

Benchmarking RGB-D Segmentation: Toy Dataset of Complex Crowded Scenes

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Keywords: Object Segmentation, RGB-D Segmentation, Benchmarking, Dataset, Complex Objects, Real World Objects.

Abstract: In this paper we present a new RGB-D dataset ^a captured with the Kinect sensor. The dataset is composed of typical children's toys and contains a total of 449 RGB-D images alongside with their annotated ground truth images. Compared to existing RGB-D object segmentation datasets, the objects in our proposed dataset have more complex shapes and less texture. The images are also crowded and thus highly occluded. Three state-of-the-art segmentation methods are benchmarked using the dataset. These methods attack the problem of object segmentation from different starting points, providing a comprehensive view on the properties of the proposed dataset as well as the state-of-the-art performance. The results are mostly satisfactory but there remains plenty of room for improvement. This novel dataset thus poses the next challenge in the area of RGB-D object segmentation.

^aAvailable at <http://robosvn.org.aalto.fi/software-and-data>.

1 INTRODUCTION

Object segmentation from visual sensor data is one of the most important tasks in computer vision. Segmentation of RGB-D scenes is especially crucial for robots handling unknown objects, an application area of special interest to us. As more efficient segmentation methods have become available, the detection of simple objects is readily accomplished. These objects may be, for instance, cereal boxes, coke cans, or bowls, which embody somewhat elementary geometrical shapes and easily distinguishable textures. Benchmarking segmentation algorithms is important to understand the state-of-the-art performance as well as open problems, and many useful datasets, including the Object Segmentation Database (Richtsfeld et al., 2012), RGB-D Object Dataset (Lai et al., 2011), BigBIRD (Singh et al., 2014), and the Willow Garage Dataset¹, are available, containing hundreds of such RGB-D images.

Many of the objects we encounter in our daily lives are, however, far more complex in terms of their shape and texture. A good example of such an object is an ordinary child's toy, which may or may not resemble any simple geometrical shape. Furthermore,

¹Available at <http://www.acin.tuwien.ac.at/forschung/v4r/mitarbeiterprojekte/willow/>.



Figure 1: Toys used in the toy-dataset.

the toy may be uni- or multicolored. Our proposed toy-dataset contains objects like this, often in crowded scenes and occluded positions, and poses the next challenge in the area of object segmentation towards general purpose understanding of complex domestic environments. The dataset consists of 449 RGB-D images with human-annotated ground truth.

Three state-of-the-art RGB-D segmentation methods are benchmarked using the dataset, in order to explore the dataset's properties as well as to assess state-of-the-art capabilities in these kind of scenes. The methods are provided by the Vision for Robotics group (V4R) (Richtsfeld et al., 2012), the Image Component Library (ICL) (Uckermann et al., 2013),

and the Locally Convex Connected Patches (LCCP) segmenter (Stein et al., 2014) available in Point Cloud Library (PCL, (Rusu and Cousins, 2011)).

Section 2 puts our contribution in context by reviewing existing RGB-D datasets. Section 3 describes in detail our proposed dataset and some of its characteristics. In Section 4 we discuss briefly how the three state-of-the-art segmentation methods function, and also present the experiments and results on the toy-dataset. In Section 5 the results are analyzed, and Section 6 states the conclusion.

2 RELATED WORK

Several datasets exist for benchmarking segmentation algorithms. Most of these previous datasets have concentrated on relatively simple objects comprised of primitive shapes, such as cuboid and spherical shapes, cylinders and combinations of these.

Among the most popular RGB-D datasets are the Willow Garage dataset and the OSD (Richtsfield et al., 2012), both created with a Kinect v1. The Willow Garage dataset contains 176 images of household objects with a little or no occlusion, as well as pixel-based ground truth annotation. The OSD consists of similar type of household objects as the Willow Garage dataset. The OSD contains a total of 111 images of stacked and occluding objects on a table along with their pixel-based annotated ground truth images. Both of the aforementioned datasets include roughly 20-30 objects with relatively simple cylindrical and cuboidal shapes and diverse texture.

Two popular datasets, the RGB-D Object Dataset (Lai et al., 2011) and BigBIRD (Singh et al., 2014), utilize a turntable to obtain RGB-D images of common household items. In addition, both datasets have been recorded using two cameras, an RGB-D camera and a higher resolution RGB camera. The data is generated by capturing multiple synchronized images of an object while it spins on the turntable for one revolution.

