KTH-3D-TOTAL: A 3D Dataset for Discovering Spatial Structures for Long-Term Autonomous Learning

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***Abstract*— Long-term autonomous learning of human environments entails modelling and generalizing over distinct variations in: object instances in different scenes, and different scenes with respect to space and time. It is crucial for the robot to recognize the structure and context in spatial arrangements and exploit these to learn models which capture the essence of these distinct variations. Table-tops posses a typical structure repeatedly seen in human environments and are identified by characteristics of being personal spaces of diverse functionalities and dynamically changing due to human interactions. In this paper, we present a 3D dataset of 20 office table-tops observed 3 times a day for 19 days (1140 scenes), manually annotated with 18 different object classes, including multiple instances. We analyse the dataset to discover spatial structures and patterns in their variations. The dataset can, for example, be used to study the spatial relations between objects and long-term environment models for applications such as activity recognition, context and functionality estimation and anomaly detection.**

I. Introduction

A complete understanding of a scene includes information on not only what objects are in the scene but also on their relative arrangement in the scene. For a robot to recognize a context it should take this into account. Our research work involves developing a mobile service robot for long-term autonomy in indoor human environments, from offices to hospitals. The ability for a robot to run for weeks or months in its task environment opens up a new range of possibilities in terms of learning capabilities. In particular, the robot would expected to learn to perform an assigned task that is repetitive with weaning supervision and human interaction. The contextual knowledge the robot can gain from the repeated attempts can make it learn so that it's subsequent attempts on the same task are improved in accuracy and efficiency.

In this paper we study spatial understanding derived from the configuration of objects in a scene. Whilst objects often change in position, their overall arrangement typically have some regularity over time as influenced by the context and functionality of that part of space. For example, there is a general structure in office employee table-tops to that of cafeteria table-tops or kitchen table-tops. The differences derive from the variety of objects and their group-configurations on the table-tops with respect to time – hours, days, weeks, months etc. For example: Office tables typically have monitors, keyboards, mouse along with papers and pens and coffee mugs arranged such that the monitors can be viewed, the keyboard typed at and the mouse easily accessed from the keyboard. The spatial configurations vary in particular instances and the arrangement change gradually over many days and minutely at different times of the day; However, cafeteria tables have cutlery, jugs, food, napkins etc. configurations of which don't vary over many days, weeks or years but vary in content and presence according to different times of every day. It is this structure and it's variants that we aim to exploit in order to improve the understanding of space.

Such structures have been exploited before in the literature for a number of different applications, such as object recognition, activity recognition, image retrieval and objects search. The intuition is that: bluntly modelling the absolute positions of objects, is likely to fail because such a model is improbable to generalise across a range of different scenes from numerous observations w.r.t. time and instance. Instead qualitative *relational* models of space, i.e. ways of encoding the qualitative position of a target object relative to the position of one or more landmark objects are investigated. For example, "the chair is *at* the table" and "the pillow *on* the bed". The exact coordinates of these objects are semantically irrelevant. We believe that representations that are to support long-term autonomy and ability to generalize knowledge require such rough discretizations of metric measurement space forming a "feature set" inherently encapsulating the generality of structure.

The main contribution of this paper is the quantitative and qualitative analysis of indoor environments to characterise some of these structures. This is an important contribution if one wants to design a representation to build a model of space and to reason about space. The prevailing approach has been to assume structures exist and define a set of descriptors/features that capture different aspects of these. We instead propose to carefully study the structures and do so over long periods of time and across several similar scenes to be able to characterise the dynamics and variability. The output of this paper can thus serve as the foundation for designing efficient representations and inference algorithms. To limit the scope, we study table-top scenes in this paper. As a basis for our study, we have constructed a large, manually annotated benchmark 3D dataset of office type table-

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top scenes called ***KTH-3D-T**able-**T**ops Dataset for Long **T**erm **A**utonomous **L**earning* (KTH-3D-TOTAL)[1] observing the same set of select tables, over many times a day and over many days in a month. Objects-of-interest have been manually annotated in 3D to provide ground truth data.

