From images to rooms

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Abstract

In this paper we start from a set of images obtained by the robot that is moving around in an environment. We present a method to automatically group the images into groups that correspond to convex subspaces in the environment which are related to the human concept of rooms. Pairwise similarities between the images are computed using local features extracted from the images and geometric constraints. The images with the proposed similarity measure can be seen as a graph or in a way a base level dense topological map. From this low level representation the images are grouped using a graph-clustering technique which effectively finds convex spaces in the environment. The method is tested and evaluated on challenging data sets acquired in real home environments. The resulting higher level maps are compared with the maps humans made based on the same data [1].

Key words: spatial representations, appearance based modelling, robotic vision, map building, spatial concepts

1 Introduction

Mobile robots need an internal representation for localization and navigation. Most current methods for map building are evaluated using error measures in the geometric domain, for example covariance ellipsis indicating uncertainty in feature location and robot location. Now that robots are moving into public places and homes, human beings have to be taken into account. This changes the task of building a representation of the environment. Semantic information must be added to the sensory data. This helps to enable a better representation (avoid aliasing problems), and makes it possible to communicate with humans about its environment. Incorporating these tasks in traditional map building methods is non trivial. Even more, evaluating such methods is hard while user studies are difficult and there is a lack of good evaluation criteria.

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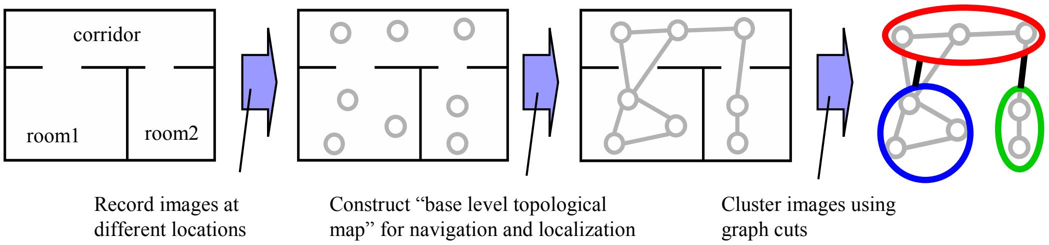

corridor
room1
room2
Record images at different locations
Construct "base level topological map" for navigation and localization
Cluster images using graph cuts

Fig. 1. An overview of the algorithm.

One of the more complicated issues is what sort of spatial concepts should be chosen. For most indoor applications, objects (and their location) and rooms seems a natural choice. Rooms are generally defined as convex spaces, in which objects reside, and which are connected to other rooms with 'gateways' [9,6]. In [17] a hierarchical representation is used in which at the low level the nodes indicate objects, at a higher level the nodes represent 'regions' (parts of space defined by collections of objects) and at the highest level the nodes indicate 'locations' ('rooms'). However, detecting and localizing objects is not yet a trivial task.

In this paper we consider the common concept of 'rooms'. We present our appearance based method to automatically group images obtained by the robot into groups that correspond to convex subspaces in the environment which are related to the human concept of rooms. The convex subspace is defined as a part of the environment where the images from this subspace are similar to each other and not similar to the other subspaces. The method starts from a set of unlabelled images. Every image is treated as a node in a graph, where an edge between two nodes (images) is weighted according to the similarity between the images. We propose a similarity measure which considers two images similar if it is possible to perform 3D reconstruction using these two images [15,24]. This similarity measure is closely related to the navigation task since reconstructing the relative positions between two images also means that it is possible to move the robot from the location from which one image is taken to the location where the other image is taken given that there are no obstacles in between. We propose a criterion for grouping the images from convex spaces. The criterion is formalized as a graph cut problem and we present an efficient approximate solution. In an (optional) semi-supervised paradigm, we allow the user to label some of the images. The graph similarity matrix is then modified to incorporate the user-supplied labels prior to the graph cut step.

The set of images is taken by the robot while it is driving through the environment. This can lead to an unbalanced dataset, in which some areas of the environment are represented by a lot of images, while other areas only with a few. We propose a resampling method to approximate a set of uniformly spread images, which leads to better grouping results.