The RGB-D Object Dataset is one of the most extensive RGB-D datasets available. It comprises of 300 common household objects and 22 annotated video sequences of natural scenes. These natural scenes include common indoor environments, such as office workspaces and kitchen areas, as well as objects from the dataset. The dataset was recorded with a prototype RGB-D camera manufactured by PrimeSense together with a higher resolution Point Grey Research Grasshopper RGB camera. Each object was recorded with the cameras mounted on three different heights to obtain views from the objects from different angles.

The BigBIRD dataset provides high quality RGB-D images along with pose information, segmentation masks and reconstructed meshes for each object. Each one of the dataset's 125 objects has been recorded using PrimeSense Carmine 1.08 depth sensors and high resolution Canon Rebel T3 cameras.

The objects in the RGB-D Object Dataset and BigBIRD dataset are, however, mainly similar to the geometrically simple objects in the Willow Garage and OSD datasets. In addition, apart from the video sequences of the RGB-D Object Dataset, the images do not contain occlusion.

The datasets provided by Hinterstoisser *et al.* (Hinterstoisser et al., 2012) and Mian *et al.* (Mian et al., 2006; Mian et al., 2010) contain more complicated objects than the previously mentioned datasets. The dataset of Hinterstoisser *et al.* consists of 15 different texture-less objects on a heavily cluttered background and with some occlusion. The dataset includes video sequences of the scenes, and a total of 18,000 Kinect v1 images along with ground truth poses for the objects. As this dataset is more aimed for object recognition and pose estimation, it does not include pixel-based annotation of the objects. The dataset proposed by Mian *et al.* comprises of five complicated toy-like objects with occlusion and clutter. The 50 depth-only images have been created using a Minolta Vivid 910 scanner to get a 2.5D view of the scene. The dataset includes also pose information for the objects and pixel-based annotated ground truth images.

As opposed to the completely textureless and unicolor objects in the dataset by Hinterstoisser *et al.*, the objects in our dataset retain some texture and many are also multicolored. Also, the dataset by Mian *et al.* contains only depth data, and is considerably smaller than our proposed dataset.

Multiple RGB-D datasets have been gathered from the real world as well. For instance, the video sequences of the RGB-D Object Dataset, Cornell-RGBD-Dataset (Anand et al., 2011; Koppula et al., 2011) and NYU Dataset v1 (Silberman and Fergus, 2011) and v2 (Silberman et al., 2012) contain altogether hundreds of indoor scene video sequences, where the three latter datasets were captured with Kinect v1. These sequences are recorded in typical home and office scenes, such as bedrooms, living rooms, kitchens and office spaces. The images are highly cluttered, and all the scenes in Cornell-RGBD-Dataset are labeled, and a subset of the images in NYU Datasets contain labeled ground truths. However, these scenes involve generally larger objects, such as tables, chairs, desks and sofas, which are not the kind of objects a lightweight robot typi-

cally manipulates.

3 TOY-DATASET

Our proposed dataset is comprised of complex objects and annotated ground truth images. The dataset contains objects which one would expect a robot to manipulate, that is, small, lightweight, and complex objects that one encounters in day-to-day life.

The objects that were chosen into the dataset represented typical children’s toys. In other words, the objects were generally multicolored, had a little or no texture and were of varied shapes. The objects were placed randomly on the tabletop; the only criteria was that they are close to one another, so that a considerable amount of occlusion is present.

First, we describe in detail how the dataset was acquired and how the ground truth images were annotated. Secondly, we contrast the proposed dataset to OSD by comparing the F-scores of V4R’s features on toy-dataset to the F-scores on OSD, and use them to describe some of the characteristics of the toy-dataset compared to OSD.

3.1 Set-up

The dataset consists of 449 RGB-D images and corresponding annotated ground truth images. The distance between the Kinect and the closer edge of the table, the further edge of the table, and the center of the table are roughly 85, 150, and 115 centimeters, respectively. There are 24 toys in the dataset in total, and, compared to the toys in the OSD, many of the toys are smaller in size. Most toys are multicolored and contain only minute texture. The number of toys per image varies according to Table 1. There are plenty of images with only a few toys to make sure model-based methods, such as V4R’s segmenter, are able to learn the correct relations of an object and between objects. The complete set of toys used in this dataset can be seen in Figure 1.

Table 1: The number of toys per image varies according to the index number of the images. The column on the left indicates the index number of an image, while the column on the right indicates the number of toys in the corresponding image.

