Automatic Place Determination using Colour Histograms and Self-Organising Maps

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Abstract— **In this paper we propose a model-free appearance-based method to automatically determine places as landmarks for topological navigation. Most of the current approaches for automatically selecting landmarks are based on template models or complex feature detectors. We use modified colour histograms, more precisely an entropy-constrained 3D colour clustering as appearance-based image features which adapt to the colour distribution of the environment.**

An unsupervised neural network learning strategy is used to automatically determine places by clustering the modified histograms.

Results from experiments in an indoor environment with a robot equipped with a panoramic camera show that the places, which were clustered in histogram space refer to physically close positions in the world domain in a large degree and can be used as landmarks for navigation purposes.

I. INTRODUCTION

Robot localisation is one of the most fundamental problems in mobile robotics [1], [2] since mobile robots must be able to locate themselves in the operating environment to accomplish their tasks. There are three main approaches to localisation: *metric*, *topological* and *hybrid*. Metric approaches typically try to estimate the position of a robot as accurately as possible with respect to a map's coordinate system. In topological systems the environment is usually represented as a graph of connected nodes where the nodes refer to places and the edges display the connectivity of the environment. That means a robot memorises several distinctive places and their connectivity [3] and it attempts to determine the place which corresponds to the robot's location. Hybrid methods combine both metric and topological approaches.

In general, both metric and topological localisation are based on *map matching* or *landmark detection*. Map matching methods usually match current sensor input to a model of the environment.

Landmark based systems rely on either *artificial* or *natural* landmarks. Artificial landmarks are easy to detect reliably but they require modifications of the environment. Natural landmarks usually consist of predefined template models like corners, doors, junctions and floors [4], [5]. As these systems use predefined templates to recognise landmarks, they are specific to particular environments and cannot be easily utilised in different kinds of environments.

With the development of image based feature detectors [4], [6]–[8], feature based landmarks have become very popular [9]–[11]. These approaches associate a set of extracted image features as a landmark for a particular place. These approaches are very reliable but are complex and computationally expensive.

Menegatti et al. suggest an appearance based method using panoramic images [12]. A reference database is created as each panoramic image is unwarped and the 15 lowest frequency Fourier coefficients of each row of the unwarped image are stored as a signature vector for a position. In the localisation step the signature of the current image is compared with the database.

Ulrich and Nourbakhsh introduced a system [1] in which representative R, G, B and H, S, V colour histograms of panoramic images are stored for particular places and labelled by a user. In the place recognition step the histograms of the current image are matched to the database and finally classified through unanimous voting of proposals of each colour band. This method requires a user who labels the data for the reference database.

Rañó et al. presented an appearance based method for localisation [13]. The colour distributions for particular places are learned by respective self-organising maps (SOM) [14] that cluster the RGB pixels of the input images which were previously associated with a certain place by hand. After training, the resulting SOMs are stored as identifiers for the places. For localisation a new SOM is trained and the result is compared with previously stored SOMs. A major problem of this system is that it learns the representation of the places only but requires an external supervisor who associates images with places.

This paper introduces an appearance-based method for automatic place determination. This method belongs to landmark based localisation systems since a place can be represented as a particular set of landmarks or features which appear at a specific location. Our approach is based on the assumption that colour histograms usually vary smoothly as the field of vision sweeps the scene when a robot follows a path through the environment. Thus, our features of interest are colour histograms, more precisely a modification which adapts to the colour distribution of the environment. If the assumption holds, it should be possible to associate the neurons of a SOM trained on the histograms with places in the world domain. That means each neuron would represent a landmark and the SOM is capable of identifying (matching) the landmarks from *similar* histograms. Although an extension of histograms incorporating information on spatial distribution of the pixels in a colour bin has been proposed elsewhere [15] we use histograms only for the sake of simplicity.

This method is model-free, that means it does not require a metric model to represent the environment and also does not need any measurement model or sensor calibration. It uses the appearance of visited regions or places in feature space only without using any previous knowledge of the environment.

