IMAGE RETRIEVAL USING LANDMARK INDEXING FOR INDOOR NAVIGATION

by

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Abstract

A novel approach is proposed for real-time retrieval of images from a large database of overlapping images of an indoor environment. The procedure extracts visual features from images using selected computer vision techniques, and processes the extracted features to create a reduced list of features annotated with the frame numbers they appear in. This method is named *landmark indexing*. Unlike some state-of-the-art approaches, the proposed method does not need to consider large image adjacency graphs because the overlap of the images in the map sufficiently increases information gain, and mapping of similar features to the same landmark reduces the search space to improve search efficiency. Empirical evidence from experiments on real datasets shows high (90-100%) accuracy in image retrieval, and improvement in search time from the order of 100-200 milliseconds to the order of 10-30 milliseconds. The image retrieval technique is also demonstrated by integrating it into a 3D real-time navigation system. This system is tested in several indoor environments and all experiments show accurate localization results in large indoor areas with errors in the order of 15-20 centimeters only.

Statement of Co-Authorship

The work presented in this thesis was accomplished under the supervision of Dr. Michael Greenspan, who provided feedback and corrections to the manuscript. The contents were accepted for publication in a conference paper cited here, which was co-authored by my colleague and Ph.D. student Mirza Tahir Ahmed and Dr. Greenspan.

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Glossary

2D Two dimensional.

3D Three dimensional.

DoF Degrees of Freedom.

DoG Difference of Gaussians.

FLANN Fast Library for Approximate Nearest Neighbor [\[49\]](#).

OpenCV Open source Computer Vision library for C++ [\[8\]](#).

PCA Principal Component Analysis.

PCL Point Cloud Library [\[60\]](#).

RANSAC RANdom SAmple Consensus.

RGBDSLAM Open source software package for SLAM using RGB-Depth sensors [\[17\]](#).

ROC Receiver Operating Characteristic.

ROS Robot Operating System [\[53\]](#).

SIFT Scale Invariant Feature Transform.

SLAM Simultaneous Localization And Mapping.

SURF Speeded Up Robust Features.

TF-IDF Term Frequency - Inverse Document Frequency.

Chapter 1

Introduction

1.1 Background

1.1.1 Indoor Navigation

Indoor navigation is the method of localizing a robot or any other user in an indoor or underground environment using a sensor or a network of sensors. Indoor navigation systems are designed not only for positioning, but for public aid and marketing purposes. They can be used to guide visually impaired people, to track packages in a large warehouse, arrange tours in educational or industrial campuses, or even navigate a robot inside abandoned underground mines. Location-based marketing technique such as targeted advertising can be integrated into such a navigation system.

Before the emergence of computer vision aided navigation, sensors like Sound Navigation And Ranging (SONAR), Radio-Frequency Identification (RFID) etc. were used. SONAR sensors can be used to find the distance from walls using the time of flight of ultrasonic signal. RFID tags are cheap, can be read even if they are invisible, and multiple tags can be read at the same time. In long tunnelways, RFID markers can be placed at different places, so that when a vehicle comes near a marker, a

controller can identify the location. The same can be applied in different floors or rooms of a building. Wi-fi is also another possibility. The intensity of the received signal, and identifying the wi-fi fingerprint are key aspects for this type of navigation. However, RFID tags can only be used when a tag comes close to a sensor, and wi-fi technology can indicate an area where a device is located instead of its pose in 6 Degrees of Freedom. Both technologies need a sufficient number of tags or access points throughout the map for accurate localization. To estimate the pose in a 3D model, some other information is required. The first applications of 3D vision in localization and mapping were done with laser scanners. They can be used to estimate roll, pitch and yaw, and full 6 DoF in pose estimation can be achieved.

1.1.2 Navigation with Landmarks

The challenge in navigation is different than Simultaneous Localization and Mapping (SLAM), mostly because mapping is not involved. In navigation, the idea is to locate a robot or a person in a map through searching the environment for at least one *landmark*. The approach of using landmarks in localization is derived from the human notion of navigation. A well-recognizable feature can be considered as a landmark of a certain region, like a geographic natural feature (*e.g.*, Barringer Meteor Crater in Arizona, US), a well-known building in a city (*e.g.*, Taj Mahal in Agra, India), or an indoor reference point like a reception desk in a hotel. In computer vision, features, or groups of features, are considered as landmarks. Se *et al.* [64] first assigned the term to visual features, and the idea is extended in this paper.

In SLAM, depending on the sensor, the landmarks can be artificial, *i.e.*, added externally to the environment. For example, previously discussed RFID markers

are artificial landmarks added to different locations in a building or a long tunnel way. For vision-based navigation, artificial landmarks may or may not be necessary. One example of modern day artificial landmarks in vision-based navigation is Quick Response (QR) codes. All smartphones currently have the capability to read QR codes, and QR codes are specifically useful because any information can be converted into a code. So exact coordinates can be encoded and placed on a wall, and the smartphone can scan it and display the location. However, computer vision enables the positioning system to identify and make use of the landmarks which naturally exist in the environment.

1.1.3 Application of Computer Vision: Image Retrieval and Visual Words

Computer vision techniques have become relevant with the topic of navigation with the development of different *feature extraction* methods. Images can be identified using *features*. A *feature point* is a point which should be distinctive, invariant to image scaling, rotation, illumination or camera viewpoint, and robust to noise. There are several algorithms to extract features from images, like SIFT [45], SURF [5], BRISK [38], FREAK [2] etc. Some algorithms provide only point locations in an image, and some algorithms provide a *feature descriptor* for the each of the points. A feature descriptor is a vector describing the unique properties of the corresponding feature point. SIFT and SURF have their own descriptors. FREAK produces only points, which can be described using descriptors like BRIEF [10] or ORB [57]. Image matching is performed in feature space. If two images have feature points described with the same algorithm, and the descriptor vector has N dimensions, then in that N -dimensional space two features from different images closest to each other are

considered a match. In a situation like navigation, a map can have several, maybe thousands of images. To identify a location, a user needs to capture a frame with a camera, and perform a feature matching with the images in the map. The image with most matches with the captured frame can present the location of the user.

There is a challenge of image identification for navigation. As stated before, a map dataset can have several thousands of images. Matching a frame with each one of them will certainly be a hindrance to real-time retrieval. A procedure is needed to reduce the search set. This motivates the work described in the thesis.

There exists a method called *bag of visual words*, first introduced by Sivic and Zisserman in 2003 [66]. An image can be compared with a document, which is an unordered collection or a *bag* of words. Image features, which are similar to each other according to some pre-defined criteria, can be classified as a *visual word*. When matching features to retrieve an image from a database, search is performed on these visual words, significantly reducing the search space. However, if image retrieval is performed for the purpose of navigation in a large map, all the features have to be taken into account to make the visual word dictionary or codebook, and some features may not be useful for identification. Moving and temporary objects like a car or people on the road cannot be taken as useful. Only distinguishable, repeatable and static features are considered favorable, and the rest should be filtered out. This requires a suitable algorithm, which is the central point of this thesis, and discussed in detail in chapter 3. The good features which are not removed from the map database are treated as visual *landmarks*.

1.1.4 Integration to 3D Processing

Current development of Point Cloud technology helps to describe a 3D model as a collection of 3D points, termed as a *point cloud*. Each point is described by its 3D coordinates with respect to a viewpoint. The coordinates are measured in distance units. There may be additional properties added to each point, such as image information like color and opacity, or geometric information like surface normals and curvature. Point Cloud Library (PCL) [60] discriminates the point clouds as either organized or unorganized. An organized point cloud has its points has no missing information from its 2D image equivalent. If a point cloud is projected on a plane perpendicular to the principal axis of the camera, then each point in the cloud can be addressed with the 2D row-column coordinates their corresponding pixel in the resultant projected image. For example, a 640×480 organized point cloud has all 307200 points, none missing, and each point can be referred with 2D row and column pixel coordinates (*e.g.*, 0-639, 0-479). This is advantageous for 3D navigation. When an image is retrieved, if the corresponding point cloud is available, all the feature matches found in the retrieval step can be translated into 3D space. These 3D matches can be readily used to register 3D frames and find the position and orientation in 6 DoF.

1.2 Problem Identification

The existing solutions for location image identification using bag of visual words process a large number of features which cannot be considered as landmarks. This makes the localization process slow, and often introduces inaccuracies at runtime. Secondly, the existing approaches to reduce the amount of features have not considered the difference between outdoor and indoor environments. Features can be filtered using

some criteria on the number of appearances in the image database, and imposing some overlap between adjacent images can be helpful to gain prior information to accurately match similar features.

1.3 Thesis Contribution

Proposed Approach. This thesis proposes a novel method which uses a feature indexing approach, which speeds up the retrieval process compared to the histogram matching of *bag of visual words*. Features from each image are extracted and duplicate features are removed, keeping only the image identification numbers they appear in. This reduced set of features are again passed through a bandpass filter to remove sporadic or too frequent features. The remaining features are considered as *landmarks*. During image retrieval, features from the query image are extracted and matched with the landmark database. Each of the training image numbers associated with the matched landmarks gets a vote, and the image number with the maximum votes is chosen as the retrieved image. The search procedure gets reduced to creating a one-dimensional array of integers and finding the maximum element. This is a significant enhancement in performance over *bag of visual words* where each image is represented as a histogram of word frequencies, and retrieval is implemented as a histogram matching procedure in a very high-dimensional space, which, due to the “curse of dimensionality”, is a time-consuming process in practical approaches. It is also shown in this thesis that the proposed landmark indexing method has a complexity $O(PN)$ which is very less than the $O(MN)$ complexity of *bag of visual words*, where P is the number of features in the query image, M is the

number of entries in landmark index and N is the number of training images.