# image	# toys
0 – 228	2 – 4
229 – 338	6 – 7
339 – 448	14 – 18

The ground truth images were annotated manually. The pixels belonging to each object were colored with a different grayscale value, while the background has a value of zero. The pixels are not annotated impeccably, since the edges of objects are not strictly one pixel wide but instead can span several pixels. Additionally, the edges of the objects are not always visible, because of, for example, the lighting of the image. Moreover, since the objects are highly occluded in most images, in some occasions it is extremely difficult to distinguish which aggregation of pixels belongs to which object.

Furthermore, we filtered the point clouds such that only the table and the objects remained. These filtered images are then used in our experiments, as explained in Section 4. The filtering is easy to implement since the planar tabletop can be easily and robustly detected. The toy-dataset contains both the filtered and the original RGB-D images.

3.2 Characteristics

The discrimination capability of a feature can be evaluated by computing an F-score for the feature (Chen and Lin, 2006). F-score measures the discrimination of two sets of real numbers and it is often used for feature selection. A higher F-score indicates that a feature is more likely to be discriminative, but unfortunately it does not reveal mutual information amongst several features. Nevertheless, the F-score measure is widely used in the machine learning literature due to its simplicity. The F-score is defined in Equation (1): r_k , $k = 1, \dots, m$, are the training vectors, n_+ and n_- are the number of positive and negative instances, respectively. Further, \bar{r}_i , $\bar{r}_i^{(+)}$ and $\bar{r}_i^{(-)}$ are the average of the i^{th} feature of the whole, positive and negative datasets, respectively, and $r_{k,i}^{(+)}$ and $r_{k,i}^{(-)}$ are the i^{th} features of the k^{th} positive and negative instances, respectively.

We exploit the F-score and V4R’s features (as presented in (Richtsfeld et al., 2014)) in order to explore the characteristics of our dataset. These F-scores are then compared to those of OSD, as given in (Richtsfeld et al., 2014). OSD is also a suitable comparison dataset as it is similar to our dataset in the sense of how the images are obtained and how the objects are placed. The datasets differ critically in the objects that are used, the objects in toy-dataset having more complex shapes and less texture; also, the images in our dataset have more occlusion.

The comprehensive set of features chosen by V4R contains commonly used features in computer vision. They measure relevant aspects of objects in the dataset, such as texture and color information.

$$F(i) = \frac{\left(\bar{r}_i^{(+)} - \bar{r}_i\right)^2 + \left(\bar{r}_i^{(-)} - \bar{r}_i\right)^2}{\frac{1}{n_+ - 1} \sum_{k=1}^{n_+} \left(r_{k,i}^{(+)} - \bar{r}_i^{(+)}\right)^2 + \frac{1}{n_- - 1} \sum_{k=1}^{n_-} \left(r_{k,i}^{(-)} - \bar{r}_i^{(-)}\right)^2} \quad (1)$$

This makes the V4R features suitable for comparing the characteristics of these two datasets. This same analysis could have been carried out using any other dataset, since the procedure is easy to implement. Furthermore, the analysis is beneficial as it gives quantitative results.

Figure 2 displays the F-scores for structural and assembly level features for both the OSD and toy-dataset. Structural features capture information such as texture and color while assembly level features capture higher level information such as distance between presegmented patches and angle between surface normals of the patches. These are explained in more detail in Section 4.1. The figure shows that structural level features are generally smaller in the toy-dataset than in the OSD. Most notable discrepancy takes place in the r_{co3} feature, which measures the color similarity on the border of two patches. Many of the toys are multicolored, and as the V4R's presegmenter does not use color information in creating the patches, the patches and their borders are typ-

ically of different colors. Also noise around the objects' edges might shift the real border of the objects to the area of another object, placing incorrect information into the feature. Despite this, the border colors alone seldom convey much information whether or not the patches belong to the same object. Additionally, the differences are remarkably high in the r_{tr} , r_{ga} and r_{fo} features, which principally measure the disparity between patch textures. Generally the objects in the toy-dataset have less texture than objects in other datasets, including the OSD, which explains the low F-scores of these features.

Many of the F-scores of assembly level features are roughly the same in the toy-dataset and OSD. The feature r_{nm} makes an exception and is significantly smaller in the toy-dataset. This feature measures the angle between surfaces' mean normals. As the shapes of the objects in toy-dataset are more varied than in the OSD, it is more difficult to determine whether the angle between normals of a patch-pair is relevant or not.

Moreover, the six rightmost assembly features in the figure, as well as r_{md} , are clearly higher in the toy-dataset. The r_{md} feature corresponds to the minimum distance between two patches and is an especially useful feature, as usually even a relatively short distance between two patches indicates that they do not belong to the same object. Many of the objects in the toy-dataset are smaller than the objects in OSD, which might explain the higher discriminative capability of this feature. The r_{dn} feature corresponds to the mean distance in normal direction of boundary points, and the five rightmost features correspond to boundary relations between the surfaces of the patches.