The rest of the paper is composed in the following way: We survey the related work in Section II. In Section III we exhibit KTH-3D-TOTAL in depth and provide an analysis of it in Section IV. We summarize and conclude in Section V.

II. Related Work

Learning a model for a type of scene is a difficult task if the raw data acquired by the sensors is used in terms of metric measurements. Many recent works have investigated how learning and modelling human environments increase in efficacy if qualitative spatial features are used instead of and/or alongside, metric ones. Spatial relations have been used previously to provide contextual information to vision-related work; [1] used a hierarchy of spatial relations alongside descriptive features to support multiple object detections in a single image. Spatial relations and contextual information are commonly used in activity recognition from video streams [2], [3]. Recent work has used object co-occurrence to provide contexts in visual tasks such as activity recognition [4]. Apart from using the mere statistics of co-occurrence, a lot of information can be exploited from *how* the objects co-occur in the scene. Recent work in 3D semantic labelling has used such geometric information along with descriptive intrinsic appearance features [5]. They achieve a high classification accuracy for a large set of object-classes belonging to home and office environments. Scene similarity measurement and classification based on contextual information is conducted by [6]. In [7], spatial relations between smaller objects, furniture and locations is used for pruning – in object search problems in human environments. In [8], [9] the authors utilise both geometric features on objects and spatial relations between objects for scene understanding.

As described in the introduction our aim is to find and exploit the spatial structures inherent in indoor environments. Three important aspects are: complete scenes, same scenes observed over long times and to many similar but not identical scenes. Several datasets have been constructed for various researches. However, these existing datasets lack these three important aspects together.

The *B3DO dataset* [10] contains many single-snapshot instances of indoor human environments having a variety in viewpoints, object-classes, scene-classes and instances. This dataset is in the form of RGB and depth image pairs with manual 2D annotations of object classes. It captures single snapshots of unique scenes for which scene classification and object classification is difficult for vision based perception systems (VPS). The *NYU Depth V1-2* [11] datasets contain different instance examples of object-classes and scene-classes captured with RGB+D images. Automated pixel clustering is conducted by using features in the RGB and D images separately and annotation of the clusters has been done manually, thereby assigning a semantic label to every pixel. The dataset contains a wide range of singular snapshots of indoor scenes from commercial and residential buildings. This dataset is primarily aimed at evaluating VPS aiming at automatic semantic segmentation and scene classification.

The *3D IKEA database* [12] has been collected using a robot – moving in different scene-class instances. The aim is to test scene-classification algorithms based on large, furniture level objects. 3D point clouds are formed by stitching a series of RGB+D images. There are very few small objects in the scenes and the annotations are provided at the scene-class level. The *WRGBD dataset* [13] is aimed to support object classification methods and contains many scene instances of isolated objects in point cloud format. Annotation is done by assigning every pixel a semantic label in each scene. Each point cloud is created from a series of RGB+D images.

The system constructed by [14] can be used to automatically generate 3D datasets of scenes using rough human annotations on 2D images as input. The system infers 3D information from the scene using the semantics of the annotated properties of important planes in the image. The generated dataset thus includes a large set of singular scenes, indoor and outdoor from very particular viewpoints, with annotations to the image components provided manually.

The *Kinect@Home project* [15] has collected a large set of crowd sourced data. People having access to a kinect like sensor have captured and uploaded data from their own environments. The data is in the form of RGB-D video sequences. The data covers a large variety of different scene types and range from single objects to whole rooms. No annotation is available. The dataset provided by [16] contains a collection of 3D images of a few table-top objects in clear view and cluttered view. This dataset has been constructed to aid VPS for object classification and segmentation functioning on 3D data. Other datasets that have been developed have mainly been for training VPS for robust indoor object classification on 3D data [17], [18].

Thusly, our dataset contributes with the following three important properties:

- captures full 3D scene instances of a particular scene type (in our case office table-tops)
- contains instances of subsets of objects-of-interest co-occurring in the scenes – manually annotated for ground truth
- provides long-term periodic observations of the same set of scenes at different times of the day, for several days.