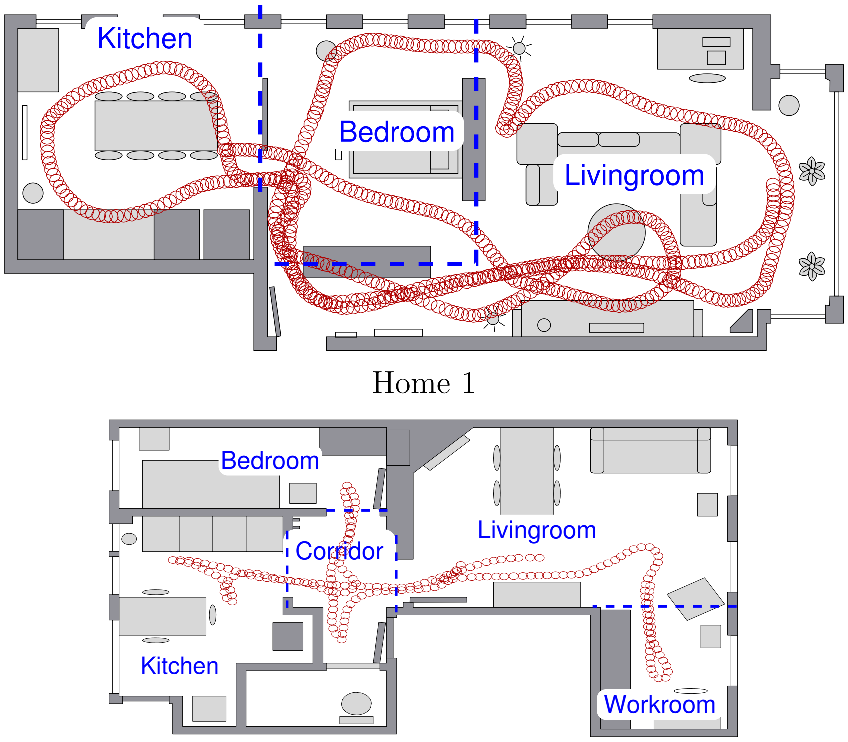
The article is organized as follows. Section 2 presents a short overview of the related work. Section 3 describes our method of constructing a low level appearance based map. In Section 4 it is explained how to find parts of this map belonging to convex spaces in the environment. The method used for resampling the datasets is described in Section 5. In Section 6 we report the experiments we did in real home environments. Our approach is also compared to other similarity measures and standard k-means clustering. Finally we draw some conclusions and discuss future work in Section 7.

2 Related work

The traditional topological maps represent the environment as a graph where the nodes present distinctive locations and edges describe the transitions [9]. The distinctive locations can be obtained from the geometric map, e.g. using Voronoi graphs [2,13] or from images, for example using fingerprint representation as in [18]. However, the extracted distinctive locations are mainly related to the robot navigation task and not the human concepts such as the rooms.

Another related task is the task of place or location recognition. To distinguish between different rooms, often visual cues are used, such as color histograms [21] or visual fingerprints [19]. A combination of spatial cues and objects detected in images taken from that room has been used by [14]. Instead of explicit object detection, also implicit visual cues such as SIFT features have been used [10]. The more general problem of recognizing scenes from images is addressed [20]. However all these approaches assume that human given labels are provided.

We present here an unsupervised algorithm to group the images into groups that are related the human concept of rooms. Our approach is similar to [24] where the images are also grouped on basis of their similarities. A similar approach was also used in [3] but for the task of finding object categories from images. In this paper we present a grouping criterion that is more appropriate for detecting convex spaces. Furthermore, in [24] the data is obtained in a highly controlled way by taking images at uniformly spaced locations. Here we will consider the realistic situation where the data is obtained by just moving the robot around the environment. The graph clustering will then depend on the robot movements. In this respect the clustering problem is related to the chain segmentation problem, where the goal is to split the whole sequence of images at the moments where transitions took place. In [7] such a method was used to group images taken in an office environment. However if a space in the environment is visited more than once, different chain segments are found which are not grouped together. Using this approach thus assumes that every location is visited only once [7]. Our approach does have these limitations.



Home 1

Home 2

Fig. 2. Ground floor maps of the two home environments. The red circles denote the positions of the robot, according to the wheel encoders, from which an image was taken. The transition between the rooms are indicated (the blue dashed lines), as well as the names of the rooms.