Experimentation. A number of quantitative experiments support that the proposed solution can accurately retrieve images from a large database very efficiently. The speed of identification is in real-time, far faster than current methods, while the accuracy is comparable to and sometimes better than those methods. In addition, the landmark indexing method is integrated into a modified RGBDSLAM framework [17] used for indoor navigation. Recorded values suggest that the navigation results are very accurate in large indoor environments, and the observed 3D registration errors are similar to the existing evaluation of the system, confirming that the image retrieval method correctly performs in any indoor navigation scenario.

1.4 Thesis Outline

The thesis is organized as follows:

Chapter 2, Literature Review: This chapter discusses different existing publications on vision-based localization and image retrieval algorithms.

Chapter 3, Landmark Indexing: This chapter describes the method to reduce image retrieval search space into a landmark index. The term *landmark* is defined, the procedure to identify landmarks is depicted, and how this algorithm can be further combined to 3D indoor navigation is explained.

Chapter 4, Experimental Results: Quantitative evidence in favor of the accuracy and speed of the proposed method is produced in this chapter. Comparison with existing approaches is shown using datasets from different types of indoor environments. Also, results of the application of landmark indexing in a 3D real-time

navigation system is described in this chapter.

Chapter 5, Conclusions and Future Work: This chapter concludes the thesis, with a short introduction to the possible future extensions and applications of the landmark indexing approach.

Chapter 2

Literature Review

2.1 Image Retrieval using Features

Image retrieval is the task of accurately matching a query image to another similar image of the same object or scene from a large set of images [72]. Image retrieval techniques may be generalized, or may have a special application, *e.g.*, trademark, face, or text-based document retrieval. All these techniques have three main aspects in common [58]:

1. **Feature Extraction:** Extract visual features such as SIFT [45] or SURF [5], and store them in a database with the image dataset.
2. **Indexing:** Identify useful images or features based on some criteria and rank them accordingly. Some example approaches are keyframe detection [16, 30], and reducing the feature set based on similarity between images [72].
3. **Retrieval:** Capture the image, and search the database to find the image, or the set of images, with the greatest number of feature matches with the query image.

Further explanation of existing feature extraction and matching methods follows.

2.1.1 Feature Extraction

Identifying features in an image is a crucial step in image matching. Each feature is an interest point in the image computed using intrinsic image properties, and a local descriptor which describes the interest point and its surrounding points. In most cases, this descriptor is a high-dimensional vector. Tuytelaars and Mikolajczyk [73] identified properties that an ideal feature must have. These are:

- **Repeatability:** Two images of same object must have a high number of common features. The features must be invariant to geometric and photometric transformations, and robust to disturbances, *e.g.*, noise, blur, compression artifacts, etc.
- **Distinctiveness:** Features must be distinguishable so that they can be recognized in a large database of objects.
- **Locality:** Local features must be robust to occlusion and clutter.
- **Quantity:** The feature detector must always generate a sufficiently large number of dense features from even small objects
- **Accuracy:** The localization of the feature must be precise.
- **Efficiency:** The feature detection method must perform in real time.

There are many popular feature extractors, starting from Moravec's interest operator [48] and the Harris corner detector [28] to modern feature detection algorithms such as SIFT [44, 45], PCA-SIFT [33], SURF [5], BRISK [38], BRIEF [10], ORB [57],

and FREAK [2]. The following discussion is mainly about SIFT and its origins, because it is still a very widely popular feature extractor, and used by the method proposed in this thesis, and also other methods it is compared against.

One of the earliest interest point detectors was Moravec's interest operator [48]. He extracted interest points by assuming a patch on each pixel of the image, and then finding the similarity between each patch and its neighbor patches in every direction (horizontal, vertical, and two diagonals). The difference between patches are measured by the sum of squared differences of the patch pixels. If the minimum of the calculated differences is high enough, then the considered pixel is chosen as an interest point. Moravec's operator is obviously anisotropic (only directions at every 45° is observed) and noisy (the patch around a point is binary and rectangular). An alternative was suggested by Harris and Stephens [28]. To overcome the anisotropic nature of Moravec, they considered the image gradient. The Harris matrix H at a pixel p is defined as:

$$H = \begin{Bmatrix} \sum G_x^2 & \sum G_x G_y \\ \sum G_y G_x & \sum G_y^2 \end{Bmatrix} \quad (2.1)$$

where G_x and G_y are the respective x and y Gradient magnitude images, and the summation is taken over all points in a neighborhood of p . The symmetric matrix H can be subjected to principal component analysis to estimate eigenvalues λ_1 and λ_2 . If both of the eigenvalues cross some threshold, then it shows strong variation in both direction, and the pixel p is considered as an interest point.

The Harris corner detector was one of the most popular interest point detectors for the purpose of image matching. However, it was not scale-invariant. Automatic scale selection during interest point estimation was suggested by Lindeberg [41], and

Figure 2.1: Block diagram of SIFT

this was further refined by Mikolajczyk and Schmid [47] with introducing the Harris-Laplacian operator. Their approach applies Harris corner detector at multiple scales, and then chooses the *characteristic* scale with the Laplacian.

Scale-Invariant Feature Transform (SIFT) was first coined in 1999 by David Lowe. Approximating the Laplacian of Gaussian (LoG) of the Harris-Laplacian operator with a Difference of Gaussian (DoG), he accelerated the performance. The complete procedure is shown in Figure 2.1.

The scale-space construction is performed using the Gaussian kernel provided by Lindeberg [40]. The DoG is computed by

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \quad (2.2)$$

Figure 2.2: Detection of extrema in scale-space by comparing a pixel (the red circle at the central scale space) to its neighbors (the green circles) in the current and adjacent scales (based on [45]).

where $I(x, y)$ is the input image, $*$ is the convolution operator, and $G(x, y, \sigma)$ is the Gaussian kernel, given by

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2.3)$$

The local extrema of $D(x, y, \sigma)$ are detected by comparing each pixel to its eight neighbors in the current scale space level and the nine neighbors in the scale above and below. This is shown in Figure 2.2. The pixel for each detected extrema is chosen as a candidate to be an interest point.

The filtering of the candidates is performed by expanding the $D(x, y, \sigma)$ function with Taylor Series approximation to quadratic terms, taking the derivative and setting it to 0, thereby finding the extremum $\hat{\mathbf{x}}$. Then, all extrema with a value of $D(\hat{\mathbf{x}})$ less than a certain threshold are discarded, and principal component analysis helps to remove unstable localized points on edges, as the DoG will have a very large principal curvature compared to the small one in the perpendicular direction.

After the interest points are extracted, orientations are assigned to each of them based on the dominant gradient orientation of the surrounding patch. Then a representation of this image patch is estimated, which is the feature descriptor of the interest point. This representation is a local orientation histogram, containing the accumulated gradient magnitude of each sample point in the patch around the interest point. Generally, 4×4 arrays of histograms with 8 orientation bins in each histogram are computed from 16×16 sample arrays. This results in 128-dimensional vectors.

Speeded-Up Robust Features (SURF) [5] provides further approximation of Laplacian of Gaussian by using Box Filter. It also uses wavelet responses for orientation assignment and feature description. The advantage of using both box filter and wavelet responses is that these operations can be easily performed with integral images. Despite the fact this faster approach than SIFT was introduced in 2006, and even though there exist several other extensions and alternate methods [2, 5, 10, 14, 15, 33, 38, 57, 74], SIFT still seems to be the most popular, because it shows all of the ideal feature characteristics [73]. Figure 2.3 shows SIFT interest points in an image. For image retrieval from a location image database, which is the main goal of the proposed method in this thesis, SIFT features are seen to perform significantly better than other feature descriptors [77].

Figure 2.3: Detection of SIFT features in a scene

2.1.2 Feature Matching

Feature matching is performed by finding nearest neighbors in the high-dimensional descriptor space. There are several techniques to match features. The methods mostly used in this thesis are discussed here.

Linear Search. This is the most trivial method of matching features. Distance between a query feature and each of the training features is calculated, and the training feature with minimum distance is chosen as the nearest neighbor. If there are m features in the query image, and n features in training set, the time complexity of this method is $O(mn)$. This is a costly mechanism, and arranging the training features in a data structure greatly improves performance.

k -D Tree. If the training features are organized in a k -d tree [21], then a depth-first search mechanism can find exact nearest neighbors in $O(m \log n)$ time for a fixed

dimension. However, performance is affected as dimensionality increases. Arya *et al.* [4] and Beis and Lowe [6] modified the algorithm by using early-stopping criteria, and Silpa-Anan and Hartley [65] proposed to use multiple randomized k -d trees to find approximate nearest neighbors to speed up the performance for high-dimensional features.

k -Means Tree. Arranging the training data in a tree generated by k -means clustering was first proposed in 1975 by Fukunaga and Narendra [22]. The tree construction is done by clustering data points into k disjoint groups, and recursively performing the same task for each group. Nistér and Stewénus [51] used a similar tree for visual vocabulary construction, which is discussed later in Section 2.2.3.

