Location Recognition and Global Localization Based on Scale-Invariant Keypoints

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Abstract. The localization capability of a mobile robot is central to basic navigation and map building tasks. We describe a probabilistic environment model which facilitates global localization scheme by means of location recognition. In the exploration stage the environment is partitioned into several locations, each characterized by a set of scale-invariant keypoints. The descriptors associated with these keypoints can be robustly matched despite the changes in contrast, scale and affine distortions. We demonstrate the efficacy of these features for location recognition, where given a new view the most likely location from which this view came is determined. The misclassifications due to dynamic changes in the environment or inherent location appearance ambiguities are overcome by exploiting the location neighborhood relationships captured by a Hidden Markov Model. We report the recognition performance of this approach in an indoor environment consisting of eighteen locations and discuss the suitability of this approach for a more general class of recognition problems.

1 Introduction and Related Work

The two main instances of mobile robot localization problem are the continuous pose maintenance problem and the global localization also known as 'robot kidnapping' problem. While the successful solution to the localization problem requires addressing both, here we concentrate only on the global localization aspect. The problem of vision-based global localization shares many aspects with object recognition and hence is amenable to the use of similar methodologies. While several instances of vision-based localization have been successfully solved in smaller scale environments [1–4], the applicability of these methods to large dynamically changing environment poses additional challenges and calls for alternative models. The methods for localization vary in the choice of features and the environment model. The two main components of the environment model are the descriptors chosen to represent an image and the representation of changes in image appearance as a function of viewpoint. Similarly as in the case of object recognition, both global and local image descriptors have been considered. Global image descriptors typically consider the entire image as a point in the high-dimensional space and model the changes in appearance as a function of viewpoint using subspace methods [5]. Given the subspace representation the

pose of the camera is typically obtained by spline interpolation method, exploiting the continuity of the mapping between the object appearance and continuously changing viewpoint. Robust versions of these methods have been applied in the robot localization using omnidirectional cameras [1]. Alternative global representations proposed in the past include responses to banks of filters [6], multi-dimensional histograms [7, 8] or orientation histograms [9]. These types of global image descriptors integrate the spatial image information and enable classification of views into coarser classes (e.g. corridors, open areas), yielding only qualitative localization. In the case of local methods, the image is represented in terms of localized image regions, which can be reliably detected. The representatives of local image descriptors include affine or rotationally invariant features [10, 11] or local Fourier transforms of salient image regions [12]. Due to the locality of these image features, the recognition can naturally handle large amounts of clutter and occlusions. The sparser set of descriptors can be, in case of both global and local features, obtained by principal component analysis or various clustering techniques.

Our approach is motivated by the recent advances in object recognition using local scale invariant features proposed by [10] and adopts the strategy for localization by means of location recognition. The image sequence acquired by a robot during the exploration is first partitioned to individual locations. The locations correspond to the regions of the space across which the features can be matched successfully. Each location is represented by a set of model views and their associated scale-invariant features. In the first localization stage, the current view is classified as belonging to one of the locations using standard voting approach. In the second stage we exploit the knowledge about neighborhood relationships between individual locations captured by Hidden Markov Model (HMM) and demonstrate an improvement in the overall recognition rate. The main contribution of the presented work is the instantiation of the Hidden Markov Model in the context of this problem and demonstration of an improvement in the overall recognition rate. This step is essential particularly in the case of large scale environments which often contain uninformative regions, violating the continuity the of the mapping between the environment appearance and camera pose. In such case imposing a discrete structure on the space of continuous observations enables us to overcome these difficulties while maintaining a high recognition rate.