This approach is inspired by the way human beings and animals localise themselves by learning to navigate using data gathered from interacting with the world. They usually do not memorise a metric map or environment model in their mind but are able to recognise landmarks in previously visited regions and places [16]. Since this recognition is not based on a specific perception method, e.g., vision or hearing, it represents a generalised approach to self-localisation.

The remainder of this paper is structured as follows: In Section II we describe our system in detail. The construction of the entropy constrained colour histograms (Section II-A) is described and Section II-B explains the utilisation of self-organising maps for clustering the histograms. Finally, based on the results from experiments in Section III we discuss the association of the neurons of the SOM with places in the world domain. This is followed by conclusions (Section IV).

II. APPEARANCE-BASED PLACE RECOGNITION

This section describes the approach we suggest for appearance-based place recognition. First, we introduce entropy constrained colour histograms as an appearance-based method for feature extraction of images and the second part of this section briefly describes self-organising maps.

A. *CONSTRUCTION OF COLOUR HISTOGRAMS*

Colour histograms have several attractive features especially for panoramic images. First, they are easy and fast to calculate and also can represent salient colour information of images in a very compact manner. Second, histograms of panoramic images are invariant to rotations of the vertical axis. Thus, an image acquired at a particular position represents all images at this position with different orientation.

Usually a colour histogram is created by calculating a N-bin histogram for each R, G, B colour band [1], [13]. This approach is very fast but the 3D spatial information of the RGB tuples in colour space is lost. To retain this information we cluster the pixels in 3D colour space.

Another drawback of simple histograms is the uniform distribution of the bins which does not correspond to the frequency of distribution of the input data. For example, in the colour histogram of a very dark image most pixels would fall in only a few bins and other bins would be almost empty. This results in the loss of important information which can be kept by a clustering system which adapts to the distribution of the input data.

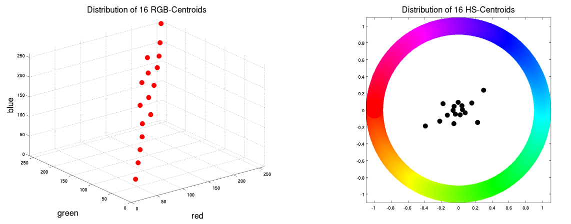

Fig. 1. Distribution of 16 centroids calculated using the entropy constrained cluster method in RGB space (left) and HS space (right).

In order to preserve the spatial information and also the distribution density of the pixel cloud we use *entropy constrained colour histograms* as a modification [17] of an iterative vector clustering algorithm [18] which minimises the distortion error subject to an entropy constraint in the colour space. This method is similar to histogram equalisation [19] but, rather than modifying the image data by a stretching function, the centroids and the size of the histogram or cluster bins adapt to the distribution of the data. Hence, by maximising the entropy of the clustering we can maximise the information of the histogram of an image.

The entropy I of a clustering to z clusters $C = \{c_1, ..., c_z | c_i \in R^n\}$ is defined as

$$I(C) = -\sum_{i=1}^{z} p(c_i) \log p(c_i) \tag{1}$$

where $p(c_i)$ is the probability of occurrence of cluster c_i [20]. A dissimilarity function

$$d(x, c_i) = (x - c_i)^2 \tag{2}$$

of an input $x \in R^n$ and a centroid $c_i \in C$ is extended by a weighted penalty parameter e_i to

$$d_e(x, c_i) = d(x, c_i) - \lambda e_i \tag{3}$$

where $\lambda \geq 0$ is a Lagrange multiplier [20] whose value maximises the output entropy of the clustering and

$$e_i = -\log p(c_i) \tag{4}$$

denotes the self-entropy of a cluster c_i. Thus, a centroid which represents many input samples gets a high penalty parameter and its cluster region decreases. Thereby, the distribution of the resulting cluster vectors reflects the distribution of the input samples.

The left part of Figure 1 shows the 16 RGB centroids from an application of entropy constrained colour histograms to the image pixels from our test dataset (see Section III). The centroids adapt to the distribution of the samples around the grey axis.