3 Image similarity measure

We start from a set of unlabelled images. In all our experiments omnidirectional images were used taken by a mobile robot while driving through the environment (see figure 2 for the image positions of the data sets used for testing). Every image is treated as a node in a graph, where an edge between two nodes (images) is weighted according to the similarity between the images. This graph can be seen as a topological map. Various similarity measures can be used. We will use here the similarity measure as in [24]. We define that there is an edge between two nodes in the graph if it is possible to perform a 3D reconstruction of the local space using visual features from the two corresponding images. We use SIFT features [11] as the automatically detected landmarks. Therefore an image can be summarized by the landmark positions and descriptions of their local appearance. The 3D reconstruction was performed using the 8 point algorithm [4] constrained to a planar camera movement [1] and the RANSAC estimator was used to be robust to false matches [4]. A big advantage of such similarity measure over the pure appearance based measures is that it also considers geometry [15].

As a result of N images we obtain a graph that is described with a set $\mathcal{S}$ of N nodes and a symmetric matrix W called the 'similarity matrix'. For each pair of nodes i,$j\epsilon[1, ..., N]$ the value of the element W_{ij} from the matrix W defines the similarity of the nodes. In our case this is equal to 1 if there is a link between the nodes and 0 if there is no link. Examples of such a graphs that we obtained from real data sets are given in Figure 4. If there is a non-zero edge in the graph this also means that if the robot is at one of the connected nodes (corresponding to one image), it can determine the relative location of the other node (corresponding to the other image) through the 3D reconstruction. If there are no obstacles in between, the robot can directly navigate from one node to the other using a visual servoing or visual homing technique. If there are obstacles, one could rely, for example, on an additional reactive algorithm for obstacle avoidance using range sensors. In this sense the graph obtained using the proposed similarity measure can be seen as a base level dense topological map that can be used for navigation and localization.

This graph contains, in a natural way, the information about how the space in an indoor environment is separated by the walls and other barriers. Images from a convex space, for example a room, will have many connections between them and just a few connections to some images that are from another space, for example a corridor, that is connected with the room via a narrow passage, for example a door. By clustering the graph we want to obtain groups of images that belong to a convex space, for example a room.

Because no global positioning information is maintained in the topological map, the method could fail to distinguish between two very similar looking areas in the environment that are far apart spatially. This is a common problem when using appearance based methods to make a map of the environment, especially when using global image features such as PCA coefficients. However by using local image features and enforcing them to be geometrically consistent, this problem does not seem to be an issue for mapping the environments considered here. For large scale environments however with lots of similar looking rooms the problem of false matching images might re-appear.

4 Grouping images

Starting from the graph representation we will group the images by cutting the graph $(\mathcal{S}, W)$, described above, into K separate subgraphs $\{(\mathcal{S}_1, W_1)..., (\mathcal{S}_K, W_K)\}$. If the subgraphs (clusters) correspond to convex subspaces we expect that there will be many links within each cluster and a few between the clusters. The subgraphs should also be connected graphs. This is formalized as a graph cut criterion further in this section. An efficient approximate solution is also presented.

Note that we assume that the images are recorded at positions that approximately uniformly sample the available space. If this is not true the images from the positions close to each which are usually very similar tend to group together and the resulting clusters depend on the positions where the images are taken.

4.1 Grouping criterion

We will start by introducing some graph-theoretic terms. The *degree* of the i-th node of a graph $(\mathcal{S}, W)$ is defined as the sum of all the edges that start from that node: $d_i = \sum_j W_{ij}$. For nodes $\mathcal{S}_j$ (where $\mathcal{S}_j$ is a subset of $\mathcal{S}$), *volume* is defined as $\mathrm{vol}(\mathcal{S}_j) = \sum_{i \in \mathcal{S}_j} d_i$. The volume $\mathrm{vol}(\mathcal{S}_j)$ describes the "strength" of the interconnections within the subset $\mathcal{S}_j$. A subgraph $(\mathcal{S}_j, W_j)$ can be "cut out" from the graph $(\mathcal{S}, W)$ by cutting a number of edges. The sum of the values of the edges that are cut is called a graph cut:

$$\mathrm{cut}(\mathcal{S}_j, \mathcal{S} \backslash \mathcal{S}_j) = \sum_{i \epsilon \mathcal{S}_j, j \epsilon \mathcal{S} \backslash \mathcal{S}_j} W_{ij} \tag{1}$$

where $\mathcal{S} \backslash \mathcal{S}_j$ denotes the set of all nodes except the ones from $\mathcal{S}_j$. One may cut the base level graph into q_1 clusters by minimizing the number of cut edges:

$$\sum_j^{q^1} \mathrm{cut}(\mathcal{S}_j, \mathcal{S} \backslash \mathcal{S}_j). \tag{2}$$

This would mean that the graph is cut at the weakly connected places, which in our case would usually correspond to natural segmentation at doors between the rooms or other narrow passages. However, such segmentation criteria often leads to undesirable results. For example, if there is an isolated node connected to the rest of the graph by only one link, then (2) will be in favor of cutting only this link. To avoid such artifacts we use a *normalized* version:

$$\sum_j^{q^1} \frac{\mathrm{cut}(\mathcal{S}_j, \mathcal{S} \backslash \mathcal{S}_j)}{\mathrm{vol}(\mathcal{S}_j)}. \tag{3}$$

Minimizing this criterion means cutting a minimal number of connections between the subsets but also choosing larger subsets with strong connections within the subsets. This criterion naturally groups together convex areas, like a room, and makes cuts between areas that are weakly connected.

However, the criterion (3) can lead to solutions where the clusters present disconnected graphs. The requirement that the subgraphs should also be connected graphs need to be considered also in addition.

4.2 Approximate solution

For completeness of the text we briefly sketch a well-behaved spectral clustering algorithm from [12] that leads to a good approximate solution of the normalized cut criteria (3):

(1) Define D to be a diagonal matrix of node degrees $D_{ii} = d_i$ and construct the normalized similarity matrix $L = D^{-1/2}WD^{-1/2}$.
(2) Find $x_1, ..., x_K$ the K largest eigenvectors of L and form the matrix $X = [x_1, ..., x_K] \in \mathcal{R}^{N\times K}$.
(3) Renormalize rows of X to have unit length $X_{ij} \leftarrow X_{ij}/(\sum_j X_{ij}^2)^{1/2}$.
(4) Treat each row of X as a point in $\mathcal{R}^K$ and cluster using for example the k-means algorithm. Instead of the k-means step in [22] a more principled but more complex approach is used following [23], where a good initial start for the k-means clustering is proposed. We tested the mentioned algorithms, and in practice, for our type of problems, they lead to similar solutions.
(5) The i-th node from $\mathcal{S}$ is assigned to cluster j if and only if the row i of the matrix X was assigned to the cluster j.

Although in practice very rarely, the normalized cut criteria (3) can lead to disconnected solutions as mentioned above. A practical split and merge solution to ensure that the subgraphs are connected is as follows:

(1) group the images using the normalized cut criteria (and using the spectral clustering technique).
(2) Split step: if there are disconnected subgraphs in the result generate new clusters from the disconnected subgraph components.
(3) Merge step: the connected clusters that minimize the normalized cut criteria (3) should be merged.

The final result presents a practical and efficient approximate solution for our criterion from the previous section. The exact solution is a NP-hard problem and usually not feasible.

Note that the proposed graph cut solution assumes that the number of clusters is known. Methods exist that partition a graph into clusters, while also estimating the desired number of clusters. In [25] we use such a method for different data sets. It turns out that it works well for environments in which transitions between rooms are narrow, as is the case with conventional doorways. In the experiments in this article however, we assume that the number was given.