Our dataset opens up the possibility to study the structures that govern how space is organised. We want to extract and later exploit these when building the models. While our dataset only captures table-tops we believe that many of our findings can be transferred to other types of scenes. As mentioned above, we expect most tables to have a monitor, a keyboard and a mouse and that these are arranged in a certain way. Many people will have the mouse to the right of the

[1] `http://www.cas.kth.se/data/KTH-3D-TOTAL/`

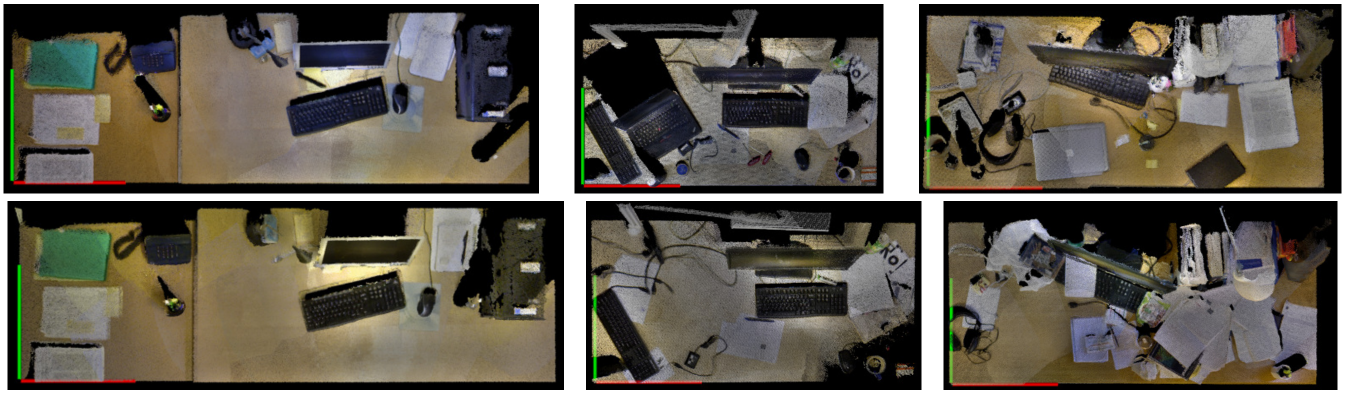


Fig. 1. Each column shows a different person's office table at two different times. The tables in the first two columns are captured in the morning and evening of the same day, whereas the table in the last column is captured 12 days apart. We can see distinct differences between different person's table but there are also many commonalities that a system should exploit.

keyboard. This is an example of a spatial structure we want to learn. Some people have a laptop on their table and they bring this laptop home in the evening. This is an example of a dynamic property of a table that we want to learn. We believe that, when combined, this type of information will allow us to reason about activities as well.

Another aim is to be able to transfer knowledge from one part of an environment to another and ultimately from one environment to the next. For example, if the robot encounters a table that it has not seen before, it should be able to make use of the models of other tables to get a good prior for what to expect. In the same way that the reader can form a mental picture of a typical office table arrangement. This way, the robot would also be able to reason more efficiently about tables that it has not yet seen but which, for example, might be referenced by a human.

In conclusion, our dataset allows us to provide training data for spatial understanding models and spatial relations. It also helps to develop representations that caters for: knowledge transfer, the ability to learn from few samples and adapting existing models.

III. Dataset

We focus on table-top scenes in our dataset because in an office environment the tables represent the work space of people. Each table-top is unique to that person but still similar to the others semantically and continuously changing. Table-tops are also well defined spatially and there are many instances of them within a single environment which means that capturing variation across instances is made more convenient.

With the aim of exploring possibilities to understand, learn and model these organisational structures amongst objects in human indoor environments, we present the dataset KTH-3D-TOTAL, which has been composed by periodically capturing observations of a fixed set of entire table-tops in an office environment. In what follows, we define a *scene* as a single observation of a table-top instance at a single instance in time. The dataset captures the individual and group variations in object pose due to humans and their regular/irregular interaction with their environment. The required regularity in instances and time was the main motivation for the construction of this dataset, as currently available datasets either are of individual objects or single instances of tables or entire rooms. This regularity in sampling and extent over time is important when studying and modelling interrelations amidst the member objects in a long-term autonomous learning.