The observed distribution of clusters suggest that it might be advantageous to use the HSI colour-space instead of RGB [19]. By applying a projection of the HSI space to the HS plane we cut off the illumination component which has the advantage of being robust to varying illuminations. Furthermore, the dimension of the pixel data is reduced from 3D to 2D and (given $H = \{h_0, h_1, ..., h_{255}\}$ and $S = \{s_0, s_1, ..., s_{255}\}$) the pixel space decreases from 256^3 to 256^2 possible different colours to less than 4% of the RGB-space. There are more sophisticated colour spaces which may be examined in further work.

The right hand part of Figure 1 shows an example distribution of N = 16 centroids on the H, S colour plane obtained through entropy constrained colour histograms.

Clearly, the calculation of the centroids is an optimisation problem that takes time, but once they are obtained the segmentation of images using this entropy constrained colour histogram technique is very fast.

B. SELF-ORGANISING MAPS FOR AUTOMATIC LANDMARK DETECTION

In this paper we use self-organising maps to find simliarities in the input space, i.e. in the histogram space. Self-organising maps have been widely used in pattern processing, classification of complex vectorial data and even in robot localisation [21]–[24].

According to the hypothesis that histograms from images taken at physically nearby positions are similar, a neuron will be tuned to a region of similar histograms. The topology conserving property in featurespace of the SOM [14] will put the most similar neurons in neighbouring position of the map. Because the histograms depend implicitly on the 2D position in space we expect the histogram vectors to occupy a 2D manifold in histogram space which the SOM will map.

A SOM is an unsupervised single-layer winner-take-all neural network which learns to categorise input patterns and to associate them to different output neurons. This is partly motivated by how visual, auditory or other sensory information is handled in separate parts of the cerebral cortex in the human brain [25]. Its principle is to map the input space $\Re^n$ onto a regular two-dimensional array of neurons or nodes, where each neuron is associated with a weight vector $w_i(t) \in \Re^n$ at epoch t. An input $x(t) \in \Re^n$ is compared with w_i and the closest weight vector is defined as the winner

$$c = \arg\min_i (d_*(x(t), w_i(t))) \tag{5}$$

where $d_*(.,.)$ denotes the dissimilarity measurement respective a particular metric. The weight vectors are adapted during the learning process by

$$w_i(t+1) = w_i(t) + \alpha(t) h_{ci}(t) \left[x(t) - w_i(t)\right] \tag{6}$$

where $\alpha(t)$ is a decreasing learning rate and $h_{ci}(t)$ the neighbourhood function. In our experiments we use a Gaussian

Fig. 2. left: Example panoramic image. right: Pre-defined mask to cut out the used pixel-ring.

neighbourhood function

$$h_{ci}(t) = e^{\frac{-d_{Euclid}(i,c)^2}{\beta(t)^2}} \tag{7}$$

where $\beta(t)$ denotes a time dependent linear decreasing neighbourhood size. The term $d_{Euclid}(i, c)$ is the Euclidean distance from cell i to the winning cell c. After training, the output space of the SOM reflects neighbourhoods of input similarity, i.e. similar input vectors are mapped to the same output neuron. Hence, the neuron represents a landmark which refers to a place to which similar input vectors, that means histograms from images, are associated with.

Utilising a SOM to automatically cluster similar features keeps the system model-free. Another advantage is the independence of the choice of sensors and measurement model is required. Furthermore, no supervision is needed to determine places because we exploit the characteristic of SOMs to cluster similar data and that close positions should appear similar.

However, due to ambiguities of appearance and also the dimension reduction through histograms it is possible that different places are associated with the same neuron. This might result in confusion but in fact, this happens also in nature. If to humans and animals visit a place that looks quite similar to another they also get disoriented and need further information.

III. RESULTS FROM EXPERIMENTS

To evaluate the proposed method we use a dataset of an indoor environment which consists of 602 panoramic images, odometry measurements and laser range scans [9]. It was recorded while driving a remote controlled mobile robot through several corridors and rooms at the University of Örebro, Sweden. Our system uses previously defined ring of pixels of the panoramic images (Figure 2). However, for evaluation purposes odometry measurements and laser range scans are processed with a SLAM algorithm to provide reliable reference locations in the real world domain and an 2D environment map (see Figure 5). Unfortunately, we do not have more image data to examine the impact of changes in illumination and minor modifications in the environment.

