# Topological Map Building and Path Estimation Using Global-appearance Image Descriptors

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Abstract: Visual-based navigation has been a source of numerous researches in the field of mobile robotics. In this paper we present a topological map building and localization algorithm using wide-angle scenes. Global-appearance descriptors are used in order to optimally represent the visual information. First, we build a topological graph that represents the navigation environment. Each node of the graph is a different position within the area, and it is composed of a collection of images that covers the complete field of view. We use the information provided by a camera that is mounted on the mobile robot when it travels along some routes between the nodes in the graph. With this aim, we estimate the relative position of each node using the visual information stored. Once the map is built, we propose a localization system that is able to estimate the location of the mobile not only in the nodes but also on intermediate positions using the visual information. The approach has been evaluated and shows good performance in real indoor scenarios under realistic illumination conditions.

## 1 INTRODUCTION

The autonomous navigation of a mobile agent in a certain environment usually requires an inner representation of the area, i.e. a map, that the robot will interpret in order to estimate its current position using the information provided by the sensors it is equipped with. Among all the possible sensors a robot can use to achieve that purpose, in this paper we focus on a visual system, since it constitutes a rich source of information and the sensors are relatively inexpensive. Specifically, in this work we use a fish-eye single camera, which provides wide angle images of the environment.

A key task in vision based navigation is matching. Through the matching of the current robot sensor view with previous information that constitutes the robot's map, it is possible to carry out its localization. Usually, this is achieved by extracting some features from the image in order to create a useful descriptor of the scene with a relative low dimension to make it useful in real time operation. In this task, two main categories can be found: feature based and global-appearance based descriptors. The first approach is based on the extraction of significant points or regions from the scene. Popular examples include SIFT features (Lowe, 2004) or SURF (Murillo et al., 2007). On the other hand, global-appearance descriptors try to describe the scene as a whole, without the extraction of local features or regions. For example, (Krose et al., 2007) make use of PCA (Principal Component Analysis) to image processing, and (Menegatti et al., 2004) take profit of the properties of the Discrete Fourier Transform (DFT) of panoramic images in order to build a descriptor that is invariant to the robot's orientation. Regarding the map representation of the environment, the existing research can be categorized in two main approaches: metric and topological. Metric maps include information such as distances respect to a predefined coordinate system. In this sense, we can find examples as (Moravec and Elfes, 1985), that presents a system based on a sonar sensor applied to robot navigation, and (Gil et al., 2010), that describes an approach to solve the SLAM problem using a team of robots with a map represented by the three-dimensional position of visual landmarks. In contrast, topological techniques represent the environment through a graph-based representation. The nodes correspond to a feature or zone of the environment, whereas the edges represent the connectivity

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between the nodes. In (Gaspar et al., 2000) a visual-based navigation system is presented using an omnidirectional camera and a topological map as a representation in structured indoor office environments. (Frizera et al., 1998) describe a similar system which is developed using a single camera.

In (Cummins and Newman, 2009), a SLAM system called FAB-MAP is presented. The description of the scenes is based on landmark extraction. Specifically, they use SURF features, and their experimental dataset is a very large scale collection of outdoor omnidirectional images. Our aim is to develop a similar system but using a wide-angle camera (which is more economical than catadioptric or spherical vision camera systems). Another difference is the kind of information we use to describe the images, since we use global-appearance descriptors.

The first step in our work consists in building a map of the environment. We use a graph representation. In this representation, each node is composed of 8 wide-angle images that cover the complete field of view from a position in the environment to map, and the edges represent the connectivity between nodes to estim.

In order to estimate the topological relationships between nodes, we use the information extracted from a set of images captured along some routes which pass through the previously captured nodes. As a contribution of this work, we apply a multi-scale analysis of the route and node's images in order to increase the similarity between them when we move away form a node. From this analysis, we obtain both an increase of correct matching of route images in the map database, and also a measurement of the relative position of the compared scenes.