It is trivial to show that the F-score depends quadratically on the prior probability of connected patches. The prior probability is the ratio of connected patch pairs (that is, patch pairs that belong to the same object) to the number of unconnected patch pairs (patch pairs that do not belong to the same object) in the training set. In other words, the prior probability tells us how likely it is that a patch pair belongs to the same object before seeing the actual features. The quadratic dependency could, at most, induce a difference in the F-scores by a factor of two when the priors of the datasets are near 0.5 compared to near zero or one. However, the prior probabilities for both structural and assembly levels are nearly the same for both datasets: For structural level the prior is 0.6019 in OSD and 0.4978 in toy-dataset, and for assembly

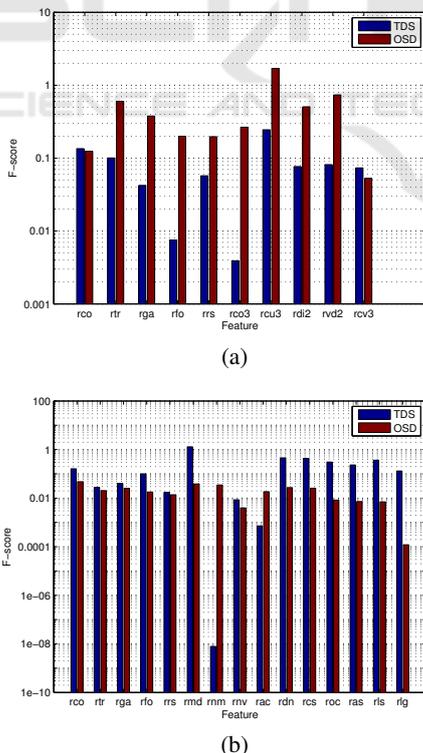


Figure 2: F-scores for both the OSD and the toy-dataset, labeled as TDS in the figures. (a) Structural level features. (b) Assembly level features.

level the prior is 0.02919 in OSD and 0.03433 in toy-dataset. Thus the differences in the priors do not explain the differences in F-scores between the OSD and toy-dataset.

Since V4R’s features utilize, for instance, the border and texture information of the presegmented patches, the F-scores presented in Figure 2 explicitly demonstrates the difference between the objects in the OSD and toy-dataset. For example, the edges of the objects are much sharper in the OSD, while the toys in our dataset contain softer edges, which affects all features that use the edge information of these objects. As a lower F-score implies that a feature is less capable to discriminate between two classes, it seems that it is more difficult to segment the toy-dataset using structural level features. However, as the F-score does not account for the joint activity of several features, this speculation is not decisive. Also, some of the F-scores in the assembly level features are higher in the toy-dataset, which yields further confusion concerning the outcome of this speculation.

4 METHODS, EXPERIMENTS AND RESULTS

The segmentation methods can be divided into model-based and model-free approaches. Model-based approaches require an additional training phase, where the segmenter is trained to identify specific features from the data. Generally the training of the segmenter is achieved using a training set of RGB-D images and corresponding ground truth data. Model-free methods, on the other hand, do not require this additional training phase, and they rely on identifying objects’ common features, for instance, convexity in the case of LCCP. However, this means that the model-free methods rely on an implicit model of the objects. If the assumed implicit model of the objects is wrong, the segmenter will perform poorly, whereas a model-based method may be able to adapt to the objects in the training phase.

While model-based methods can in general learn to segment or detect more complex objects, the model-free methods are typically faster. One of the segmenters we apply on the toy-dataset is model-based, namely the V4R segmenter, while the two others are model-free.

4.1 V4R

The segmentation pipeline in V4R’s method (Richtsfeld et al., 2012) is as follows: First, two support vector machines (SVM, (Burges, 1998)) are trained us-

ing a training set of RGB-D images and corresponding ground truth images. Secondly, these SVMs and a graph cut are used to find an optimal segmentation on an input image given to the segmenter.

The images in the training set contain one or more objects, and they may be in any position or occluded. Each image is then presegmented in order to obtain an oversegmented set of patches. Next a relation vector is computed for each patch pair. The computed features differ for the two SVMs: the neighborhood relation of the patch pair determines which set of features is computed. If the patches are neighbors, that is, they share a border in the 2D image and are close enough to each other in 3D space, features such as patch texture, color and features concerning the border pixels are computed. Otherwise the patches are not considered neighbors, and another set of features – such as minimum distance between patches, angle between surface normals, collinearity continuity – is computed. Once all the relations between patch pairs are gathered, the SVMs are trained using the freely available LIBSVM package (Chang and Lin, 2011). More specifically, relations concerning neighboring patches (Richtsfeld *et al.* use the term structural level when referring to these) are used to train one of the SVMs, and the relations of non-neighboring patches (assembly level) are used to train the other SVM.