A. EVALUATION METHOD

The evaluation of the performance of our approach to associate similar colour histograms with physically close positions, requires some previous considerations. Basically, as the place recognition system is to be used for topological

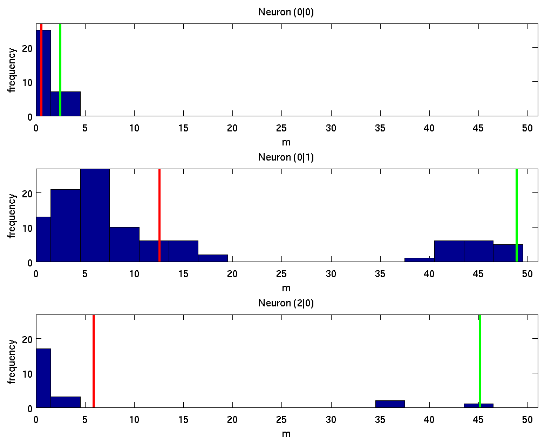

Fig. 3. Three histograms of the distances from associated positions mode of a neuron in the physical space are shown. Further, the mean (red) and the maximum (green) distance of the associated positions are displayed. The top histogram indicates a neuron representing one place with cohesive positions. The histogram in the middle refers to a neuron which is an alias, which means it represents more than one cohesive place. The bottom histogram shows a place with 2 outliers, that means 2 positions in the environment which are not cohesive and far away from the neurons mode.

localisation, we evaluate the performace in the physical space. Clearly, his may not be necessarily the best clustering with respect to the distortion measure in the feature domain.

In the best case, each of the neurons of the SOM represents several images recorded at cohesive positions in the world domain. A way to measure this is using a histogram of the distance in the world domain from the neuron to the location where the images associated with this neuron were taken. The position of a neuron in the world domain is given by the image with the most similar histogram. Consecutive positions in the world domain are represented as consecutive non-empty bins (Figure 3, top). A histogram with more than one consecutive non-empty neighbourhood may indicate aliases, that means different regions in the environment which appear similar in feature space (Figure 3, middle). Further, due to the massive dimension reduction in feature space and also the evaluation in the physical but not in the feature domain there might be some single images which are falsely classified, which means they associated with a neuron whose main region is physically in another part of the environment (Figure 3, bottom).

To evaluate the performance of the system we consider the mean distance σ_i and the accumulated maximum distance d_i of the neuron i and the associated positions of the recorded images in physical space. A large maximum distance of a neuron indicates non-cohesive reference positions and thus aliases or false classified positions. In contrast, a small mean distance and a small maximum distance is supposed to associate generally cohesive reference positions (Figure 3). So far, we do not distinguish false classifications and aliases as we want to avoid both. However, disambiguating the aliases is unlikely and thus we consider the average mean distance $\bar{\sigma}$ of all neurons of the SOM as the crucial parameter for evaluation of the entire system.

We processed the images with entropy constrained colour histograms for 16, 24, 32 and 64 clusters in both RGB and HS colour space. Although, we can not prove illumination invariance because of limitations of the data it is worthwhile to examine the transformation to the HS colour space as it reduced the dimension of the feature vector significantly.

The proposed approach depends on several parameters. First, the size of the SOM determines how many places the system can learn at most. We investigate how the system performs for 12 different sizes of SOMs (Figure 4). Although the current method requires us to pre-select the number of neurons of the SOM in advance, we could use a growing SOM [26] to address this problem. To explore how the performance depends on the number of training epochs the SOM was subjected to 100, 500 and 2000 training cycles. Further, since the neighbourhood size $\beta(t)$ affects the learning process we also analyse 4 different sizes of neighbourhood starting at the smaller of the dimensions of the SOM and reduce $\beta(t)$ to one fourth of it. The learning rate $\alpha(t)$ is reduced linearly from $\alpha(t) = 1$ to $\alpha(t) = 0.05$ and decreases inversely proportional to the number of epochs. We also investigate the sensitivity of the proposed system to different dissimilarity metrics (Euclidean distance, Manhattan distance, Kolmogorov distance, Jeffrey divergence and histogram instersection) in the SOM (Equation 5).