Once the map is built, as a second step we have designed a path estimation algorithm that also takes profit of that scale analysis to extrapolate the position of the route scenes not only in the nodes but also in intermediate points. The algorithm, which is also a contribution of this work, introduces a weight function in order to improve the localization precision.

The remainder of the paper is structured as follows. Section 2 introduces the features of the dataset used in the experimental part, and the global-appearance descriptor selected in order to represent the scenes. Section 3 presents the algorithm developed to build the topological map. In Section 4 we explain the system that builds the representation of route paths, and experimental results. Finally, in Section 5 we summarize the main ideas obtained in this work.

TERMINOLOGY: We use the term *node* to refer to a collection of eight images captured from the same position on the ground plane every 45°, covering the complete field of view around that position. We denote the collection of images of the nodes as *map's images* or *database's images*. The graph that represents the topological layout of the nodes is named *map*. The process of finding the topological connection between nodes and their relative position is the *map building*. We call the relative position between nodes *topological distance*. When we write *image distance* we refer to the Euclidean distance between the descriptors of two images. The topological distance between two images is denoted as $l$, and the topological distance between nodes as $c$.

## 2 DATA SET AND DESCRIPTOR FEATURES

In this section, we present the features of the images' data set, and the global-appearance technique we use in order to create a descriptor of the scenes.

The images are captured using a fisheye lens camera. We choose this kind of lens due to its wide-angle view. Specifically, the model used is the Hero2 of GoPro (Woodman Labs, 2013). The angle of view of the images is 127°. Due to the fisheye lens, the scenes present a distortion that makes it impossible to obtain useful information from the images using global-appearance descriptors, since they are based on the spatial distribution and disposition of the elements in the scene, and the distortion makes the elements to appear altered. For that reason, we use the Matlab Toolbox *OCamCalib* in order to calibrating the camera and computing the undistorted scenes from the original images (Scaramuzza et al., 2006). In the reminder of the paper, the term *image* refers to the undistorted transform of the original scenes.

Since the aim of this work is to solve the problem of place recognition using the global-appearance of images, it is necessary to use descriptors that concentrate the visual information of the image as a whole, being also interesting the robustness against illumination changes and the capacity of dealing with little changes in the orientation of the scenes. Some works, as (Paya et al., 2009), have compared the performance of some global-appearance descriptors. Taking them into account, we have decided to choose Gist-Gabor descriptor (Torralba, 2003), (Oliva and Torralba, 2001) as it presents a good performance in image retrieval when working with real indoor images. It also shows a reasonable computational cost. With an image's size of 64x32 pixels, the algorithm spent 0.0442 seconds to compute the descriptor using Matlab R2009b running over a 2.8 GHz Quad-Core Intel

Table 1: Number of Images per Area

| | # Images Area 1 | # Images Area 2 |
|---|---|---|
| **Nodes** | 352 | 52 |
| **Route 1** | 110 | 100 |
| **Route 2** | 50 | 72 |
| **Route 3** | 67 | 66 |
| **Route 4** | 58 | 125 |
| **Route 5** | 62 | - |
| **Route 6** | 46 | - |
| **Route 7** | 69 | - |
| **Route 8** | 67 | - |
| **Route 9** | 40 | - |