FLANN. Muja and Lowe [49] proposed a method to automatically select an approximate nearest neighbor algorithm. Their algorithm can reduce either the tree building time, or reduce the time for searching. They compute a cost of each algorithm based on building time and memory consumption when applied on a given training dataset, and the algorithm with the lower cost is chosen. They released Fast Library for Approximate Nearest Neighbor (FLANN) with two algorithms, (1) randomized k -d tree [65] and (2) hierarchical k -means tree [22, 51].

An example result of SIFT feature matching between two scenes is shown in Figure 2.4. The image in the left side has 1123 features, and the image in the right side has 852 features. Table 2.1 shows the time performance and matches found by each matching algorithm.

Figure 2.4: SIFT feature matching example

Table 2.1: Time performance and matches found by different methods matching SIFT features from the two images of Figure 2.4

Method	Search time	Matches found
k -D tree	20 ms	334
k -Means	20 ms	362
FLANN (Auto-tune)	10 ms	388

2.2 Bag of Visual Words and Related Work

Storing an exhaustive set of features from all images of a map decreases the performance of the retrieval system as the number of training features increases. In 2003, Sivic and Zisserman proposed to represent an image as a *bag of visual words* [66]. This is comparable to the representation of a text document as a *bag* of words, where a *bag* means an unordered collection. According to Sivic and Zisserman, a *visual word* is a quantization of several feature descriptors.

2.2.1 Feature Quantization

Each feature is a point, or a vector, in a high-dimensional space, and quantization through any clustering algorithm is possible. The most popular method for clustering features is k -means clustering [46]. This algorithm partitions n features into $k < n$ groups. This k is pre-determined by the user. The algorithm has multiple passes. On the first pass it randomly generates k vectors as cluster means, and associates every other feature vector with the nearest mean. In each of the following passes, the centroid of each cluster becomes the new mean, and the feature association is again performed. The whole process is repeated until convergence is achieved. Mathematically, the objective is to minimize the error function

$$E = \sum_{i=1}^k \sum_{f_{ij} \in C_i} (f_{ij} - \mu_i)^2 \quad (2.4)$$

where there are k clusters $\{C_1, C_2, \dots, C_k\}$ with cluster means $\{\mu_1, \mu_2, \dots, \mu_k\}$, and $\{f_{i1}, f_{i2}, \dots\}$ are feature vectors in the i^{th} cluster C_i .

This method is used to cluster SIFT descriptors into visual vocabularies in Bag of Visual Words.

2.2.2 Bag of Visual Words Approach

The features used by Sivic and Zisserman [66] are SIFT, each descriptor being a 128-D vector. The similarity of two descriptors can be evaluated by calculating their distance in 128-dimensional feature space. The distance measure used here is Mahalanobis distance. Between two features f_1 and f_2 of the same distribution with covariance

matrix S , the Mahalanobis distance function is given by:

$$dist_M(f_1, f_2) = \sqrt{(f_1 - f_2)^T S^{-1} (f_1 - f_2)} \quad (2.5)$$

Using this distance measure, the features are clustered using a k -means clustering algorithm. The choice of number of clusters k is done empirically to optimize performance. Automatic algorithm configuration from Fast Library for Approximate Nearest Neighbor [49] is used here. The resultant cluster regions are the *visual words*, and are represented by the cluster means [66, 76]. During query, a term-frequency inverse-document-frequency (*tf-idf*) ranking scheme, which is seen in text retrieval and document identification, is used to rank the images. If there are n words in the vocabulary, and a total of N images, then the *tf-idf* weight for i^{th} word in the j^{th} image is given by:

$$t_{ij} = \frac{x_{ij}}{\sum_i x_{ij}} \log \frac{N}{\sum_j x_{ij}}, i \in [1, n], j \in [1, N] \quad (2.6)$$

where x_{ij} is number of times i^{th} word appears in the j^{th} image. Every image including the query is represented by a vector of *tf-idf* weights $\{t_1, t_2, \dots, t_n\}$. The scalar product of each vector from training images with that of the query image is calculated, and image retrieval is performed by finding the image corresponding to the maximum of these scalar products. Sivic and Zisserman retrieved shots from a movie using this approach. Yang *et al.* modified the approach by replacing the features descriptors from vanilla SIFT to PCA-SIFT [33], which gives 36-dimensional vectors instead of 128.

The general framework to create a *bag of visual words* vocabulary is shown in the

Figure 2.5: Block diagram of Bag of Visual Words

figure 2.5.

If k -d tree is used to search each word in the features from query image, then for a vocabulary size M and a training image database size N , to perform a single query, it takes:

- $O(M \log P)$ time to build the term frequency histogram for the query image ($O(\log P)$ for each word), where P is the number of features in the query image;
- $O(MN)$ time to find the scalar product of the query histogram with those from the N training images (linearly traversing the database), and find the largest

scalar product.

2.2.3 Proposed Extensions

Tirilly *et al.* [70] and Yang *et al.* [76] compared different variations of the *bag of visual words* methods. Tirilly *et al.* described different forms of *tf-idf* weighting schemes. Yang *et al.* further proposed different feature selection criteria. They also showed the effect of different weighting schemes in accuracy and performance. The weighting schemes can be summarized into:

- **Binary weight:** 1 if a term is present in an image, 0 if not;
- **Term frequency:** Same as x_{ij} from Equation 2.6;
- **Normalized term frequency:** $\frac{x_{ij}}{\sum_i x_{ij}}$;
- **Term frequency - inverse document frequency:** t_{ij} , which is defined in Equation 2.6;
- **Normalized tf-idf:** $\frac{t_{ij}}{\sum_i t_{ij}}$.

Yang *et al.* [76] noted that normalization is not preferable, because it reduces the distinctiveness of images as the effect of eliminating difference between similar visual words appearing in images of two areas differing in feature density. They also showed that binary weighting outperforms *tf-idf* for large training databases.

Subsequent publications using the idea of *bag of visual words* talk about creating a *visual vocabulary* and recognizing patterns with it. In 2006, Nistér and Stewénus [51] proposed a hierarchical *tf-idf* scoring using hierarchically defined visual words that form a vocabulary tree. The use of a tree structure for feature matching comes

from David Lowe [45], who used a best-bin-first k -d tree to find approximate nearest neighbor to SIFT features. The vocabulary tree of Nistér and Stewénus is basically a hierarchical k -means tree. The training features are clustered using k -means clustering, the cluster means being the leaf nodes. Then, k -means clustering is re-applied on this set of cluster means to generate bigger clusters that are fewer in number. When assigning a feature to a visual word, search begins at the root, moves through branches containing close matches and ends when the leaf node with the closest matching visual word is found.

The vocabulary tree method was later adopted by Schindler *et al.* [62] in 2007. Their database consists of images with a considerable amount of overlap, so that the same areas are re-observed from different viewpoints. This knowledge of the overlapping frames helps to identify when the same visual words occur in multiple images, thus aiding in recognizing the images of the same location. This concept can be compared to the concept of information gain. If two random variables, L and W , following a Bernoulli distribution, are defined on the event of being present on a certain location l and the visibility of a particular visual word w respectively, then the information gain on w being visible at location l is given using the entropy function $H()$:

$$IG(L, W) = H(L) - H(L|W) \quad (2.7)$$

where the entropy function $H(X)$ for a random variable X is defined as

$$H(X) = - \sum_x P(X = x) \log[P(X = x)] \quad (2.8)$$

and the conditional entropy is given by

$$H(Y|X) = - \sum_x P(X = x) H(Y|X = x) \quad (2.9)$$

Schindler *et al.* showed that $H(L)$ is constant for all visual words at location l , so to maximize the information gain, minimizing of the conditional entropy $H(L|W)$ is required. This conditional entropy, and therefore the information gain, can be expressed as a function of the $N_{w,l}$ (number of times w appears at location l) and $N_{w,\bar{l}}$ (number of times w appears everywhere else). The maximum value of information gain in equation 2.7 can be reached when $N_{w,\bar{l}}$ is minimized.

Further, [62] presents a generalization of the search algorithms for vocabulary trees. This algorithm is named Greedy N-Best Paths (GNP) algorithms, which can proceed on multiple branches at each level rather than finding the branch containing features closest to the query one.

Philbin *et al.* [52] improved the performance of searching in visual vocabulary using approximate nearest neighbor search algorithms. They compared their method, named approximate k -means clustering, with hierarchical k -means tree as proposed in [51]. The approximate k -means tree does not find exact nearest neighbor matches of features and cluster centers, but rather employs a forest of multiple randomized k -d trees built on each cluster center on every iteration. This reduces the complexity of standard k -means algorithm from $O(nk)$ to $O(n \log k)$, where n is the total number of features. Experimental results in [52] show that this method outperforms the hierarchical k -means tree. Also, they incorporated a spatial verification in the ranking system by estimating the transformation between query and target images.

Fraundorfer, Stewénus and Nistér [20] discussed how to overcome the limits of a computer being used to search an image from a large dataset. They proposed a binning scheme for fast hard drive search. Each of the bins represents a similar set of images stored in the hard disk. The search mechanism is hierarchical, *i.e.*, the visual words from a query image are first looked up in the bins, and then the identified bins are fetched from the hard disk to retrieve the actual image. To find matches between features, they use Locality Sensitive Hashing (LSH) on binary descriptors.

Jégou *et al.* [32] stated that the approximate nearest neighbor matching techniques for visual words have some disadvantages. For a large visual dictionary, many true matches can be missed, and for a small dictionary, many false matches can appear. Hamming embedding solves the problem by computing a binary signature for a descriptor and incorporating the hamming distance of binary signatures of two features in nearest neighbor finding. Also, integrating a weak geometric consistency verification helps to improve the image ranking method of previous approaches. It is a low cost approach and can be applied to all images, where previous geometric verification approaches short-list only a few hundred images from a large dataset.