B. RESULTS

In terms of analysing how the neighbourhood size may influence the results we could not find a tendency to a particular size. Also, we cannot determine any correlation of the number of used training epochs and the performance of the place recognition system. In the remainder we always refer to the best neighbourhood size and number of loops for a particular evaluation.

Analysing different dissimilarity metrics, we found that in general Kolmogorov distance and Histogram Intersection perform not as well as the other investigated metrics (Figure 4, top). Euclidean, Manhattan and Jeffrey distance seem to achieve similar results. In fact, as the Manhattan dissimilarity metric is very fast in calculation and does not strongly decrease the performance of the system applying this metric can speed up the place determination and recognition process.

The place determination seems to perform slightly better with an increasing amount of features, that means the size of the input feature vector for the SOM (Figure 4, middle). Further, we found, that in general, using the RGB colour space performs only slightly better than the HS colour space, and for small SOMs the HS space performs even better (Figure 4, bottom). This is very important as we can use a colour space with lower dimensionality without a significant decrease of performance. Further, the HS colour

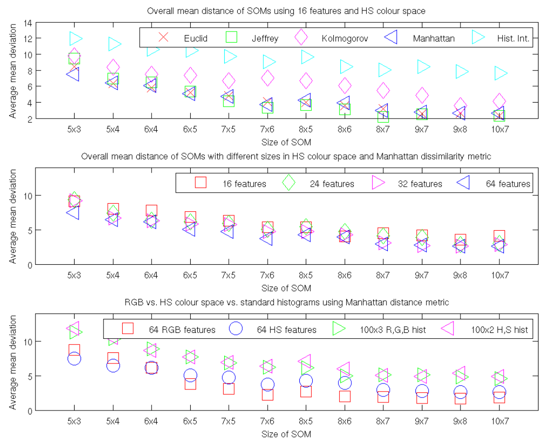

Fig. 4. top: Dissimilarity metric analysis for 16 HS centroids and different SOM sizes. middle: Impact of the size of the feature vector analysed using the Manhattan distance in the HS colour space. bottom: Evaluation of the RGB vs. the HS colour space using the Manhattan distance and 64 features. This chart also shows the results of standard R, G, B and H, S histograms with 100x3 and 100x2 bins.

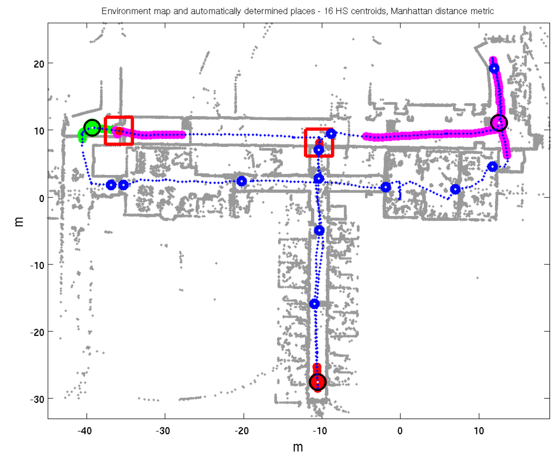

Fig. 5. A reference map (gray) of the test environment and the traversed path (blue) of the robot is plotted. Big blue-white dots show the automatically learned places of a 5x3 SOM. Three learned places and the associated positions of three particular neurons are plotted: Neuron [2,0](red), Neuron [0,0](green) and Neuron [0,1](magenta). The modes of these neurons are circled black. The red boxes indicate positions which are falsely classified to Neuron [2,0](red). It is also easy to see that Neuron [0,1](magenta) is an alias and consists of two cohesive regions.

space is supposed to be invariant to illumination changes. However, due to the limitations of the given data set we can not examine this feature of the HS colour space.