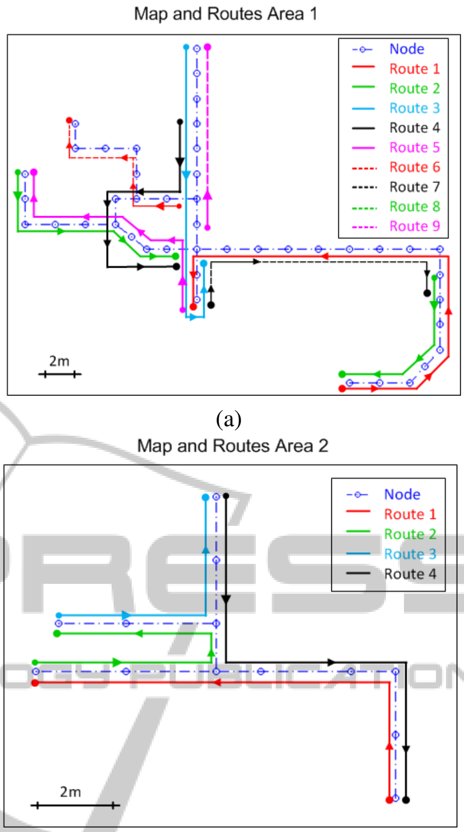
Xeon processor, requiring 4,096 bytes of memory per image.

The dataset is divided in two different areas. The Area 1 is composed of 44 nodes, whereas Area 2 has 13 nodes. The nodes are taken every 2 meters as a rule, but in places where an important change of appearance in the area is produced, i.e. crossing a door, we capture a new node independently of the distance. For that reason, the distance may be lower. As stated above, each node has 8 images captured every 45° approximately regarding the floor plane, covering the complete field of view.

We have also captured images along routes in both areas. The information of those routes is used first in order to find the topological relationships between nodes and build the graph representation in the map building task, and next to carry out the path estimation of those routes in the localization experiments. Regarding the routes, the images are taken every 0.5 meters in Area 1, and every 0.2 meters in Area 2. In changes of direction, we increase the frequency of images captured. We take a minimum of four images per position when a change of orientation is produced. In Area 2, that frequency increases with a minimum of 6 images per position. In Fig. 1 we can see the distribution of the nodes and the routes in a synthetic representation.

## 3 MAP BUILDING

In this section we describe the algorithm we have developed in order to create the robot's inner representation of the environment. Since we propose a topological representation, the map building process relies on finding the adjacency relations and relative disposition of the nodes to create the map. For that purpose, we use the route images. So then, the map is built as a graph were the nodes represent a location of the environment, whereas the edges provides information about the topological distance and direction of adjacent nodes. We have no previous information neither about the order of the nodes nor its disposition in the world. However, we know in which order the 8 images of each node were captured. The node's images make up a retrieval database. The system uses the images of the route to arrange and find the spatial relations between nodes by matching its images with the map's images. Since the route images are ordered, we add information to the map's graph incrementally through the retrieval of the node's images using the route scenes.




(b)

Figure 1: Synthetic distribution of nodes and routes for (a) Area 1 and (b) Area 2.

In this process, we make use of some artificial zooms of the images to increment the likelihood of retrieving the correct nearest node's image given a route image. In Fig. 2 we can see a representation of the disposition of the route's images regarding the nodes, and examples of the scenes. Figure 2(b) is an image of the route, Fig. 2(a) is the closest node's image, and Fig. 2(a') represents a zoom in of the node's image. Comparing the route image with both the original node's image and its zooms in, we can realize that the appearance is more similar with the zoomed scene. This is especially interesting for finding the correspondence of images located halfway of two nodes, since the similarity in that positions significantly decreases regarding the nearest nodes. Using the zooms we increase the probability of a correct retrieval.

In our algorithm, we use zooms in of both the node's images and the route's images. Given a route image, the algorithm compares several scales of this image with different scale representations of the node's images. After these comparisons, we select the experiment with the minimum image distance. $s_n$ and $s_r$ represent the specific scale values of the node and the route images respectively for which the minimum image distance happens during the retrieval. The topological distance $l$ between the route image and the node can be estimated using that coefficients as:

$$l = s_n - s_r \tag{1}$$

As we can see in Fig. 2, if an image of the route (b) is ahead a node (a), the most similar appearance will correspond to a zoom in the node's image (a'). That would mean a positive value of $l$. On the other hand, if the current position of the route is behind a node, the most similar appearance is between a zoom in of the image test (c') and the node's image (d), which means a negative value of $l$.