The concept that not all images or features are useful in matching a query image to a large dataset, is explored by Turcot and Lowe [72]. They label some of the features in the image database as *useful*, which are robust and distinctive. They use each of the images in the database as a query, and rank each image according to the similarity between the query and itself. This ranking helps to construct an image adjacency graph $G = (V, E)$, in which every image is represented as a vertex $v_l \in V, l \in \{1, N\}$, and each edge $e_{ab} \in E, a \neq b$ represents adjacency between v_a and v_b . Each vertex is described with feature descriptors present within itself and also

those from its neighboring images. This affects the *tf-idf* weights. In equation 2.6, x_{ij} 's can be replaced with:

$$y_{ij} = x_{ij} + \sum_{\substack{k \\ e_{jk} \in E}} x_{ik}, i \in [1, n], j \in [1, N]. \quad (2.10)$$

The number of similar descriptors common to two adjacent images adds weight to the edge between them. Retrieving an image follows the same method. When a query image comes, it ranks the database images according to feature similarity and finds the nearest vertex to the query.

Knopp *et al.* [34] presented a very similar work. Their method approaches to recognize a place in a query image by matching with a city-wide database of street side images. They acknowledge the fact that there can be a lot of similar objects like trees, road markings, cars etc. to introduce confusion. However, they use the advantage of geotags present in the images to rule out confusing objects.

In 2010, Gavves and Snoek [23, 24] defined *visual synonyms*. They use a similar idea to [72] and rank the images according to query-training feature similarity, only to further process the top ranked retrieved images for a geometric verification. Geometric connectivity is determined by estimating a homography matrix. Two matched features, mapped to different visual words, but consistent in geometric location, makes the corresponding word pair a candidate for visual synonyms. Word pairs that occur very rarely are rejected, and the remaining candidates are recognized as visual synonyms. The top ranking images containing the visual synonyms, and therefore become the result images of the retrieval process.

2.3 Localization

There are two different approaches to register 3D frames to find the transformation matrix between them. The first approach is direct 3D registration, which involves extraction of 3D features from point clouds, the other one is to find 2D features in images, find matches, and translate the 2D matches to 3D.

2.3.1 Direct 3D Registration

The steps to perform direct 3D registration of two point clouds are similar to 2D image matching. They are:

1. **Feature Extraction:** Extract 3D features [59,79] from point clouds. These 3D features, in contrast to 2D features which rely on intensity, are computed using surface normals and curvature. This is the main bottleneck of this approach. The surface normals on each point in the point cloud must be known, which takes the longest time to compute. For a noisy sensor like Kinect [3], each cloud must undergo pre-processing for noise removal. To increase computation efficiency, the point clouds can be downsampled, but it sacrifices accuracy of registration.
2. **Feature Matching:** Match features using methods previously described in 2.1.2.
3. **3D Transformation Estimation:** Use RANSAC to calculate the camera pose matrix with respect to the world coordinate system using the correspondences. In the RANSAC method, three correspondences are selected, and the 6 DoF rigid transformation is calculated. Then, the re-projection error is found, and if it is

---

```

Data : Set of point-to-point correspondences  $C$ 
Result: Pose matrix  $T$ 

PoseList  $\leftarrow \phi$ ;
ErrorList  $\leftarrow \phi$ ;
for  $i \leftarrow 1$  to  $nIterations$  do
     $C_{sub} \leftarrow \text{pickRandomSubsetOf3}(C)$ ;
     $T_1 \leftarrow \text{calculatePoseMatrix}(C_{sub})$ ;
     $RE_1 \leftarrow \text{findReprojectionErrorOnRandomPoints}(T_1, C)$ ;
    if  $RE_1 \leq \tau_1$  then
         $C_{in} \leftarrow \text{removeOutliers}(T_1, C)$ ;
         $T_2 \leftarrow \text{calculatePoseMatrix}(C_{in})$ ;
         $RE_2 \leftarrow \text{findReprojectionError}(T_2, C)$ ;
        if  $|C_{in}| \geq \tau_2$  and  $RE_2 \leq \tau_3$  then
             $PoseList \leftarrow PoseList \cup \{T_2\}$ ;
             $ErrorList \leftarrow ErrorList \cup \{RE_2\}$ ;
        end
    end
end

 $T \leftarrow \text{findPoseWithLeastError}(PoseList, ErrorList)$ ;

```

Algorithm 1: RANSAC Pose Determination Algorithm

too high, then the chosen correspondences are rejected. This approach removes any false matches. This process is repeated, until a suitable match is found, or an iteration threshold is exceeded. This best match is determined from the number of inliers being over a certain threshold and the re-projection error being below the tolerance level. This best pose is saved. The whole process is again repeated a pre-determined number of times and the best pose matrix is chosen from all those iterations. The algorithm is given as pseudocode in Algorithm 1.

2.3.2 Image-based Localization

Image-based localization is the process of determining the exact location where a query image is taken [61]. If only the general image location is needed, then performing simple image retrieval is sufficient. If both the 3D position and orientation in 6 Degrees of Freedom are to be estimated, then either direct 3D frame acquisition with some sensor like LIDAR, or reconstruction of 3D model with Structure From Motion (SFM) approaches [1, 13, 19, 67, 69] is required. If correspondences between 2D features and 3D points are given, the camera position and orientation can be computed [29]. Direct registration of 3D frames instead of 2D image matching is also used, but it is more memory and time consuming, while image retrieval is possible in real time.

In Simultaneous Localization and Mapping (SLAM), image retrieval techniques can be used to identify *loop closure*. *Loop closure* is closed traversal of an environment, *i.e.*, the start location is re-visited during traversal, creating a loop. When loop closure is achieved, the localization error can be minimized and propagated throughout the entire map. Since image retrieval can be performed in real time, it is preferred over 3D matching techniques. Navigation in a pre-existing map is actually a repeated loop closure check.

The basic steps of image-based localization are:

1. **Image Retrieval:** Capture an image with a sensor, and retrieve the map image which is the closest match with the query image.
2. **Matching:** Use RANSAC to identify inliers in the correspondences of the query and retrieved images.

Figure 2.6: Block diagram of image-based localization, adapted from Henry *et al.* [31]

3. 3D Transformation Estimation: Acquire 3D frame from the sensor, translate the 2D correspondences from previous step to 3D, and use them to calculate the camera pose matrix with respect to the world coordinate system. Iterative Closest Point algorithm [7] can be used to refine this RANSAC estimated pose matrix [31].

The complete procedure is presented as a block diagram in Figure 2.6.

Related Works

In vision-based navigation, feature-based location detection works best in a dense feature-rich environment, such as urban corridors, or indoor areas. Image retrieval techniques are developed to identify key locations in query images. Large image

databases of places can be stored in the system as individual images, or as features extracted from those images to reduce the storage space [45]. Once the image is retrieved, it can be verified by fetching the corresponding 3D organized point clouds and finding the orientation and translation of the camera in 6 Degrees of Freedom. This method of verification is discussed in detail in chapter 3 and results are presented in Chapter 4.

One of the first works on vision-based localization and mapping techniques is done by Se, Lowe and Little [63]. The method describes tracking of SIFT features [45], and estimation of 3D location with the help of Triclops [50], a trinocular stereo camera system. They perform a stereo matching algorithm on the images from the left and right cameras, and use the top camera to impose constraints on the matching. The robot movement is tracked through tracking of the features, or *landmarks*. This approach of using features as landmarks is further expanded in the work described in this thesis (see section 3.2).

Earlier approaches [54, 78] in image retrieval-based navigation involved comparing query images with an exhaustive set of training images. This method was introduced by Robertson and Cipolla [54]. In their approach, a map is a database of photographs of multiple buildings in an area. The first step in localization is to perform image retrieval on the database using vertical vanishing direction for alignment of a building view in the query image to the canonical view in the database. It is followed by the pose estimation using point feature matching. Zhang and Kosecka [78] proposed a similar method, retrieving image by matching of SIFT features, and estimating the motion by computing the essential matrix between the query and best-matched reference images, and finally calculating the pose from triangulation.

David Filliat [18] proposed an incremental *bag of visual words* approach for localization. He used a classifier on the words extracted from images. The classifier can be a Support Vector Machine (SVM) or a Bayesian classifier. The incremental training method of the classifier helps to add new classes of words from new queries without processing old set of words. He performs experiments using different features such as SIFT and local color histograms. The distance between the feature vectors are replaced from Mahalanobis distance (equation 2.5) to chi-square distance:

$$dist_{\chi^2}(f_1, f_2) = \frac{(f_1 - f_2)^2}{f_1 + f_2} \quad (2.11)$$

Henry *et al.* [31] proposed the idea of using both RGB and depth data for frame-to-frame alignment of point clouds and loop closure detection. The proposed method extracts sparse features from RGB and depth images, and creates the dense point cloud in parallel. SIFT point features are extracted from each of the frames, and RANSAC is performed over these two sets of point features. This alignment is then refined using ICP. To minimize the error between the matched pairs of dense points, a Levenberg-Marquardt optimizer is used on a point-to-plane error metric along each target point's normal. The concept of *keyframes* is also introduced here. These keyframes are determined using the RANSAC inlier threshold, and every time a keyframe is created it is matched with all the previous keyframes for a loop closure detection. A graph optimization technique TORO [26, 27] is employed to minimize the conflict between sequential constraints and loop closure constraints. This work is extended [30] in 2012. The Euclidean-space RANSAC is replaced with frame-to-frame alignment RANSAC, SIFT feature points and descriptors are replaced with FAST features [55, 56] and Calonder descriptors [9], TORO is replaced with Sparse

Bundle Adjustment [35,43,71], and the efficiency of loop closure detection is improved with place recognition. Here the method of Nistér and Stewénus [51] of creating a hierarchical visual word vocabulary tree is used.