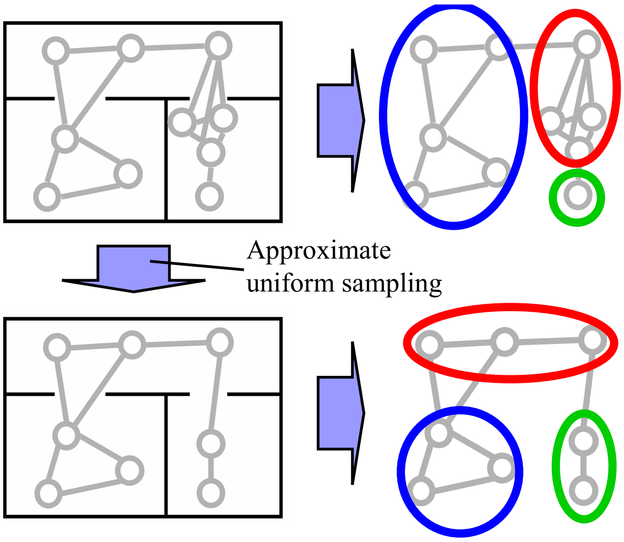


Fig. 3. Top image depicts an example of non-uniformly sampled data and undesired clustering results. The clustering results can be improved by detecting such situations and generating a new graph with approximately uniformly sampled images as depicted below.

4.3 Semi-supervised learning

This framework allows the introduction of weak semi-supervision in the form of pairwise constraints between the unlabelled images. Specifically, a user may specify cannot-group or must-group connections between any number of pairs in the data set. Following the paradigm suggested in [5], we modify the graph $(\mathcal{S}, W)$ to incorporate this information to assist category learning: entries in the affinity matrix S are set to the maximal (diagonal) value for pairs that ought to be reinforced in the groupings, or set to zero for pairs that ought to be divided.

In this way it is possible to incorporate high level knowledge to the spatial representation, for example as given by a person guiding the robot [16]. The human guide can name certain spaces while walking through the environment, which the robot then stores with the images. If the guide informs the robot on two different positions that they are in the same space, the images taken from those positions are put in the must-group. On the other hand, if the guide tells the robot two positions are taken in different spaces, the images are put in the cannot group.

5 Realistic (non-uniform) sampled data

The images should be recorded at positions that approximately uniformly sample the available space. However, this is often difficult to perform in practice. For example some of the data sets we will consider in the experimental section were recorded by letting the robot record the images at regular time intervals. For such data the clustering will depend on the robot movements. An illustration of a non-uniformly sampled data set is given in Figure 3. The images taken close to each other depicted in the figure near the transition from 'room2' to 'corridor' will usually be similar to each other and therefore grouped together. The on-line appearance topological mapping [18] will also suffer from the same problem. In this Section we will use information about Euclidean geometric distances between the images and present a simple sampling approach aimed to approximate the uniform sampling of the space and improve the clustering results.

5.1 Importance sampling

Let there be N images recorded while the robot was moving around in the environment and let $x^{(i)}$ denote the 2D position where the i-th image was recorded. We can consider the $x^{(i)}$-s as N independent samples from some distribution q. A sample based approximation is $q(x) \approx \sum_{i=1}^{N} \delta(x - x^{(i)})/N$. Then we can approximate uniform distribution using importance sampling:

$$\text{Uniform}(x) = c = \frac{c}{q(x)} q(x) \approx \sum_{i=1}^{N} \tilde{w}^{(i)} \delta(x - x^{(i)}) \tag{4}$$

where $\tilde{w}^{(i)} = w^{(i)} / \sum_{j=1}^{N} w^{(j)}$ and $w^{(i)} = c/q(x^{(i)})$. One can interpret the $\tilde{w}^{(i)}$ as correction factors to compensate for the fact that we have sampled from the "incorrect" distribution $q(x)$. Approximate uniform sample can be generated now by sampling from the sample based approximation above. This is equivalent to sampling from the multinomial distribution with coefficients $\tilde{w}^{(i)}$. The distribution of the original sampling $q(x^{(i)})$ can be estimated for example using a simple K-nearest neighbor density estimate $q(x^{(i)}) \sim 1/V$ where the $V = d_k(x^{(i)})^2$ and $d_k(x^{(i)})$ is the distance to the k-th nearest neighbor in the Euclidean 2D space. For all our data we used $k = 7$. However a large range of values for k leads to similar results. The distances can be obtained from odometry information. It would be better to use corrected positional information using some SLAM procedure. For the relatively small environments considered in this article however odometry is sufficient. Alternatively the distances can be approximated from the images directly.