One of the most influential factors is the number of neurons of the SOM. Clearly, with an increasing number of neurons there are more places available to distinguish. This can be seen by regarding the decay of the overall mean distance in the charts of Figure 4. However, if we consider the overall maximum distance we did not achieve a significant improvement. Obviously, some regions appear similar and thus are associated to the same neuron and place, respectively.

Further, the bottom part of Figure 4 compares the entropy constrained colour histograms with standard histograms. The improvement of the entropy constrained histograms ranges in the RGB colour space from 30% (5×3 neurons) to almost 200% (9×8 neurons) and in the HS colour space from 42% (6×4 neurons) to 100% (9×8 neurons). Note, the standard histograms are evaluated for big feature vectors of 100×3 for R, G, B histograms and 100×2 for H, S histograms compared to the entropy constrained colour histograms which increases the computational costs.

Figure 5 shows the application of the proposed system to the previous described indoor data set for 16 HS centroids and a SOM with 5×3 neurons. For better understanding a reference map (gray) is plotted and the blue dots show the reference positions of the robots path. The big blue-white dots display the learned places of the SOM. Three learned places and their mode (black circle) are shown in red (Neuron [2,0]), green (Neuron [0,0]) and magenta (Neuron [0,1]). The distance histograms of these neurons are shown in Figure 3.

Neuron [0,0] is associated with consecutive positions in the world. A close look to this area of Figure 5 shows that this region is bounded by two doors and corresponds in fact to a room or hallway which is traversed partially by the robot.

Two alias regions are represented by Neuron [2,0](magenta) which consists of two cohesive regions. Considering the original images recorded at these positions we found that they are probably dominated by the same colour of the floor which might explain both, the big regions covered from the neuron and also the two (cohesive) regions. A closer look at the smaller of these two regions shows again that it is framed by two doors and thus represents a room in the environment.

The positions associated with the third considered neuron (Neuron [0,1](red)) are also mostly cohesive. However, there are 2 false classifications, indicated by red boxes. This might be an artefact of the massive dimension reduction of the entropy constrained colour histograms. Further, these false classifications appear at transitions between two rooms and thus are difficult to associate as their appearance in the feature space is neither the previous room nor the next room.

IV. CONCLUSION

In this paper we show that in the available data set places can be inferred by a neural net from colour histograms from panoramic images and that in this way a fully automatic landmark determination can be constructed.

We introduced entropy constrained colour histograms which adapt to the colour distribution of the pixels in a certain environment. On the available data set this modification increases the performance of the system up to 200%. Transforming RGB data to the HS colour space yields a significant reduction of the feature space with just a slight decrease of performance for big SOMs and even better performance for small SOMs.

We analysed the system for several numbers of histogram bins, different sizes of SOMs and also different dissimilarity metrics. We found that the performance slightly increases with an increasing amount of histogram bins. However, as the improvement is very small it is to trade off against the increasing computational costs which are caused by a bigger feature vector. In terms of dissimilarity metrics it was not possible to determine the best one but the usage of Kolmogorov distance and Histogram Intersection perform worse then the other analysed metrics.

Clearly, this approach is limited in accuracy and if different regions in an environment appear similar our system is not yet able to distinguish between them. But we can conclude that the current system is able to associate colour histograms from different positions with respective places and is probably robust to noisy sensor data and partially dynamic and varying environments. If, e.g. a chair or desk is moved or as well a person moves in a room the method should work well. As Figure 5 shows in general a neuron or a set of neurons can represent a place which consist of cohesive positions. This supports the basic assumption that colour histograms vary smoothly with the field of vision of a moving robot. Further, our system memorises a very compact and abstract representation of previously visited places.

Further work will is needed for creating and learning the topology and connectivity of the distinguished places so that it could represent a complete topological map for navigation purposes. Also the place recognition system can be entropy constrained by an extension to the usage of other simple or more sophisticated features. As the use of small and cheap digital cameras is more widespread it would be useful to extend the investigated approaches to the usage of non-panoramic cameras.

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