Du *et al.* [16] also proposed combining RGB and depth data to form a 3D model. They partition the registration process into *local alignment* and *global alignment*. This is actually similar to [31] because *local alignment* handles the frame-to-frame registration, and *global alignment* uses loop closure information to optimize the poses of the frames to make them consistent with respect to a world reference frame. The idea of *keyframes* is applied here to detect the loop closure. The difference between [31] and this method is that Du *et al.* introduced a user feedback system for error handling. The system can inform the user if there is any error in registration, and the user can rewind and restart the process. When a loop closure is detected, the user can verify it through visualization. This visualization component also helps the user to check if there is any incomplete area in the map, and visit corresponding areas to capture frames and fill those holes. For the registration procedure, they use RANSAC to determine the rotation-translation vector pair, then apply a *visibility conflict* check with the inlier threshold. This *visibility conflict* is actually a verification that, if two cameras have an overlapping view of a plane, then after pose determination, the overlapped area must appear on the same image plane for both cameras. If points on that overlapping plane observed by camera 1 exist between the image plane of camera 2 and the camera 2 itself, then a conflict arises. In case of such conflict, the registration is considered incorrect and is reported to the user.

In a paper published in IPIN 2013, Liang *et al.* [39] described a method to use image retrieval to navigate in a shopping mall environment with a portable backpack

arrangement of sensors [12, 42]. They proposed the idea of storing features instead of images in the map database. They extract SIFT features from all the training images, and store them in a data structure with the indexes of images where each feature appears. When a query image is captured with the camera being used for navigation, all the features are extracted from that query image and matched using a k -d tree. A geometric consistency check is applied over the found matches, and after computing the fundamental matrix between the database and query images, the feature matches which do not follow the epipolar constraint are removed. The image from which most features are matched is identified. The roll and pitch are retrieved from cell phone sensors, and yaw is estimated. RANSAC is applied to find the translation between query and database images. The whole process may take 4-14 seconds. Now a confidence estimation procedure is employed, which measures retrieval confidence and pose confidence. The retrieval confidence relies on the number of geometrically consistent feature matches between query and retrieved images. The pose confidence is based upon the number of inliers in RANSAC homography computation and re-projection error.

2.4 Discussion

The *bag of visual words* presents a solution for reducing the set of features of the map. It is very useful, but also an approximation of direct matching and decreases matching accuracy compared to the brute-force approach. Moreover, the term frequency histogram matching in a very high dimensional space (the dimension of the histogram is same as the number of training images) greatly affects performance. Some of the other described extensions of this method try to speed up the process by improving

feature-visual word assignment, or improving the search mechanism [32]. Mapping multiple features to a single visual word also helps, but this may show no increase in accuracy, and with increasing number of features mapped to the same word, accuracy will certainly decrease. A more accurate matching and assignment process is therefore needed.

Schindler *et al.* [62] justified the use of overlapping images of an environment in recognizing visual words from the same location appearing in different images. This concept is used in the proposed method in this thesis, where the images acquired must be overlapping.

The Turcot-Lowe method [72], as described before, removes useless features with some ranking of the images and creating an image adjacency graph. However, there is a difference of assumption in the method proposed in this thesis. The agreement on the observation, that the number of useful features in a dataset is a small fraction of the total number of features, is the only similarity between both approaches. The difference lies in the targeted environment. As said earlier, the Turcot-Lowe method finds landmarks in buildings in a city area. Most large scale landmark image search methods [11, 23–25, 32, 34] work with this assumption. In an outdoor environment with wide-angle shots of the buildings, the number of stationary and re-observable features found will be small. People, cars or other non-landmark objects occupy most areas of the images taken in their dataset. This is not the case when performing navigation in an indoor context. The mapping is done systematically, with the images having a sequence rather than arbitrary images of different corners. So the burden of the image graph generation is not required. Also, in this scenario, the number of stationary objects is much greater. Features from desks, tables, windows, doors,

posters on the wall, everything can contribute in the landmark database. From this observation, it can be assumed that culling of features applied to an indoor map will not be able to eliminate as much as 96% of the features which is shown in [72], and this is confirmed by experimental results presented in the following chapter 4.

In the recently proposed method of Liang *et al.* [39]. They have presented the idea of image retrieval, but it has several drawbacks. First, although the data structure storing feature described is similar to the one proposed in this thesis, they use an exhaustive set of feature descriptors. They do not remove anything that can be a potential non-landmark. Secondly, the search mechanism employed was k -d trees, where there are other techniques like k -means clustering which can provide much more accurate and fast matches between features. The employment of a geometric consistency matching technique during runtime makes Liang's approach take 2-4 seconds in the retrieval steps alone, and far more for the pose estimation. This is unacceptable in a GPS style localization system, which may be used as a guidance system for visually handicapped people, or automated robots designed for fast response. The conducted experiments depicted in chapter 4 show that the landmark indexing method retrieves images in real-time, which aids in real-time navigation.

Chapter 3

Landmark Indexing

3.1 Problem Formulation

The problem of image retrieval can be defined as:

Find the set of images R given a query image q , such that:

$$R = \{I \mid |F_{Iq}| \geq \tau, I \in I_T\} \quad (3.1)$$

where F_{Iq} is the set of features matched between image I and the query image q , τ is a lower limit of the number of feature matches for I to become the result image, and I_T is the set of training images.

There is a trade-off between performance and accuracy in feature matching procedures. As the number of images in the map is large, the set of features in the map is also large. Search timing can be made faster by using approximate nearest neighbor techniques rather than the exact match, but accuracy is affected as more approximation is introduced. To counter this problem, the search space must contain only the set of features which are relevant to the retrieval process, without any duplicates.

The landmark index contains feature descriptors in a data structure that also

keeps the identification numbers of the frames in which a certain feature is present.

Each entry in the structure is given by

$$\langle f_i, \langle c_{i1}, c_{i2}, \dots, c_{iN} \rangle \rangle, i \in [1, M]$$

where M is the total number of features, N is the total number of images, f_i is the i^{th} feature descriptor and $c_{ij}, j \in [1, N]$ is a boolean value which is

$$c_{ij} = \begin{cases} 0 & \text{if } f_i \text{ does not appear in frame } j \\ 1 & \text{if } f_i \text{ appears in frame } j \end{cases}$$

With the search space being reduced to a set of features, the image retrieval process is modified to:

First, find the set of indices X of features from training database F_T which match with query feature set F_Q .

$$X = \{x \mid \|f_x - f_q\| < \epsilon, f_x \in F_T, f_q \in F_Q\} \quad (3.2)$$

where ϵ is the maximum distance between features to be considered a match. An appropriate ϵ can be determined empirically with different experiments of feature matching between indoor images.

Then, find the retrieved frame index $k \in [1, N]$ such that

$$\sum_{x \in X} c_{xk} \text{ is maximum and } \geq \delta$$

where δ is the pre-set minimum number of matches for retrieval.

3.2 Landmarks

A landmark is defined as a set of distinguished features which are regularly observed and re-observed in the mapping environment. For a feature to be a landmark, it must satisfy a few criteria [68, 72, 75]:

- **A landmark must be stationary.** Features from a moving object cannot be a landmark. In an indoor scenario, moving objects, except people, are fewer in number. Moving people generally do not appear in more than one or two frames, so those features can be discarded by filtering.
- **A landmark must be distinctive in a map.** For example, two similar looking shelves in two sides of a room may lead a system to miscalculate the correct location, and hence they cannot be taken as landmarks. A landmark must be distinctive from its surroundings.
- **A landmark must be repeatable.** If a region containing a landmark is photographed or visualized from different angles, then the landmark should be present in all of the frames.
- **A landmark should be robust against noise and lighting conditions.**

Also, a map should have multiple distinguishable landmarks; otherwise navigation becomes difficult. For this reason, environments with few features, like an urban tunnel, or a hospital floor where all the rooms look very similar, provide a challenge for vision-oriented localization and mapping.

The density of landmarks is another issue in a map. Even if the map has multiple landmarks, it may happen that they are so close together that some of the areas do

not have any identifiable landmarks. In the proposed algorithm, there is no hard threshold on the number of frames in a map that must contain a landmark, but it is assumed that a sufficient number of images of each area in the indoor environment has at least one distinguishable landmark.

The idea of using features as landmarks was first demonstrated by Se *et al.* [64] using SIFT features. The landmark identification method described in this thesis follows a similar idea. The map, in this case, consists of multiple overlapping RGB images and corresponding 3D point clouds. The overlap between the images helps to accurately determine a position using multiple frames. For a feature to become a landmark, a number of criteria are imposed in addition to the ones mentioned before.

- **A landmark must appear more than once, and in adjacent frames.**

This ensures that the landmark is repeatable.

- **A landmark must not appear in more than a certain number of images.** This determines that the landmark is distinguishable, and does not originate from a moving object.