After the training is complete, any RGB-D image can be fed into the segmenter. The SVMs provide a probability for each patch pair, which tells us how likely it is that the patches belong to the same object. Afterwards a graph cut is utilized to choose the optimal segmentation on global level.

This Gestalt-inspired segmenter of Richtsfeld *et al.* manages to segment nearly perfectly the objects in the OSD, as explained in (Richtsfeld et al., 2014). However, the training phase of the segmenter is quite laborious, since the ground truth images need to be generated by hand. Furthermore, the computation of relation vectors for patch pairs is compute-intensive, especially if there are large numbers of presegmented patches in the training images.

4.2 ICL

Another high-performance approach is the segmenter developed by Uckermann *et al.* (Uckermann et al., 2013), which is available in the Image Component Library². Their model-free segmentation method runs in realtime and provides comparable results with the V4R segmenter in the OSD. The method successfully handles unknown, stacked, and nearby objects, given

²Website <http://www.iclcv.org/>

they are relatively simple objects comprised of, for example, boxes, cylinders and bowls.

Their method can be split into two main parts. First the algorithm determines surface patches and object edges from the raw depth images using connected component analysis. Afterwards these low-level segments, the surface patches, are combined into sensible object hypotheses using a weighted graph describing the patches' adjacency, coplanarity, and curvature relations. Finally a graph cut algorithm is deployed to achieve likely object hypotheses.

However, as (Uckermann et al., 2013) mentions, this model-free method has its limitations compared to model-based approaches, especially in segmenting highly complex object shapes.

4.3 LCCP

The third state-of-the-art method is the LCCP by Stein *et al.* (Stein et al., 2014), available in the Point Cloud Library³. This model-free method is extremely simple while still providing nearly as good results as V4R on, for instance, the OSD. It should be also noted that the actual goal of Stein *et al.* is to partition complex objects into parts, not to segment complete objects.

The motivation for their algorithm stems from psychophysical studies, where it has been shown that the transition between convex and concave image parts might indicate separation between objects or their parts. The algorithm first decomposes the image into an adjacency-graph of surface patches based on a voxel grid. Edges in the graph are then classified as either convex or concave using convexity and sanity criteria which operate on the local geometry of the patches. This leads into a division of the graph into locally convex connected subgraphs which represent object parts.

All three methods described above have been proven to work extremely well with relatively simple objects. As the approach used by Richtsfeld *et al.* relies on training the algorithm with ground truth data, it learns to recognize more complex objects, provided the training data is extensive enough. The method by Uckermann *et al.* on the other hand is model-free and relies on straightforward measurements of similarity, so it cannot present complex object hypotheses. And, likewise, the simple and model-free method of Stein *et al.* is designed to extract object parts, and thus may not be able to segment the complete objects in our toy-database.

These methods take on the problem of segmentation from different starting points, and represent the

³Website <http://pointclouds.org/>

state-of-the-art in the area of RGB-D object segmentation. We use these methods to assess the difficulty and quality of our proposed toy-dataset.

4.4 Modifications

Only minor parameter changes were applied to the segmenters. V4R's original parameter values caused severe undersegmentation on the toy-dataset in the presegmentation phase. Thus one of the original parameters was tweaked to prevent the undersegmentation: the value of `_epsilon_c` was changed from 0.58 to 0.38. The new value was chosen by hand such that the number of patches – and consequently feature vectors – was as low as possible, while still retaining oversegmentation. It is important that the presegmented images are oversegmented, so that the patches include only parts of one object. This allows the SVMs to learn correct relations between the patches. Nonetheless, a low number of presegmented patches is preferred, since a higher number of patches means a higher number of feature vectors, which slows down the training of the SVMs.

V4R's support vector machines use 10 and 15 features for the structural and assembly level, as explained in (Richtsfeld et al., 2014). For the structural level SVM there were 8 226 feature vectors extracted from the training set. All these vectors were used to train the structural level SVM. For the assembly level SVM there were 171 768 feature vectors extracted from the training set. The training of the SVM would take days if we used all these feature vectors, which is not acceptable for practical reasons. Therefore we randomly sampled a set of 15 000 feature vectors which were used in the training.