We start with the original graph $(\mathcal{S}, W)$ and an empty graph $(\mathcal{S}^{\text{resampled}}, W^{\text{resampled}})$. The practical algorithm we will be using is as follows:

(1) Compute the local density estimates and the weight factors $\tilde{w}^{(i)}$.
(2) Construct a new graph sampling N samples from the multinomial distribution with coefficients $\tilde{w}^{(i)}$. The corresponding nodes and links from the original graph $(\mathcal{S}, W)$ are added to the new graph $(\mathcal{S}^{\text{resampled}}, W^{\text{resampled}})$.
(3) If the new graph $(\mathcal{S}^{\text{resampled}}, W^{\text{resampled}})$ is not connected continue sampling and adding nodes as in the previous step until it gets connected.

The result is the new graph $(\mathcal{S}^{\text{resampled}}, W^{\text{resampled}})$ where the images come from positions that approximately uniformly sample the available space.

6 Experiments

The method of finding the convex spaces in an environment is tested in two real home environments and is compared to the annotation based on the same sensor data. Our mobile robot was driven around while taking panoramic images with an omnidirectional camera, see figures 2 for ground floor maps of the environments and the positions where images were taken. The task of building a map using these image sets is challenging in a number of ways. First of all the lighting conditions were not good, much worse than the conditions during previous evaluations in office environments. Also, people were walking through the environment blocking the view of the robot. Furthermore, the robot was driven rather randomly through the rooms, which has the effect that some parts of the environment are represented by a lot of images while others parts only with a few (see www2.science.uva.nl/sites/cogniron/ for videos acquired by the robot).

The data sets were annotated by a person outside of the research group. For annotating the maps as shown in figures 2 were used augmented with the labels of a large set of objects. Also the sets of images were provided as videos to give a good idea of the general layout of homes. However the person had never visited one of the two houses. For both homes labels were provided corresponding to the rooms, from which one should be picked per panoramic image. Between some of the rooms there was no good geometrical boundary separating them, so from most places in one room the other room was still clearly visible and vise verse. This is common in real home environments but makes conceptualization of it harder.

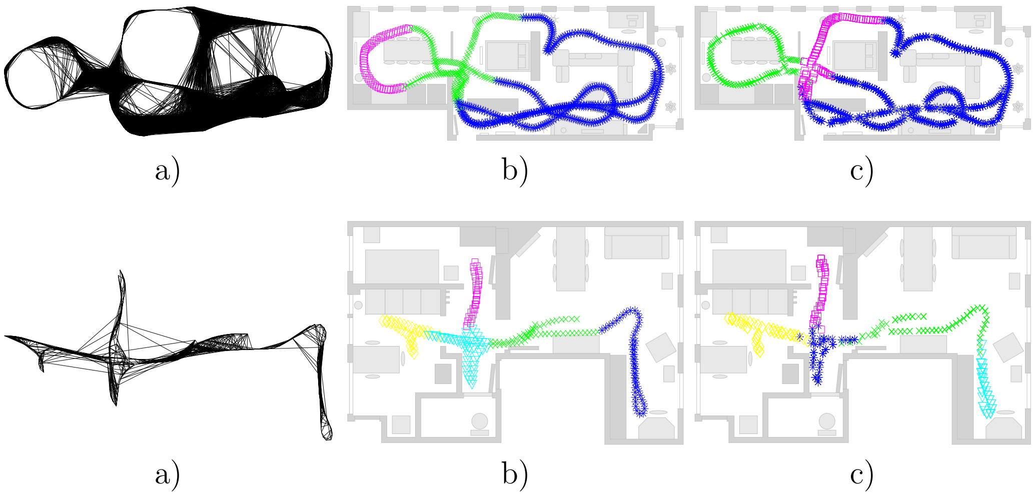


Fig. 4. The clustering results for the Home 1 (above) and the Home 2 (below) data sets. a) The appearance based graph. Each line indicates two matching images. b) The clusters found in the whole dataset. c) Clusters found in the resampled dataset. Note that the odometry data used to draw these figures are not used for building the graph or clustering it, it was only used for the resampling and the visualization of the results.

The whole framework was tuned during preliminary testing at our university building. This office environment is much different than the two home environments for which we present the results. Also, it must be noted that the two home environments themselves were quite different, not only with respect to the lighting and the furniture, but also the layout of the rooms and the transitions between the rooms.