3.3 Landmark Index Generation

3.3.1 Image Acquisition

Image acquisition is done with a monocular camera. A monochrome camera is sufficient because feature detectors like SIFT work on monochrome images. Each frame is captured in sequence with sufficient overlap with one or more of the previous frames. The overlap region between two frames helps to register the frames to form a single map. There is not a strict rule on how much overlap should exist between two frames.

In practice, it is found that an overlap of about 30-40% of image size leads to good performance in the experiments in areas with high feature density, while this may need to increase to 70-80% for areas with fewer features.

There can be several rounds of collecting images from an environment, because multiple images of the same scene from different angles will not only enrich the collection of features, but also will help to determine which features are re-observed the most number of times. A simple way of performing this task is to first place the camera at the center of a room or hall, rotate the camera 360° around its vertical axis, and capture all frames. Then move towards the outer edge of the environment, and acquire images around the periphery, which will contain finer features. This further ensures that every visible feature of the entire map is captured in the training images.

The justification of overlapping images in the database, as previously stated, is given by Schindler *et al.* [62], where they use the concept of information gain. In our method, a feature will be treated as a landmark if it appears in a sufficient number of frames. Overlapping images increases the importance of stable features in this procedure. Stable features will be visible in more sequential frames than unstable ones, increasing the information gain on those features being visible at that location, and thus making them more likely to be chosen as landmarks.

3.3.2 Implementation

Figure 3.1 provides a block diagram of the landmark index generation procedure. The landmark index contains SIFT feature descriptors, and the frames in which they appear, in the same data structure described in Section 3.1. In an iterative procedure, from each map image, features $\{f_1, f_2, \dots\}$ are extracted. On the first iteration, all

Figure 3.1: Block diagram of landmark index generation procedure

features from the first frame are entered in the index.

$$f_i^1 \rightarrow l_i \quad (3.3)$$

where f_i^1 is the i^{th} feature of the 1st frame and l_i is the i^{th} element in the landmark index.

Subsequently, in each iteration, the extracted features are matched with the existing ones in the index. If a match is found, the existing feature in the index represents both itself and the newly matched feature, given that the distance between the

matched features is acceptable.

$$f_i^j \rightarrow l_k = \arg \min_{l_k} \text{dist}(f_i^j, l_k) \text{ s.t. } \text{dist}(f_i^j, l_k) \leq \tau_d \quad (3.4)$$

where τ_d is the upper threshold for match distance.

If matches are not found, then the new unmatched feature is simply added to the index. With the addition of each of the matched and unmatched features, the boolean variable (c_{ij}) associated with frame number is set to 1.

As stated previously, features must appear in more than one frame and must not appear in all of the frames to be treated as landmarks. Based on this, a post-processing is applied on the landmark index to filter out the non-landmarks. This post-processing is band-pass filtering, with two thresholds defined on the number of occurrences of the features:

- The lower threshold, L_{th} , represents the minimum number of frames a feature must appear in to be considered as a landmark. This value can be adjusted depending on the image set.
- The upper threshold, U_{th} , is the maximum number of frames in which a feature should occur. If a feature appears in more frames than this number, then it is not considered distinctive. This upper threshold can be a percentage measure on the highest number of times a feature appears in the unprocessed index.

When the processing is complete, the remaining features in the database are considered as landmarks. Algorithm 2 is the complete algorithm to generate the landmark index.

```

Data : Set of images  $Im$  of size  $N$ , with sufficient overlap between each
         adjacent pair of images
Result: Data structure LandmarkList containing feature descriptors, with
         the frame numbers they appear in

ImageFeatures  $\leftarrow$  ExtractFeatures( $Im[1]$ );
LandmarkList. AddFeaturesWithFrameNumber(1, ImageFeatures);
for  $i \leftarrow 2$  to  $N$  do
    ImageFeatures  $\leftarrow$  ExtractFeatures( $Im[i]$ );
    common  $\leftarrow$  FindCommonFeatures(LandmarkList, ImageFeatures);
    uncommon  $\leftarrow$  LandmarkList - common;
    LandmarkList. UpdateWithNewFrameNumber( $i$ , common);
    LandmarkList. AddFeaturesWithFrameNumber( $i$ , uncommon);
end

LandmarkList. RemoveSeldomAppearingFeatures();
LandmarkList. RemoveTooFrequentlyAppearingFeatures();

```

Algorithm 2: Landmark Indexing Algorithm

3.4 Search Technique

Figure 3.2 presents a block diagram of the image search procedure. Features are extracted from each query image, and a nearest neighbor search mechanism is employed to match the query features with the landmark index. The Fast Library for Approximate Nearest Neighbor (FLANN) [49] is used for this purpose. The automatic algorithm and parameter configuration of FLANN helps to select the most suitable algorithm between randomized k -d trees and hierarchical k -means tree and determine the optimal parameters for the selected approach. The optimization process can be geared towards either faster training with slow searching time, or more training time to make the search faster. The second approach is taken here, because the training is done only once during loading the landmark index before searching. The parameters can be saved for reuse of the same map. For each of the feature-to-landmark matches, each frame in the index entry for every matched landmark gets a vote. Once voting

Figure 3.2: Block diagram of image search procedure

is finished, a linear search is performed to find the frame with maximum number of votes. This frame is output as the retrieved image.

From a database containing N training images, a landmark index is built which has M entries, and k -d tree is used to find nearest neighbors, then to perform a single query:

- $O(P \log M)$ time is needed to perform feature matching using k -d tree ($O(\log M)$ time for each feature), where P is the total number of features in the query image;
- $O(PN)$ time is needed to use linear search on the frame number list, and vote

for all frames for each of the P matches;

- $O(N)$ time is required to perform another linear search on the frame number list to find the frame with maximum vote.

It can be recalled from previous discussion (Section 2.2) that, *bag of visual words* takes:

- $O(M \log P)$ time to build the term frequency histogram for the query image;
- $O(MN)$ time to find the scalar product of the query histogram with those from the N training images, and find the largest scalar product.

Considering $M \gg P$, the total time complexity of image retrieval using landmark indexing, $O(PN)$ is much less than that using *bag of visual words*, $O(MN)$.

Image retrieval depending on feature matches only may result in false positives because of outliers that do not satisfy the epipolar constraints between two images. To correct this problem, the fundamental matrix is estimated from the feature correspondences. If there are at least 8 correspondences, a RANSAC approach is applied, and outliers are removed which do not fall inside the inlier threshold. If the retrieved image, which has the maximum vote using the landmark index, does not contain enough matches after filtering out the incorrect correspondences, then that match is rejected, and the candidate with the second highest number of votes is considered. This goes on until an image is found which satisfies the epipolar constraint, or the remaining candidates are found to have votes $< \delta$ (the previously defined minimum number of matches for acceptable retrieval), in which case no suitable match is retrieved for the query image.

3.5 Demonstration in 3D Navigation

The image retrieval system using landmark indexing can be demonstrated in an indoor navigation application. A brief overview of the navigation system is described here. The system has two phases: pre-processing (mapping) and runtime (navigation).

3.5.1 Pre-processing

The pre-processing phase is mainly the map generation and storage procedure. A *map* is a collection of 2D images and corresponding 3D point clouds, organized in a data structure with the registration information. For the runtime navigation phase to work, all components of the map should be properly stored. This phase is performed with a Kinect camera and a modified RGBDSLAM [17] interface. As suggested in Section 3.3.1, to create the map, the recommended procedure is to position the camera at the center of the room, rotate 360° and capture all frames for processing. Once this is complete, the camera should be moved towards corners and far ends of the room to capture detailed frames with close up shots. This helps to identify landmarks from any distance during navigation. Also, the frames must overlap to identify the common features as potential landmarks.

For the purpose of 3D registration error minimization only, RGBDSLAM uses a graph optimization algorithm, which is discussed later. This graph representation is not related to the image retrieval procedure.

The framework for pre-processing phase is given in Figure 3.3.

Figure 3.3: Block diagram of pre-processing

Feature-based Matching

Both 2D and 3D frames are captured with the help of the Kinect camera. From the 2D RGB frames, features are extracted. To be consistent with the rest of the work, only SIFT features are used here.

When each frame is captured, it is matched with the pre-existing frames. This is performed with Fast Library for Approximate Nearest Matching (FLANN). The correspondences found between two images are filtered in two steps.

1. The matching is performed twice. The query and training images are swapped and re-matched. Common correspondences from both rounds are considered as correct.
2. From the correspondences, the fundamental matrix between the two images is computed. This matrix is applied on the query image to match with the target, and the re-projection error is estimated. The match is considered accurate if the error lies below a threshold.

These steps may take some time. However, the pre-processing phase does not need

to be fast; it only needs to be accurate so that the navigation phase can be real-time.

3D Pose Determination using RANSAC

This is done using the same procedure described in the Section [2.3.1](#).

The 2D feature correspondences found in the previous step are transformed into 3D point correspondences between the point clouds. This is possible because the point clouds are organized in a 640×480 pixel grid, which means all 3D points can be addressed with 2D image coordinates. The RANSAC algorithm (Algorithm [1](#)) estimates the pose of each frame from these correspondences.

Graph Representation of Map

In a graph representation $G = (V, E)$, each vertex/node $v \in V$ contains a frame of the map:

$$v = (I_i, I_d, F_i, C, P_c)$$

where I_i is the intensity image, I_d is the depth image, F_i is the set of image features (both interest points and feature descriptors), C is the 3D point cloud and P_c is the set of 3D interest points. Additional information may be added if required.