First, we have to build the map database $\mathbf{Z}$. This database will be used in order to carry out the retrieval node's scenes using the route images. For that purpose, we compute the descriptor $z^n \in \mathbb{R}^{1\times y}$ of the node imagery, being $y$ the number of components of each descriptor. The descriptors are stored as the columns of a matrix, which is the map database $\mathbf{Z} = [z_1^n \quad z_2^n \dots z_i^n \dots z_m^n]$, being $m$ the number of images of the database, that corresponds with the number of nodes multiplied by the number of orientations per node and by the number of zooms per node's image.

Since the descriptors are stored following the same order as the database images, it is possible to find out the corresponding node $n$, orientation in the node $\theta$ and image scale $s_n$ of an image from the position of its descriptor in the matrix $\mathbf{Z}$. Denoting $i$ as the number of column of $\mathbf{Z}$,

$$[n, \theta, s_n] = f(i). \tag{2}$$

When a new image arrives, we match it with the most similar scene included in the map database. For that purpose, we first compute its descriptor $z^r$ and calculate its Euclidean Distance $d$ with all the descriptors included in $\mathbf{Z}$:

$$d_i^r = \sqrt{\sum_{a=1}^{y} (z_{i,a}^n - z_a^r)^2}, i = 1 \dots m. \tag{3}$$

$d_i^r$ gives information about the appearance similarity between an input image and all the images of the map, and it is used as a classifier. The algorithm selects the Nearest Neighbor, and associates to $d$ the corresponding values of $n$, $\theta$ and $s^n$ of the retrieved node's image. We repeat this process for different zooms of the route's image. Then, we select the Nearest Neighbor using again $d$ as a classifier between the retrieved cases for each $s_r$. This way, from each image of the route we obtain the information vector:

$$[n \quad d \quad \theta \quad s_n \quad s_r]. \tag{4}$$

Up to this point, we have presented the matching process between the node and the route images using different scales from which we obtain a higher precision in the image retrieval and the relative position of the images. Now, we continue describing the graph creation process using the information included in (4).

The decision of adding a new node to the map involves the lasts route retrieval image results. Specifically, we study the previous five information vectors included in the algorithm. First, we estimate the mode of the nearest nodes, $n_m$, included in these five information vectors. Being $M$ the number of times that $n_m$ appears in the last five image matchings, and $\mu$ and $\sigma$ the mean and standard deviation of all the $d$'s included in the information vectors so far, a new node is included in the graph if any of these two conditions is achieved:

- $M \geq 3$
- $M = 2 \quad$ and $\quad d_{n_m} < \mu - \sigma$

When the information vector has a retrieval with an associated image distance $d > \mu + 2\sigma$, it is not taken into account, since a high value of $d$ indicates low reliability in the association.

To estimate the topological relations between nodes, we create the adjacency matrix $A \in \mathbb{R}^{N\times N}$, being $N$ the number of nodes. $A$ is a sparse matrix with rows labelled by graph nodes, with 1 denoting adjacent nodes, or 0 on the contrary.

Regarding the topological distance of the nodes in the graph, we use the scale factors to determine it. Being $l^f$ and $l^l$ the differences of scales of the first and last image of the route where the same node is detected, the topological distance $c$ between a node $n_i$ and $n_{i+1}$ is defined as:

$$c_{i,i+1} = l_i^l - l_{i+1}^f \tag{5}$$

In order to build the graph, we also estimate the relative orientation between nodes. $\theta_i^f$ denotes the orientation associated with the first route image that retrieves the node $i$, and $\theta_i^l$ the orientation of the last one before a new node is found. We assume that $\theta_i^l$