2 Scale-Invariant Features

The use of local features and their associated descriptors in the context of object recognition has been demonstrated successfully by several researchers in the past [13–15]. In this paper we examine the effectiveness of scale-invariant (SIFT) features proposed by D. Lowe [10]. The SIFT features correspond to highly distinguishable image locations which can be detected efficiently and have been shown to be stable across wide variations of viewpoint and scale. Such image locations are detected by searching for peaks in the image $D(x, y, \sigma)$ which is

obtained by taking a difference of two neighboring images in the scale space

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma). \end{aligned} \tag{1}$$

The image scale space $L(x, y, \sigma)$ is first build by convolving the image with Gaussian kernel with varying σ, such that at particular σ, $L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$. Candidate feature locations are obtained by searching for local maxima and minima of $D(x, y, \sigma)$. In the second stage the detected peaks with low contrast or poor localization are discarded. More detailed discussion about enforcing the separation between the features, sampling of the scale space and improvement in feature localization can be found in [10, 16]. Once the location and scale have been assigned to candidate keypoints, the dominant orientation is computed by determining the peaks in the orientation histogram of its local neighborhood weighted by the gradient magnitude. The keypoint descriptor is then formed by computing local orientation histograms (with 8 bin resolution) for each element of a 4×4 grid overlayed over 16×16 neighborhood of the point. This yields 128 dimensional feature vector which is normalized to unit length in order to reduce the sensitivity to image contrast and brightness changes in the matching stage. Figure 1 shows the keypoints found in the example images in our environment. In the reported experiments the number of features detected in an image of size

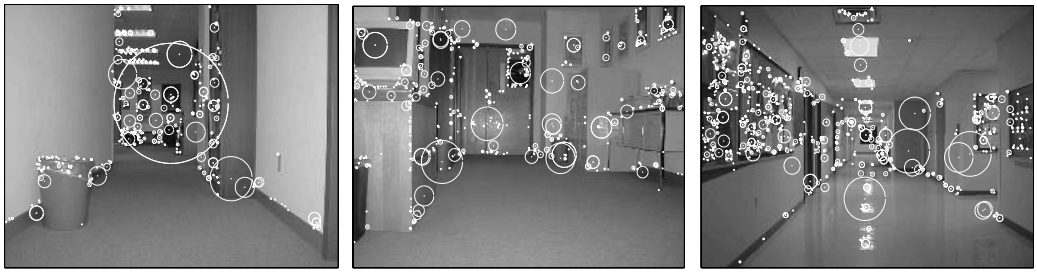


Fig. 1. The circle center represents the keypoint's location and the radius the keypoint's scale.

480×640 varies between 10 to 1000. In many instances this relatively low number of keypoints, is due to the fact that in indoors environments many images have small number of textured regions. Note that the detected SIFT features correspond to distinguishable image regions and include both point features as well as regions along line segments.

3 Environment Model

The environment model, which we will use to test our localization method is obtained in the exploration stage. Given a temporally sub-sampled sequence

acquired during the exploration (images were taken approximately every 2-3 meters), the sequence is partitioned into 18 different locations. The exploration route can be seen in Figure 2. Different locations in our model correspond to hallways, sections of corridors and meeting rooms approached at different headings. In the current experiment, the environment is mostly comprised of network of rectangular corridors and hallways which are typically traversed with four possible headings (N, S, W, E). The deviations from these headings can be handled as long as there is a sufficient overlap between the model views acquired during the exploration and current views. In case the current view cannot be matched successfully, a new location is added to the model. The number of views per location vary between 8 to 20 depending on the appearance variation within the location. The transitions between the locations occur either at places where navigation decisions have to be made or when the appearance of the location changes suddenly. The transitions between individual locations are determined

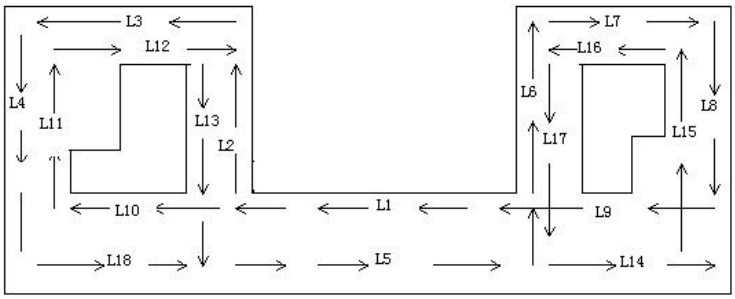


Fig. 2. The map on the fourth floor of our building. The arrows correspond to the heading of the robot and the labels represent individual locations.