Each edge $e \in E$ between two vertices v_1 and v_2 contains match information between them:

$$e_{v_1, v_2} = (X_1, X_2, t, w)$$

where X_1 and X_2 are the lists of indexes of points in frames of v_1 and v_2 respectively, and t is the transformation matrix of v_2 with respect to v_1 , and w is a weight assigned to the edge. The number of feature correspondences between two frames can be used as the weight on the edge, because fewer correspondences most probably

means a wrong frame match, and more correspondences most probably means better frame-to-frame registration. This weight is used in traversal and optimization of the graph structure. Further emphasis on the weight can be applied by using a higher exponentiation on the count of correspondences.

The graph optimization algorithm used here is g^2o (for *general graph optimization*) [37]. It is a generalized, least squares optimization technique of an error function represented in a graph. This optimization procedure is very useful in *loop closure* detection, which is the identification of revisiting previously explored locations. Any accumulated error can be minimized during loop closure by revisiting old locations, and propagated throughout the graph to correct the entire 3D model.

Map Saving

The final step of the pre-processing phase incorporates saving the RGB image of each frame, as well as the 3D point cloud, and the transformation matrix with respect to the first frame. The first frame is taken as the base frame and has a identity matrix as its transformation.

3.5.2 Runtime

The steps performed in the runtime or navigation phase are not entirely different than pre-processing, except that the landmark indexing technique is used to retrieve images and localize in real time. The 3D pose calculation is the same as before. The procedure is depicted in a flowchart in Figure 3.4.

Figure 3.4: Block diagram of runtime

Application of Landmark Indexing

The graph traversal method of RGBDSLAM is replaced here with the feature-based landmark indexing. Each image of the map is passed through Algorithm 2 to generate the index. This can be done during loading time of the map into the navigation system, or can be processed at the map generation phase and saved in a file during the pre-processing phase.

In runtime, the Kinect camera captures frames and goes through the image retrieval procedure. This procedure can be modified to present multiple output frames instead of one, so that, if the captured frame is put as a node in the graph representation of the map, it can have multiple edges with the map nodes. In this case, the most probable map frames that match current captured frame are the neighbors of the best matched image. More than one edge for a node also helps in the optimization process of the graph. There may be outliers, but those can be detected with a threshold on

the number of correspondences found in the matching process, because any outlier should have a significant low number of matches. Further filtering can be performed with the previously discussed epipolar constraint verification.

Pose Determination and Addition to Graph

Once the image is retrieved, The previous 3D pose determination step is followed. Then, the frame is added to the existing map graph as a node, and an edge with the correspondence count and transformation matrix is added. If multiple images are retrieved, one edge is added for each of them. Then the g^2o optimization procedure is applied over the graph.

Adding nodes in graph makes the system remember the previous location and orientation. If there is any such previous memory, which will occur after the first node is added in runtime, then an edge can be added with this previous node. This improves localization. However, if the camera is moving very fast, then there may be a large rotation or translation factor between those two frames, and this edge can be neglected. The maximum allowable movement speed depends on the processing time of the algorithm. Generally, from practical experience on RGBDSLAM, it is normal human walking speed, which is approximately 1.5 m/s. Also, if the camera is not moving at all, then the transformation matrix will be close to an identity matrix. This condition can be used to abort the unnecessary registration procedure.

Error Avoidance and Correction

The g^2o optimization helps to minimize error between the added frame and map. However, the chance of accumulation of error is never diminished. The result will

be similar to that when a GPS receiver fails to locate itself and shows the user a completely different street address. So, as a fail-safe, a certain maximum number of nodes can be remembered by the system. After exceeding this limit, the system clears all the navigation data except the map itself, and relocates itself using image retrieval.

Chapter 4

Experimental Results

Experiments were performed to retrieve location images from different image datasets. These datasets were either downloaded from online sources or captured manually, and in both cases the proposed landmark indexing algorithm performed better than the method of Liang *et al.* [39] or the *bag of visual words* [66]. The method was further applied to localize a user in a 3D map in real time, as described in the previous chapter.

4.1 Data Acquisition

The image retrieval method for landmark indexing was tested on a few different datasets. Three of these datasets consisted of images acquired by the author, one was an indoor navigation dataset available online, and the third was created from recorded videos in an underground mine tunnel.

Manually acquired sets. These datasets consisted of frames extracted from videos captured in the following areas:

1. Queen’s University Electrical & Computer Engineering (ECE) Department

office;

2. A laboratory room;
3. Partial 1st and 2nd floors of Cataraqui Shopping Center, Kingston.

The videos were captured with the 8 megapixel camera of a Samsung Galaxy S4 phone. All extracted frames were downscaled to 640×480 . They had considerable overlap, which can be seen in a partial shopping center dataset shown in Figure 4.1. Some images were separately captured at random locations in these areas and used as query.

Figure 4.1: Partial shopping mall dataset which shows the overlapping training images.

Online dataset. The Cognitive Navigation [36] dataset consists of 640×480 images of different indoor areas (a corridor, an office, a laboratory, an elevator area and a bathroom). It is a three-part dataset, where the first part contains images of individual areas separately in natural illumination conditions, the second part is the same but captured at night with artificial lighting, and the third part is a continuous exploration of all the places in artificial illumination conditions. The images are captured with a Microsoft Kinect. For the experiment, the 3rd part was chosen, because it had more than 500 images with sufficient overlap, from which nearly 450k features could be extracted. Due to the absence of separate query images, some random images were chosen as queries and were not included during training.

Underground mine tunnel. Two high-quality videos captured with a video camera mounted on a mine vehicle were used for experimenting. Both videos showed the same tunnel, the only difference being the driving direction. The first video captured the tunnel as the vehicle moved forward. In the second video, the vehicle was on reverse gear. Focused lighting from the headlights of the vehicle and occasionally present overhead lights were the sources of illumination in the tunnel. 598 frames extracted from the first video were used to build the landmark index, and 65 images extracted from the second video were used as query. All images were downscaled to 640×480 .

For the demonstration of the landmark indexing in indoor navigation, 3D point clouds were collected in the ECE Department office, and GeoDigital International lobby, with a Microsoft Kinect. All frames were 640×480 organized point clouds.

4.2 Filter Parameter Estimation

To estimate the best parameter for the bandpass filter, image retrieval experiments were performed using different values of the lower and upper thresholds, and it was estimated which values provide the shortest length feature index with maximum retrieval accuracy. The result of this experiment was a pair of the highest possible lower threshold and the lowest possible upper threshold (L_{th}, U_{th}) for each dataset. To find this, the following were measured:

- *True Positive Rate (TPR) or Recall* $= \frac{TP}{TP+FN}$
- *False Positive Rate (FPR)* $= \frac{FP}{FP+TN}$
- *Accuracy* $= \frac{TP+TN}{TP+FP+TN+FN}$

where TP = number of true positives, TN = number of true negatives, FP = number of false positives, and FN = number of false negatives. Each pair of (L_{th}, U_{th}) thresholds generated a single (FPR, TPR) point in a Receiver Operator Characteristic (ROC) space. In this space, the point closest to $(0, 1)$ showed the best parameters. However, multiple threshold values might generate the same TPR and FPR. To choose the best parameters, the closest point to $(0, 1)$ in ROC space was selected, and then from all of the corresponding pairs (L_{th}, U_{th}) , the one which created the smallest set of landmarks and showed the highest accuracy was chosen. For the lab dataset, the pair $(12, 80\%)$ gives the lowest FPR, with a sufficiently high TPR and the highest accuracy. So, $(12, 80\%)$ are the optimal parameters for the lab dataset. Parameters for all datasets are listed in Table 4.1. An example ROC plot for the Laboratory dataset is shown in Figure 4.2.

Figure 4.2: ROC plot for different lower and upper thresholds of the bandpass filter applied on the laboratory dataset. Multiple threshold pairs can generate same (FPR,TPR) point. The threshold pair that generates a point closest to (0,1) in ROC space and creates the landmark index with smallest size is chosen for the particular dataset.

Table 4.1: Optimal filter parameters for different datasets

Dataset Name	Optimal (L_{th}, U_{th})
Office	(6, 80%)
Lab	(12, 80%)
Cataraqui Mall	(6, 80%)
Cognitive Navigation	(14, 50%)
Mine tunnel	(0, 100%)

The above table shows that none of the features were removed from the landmark index for the mine dataset. The reason for this was the presence of a very low number of features in the environment, so that any removal would increase the error.

4.3 Landmark Index Generation Results

Table 4.2 presents the size of each landmark index after applying the optimal parameters for each dataset. The Turcot-Lowe method [72], as described in Section 2.2, reduces the feature set to about 4% of the complete collection using image adjacency graphs. In the described experiments, it was seen that the landmark index contained 14-18% of all features. The reason is that while [72] uses random outdoor images of buildings in a city, the proposed method works with indoor environments. In an outdoor image, due to the presence of people and moving vehicles, the features on the buildings and stationary roadside objects are fewer. In an indoor setting, chairs, tables, decorations on the wall, poster, signboards etc. provide a very large set of landmarks. In our experiments, it was found that reducing the feature set below this optimal level started introducing errors in image retrieval.