A. Dataset Design and Concept

We want to provide intelligence to a long-term operating, autonomous robot for indoor human environments. The KTH-3D-TOTAL dataset has been composed by capturing and manually annotating 3D point clouds of office type table-tops, for a fixed set of people, at fixed times of the day and for a span of weeks. Observing[2] the table-tops of the same set of people at different times of the day gives insight about the daily interactions a human has with his table and over many days gives an understanding of the gradual variances of the configuration of these table-tops. If the data is observed for an entire week, including weekends, features in the table-top configurations, that can be used for estimation of the type of the day of the week, can be extracted (e.g. Weekdays, Fridays, Weekends). Table-top models can also be learnt for all the people put together – which gives a gross functional representation of an office table-top in general in office environments – or for individual people which helps to build unique functional representations of office table-tops for individuals, for different activities and so on (Figure 1). In summary: When the dataset is designed such that when it is partitioned in different ways with respect to time, people or object instances, it richly yields knowledge of table-tops in office environments supporting building representations of the same.

[2]Data collection protocol: At the designated collection times, people amidst their activities were asked to abruptly step aside from their tables and not allowed to alter the table-top or contribute to the occlusion of the table-top.

B. Dataset Realization

In KTH-3D-TOTAL, 3D point clouds representing 20 people's tables were captured regularly 3 times a day for 19 days. The data was collected by carefully scanning each table-top using an *Asus Xtion Pro Live* RGB-D camera. The raw RGB-D data stream is aggregated into a single high resolution point cloud (.pcd format) using the *SCENECT* software [19].

The scenes were recorded as periodically as possible and at three fixed times each day: *Morning* (09:00 hrs), *Afternoon* (13:00 hrs) and *Evening* (18:00 hrs). Scenes contain tables of 20 different people collected over 19 days including weekends. A *Scene_ID* is attached to each scene to indicate who the table belongs to and the date and time of the recording. These Scene_IDs help in partitioning the dataset with respect to time of the day {Morning, Afternoon, Evening}, person {Carl, Nils, ...}, or day {2013-11-01, 2013-11-06, 2013-11-13, ...}.

A 3D annotation tool was developed for manually segmenting out objects-of-interest from the point clouds. On average, 12 different objects were labelled, including repeating instances of the same object class, per scene depending upon feasibility and occurrence. The objects belong to the following super set - {Mouse, Keyboard, Monitor, Laptop, Cellphone, Keys, Headphones, Telephone, Pencil, Eraser, Notebook, Papers, Book, Pen, Highlighter, Marker, Folder, Pen-Stand, Lamp, Mug, Flask, Glass, Jug, Bottle}. The information about every scene and object is available in XML and JSON formats. In these files, each scene has a nested list of object data containing {Position, Orientation, Size, Date and Time of recording, Person ID, Point Indices of the points in the point cloud that have been labelled as belonging to the Object}. This manual annotation provides the required ground truth data for long-term autonomous learning.

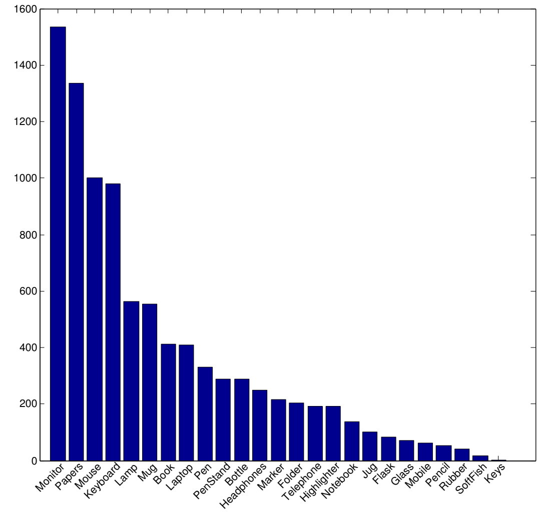
C. Dataset Summary

This section gives a bullet-summary of the dataset to serve as a quick reference. KTH-3D-TOTAL has:

- scenes collected from 20 unique tables, 3 times a day for 19 days and hence in total, approximately 1140 scenes.
- each scene manually annotated with 18 possible object classes and an average of 12 object instances, from these classes, annotated per scene, including multiple instances
- annotations stored in XML and JSON formats containing scene instance and it's object instances' specifications.
- occurrences of object instances as depicted in Figure 2(a) and annotations as exemplified in Figure 2(b), 2(c)

IV. Analysis

In this section we perform an analysis of the data to highlight some interesting aspects of it. In particular we will show that there are structures in the data that can be exploited by a system for more efficient representations and better reasoning with less data. This analysis then gives us insight into what we will later be able to learn from this dataset and how to design such learning.