From both image sets an appearance graph is made using the methods explained in Section 3. These graphs are then used as input for the clustering algorithm to find convex spaces in environment, first with all images and then with a subset obtained by resampling. The results are compared with the annotation, to see how well the convex spaces found by clustering correspond to separate rooms.

6.1 Results

In Figure 4 it can be seen that the appearance based methods were quite successful in creating a low level topological map. All links of the graphs connect nodes originating from images that were taken close to each other in world coordinates. In some parts of the graph the nodes are more densely connected than others. This could be the result of bad image quality for example caused by changing lighting conditions, but it could also be the result of lack of features in that part of the environment.

True label	**Inferred label**		
	Living r	Bedroom	Kitchen
Living room	**0.9681**	0.0319	0
Bedroom	0.1832	**0.8168**	0
Kitchen	0	0.5000	**0.5000**

Table 1
Confusion matrix of the automatically grouped images (Inferred label) and the human labeled images (True label) of Home 1. Half of the images of the kitchen were wrongly put in the group of images taken in the bedroom.

Clustering without resampling (see Figures 4b) results in a grouping of the images which is not perfect. As can be seen in Figure 4 some of the images of Home 1 are grouped together which were taken from completely different positions and that images taken in the kitchen are split among two clusters. In Figure 4 it can be clearly seen that some images taken in the living room are grouped with images taken in the work room. After the split and merge steps these images are regrouped with the living room images.

Better clustering results are obtained after resampling the data as indicated by figure 4c. Both data sets are clustered almost perfectly, often cutting the graph at nodes corresponding to images taken at the doorpost between the rooms. The only error left is at the bedroom of Home 1, from which images are grouped with images from the living room. This is probably caused by the large opening between the two rooms, as can be seen in Figure 2.

The mismatch between the clusters found by our method and the labels provided by the annotator is made clear by the confusion matrices, see tables 1 to 4. Of course the clustered data does not provide a label. Each cluster is appointed the label corresponding to the true set with which it has the largest overlap, taking care that no two clusters get the same label. The percentage of correctly clustered images from home 1 is 85% for the whole dataset and 92% for the resampled set. For home 2 this was 73% and 83%.

6.2 Comparison with other clustering methods and similarity measures

We compare our method with the common k-means clustering and a PCA based similarity measure [8]. We used 10 PCA components and clustered the images using k-means. We also used the Euclidean distances in the PCA space and applied spectral clustering. The results were poor compared to our method. The results also show that this simple appearance based similarity is not suitable for spectral clustering methods.

True	**Inferred label**		
label	Living r	Bedroom	Kitchen
Living room	**1.0000**	0	0
Bedroom	0.3014	**0.6915**	0.0071
Kitchen	0	0.0396	**0.9604**

Table 2
Confusion matrix of the automatically grouped images (Inferred label) and the human labeled images (True label) of the resampled dataset taken in Home 1. Note that after resampling most of the images taken in the kitchen are grouped in the same cluster. The values are averages over 10 trials with different resampling.

True	**Inferred label**				
label	Corridor	Living r	Bedroom	Kitchen	Work r
Corridor	**0.6812**	0.1159	0.2029	0	0
Living room	0	**0.5732**	0	0	0.4268
Bedroom	0	0	**1.0000**	0	0
Kitchen	0.0556	0	0	**0.9444**	0
Work room	0	0	0	0	**1.0000**

Table 3
Confusion matrix of the images taken in Home 2. The values on the diagonal are close to 1, indicating a large correspondence between the grouping of the cluster algorithm and the groups of images labeled manually. Nevertheless half of the images taken in the living room were grouped with images taken in the work room, adjacent to it.

True	**Inferred label**				
label	Corridor	Living r	Bedroom	Kitchen	Work r
Corridor	**0.6344**	0.0323	0.2473	0.0860	0
Living room	0.0291	**0.8301**	0	0	0.1408
Bedroom	0	0	**1.0000**	0	0
Kitchen	0	0	0	**1.0000**	0
Work room	0	0	0	0	**1.0000**

Table 4
Confusion matrix of the resampled dataset taken in Home 2. The correspondence between the inferred and the true label is slightly better than without resampling.