In the ICL's segmenter the parameters were originally adjusted for QVGA resolution, so we had to modify the parameters slightly to account for Kinect's VGA resolution. For the LCCP segmenter we hand-picked parameter values `-sc = 20` and `-ct = 20` to avoid excessive over-segmentation.

4.5 Experiments and Results

We compared the performance of the three segmenters by applying them on a set of RGB-D images from our dataset.

The toy-dataset was divided into training and test sets, although only V4R's segmenter needs to be trained. The training set was formed by choosing randomly 200 images, and thus 249 images remained in the test set. One of the test set images (image number 296) was discarded due to an unsolved bug within the V4R segmenter, which made the segmenter crash

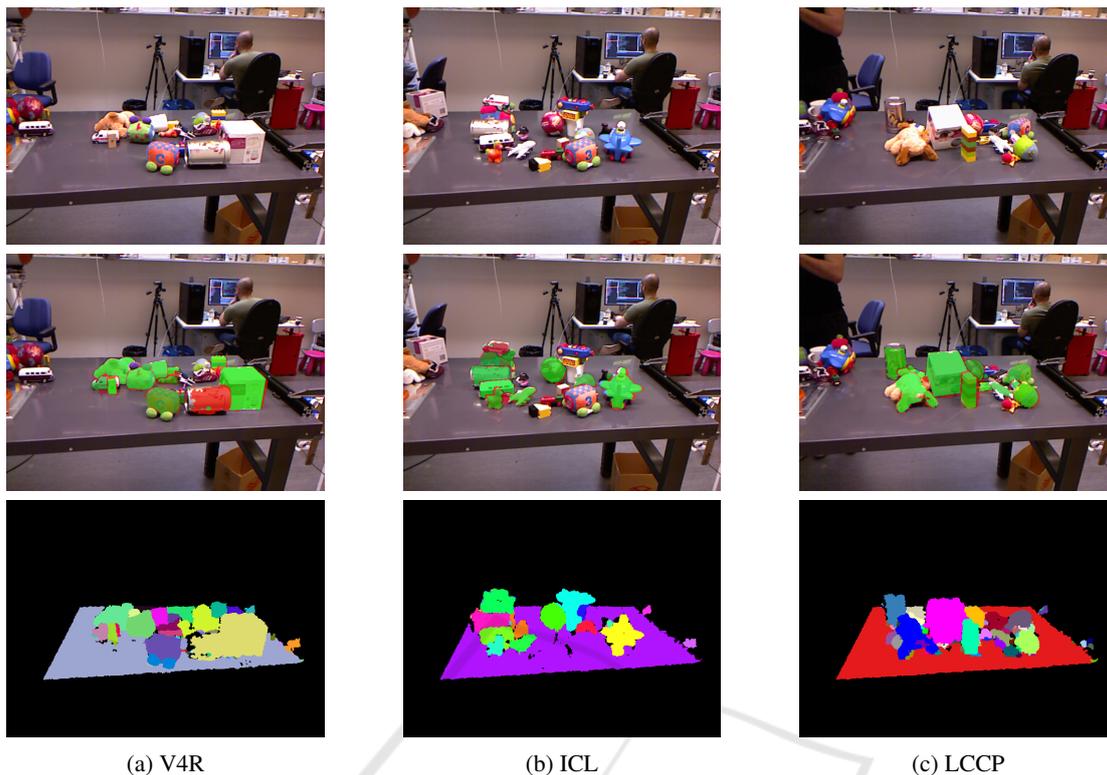


Figure 3: Three example images from the toy-dataset. The upper row presents the original images. The second row displays the result for an image by V4R, ICL and LCCP, respectively, when the true positive pixels are colored with transparent green, and the false positive pixels are colored with transparent red. The lowest row displays the actual results from the segmenters, where a color corresponds to a segmented object.

when processing the image. Hence, ultimately there were 248 images in the test set and 200 images in the training set.

We went through all images in the test set using each of the three segmenters, and received segmented images. From the segmented images we compute the amount of correctly segmented pixels, as well as the amount of incorrectly segmented pixels, and use these to compute the true positive rate and false positive pixel rates for each image. After we have acquired the true and false positive rates for each image, we take their average and 95 % confidence interval using bootstrapping.

We follow roughly the same procedure for computing the results as (Uckermann et al., 2013) uses. Their method differs in the way the average of true and false positive pixels is computed for one image. Uckermann *et al.* compute the true positive and false positive rates for each object in an image, and then average across the objects. We, on the other hand, use all true and false positive pixels, irrespective of which object they belong to, to compute the average true and false positive rate for an image. This way a failed segmentation of a small object will not affect the results

as much as compared to the way Uckermann *et al.* compute the results.