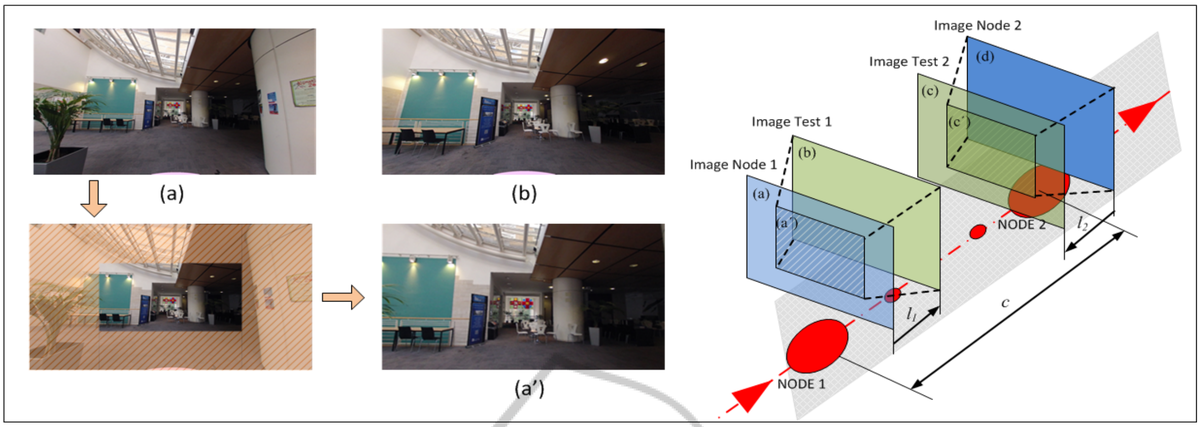



Figure 2: Example of two test images located in different relative positions regarding the closest node. (a) Image node 1, (a') Zoom-in of the Image Node 1, (b) Image Test 1, (c) Image Test 2, (c') Zoom-in of the Image Test 2 and (d) Image Node 2. On the right, it appears samples of the images (a), (a') and (b) to show the zoom process and appearance similarity improvement. $l_1$ and $l_2$ are topological distances between a node and a route image, and $c$ the topological distance between nodes.

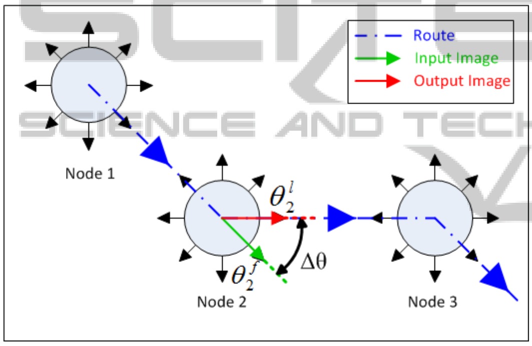
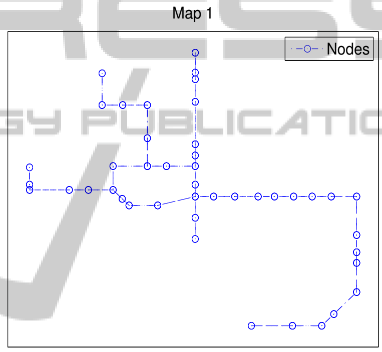
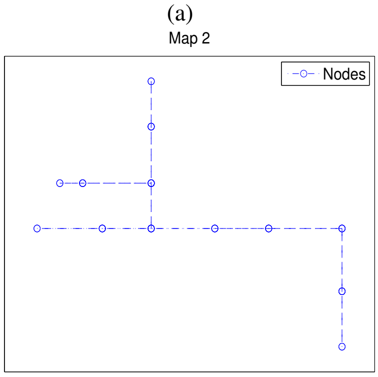



Figure 3: Phase change estimation in a node.