depending on the number of features which can be successfully matched between the successive frames. These are depicted in Figure 3 for a sequence captured by a still digital camera along the path which visited all eighteen locations (some of them twice) and for a video sub-sequence along a path which visited three locations. The transitions between individual locations are marked by the peaks in the graph, corresponding to new locations. In order to obtain a more compact representation of each location a number of representative views is chosen per location, each characterized by a set of SIFT features. The sparsity of the model is directly related to the capability of matching SIFT features in the presence of larger variations in scale. The number of representative views varied between one to four per location and was obtained by regular sampling of the views belonging to individual locations. Examples of representative views associated with individual locations are depicted in Figure 4.

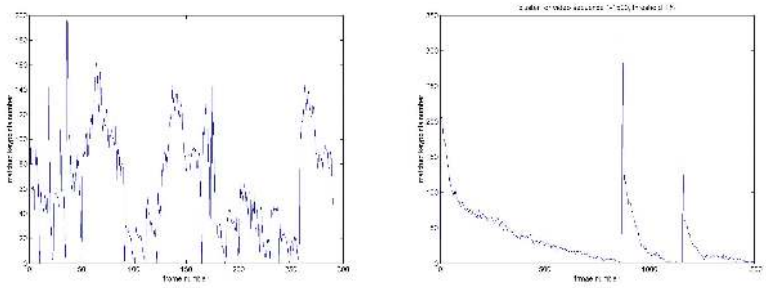


Fig. 3. The number of keypoints matched between consecutive views for the sequence comprised of 18 locations (snapshot was taken every 2-3 meters) captured by a digital camera (left); the number of keypoints matched between the first and i-th view for a video sequence comprised of 3 locations (right).

Fig. 4. Examples of representative views of 14 out of 18 locations.

4 Location recognition

The environment model obtained in the previous section consists of a database of model views [1]. The i-th location in the model, with $i = 1, \ldots N$ is represented by n views $I_1^i, \ldots, I_n^i$ with $n \in \{1, 2, 3, 4\}$ and each view is represented by a set of SIFT features $\{S_k(I_j^i)\}$, where k is the number of features. Given the environment model we now want to classify the new images as belonging to particular locations. The location recognition is accomplished by using a simple voting scheme. For a new query image Q and its associated keypoints $\{S_l(Q)\}$ a set of corresponding keypoints between Q and each model view I_j^i, $\{\mathcal{C}(Q, I_j^i)\}$, is first computed. The correspondence is determined by matching each keypoint in $\{S_l(Q)\}$ against the database of $\{S_k(I_j^i)\}$ keypoints and choosing the nearest neighbor based on the Euclidean distance between two descriptors. We only consider point matches with high discrimination capability, whose nearest neighbor is at least 0.6 times closer then the second nearest neighbor. More detailed justification behind the choice of this threshold can be found in [10]. In the sub-

[1] It is our intention to attain a representation of location in terms of views (as opposed to some abstract features) in order to facilitate relative positioning tasks in the later metric localization stage.

sequent voting scheme we determine the location whose keypoints were most frequently classified as nearest neighbors. The location where the query image Q came from is then determined based on the number of successfully matched points among all model views

$$C(i) = \max_j |\{\mathcal{C}(Q, I_j^i)\}| \text{ and } [l, num] = \max_i C(i)$$

where l is the index of location with maximum number num of matched keypoints. Table 1 shows the location recognition results as a function of number of representative views per location on the training sequence of 250 views and two test sequences of 134 and 130 images each. All three sequences were sparse with images taken 2-3 meters apart. The two test sequences were taken at different days and times of day, exhibiting larger deviations from the path traversed during the training. Despite a large number of representative views per location relatively poor performance on the second and third test sequence was due to several changes in the environment between the training and testing stage. In 5 out of 18 locations several objects were moved or misplaced. Examples of dynamic changes can be seen in Figure 5.

sequence (# of views)	NO.1 (250)	NO.2 (134)	NO.3 (130)
one view	84%	46%	44%
two views	97.6%	68%	66%
four views	100%	82%	83%

Table 1. Recognition performance in terms of % of correctly classified views.