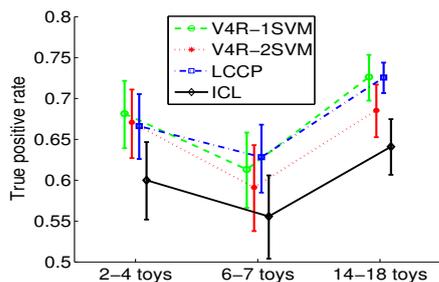
A segmenter divides an image into objects by labeling pixels in the image (see Figure 3 lowest row for an illustration). To count the number of correct and incorrect pixel labelings, the evaluation procedure first assigns to each ground truth object a pixel label according to the following rules: 1) assign most frequent label X to the object, 2) over half of the pixels with label X must reside on the annotated object. For some objects, there may be no pixel labels which satisfy both 1) and 2). Figure 5 shows an example of how segmentations are assigned to ground truth objects.

True positive pixels are pixels that have been assigned to an object and coincide with the annotated pixels of said object in the ground truth image. False positive pixels are pixels that have been assigned to an object, but do not coincide with the annotated pixels. See Figure 3 middle and lowest row for a visual presentation of the true and false positive pixels. The true positive rate tp for one object is then computed as

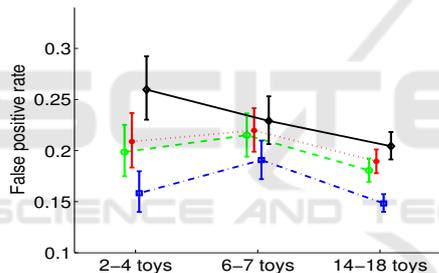
$$tp = \frac{|S_{assigned} \cap S_{annotated}|}{|S_{annotated}|}, \quad (2)$$

Table 2: True positive rate (**tp**) and false positive rate (**fp**) for each method. The best results, highest true positive rates and lowest false positive rates, are bolded. In "V4R one SVM" we have used only structural level SVM, and in "V4R two SVMs" we have used structural+assembly level SVMs, similarly as in (Richtsfeld et al., 2014).

	tp		fp	
	<i>mean</i>	<i>95% confidence interval</i>	<i>mean</i>	<i>95% confidence interval</i>
V4R one SVM	0.6766	(0.6510, 0.7017)	0.1979	(0.1840, 0.2126)
V4R two SVMs	0.6556	(0.6286, 0.6816)	0.2065	(0.1924, 0.2220)
LCCP	0.6723	(0.6489, 0.6948)	0.1635	(0.1528, 0.1756)
ICL	0.5999	(0.5717, 0.6277)	0.2383	(0.2220, 0.2561)



(a) True positive rates



(b) False positive rates

Figure 4: Results for different number of toys in test set images, partitioned as in Table 1. The test set contained 126 images with 2-4 toys, 59 images with 6-7 toys and 63 images with 14-18 toys.

where $S_{assigned}$ is the set of pixels assigned to a given object, and $S_{annotated}$ is the set of annotated pixels in the ground truth image for that object. Hence, the true positive rate for one object is the number of true positive pixels divided by the number of annotated pixels. Likewise, the false positive rate fp for one object is

$$fp = \frac{|S_{assigned} \setminus S_{annotated}|}{|S_{assigned}|}. \quad (3)$$

The false positive rate is the ratio of assigned pixels that do not coincide with the annotated pixels to the number of assigned pixels in total.

Table 2 shows the results for each method when the whole test set is used. From the results we see that V4R's segmenter and LCCP have the highest true

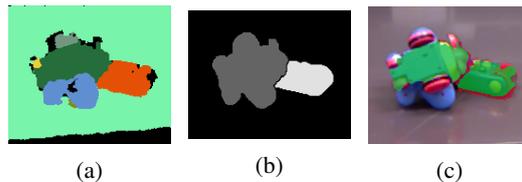


Figure 5: Example of a segmentation with two objects. (a) shows the segmentation where each color corresponds to a segmented object. The ground truth image (b) shows the actual pixel labels. (c) shows the evaluation where transparent green highlights true positives and transparent red false positives. In (a), several segmented objects overlap the actual object on the left. The evaluation procedure assigns the segmented object with the most overlapping pixels to the actual object: for the left object the object segmented with dark green in (a).

positive rates on the test set, while LCCP has a lower false positive rate than V4R. Figure 4 displays results for each segmenter when we have divided the test set into partitions according to how many toys there are in the images. The confidence intervals are the longest in the set with 2-4 toys, because the impact of incorrectly segmenting objects is larger. For instance, if a segmenter fails to segment both of two objects, the resulting true positive rate for that image will be zero. Then, if there are, say, 18 objects in an image and the segmenter fails to segment 2 of those objects, the true positive rate is still significantly higher than zero. This leads to higher variance in the results of images with less toys, and hence longer confidence intervals.