(a)




(b)

Figure 4: Graph representation of the node's arrangement obtained with the map building algorithm for (a) Area 1 and (b) Area 2.

is the direction that the robot has to follow in order to arrive to the next one. We estimate the phase lag produced in a node as:

$$\Delta\theta_i = \theta_i^l - \theta_i^f \tag{6}$$

In Fig. 3 we can see a graphical representation of the phase change estimation in a node. We set the orientation of the map by defining the direction of the output image for the first node. That direction defines the global orientation system of the map. After that, the orientation of the graph is updated in every node using $\Delta\theta_i$. Although the map and the nodes use different angle reference systems, it does not affect to the results since we compute angle differences. Once we have defined the global map orientation reference, we can compute the phase lag with each node local orientation system. That information will be used during the path estimation task.

When a new route is studied, the algorithm initializes a new coordinates system. That route will be analyzed independently of the global graph until a common node is found. Using the position and orientation of the common node regarding both systems, we are able to add the new nodes to the global graph correctly. If the path of a new route coincides with a previous one, the topological distance $c$ of the nodes is estimated again, and the result included in the map by calculating the mean with the previous values.

In Fig. 4 it is possible to see the map's graph of (a) the Area 1 and (b) the Area 2. In the experiments, we use a high number of scales in order to increase the precision in the topological distance estimation. In particular, $s_n$ has a maximum value of 2.5 with a step of 0.1, and $s_r$ reaches 1.4 with an increment of 0.05. With that parameters, the time spent to make the necessary comparisons per route image is 720 ms. We can appreciate that the algorithm is able to estimate the connections between nodes maintaining the appearance of the real layout of both areas. The Area 1 has been the most challenging due to the higher number of nodes, the transition from different rooms and the loop in the map. The graph representation slightly differs from the real layout, specially in the angle of the right lower part nodes of the loop. Those nodes are where the loop closure is produced, and the angle difference is due to the accumulated error in the distance estimation of the nodes in the loop, not in the angle estimation. Since the estimation of the phase lag between nodes is correct, the navigation is not affected despite of the inaccuracy in the graph representation.

If there is not enough distance between adjacent nodes, or the frequency of the route's images is low, a node might not be included in the graph, as the algorithm does not find the necessary repetitions of the node in the information vector when doing the node retrieval. The system is especially sensitive in the phase lag between nodes, since it is based on the angle estimation of the input and output node's images. For that reason, it is advisable to raise the frequency of the image acquisition in the nodes where there is a change in the direction.

## 4 PATH ESTIMATION ALGORITHM

Once we obtain the graph of the map, our following objective is to estimate the path of the routes in the map. This can be faced as a localization problem using visual information. If we base the localization of the route just on the retrieval of the nearest node's images, our knowledge of the positions will be limited to node's location. In these experiments we try to improve the localization extending it also to intermediate points between map nodes. We use the scale analysis of the images to carry out this task in a similar way as seen in section 3. The algorithm uses the adjacency matrix $A$ and the map database $\mathbf{Z}$ that includes the descriptors of the node's images obtained during the map building. The comparison of the global-appearance descriptor of a route image $z^r$ with $\mathbf{Z}$ provides a measurement of their similarity with all the node's descriptors using (3). On the other hand, the matrix $A$ contains information about the topological distance of the matched nodes, making it possible to find out the minimum topological distance between two nodes of the map.

Once the descriptor $z^r$ of an image's route has been built, the first step consists in calculating the Euclidean distance between it and the descriptors included in the map database (i.e., the descriptors of the node's images). We obtain $d_i^r$ for $i = 1 \dots m$. We identify each $d$ with its corresponding node $n$, angle $\theta$ and node image scale $s^n$. Then, we classify the results regarding $d$. We select the k-nearest-neighbors, and repeat the experiments for different route images scales $s_r$. Specifically, we use $k = 10$ neighbors.

Next, we weight the image distance $d$ of every selected neighbor using their position and orientation. The aim is to penalize the probability of neighbors that are geometrically far from the last robot pose. Since our classifier uses the minimum image distance $d$ as a criteria, we define a function that multiplies the image distance of each neighbor regarding a factor that increases according to the topological distance and phase lag.