PCA + k-means	PCA + spectral clustering	our method	our method (with resampling)
0.60	0.38	0.73	**0.83**

Table 5
Clustering accuracy for various clustering methods for the Home 2 data set. PCA projection with 10 components were used.

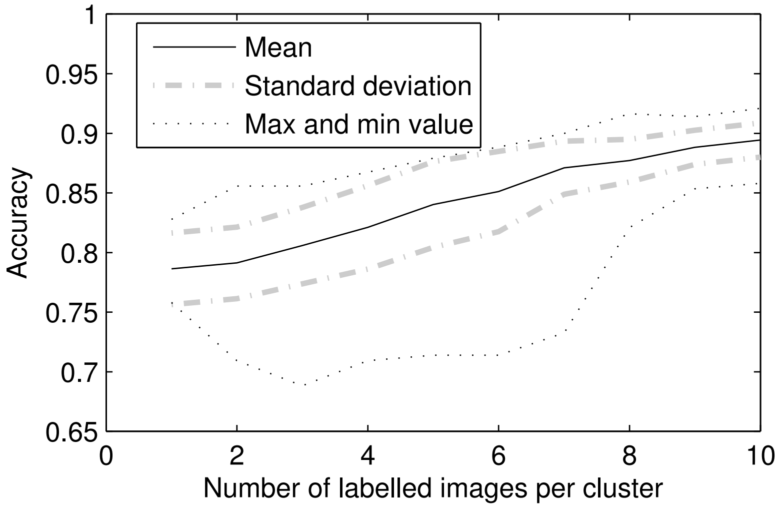


Fig. 5. The clustering accuracy for the semi supervised case - average from 100 trials. Different number of randomly chosen ground truth labels per cluster are used to simulate user input.

6.3 Semi-supervised clustering

To demonstrate the semi supervised learning we used a set labelled points to enforce that the points with the same label should group together and the points with different labels should not group together. The set of the labelled points is randomly chosen and the results for the Home 2 data set are presented in Figure 5. The graphs show how the accuracy increases with the amount of labelled images.

7 Conclusion

'Room' is a common concept used by humans to denote a convex subspace in typical indoor environments. In this paper we presented a framework for extracting the convex subspaces from a set of images obtained by the robot that is moving around in an environment. Pairwise similarities between the images are computed in a robust way by using local features extracted from the images and geometric constraints. We formulate a graph-clustering criterion which intuitively groups images from different convex subspaces by requiring that the images from one subspace are highly similar to each other while the images from different subspaces should not be similar. The method is tested and evaluated on challenging data sets acquired in real home environments. The results demonstrate that the automatic image grouping obtained by the algorithm is very close to human assignment of the images to different rooms from two real home environments. Furthermore, the proposed unsupervised image grouping method is extended to a semi supervised method that can take into account if there are already human given labels for some images. This is particulary interesting for the 'guided tour' scenario where a human guide is teaching the robot about the different rooms in the environment.

The concept of convex space is described here by the normalized graph-cut criterion in an intuitive way. However, the criterion also implies that the spaces should not be too different in size. This works well for home environments as considered in this article. For other types of environments this could pose a problem. This is for example the case in office domains, where there are large corridors and hallways as opposed to the small office rooms [25]. The proposed method tends then to split the hallways in different groups, instead of seeing them as elongated convex spaces. For these specific domains, other criteria could be more suitable. Additional point of concern is that the clustering criterion relies on a "good" sampling of the environment, which was clearly visible tests in Home 1. In table 1 it can be seen that the kitchen is split into two parts. This can be somewhat resolved by the resampling as described in Section 5. After resampling (table 1) 96% of the image annotated as the kitchen fell in a single cluster.

In conclusion, the proposed method provides promising results for extracting the common human spatial concept of 'room' from robot sensory data. The framework can take into account if there are already human given labels and therefore could serve as a basis for a system that can build its representation guided by a human. For example if the guide says to the robot that they just entered the kitchen, then this information should be used to build the higher level representation. Problems might occur if the user is using different labels for the same space or when the clustering obtained by the robot does not correspond to the human concept. These problems need to be addressed and resolved for example through dialog with the user. Finally, the algorithms should be extended to work online in order to facilitate interaction between the map building process and the guide.

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