5 DISCUSSION

As expected, ICL did not fare well with the dataset's complex toys. What is surprising, however, is that LCCP and V4R did equally well in the true positive rate, and LCCP had significantly lower false positive rate than V4R. The low false positive rate is due to comprehensive oversegmentation in the LCCP's pre-segmentation phase, which results in multiple non-connected patches in some of the objects. This pre-

vents the occurrence of false positives, as the segmented pixels are always in the area of the annotated ground truth pixels. However, it also lowers the true positive rate since these patches are not connected to the patch that is assigned to the object.

By examining the segmented images by each method, we made a few observations. ICL failed many of the objects completely by segmenting them as part of the table, which reduces the true positive rate significantly. This happened to other methods as well, though not so frequently. Furthermore, all the methods often incorrectly joined two or three objects together, which explains the high false positive rates. Figure 3 demonstrates some of the aforementioned observations for three different images from the toy-dataset.

ICL’s poor results might originate from their weighted similarity graph, which considers the adjacency, curvature and coplanarity of found surface patches. Out of these three attributes especially the curvature and coplanarity incur problems, since many of the presegmented surface patches are not symmetrical or similar. In other words, the shapes of the patches differ from each other and they are not coplanar.

Table 2 contains results for V4R with one and two SVMs, or structural and structural+assembly level SVMs, as Richtsfeld *et al.* also used both methods on OSD in their paper (Richtsfeld et al., 2014). It is not obvious which method, one or two SVMs, performs better in the OSD, for when using only one SVM the precision is higher but recall is lower as opposed to using two SVMs. In our dataset, however, using only one SVM, the structural level SVM, seems to be a preferred choice.

As we discussed in the beginning of Section 4, a model-free method will perform poorly if its implicit model of the objects is wrong. In this case it seems that the implicit model of the convexity-based LCCP is more appropriate to the toy-dataset than the implicit model of ICL. It is also noteworthy that ICL and V4R received similar results in the OSD, whereas here V4R was more efficient than ICL. It seems that the implicit model of ICL is better suited to the kind of objects found in OSD than the objects in the toy-dataset.

In any event, there are some sources of errors that affect the computed results. When viewing the point clouds of the images, it is apparent that the RGB and depth images are not completely aligned at some places. Since the ground truth images are created from the RGB images, the misalignment implies that the segmented pixels cannot coincide with annotated pixels of an object. This basically shifts some of true

positive pixels into false positive pixels, reducing the true positive rate and increasing the false positive rate. Also, there is often noise around the edges of the objects, which affects the true and false positive rates, and further, there exists the already mentioned difficulties (Section 3.1) with annotation of the ground truth images.

Regardless, the slight misalignment of color and depth images, as well as the noisy observations of the objects, reflect the commonplace problems of a robot operating in the real world. Accordingly, our dataset corresponds to real circumstances under which a robot usually operates, along with the non-ideal lighting conditions and a relatively poor quality RGB-D sensor.

6 CONCLUSION

In this paper we presented a novel RGB-D dataset designed for shifting the focus from relatively simple objects to more complicated ones in the object segmentation scene. The dataset contains 449 highly occluded images of 24 toys, which vary greatly in shape, color and size, and contain minute texture.

Also, the toy-dataset provides a new benchmark against which forthcoming segmenters can test their performance. Our experiments demonstrated that the V4R and LCCP segmenters performed equally well on our dataset of toys, even though the model-based V4R was trained using data from the toy-dataset. It seems that the features used by V4R might need some alteration to account for the complex objects in our dataset. Furthermore, the actual goal of the LCCP segmenter is to partition complex objects into parts, which generates oversegmentation. This oversegmentation however has both an upside and a downside, as it lowers both false and true positive rates. Lastly, the ICL segmenter seems to perform better on symmetrical objects, such as boxes, bowls and cylinders found in the OSD, but the asymmetric objects in our dataset deteriorate the performance of the segmenter.

ACKNOWLEDGEMENTS

This work was supported by Academy of Finland, decisions 264239 and 271394.

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