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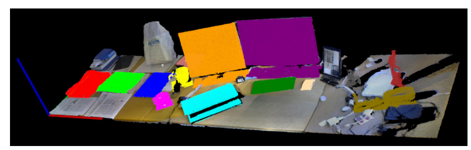

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Fig. 2. (a) Objects annotated in 3D Long-Term Dataset, sorted in descending order of count of occurrences. X-axis=Object Name, Y-axis=Occurrence Count. (b) Screenshot of one table scene, along with it's annotations in (c).

Figure 1 shows three table-top scenes. Each column shows the same table at two different times. The leftmost two columns contain scenes from the same day, whereas the two scenes in the third column were sampled 12 days apart in time. Notice in Column 1: the slight changes in position of the keyboard, mouse, papers and pen; Column 2: the relatively big changes in position of laptop, mouse, papers, pen, keyboard, lamp. When objects in columns 1,2,3 are compared there is a certain generality in structure (keyboards are in front of monitors), but also a specificity for each person (occurrence of headphones, position of mouse w.r.t. keyboard, etc.).

Studying the scenes could also allow a system to infer the activity of people. We can see that there are changes to the first table suggesting that someone was there during the day. Consider the table scenes in Figure 3, which captures the variations over the same person's table over many days. Notice that between 28 Oct and 08 Nov the setup of the table does not change very much – this reflects the ground

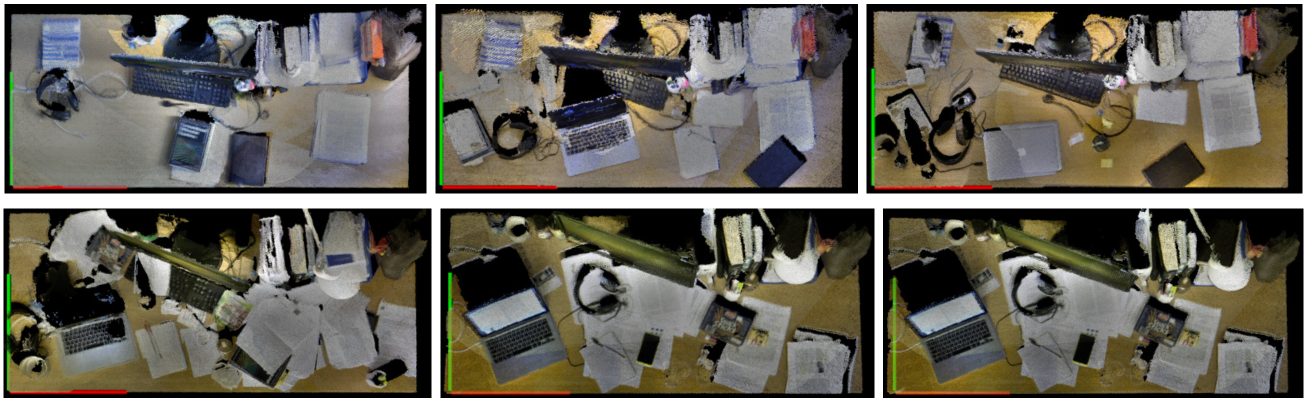


Fig. 3. This is the table of a single person, observed during the evening over many days: {L to R – Row 1: 24 Oct, 28 Oct, 08 Nov; Row 2: 13 Nov, 14 Nov, 16 Nov 2013}.

truth that this person was working in another lab (room) and visited her table only to maybe, check emails. Now consider the variations between 08 Nov and 13 Nov – this clearly indicates that the person was at her table and involved in working on the computer, reading and referring to papers and books, etc. There is a normal, day's worth of variation in between the images of 13 Nov and 14 Nov, however there is almost no variation between 14 Nov and 16 Nov – which indicates that the person was absent over the weekend – again a desirable property that ought to be captured by the long term autonomous systems.