Table 4.2: Landmark Index Generation Results

Dataset Name	Total # of Frames	Total # of Features from Frames	# of Landmarks in Database
Office	176	43886	7837 (17.86%)
Lab	220	127558	20392 (15.98%)
Mall 1 st Fl.	255	232829	41545 (17.84%)
Mall 2 nd Fl.	285	251260	43430 (17.28%)
Cognitive Navigation	532	456221	62304 (13.66%)
Mine tunnel	598	141285	91117 (64.49%)

The underground mine is a special scenario regarding presence of features. 598 frames were extracted from the training video, and only 141285 features were extracted from these frames. In comparison, the indoor environment from Cognitive Navigation dataset with more than 500 frames could produce more than 450k features. Initial experiment with this dataset showed that using the feature matching resulted in generating a landmark index containing only 23715 features, and image retrieval experiments using this index showed a very low (40.32%) accuracy.

To solve this problem, the first approach taken was to incorporate all 141285 features in the landmark index. Searching using this set of landmarks produced 100% accuracy.

The second solution was to use an upper threshold for match distance to filter the

feature matches. Because most of the features in mine were very similar, simply finding the nearest neighbor did not consider the subtle differences between two similar feature descriptors. This distance was measured in 128-D feature descriptor space. A threshold of 150.0 units was found optimal, which generated a landmark index with 100% search accuracy.

4.4 Search Accuracy and Performance

Table 4.2 presents the accuracy and performance of searching using landmark index for each dataset. The performance was measured by taking the average of search time for all queries. Figure 4.3 shows how the database image with the maximum landmark match count is chosen as the retrieved image. The landmark match count histogram for each example in Figure 4.3 depicts the number of query-feature-to-landmark matches, *i.e.*, $\sum_{x \in X} c_{xk}, k \in [1, N]$ as described in Section 3.1, for all the training images. Figure 4.4 shows some examples of incorrect retrieval. Figure 4.5 shows a comparison of the accuracy and performance of our landmark indexing method with those of the exhaustive feature set method of Liang *et al.* [39], and *bag of visual words* [66].

Table 4.3: Search Accuracy and Performance

Dataset Name	# of Query Images	Accuracy with Landmark In-dexing	Average Search Time
Office	38	100% (38)	10 ms
Lab	47	95.74% (45)	15 ms
Mall 1 st Fl.	55	90.91% (50)	30 ms
Mall 2 nd Fl.	60	93.33% (56)	28 ms
Cognitive Navigation	60	100% (60)	20 ms
Mine tunnel	62	100% (62)	20 ms

It can be observed that the landmark match count histograms for false positives were much flatter than those for true positives. The reason was the existence of query features which were very common to the environment. For example, Figure 4.4a shows a query image, which has computers and tables that are common to the rest of the lab area, so feature-to-landmark match counts are almost evenly distributed for the training images. Similarly in Figure 4.4b features from mall windows and mannequins cause false positive retrieval. Determining the nature of histograms can be used to predict false positives in future developments of the search algorithm.

From Figure 4.5b it can be observed that the average time consumption for image retrieval using Liang *et al.* is much less than reported (2-4 seconds) in [39]. However, with increasing size of image dataset, the feature collection will also increase, and the performance will be significantly affected. Their exhaustive feature set will increase

linearly with addition of each image in the dataset, but it will be much less, possibly logarithmic, in landmark indexing because of internal feature matching and removal of useless features. This can be verified in future work.

Figure 4.3: **True Positive** image retrieval results using landmark indexing. **left)** Query image, **center)** Landmark match count histogram between the query and each database image, **right)** Matched image from training dataset, which corresponds to the peak in the histogram.

Figure 4.3: (Continued) **True Positive** image retrieval results using landmark indexing. **left)** Query image, **center)** Landmark match count histogram between the query and each database image, **right)** Matched image from training dataset, which corresponds to the peak in the histogram.

Figure 4.3: (Continued) **True Positive** image retrieval results using landmark indexing. **left)** Query image, **center)** Landmark match count histogram between the query and each database image, **right)** Matched image from training dataset, which corresponds to the peak in the histogram.

Figure 4.4: **False Positive** image retrieval results using landmark indexing. **left)** Query image, **center)** Landmark match count histogram between the query and each database image, **right)** Matched image from training dataset.

(a) Accuracy Comparison

(b) Performance Comparison

Figure 4.5: Image retrieval accuracy and performance comparison between our method, the exhaustive feature set approach of Liang *et al.* and *bag of visual words*. All methods show comparable accuracy, however, the time performance of our Landmark Indexing method is much better than *bag of visual words*.

Figure 4.6: The Indoor Positioning System Setup

4.5 Indoor Navigation

3D maps for this experiment were constructed using the Microsoft Kinect camera, and the modified RGBDSLAM interface. The indoor navigation system was designed by mounting the camera on a tripod, and then keeping the tripod, the controlling laptop, and a portable power source on a hand-cart. The tripod was adjusted to maintain the Kinect at eye level. The system is pictured in Figure 4.6. 3D map building was not of concern because the goal was to demonstrate the landmark indexing method in a practical application. It was manually verified that the map generation process was visually satisfactory, and the average RANSAC registration error for all of the frames in the map were recorded.

The starting point of the cart was located in the map through manual measures, and the path followed by the cart was marked on the floor to be used as ground truth. The speed of the cart was same as normal walking speed, about 1.5 m/s. Going faster caused blur in Kinect-captured image, and registration could not be performed.

Figure 4.7 shows the highlighted ground truth and the path estimated by the system in the ECE Department Office model. A gap can be noticed in the estimated path. The cause of this was incorrect location image retrieval due to either focusing the camera towards a feature-less area, or image blur caused by fast movement speed. Where the path is visible in the figure, 3D registration was being performed. The transformation matrix was estimated between each 3D frame using RANSAC on the feature correspondences, and the re-projection error was recorded.

Figure 4.7: The indoor navigation results in the Queen's ECE Dept. office. The red line is ground truth, and the green line highlights the estimated path.

The indoor navigation system is used in two environments:

1. Queen's University ECE Department office;
2. GeoDigital Ottawa Lobby.

Table 4.4 shows the average 3D re-projection error for each of the datasets. The 3D registrations performed during building the map and during navigation followed the same mechanism, so similar errors were observed in both phases. These errors conform with those recorded in the evaluation [17] of the RGBDSLAM system being used with a Kinect.

Table 4.4: RANSAC Registration Error in Navigation

Dataset Name	Average Registration Error in RANSAC
ECE Dept. Office	0.173 m
GeoDigital Ottawa Lobby	0.232 m

Chapter 5

Conclusions and Future Work

5.1 Summary of Conclusions

A novel image retrieval algorithm, *landmark indexing*, is introduced in this thesis. This algorithm can be applied on overlapping indoor location images. The overlap is necessary because it provides information on the distinctiveness and repeatability of features upon which the landmark indexing method relies.

Recent publications in the field of location image retrieval are mostly extensions of the *bag of visual words* method. The main drawback of this methods is identified in this thesis, it creates high dimensional term-frequency histograms for each image in database, each histogram having a dimension of the size of the *visual word* vocabulary created by extracting features from the training images. Some recent publications use an exhaustive feature set method, which reduces the search space by using features instead of images, but not identifying and removing useless features reduces performance. The proposed landmark indexing algorithm reduces the search space mapping similar features to a particular landmark, and removing the features which are not distinctive or repeatable in the environment. Also, it reduces the high-dimensional

histogram searching of *bag of visual words* to a linear search in an array by using a voting scheme on landmarks. The method is tested against the exhaustive feature set method of Liang *et al.* [39] and *bag of visual words* [66], on both manually captured and online provided datasets. Experimental results show that the landmark indexing method significantly outperforms the other two methods, and is comparable to and sometimes better in accuracy than the other ones. At runtime, depending on the processor performance, retrieval of an image can be executed in 10-50 ms from a map of over hundreds of frames and more than 40k landmark features.

The proposed image retrieval method is applied in a 3D indoor navigation system, and a series of experiments show that it is able to localize an user, in real-time, with a maximum error of about 200 mm. Given the sensor noise of Microsoft Kinect camera, the error is low. Also, using the Kinect camera, which can provide both 2D and 3D data, the implemented navigation system is one of the cheapest alternatives to a complex system involving multiple cameras and costly laser range finders.

5.2 Future Work

There are some improvements that can be performed on the system. The search mechanism being used is multiple randomized k -d tree provided in the FLANN library. Although there is an automatic algorithm adjustment method in FLANN, both multiple randomized k -d tree and hierarchical k -means clustering are not always very reliable. Dynamically determining k -value and cluster size may achieve improved search performance. Another improvement is possible by introducing hashing in the landmark indexing, so that the search operation can be performed in $O(1)$ time.

As discussed in Section 4.4, false positive results show flat feature-to-landmark

match histograms for training images. Determining the nature of the histogram by fitting appropriate distributions can predict false positives, so post-retrieval refinement can be targeted to those cases rather than all results including true positives.

A limitation of the image retrieval is dynamically changing environment. Although during data acquisition, multiple images are taken of the same location, minor changes may affect features, such as, lighting conditions. In every experiment described in this thesis, query and training images were collected at same time of the day, so lighting conditions are assumed to be unchanged. There are other factors in indoor environments like a door hiding or revealing new areas of the map. The solution may be to implement an update procedure to update the landmark index during runtime.

The scalability of the landmark indexing method can also be verified with a bigger dataset, maybe consisting of more than a thousand or 10 thousand images. It can be speculated that while for other image retrieval methods the feature collection would increase linearly, the proposed landmark index will show a logarithmic style of increase because of internal feature matching.

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