Fig. 5. Changes in the appearance of location L_4 and L_6 between the training and testing. In the left image pair the bookshelve was replaced by a table and couch and in the right pair recycling bins were removed.

The poorer performance due to dynamic changes is not surprising, since the most discriminative SIFT features often belong to objects some of which are not inherent to particular locations. In the next section we describe how to

resolve these issues by modelling the spatial neighborhood relationships between individual locations.

5 Modelling spatial relationships between locations

We propose to resolve these difficulties by incorporating additional knowledge about neighborhood relationships between individual locations. The rationale behind this choice is that despite the presence of ambiguities in recognition of individual views the temporal context should be instrumental in resolving them. The use of temporal context is motivated by the work of [17] which addresses the place recognition problem in the context of wearable computing application. The temporal context is determined by spatial relationships between individual locations and is modelled by a Hidden Markov Model (HMM). In this model the states correspond to individual locations and the transition function determines the probability of transition from one state to another. Since the locations cannot be observed directly each location is characterized by the location observation likelihood $P(o_t|L_t = l_i)$. The most likely location is at each instance of time obtained by maximizing the conditional probability $P(L_t = l_i|o_{1:t})$ of being at time t and location l_i given the available observations up to time t. The location likelihood can be estimated recursively using the following formula

$$P(L_t = l_i|o_{1...t}) \propto P(o_t|L_t = l_i)P(L_t = l_i|o_{1:t-1}) \tag{2}$$

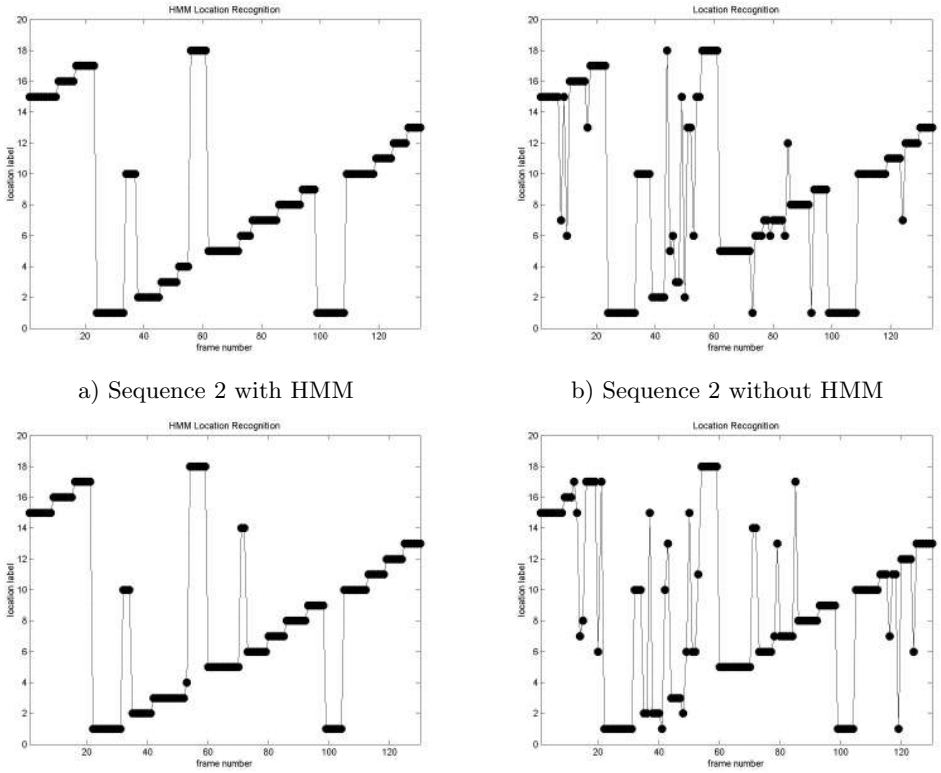
where $P(o_t|L_t = l_i)$ is the observation likelihood, characterizing how likely is the observation o_t at time t to come from location l_i. The choice of observation likelihood depends on the available observations and the matching criterion. When local descriptors are used as observations, several such choices have been proposed in the context of probabilistic approaches to object recognition [18, 19]. The proposed likelihood functions properly accounted for the density and spatial arrangements of features and improved overall recognition rate. In the case of global image descriptors the locations were modelled in terms of Gaussian mixtures proposed in [17]. Since the location recognition problem is notably simpler then the object recognition problem due to occlusions and clutter not being some prominent, we used a simpler form of the likelihood function. The conditional probability $p(o_t|L_t = l_i)$ that a query image Q_t at time t characterized by an observation $o_t = \{S_l(Q_t)\}$ came from certain location, is directly related to the cardinality of the correspondence set $C(i)$, normalized by the total number of matched points across all locations