Observing the tables can also infer a little about the working style of the people. In Figure 1, the first table suggests that this person is tidy. The second table is missing the laptop in the second observation. This might suggest that the person has left the table, maybe for the day. The third table seems to be occupied by someone that is less sensitive to clutter. With only two observations of each tables these are just speculations but by looking at the data over 19 days stronger claims could be made.

One of our hypotheses is that a qualitative model will be needed to achieve efficient and powerful representations of space, at least if the amount of data is limited as it will be in realistic cases. Such qualitative models could allow some of the inherent structure in the environment be encoded in the representation itself. We have already seen in Figure 1 that monitors are typically at the rear end of the table, while a keyboard is usually in front of it and the leftmost table shows an example of a mouse ordinarily being to the right of a keyboard.

Figure 4 shows a scatter plot over the position of keyboards and mice when found in the same scene. The table outline gives an example of a prototypical table to make it easier to interpret the data. In the top part of the figure, the green circles mark the position of the centroid of each keyboard that exist in a scene where there is at least one mouse. The red square shows the mean position of all these centroids. The black crosses show the position of all mice in scenes with at least one keyboard. In the bottom part of the figure the position of the mouse relative to the keyboard is shown for each observed pair in the data. As expected most mice are qualitatively to the right of the keyboard. There are some outliers. However, encoding the position of the mouse as being to the right of a keyboard would capture most of the information. The largest cluster of points in the lower part of Figure 4 contains about 95% of all data points. Notice how this structure in the data is lost, at least visually, when looking at the position of the keyboard and mouse in the table frame (top figure) and how it pops out when looking at the relative positions (bottom figure). We want our representation to be able to capitalize on this structure. Clearly, in this case, the position of the keyboard contains almost all information that is needed to represent the position of the mouse as well. The figure also clearly shows how the distribution varies across person instances (the different colours in the bottom part). Note how each person has a lot less spread in the distribution than when considering them all at once. This is a good illustration of the difference between general models of space and models of specific instances of space; and the importance of the richness of the training data to provide for these two models.

To further investigate the correlation between different object classes, and thus look for other inherent structures in the data, we look at the relative position of all objects of class C_j w.r.t. to objects of class C_i present in the same scene and turn to information theory for the analysis. We calculate the entropy over the histogram of the distributions of relative positions (i.e. histogram over bottom figure in Figure 4, for instance). Entropy measures the predictability of the information. A low entropy means that there are informative features available to make prediction, i.e. there is an underlying structure. A large entropy on the other hand means that it is very hard to make predictions and the resulting distribution would be close to uniform. We calculate the entropy as

$$E = -\sum (\frac{n_i}{N}) ln(\frac{n_i}{N}) \quad (1)$$

where n_i is the number of samples that fall in cell i in a

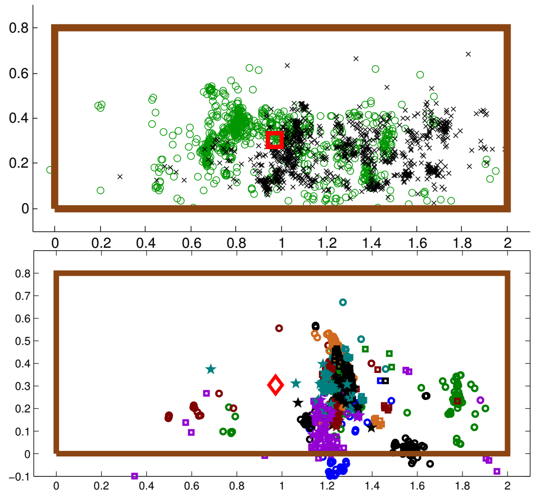
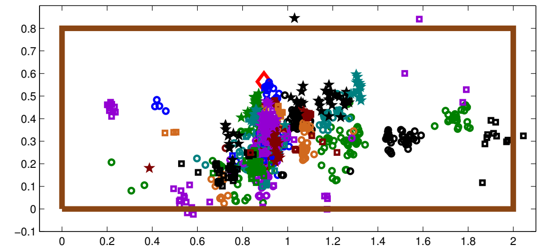