To carry out this process, we first estimate the topological distance between the position of the previous route image and every neighbor selected during the matching. We are able to find out the shortest path between two nodes using the information stored in $A$. Since we have a connected graph, a path that connects two nodes of the map can always be found. Being $c_{n1,n2}$ the cost to traverse two adjacent nodes $n_1, n_2 \in A$, and $P_{i,j} = [n_i, \dots n_j]$ the sequence of nodes of the shortest path that connects $n_i$ and $n_j$, the cost $C_{i,j}$ associated with $P_{i,j}$ can be defined as:

$$C_{i,j} = \sum_{n_i}^{n_j} c_{n_i,n_{i+1}} \tag{7}$$

being $c_{n_i,n_{i+1}}$ the topological distance between adjacent nodes defined in (5).

Our weighting function takes into account changes in both position (nodes) and orientation. Considering the image $i-th$ of a route, the value of $d$ is updated as:

$$d' = d \times [w_1 \cdot C_{i,i-1} + w_2 \cdot \Delta\theta_{i,i-1}] \tag{8}$$

$w_1$ and $w_2$ are weighting constants. Specifically, $w_1$ is related with the topological distance, and $w_2$ weights changes in the path orientation. The function updates the image distance $d$ based on the topological distance and phase lag between each neighbor and the previous localization of the path. The multiplier weighting term increases as the neighbors present higher topological distance and orientation difference