$$p(o_t|L_t = l_i) = \frac{C(i)}{\sum_j C(j)}.$$

The second term of equation (2) can be further decomposed to explicitly incorporate the location neighborhood relationships

$$P(L_t = l_i|o_{1:t-1}) = \sum_j^N A(i,j)P(L_{t-1} = l_j|o_{1:t-1}) \tag{3}$$

where N is the total number of locations and A is a $N \times N$ matrix, where $A(i,j) = P(L_t = l_i | L_t = l_j)$ is the probability of two locations being adjacent. In the presence of a transition between two locations the corresponding entry of A was assigned a unit value and in the final stage all the rows of the matrix were normalized. The results of location recognition employing this model are



a) Sequence 2 with HMM

b) Sequence 2 without HMM

c) Sequence 3 with HMM

d) Sequence 3 without HMM

Fig. 6. Classification results with for Sequence 2 and Sequence 3 with (left column) and without (right column) considering the spatial relationships modelled by HMM. The black circles correspond to the location labels assigned to individual frames of the video sequence.

in Figure 6. For each frame of two test sequences Figure 6 we plot the location label which had the highest probability. Both sequences visited the locations in the same order at different days, exhibiting different deviations compared to the training sequence. The recognition rate with HMM for Sequence 2 was 96.3% and for Sequence 3 it was 95.4%. While in both cases some images were misclassified the overall recognition rates are an improvement compared to the rates

reported in Table 1, which reports rates of single shot recognition. Despite some classification errors in Sequence 2, the order of visited locations was correctly determined. For Sequence 3, where we exhibited some intentional deviations between the path taken during training and testing, the classification of frames 69-70 as location 14 was incorrect (Figure 6c) . The effect of HMM model can be examined by making all the probabilities in the transition matrix A uniform and essentially neglecting the knowledge of location neighborhood relationships. The assigned location labels for this case are in the right column of Figure 6. Comparing the result with Figure 6a which is closest to ground truth, the recognition performance in 6b and 6d degraded noticably.

6 Conclusions and Future Works

We have demonstrated the suitability and the discrimination capability of the scale-invariant SIFT features in the context of location recognition and global localization task. Although the matching and location recognition methods can be accomplished using an efficient and simple voting scheme, the recognition rate is affected by dynamic changes in the environment and inherent ambiguities in the appearance of individual locations. We have shown that these difficulties can be partially resolved by exploiting the neighborhood relationships between the locations captured by Hidden Markov Models.

Since the notion of location is not defined precisely and is merely inferred in the learning stage the presented method enables only qualitative global localization in terms of individual locations. We are currently extending the proposed method by endowing the view matching scheme by geometric information which enables us to compute the relative pose of the robot with respect to the closest reference view [20] and hence facilitate various relative positioning tasks. More extensive experiments are currently underway. The presented approach suggests an alternative models which can be efficiently exploited in the context of 3D-object recognition and classification of object classes.

7 Acknowledgements

The authors would like to thank D. Lowe for making available the code for detection of SIFT features. This work is supported by NSF IIS-0118732 and George Mason University Provost Scholarship fund.

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