Fig. 4. This figures shows how a relative position representation (bottom) is able to expose a structure that is not visible in absolute coordinated (top). Top: The green circles shows the positions keyboards(red square shows mean of keyboards). The black crosses show the position of all mice in these scenes. Bottom: Mean position of keyboards (red square) and relative position of mouse relative to it. Each color shows a different person. The brown rectangle gives a rough idea about where the borders of a typical table would be.

grid discretization of the table and N is the total number of samples. Each sample corresponds to one object pair in one scene. The true entropy will only be estimated well when N is large. We therefore limit this investigation to pairs of objects that occur more than a certain number of times in the data. Figure 5 shows these entropies for 10 of the objects in the dataset. From this figure we can, for example, see the low entropy in the relation between keyboard and mouse (elements 1,3 and 3,1 in the matrix). The relative positions of monitors and keyboards also have a fairly low entropy. We also see that the position of papers is largely uncorrelated with many other objects (uniform distribution gives high entropy). The values from such an entropy matrix could give suggestions toward hypothesizing a possible hierarchy in data organisation for the robots. Those objects that have a lot of positional variance could be described as target objects with respect to landmark objects that do not vary as much. This organising tree structure could also potentially be autonomously learnt – leading to more than one landmark object in a scene. A keyboard-mouse-monitor-laptop could be organised in a parallel sub-tree alongside a mug-glass-jug-flask sub-tree. We make these suggestions purely based on conjecture, which we aim to verify in our following research work.

In Figure 6 we look closer at some of these relations. Figure 6(a) shows the position of the keyboard w.r.t. to the monitors. Our intuition that keyboards are placed mostly in front of monitors is supported by data. Figure 6(b) shows the position of the mug w.r.t the keyboard. We see that the mug is rarely very close to the center of the keyboard but rather positioned around the keyboard. Taking function into



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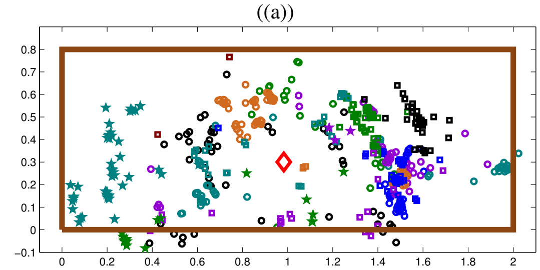

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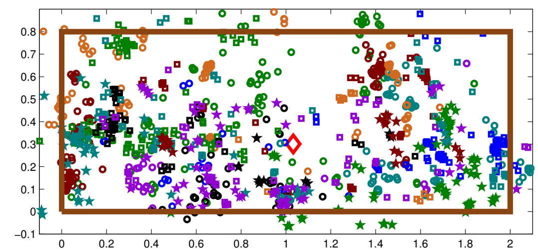
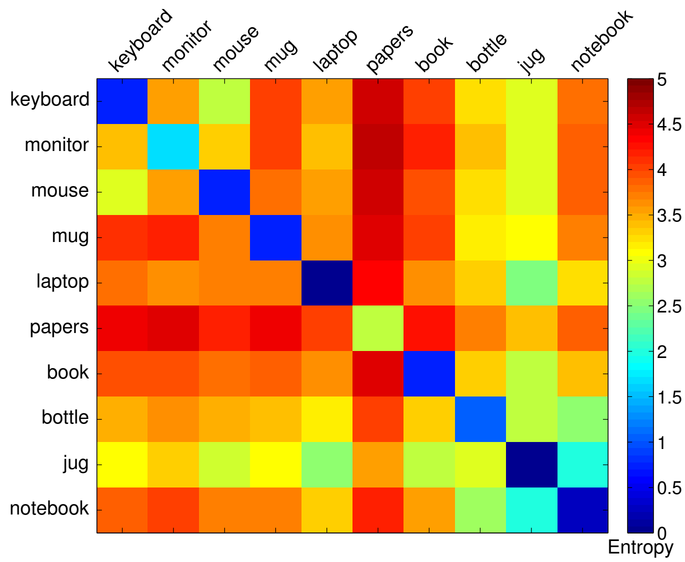