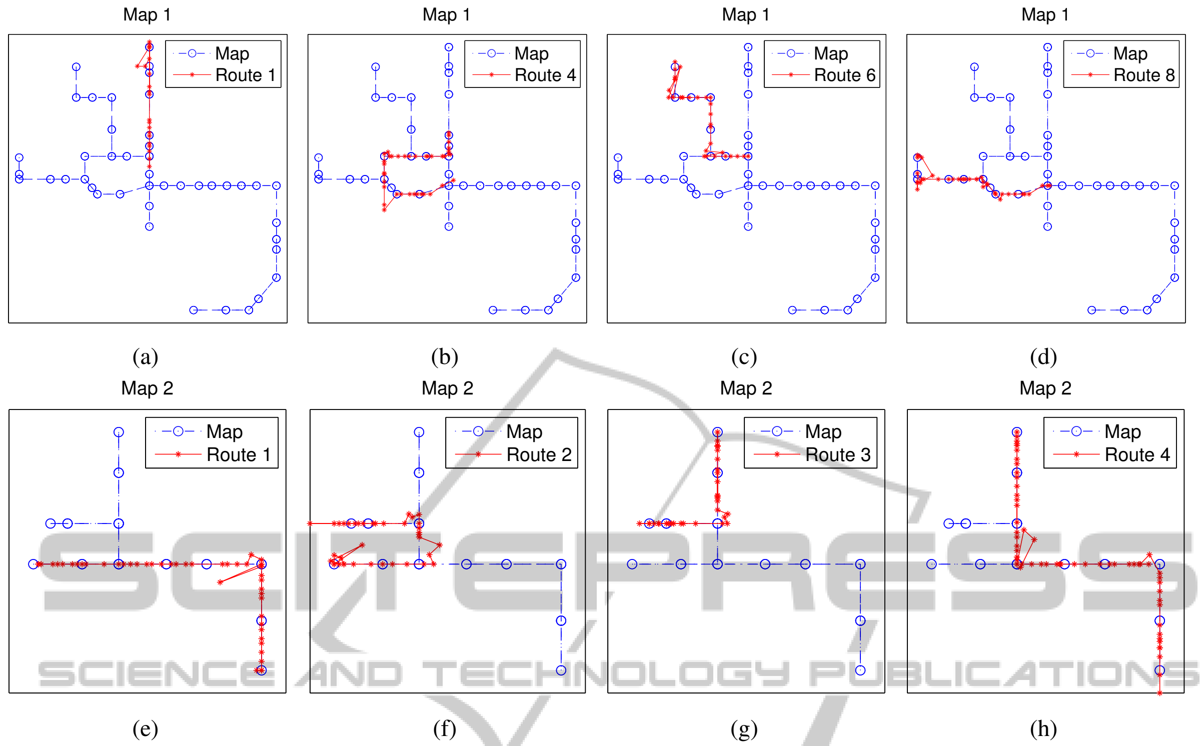





Figure 5: Path estimation of the (a) Route 1, (b) Route 4, (c) Route 6 and (d) Route 8 of the Area 1 over the created graph, and path estimation of the (e) Route 1, (f) Route 2, (g) Route 3 and (h) Route 4 of the Area 2 over the created graph

regarding the last path location. By incrementing the image distance of an experiment, we reduce its likelihood of being chosen as nearest neighbor. That way, the function penalizes important changes in position and orientation between consecutive route scenes. The multiplier term might change for each neighbor of the current node, since the estimated nearest node and orientation may vary in every particular case. We determine the constants' value experimentally. In our function, we choose $w_1 = 0.15$ and $w_2 = 0.1$.

Once the image distances are updated, we classify the selected experiments regarding $d'$, and choose the Nearest Neighbor. As a result, we find out the closest node $n$ to the route image, its orientation $\theta$, and the scales of both the node's image $s^n$ and the route's image $s_r$. We have to take into account that $\theta$ must be corrected with the phase lag between the map global system and the node reference system, estimated previously in the map building. The current position of the robot in the graph is estimated using the nearest node and the relative position with that node ($l$) using (1).

Figure 5 shows the path estimation of different routes of the two areas. The dots in the route's paths represent the position of the different images studied. The values of $s_n$ and $s_r$ have been determined experimentally, being 2.2 the maximum scale with a step of 0.4 and 0.3 respectively. The time necessary to carry out the localization of an input image is 330 ms.

We can compare the results with the synthetic routes path representation in Fig. 1. As it can be seen, the algorithm deals with the interpolation of the location estimation in halfway positions of the nodes using the image's scales information. In general, the location precision in changes of direction in the routes decreases. It is also important that, despite the fact that we introduce the weighing function, the algorithm is capable of finding again the correct position although a previous estimation is not correct, as we can see in Fig. 5(a) and (c). The result in the path representation of the fourth route of Area 1 (Fig. 5(b)) is also interesting. As we can appreciate in Fig. 1(b), the route 4 presents a path that differs from the layout of the nodes, and the algorithm is able to estimate the position accurately despite that fact.

Therefore, the results prove that our algorithm deals with the estimation of the route path in intermediate positions of the nodes and also deals false association in former experiments of the route despite using a weighting function.

## 5 CONCLUSIONS

In this paper we have studied the problem of topological map building and navigation using global-appearance image descriptors. The map building algorithm developed is able to estimate the relations between nodes and create a graph using the information captured along some routes in the environment to map. Moreover, we introduce a study of the image's scales in order to find out the topological distance between nodes which can be considered to approximately be proportional to the geometrical distance. The results present a high accuracy in the node detection and estimation of its adjacency and relative orientation as it can be seen in the graphs obtained in the map building process. All that information arranges the representation of the map through a graph.

We have also created an algorithm which estimates the path of routes along the area. It takes profit of the image's scale study to improve the location with an interpolation of the route position between nodes. The use of a weighting function to penalize changes in position and orientation in consecutive images during the navigation improves the localization accuracy. Despite that weight, the algorithm is able to relocate the robot correctly although a previous image of the route would introduce a false retrieval.

The results obtained both in the map building and the path representation of routes encourage us to continue studying the possibilities of the application of global-appearance image descriptors to topological navigation tasks. It would be interesting to extend this study in order to find the minimum information necessary to make the navigation optimal, the application of new global-appearance descriptors, or the improvement in the phase estimation in order to make the algorithm able to correct small errors in the orientation.

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