more descriptive and discriminative. Visual features should be considered for this improvement.
- A comparative evaluation can be done between object detection by a known high performance detector with using context model and without.
- Develop the system to be able to run in real time and on-line situations.
- Employ and experiment place categorization using this model and the proposed method.

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