((c))

Fig. 6. The figures show the relative position of a) keyboard w.r.t. monitor, b) mug w.r.t. keyboard and c) papers w.r.t. keyboard. Qualitatively keyboards are mostly infront of monitors, mugs are around the keyboard and the position of papers is mostly independent on the position of the keyboard. The different colors/markers show data from different people in the data.

account the data might suggest that the mug is in fact often placed at arms length from the person working on the table to keep it at safe distance from the keyboard but still within reach. We see a bias towards the right side, probably a result of most people being right-handed. In Figure 6(c) we see that the distribution for the relative position of papers w.r.t. to the keyboard is almost uniform, suggesting that they are largely uncorrelated. Upon keener observations we can see that there are some clusters of similar markers which indicate that papers are not as dynamic as the mouse or mug, and hold their place usually for a couple of days on average. The fact that there are often many papers in a scene adds to the uniformity.

To summarize the analysis, we have shown that the data has many structural properties that a method for representing and reasoning about space should exploit. If the aim is to represent typical configuration of objects, this preliminary analysis suggests that a significant part of such knowledge can be encoded well with qualitative spatial relations, such as the mouse is to the *right of* the keyboard, while keeping in mind that this represents the typical case and not the only possible situation. We can also see that a system that observes



	key	mon	mou	mug	lap	pap	boo	bot	jug	not
key	0.76	3.54	2.79	4.01	3.56	4.57	4.00	3.25	2.95	3.78
mon	3.41	1.65	3.35	4.06	3.39	4.63	4.19	3.37	2.95	3.86
mou	2.89	3.59	0.73	3.81	3.59	4.56	3.96	3.27	2.93	3.84
mug	4.08	4.21	3.71	0.74	3.67	4.47	3.99	3.17	3.08	3.73
lap	3.79	3.60	3.67	3.70	0.05	4.34	3.67	3.30	2.47	3.23
pap	4.45	4.50	4.22	4.41	4.01	2.76	4.30	3.72	3.36	3.84
boo	3.96	3.93	3.81	3.86	3.67	4.49	0.77	3.35	2.81	3.42
bot	3.47	3.64	3.44	3.42	3.17	4.03	3.33	1.03	2.74	2.58
jug	3.05	3.34	2.85	3.11	2.54	3.56	2.81	2.95	0.00	1.97
not	3.90	3.99	3.68	3.70	3.29	4.16	3.59	2.62	1.97	0.28

Fig. 5. The figure illustrates the entropy value in the distribution of relative positions of one object (column) w.r.t. to another object (row). Dark red indicates high entropy (more uniform distribution) and dark blue low entropy (more peaky distribution). We show this for the most frequently occurring object pairs in the dataset (i.e. most statistics). The table shows the actual entropy values corresponding to the above illustration.

these tables for an extended period of time will be able to learn quite a lot about the habits of the owners of the tables and even the current activity in many cases. It is important to differentiate between typical knowledge, i.e., knowledge about what the world typically is like and specific instance knowledge, i.e., knowledge about a particular scene at a specific time. It is to capture the first kind of knowledge that we believe qualitative spatial representations will be most beneficial.

V. Conclusions

We have shown that there is structure in the way that objects are arranged in scenes. We can expect that robots operating over long periods of time, repeatedly observing the same scenes and types of scenes, will be able to learn models of this structure – preserving the temporal and instance variations in the scenes. The large, manually annotated, benchmark 3D dataset we present, is one-of-a-kind – providing the means to train long-term autonomous learning systems for spatial understanding.

Our immediate research plans for this data are to learn and model the spatial relations amidst objects contained in the scenes. Such models and spatial relations can subsequently be tested, verified and also used by the autonomous robots in our collaborative research project (STRANDS) while they operate over months at various sites. These will allow for activity recognition, anomaly detection, and context recognition which are the crux of such long-term autonomous service robots.

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