Comparison of Appearance-Based Topological Mapping Methods♠

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Abstract—In this paper, we develop and compare two methods to carry out topological mapping using only some visual information captured by an omnidirectional camera mounted on a mobile robot by means of an appearance-based method. The first step consists in studying the kind of information to store and the form of the database so that the robot can estimate its position and orientation within the map with robustness against changes in the lighting conditions of the environment. Also, it is important to remove redundant information to get an acceptable computational cost during the localization process. With this aim, we have studied and compared the performance of several techniques to extract the most relevant information from a set of panoramic images and several filtering techniques. We have carried out some experiments to study the performance of the filters in a localization process using Recall and Precision charts. On the other hand, it is also important to establish the topology of the map created since it will make possible a high-level planning of the path to move to the target points. With this aim, we study two approaches: batch and incremental. We have also carried out an exhaustive experimentation to study the validity of the proposed mapping methods and to perform an objective comparison between them. Also, we have tested the time consumption to create the topological map and the geometrical shape obtained using each one of the two methods.

Keywords: Incremental topological mapping, appearance-based methods, omnidirectional vision, lighting effects filtering, Recall and Precision charts.

1. INTRODUCTION

When a mobile robot or a team of mobile robots have to carry out a task in a large environment, in most cases, they have to take decisions about their localization and about the trajectory to follow to move from their current position to the target point. To solve this problem, a map or an internal representation of the environment is needed. Omnidirectional visual systems are commonly used at this kind of applications due to their low cost and the richness of the information they provide. Currently the study of how to construct this representation of the environment using only visual information is a very active field in robotics. This mapping problem has been often solved thanks to the extraction of landmarks or other salient features from the images (Gil et al., 2005 or Murillo et al., 2007). However, when working in unstructured environments where the creation of appropriate models of recognition can be an arduous chore, it is useful to use appearance-based techniques, which work with the information in the images as a whole.

Appearance-based techniques offer a systematic and intuitive way to construct the map. Nevertheless, as no relevant information is extracted from the images, it is usually necessary to apply a compression technique to reduce the computational cost of the mapping and localization processes.

PCA (Principal Components Analysis) is a widely extended method that meets this requirement. One example is the database created by Kröse et al. (2004). The main problem of PCA methods is that they are not inherently invariant to the orientation of the robot. Taking into account this fact, Ueonara et al. (1998) studied the problem of invariance to ground-plane rotations and Jogan et al. (2000) applied these concepts to build an appearance-based map of an environment using a variation of PCA, including information not only about the localization where the images were taken, but also about the possible orientations at that points. Other researchers rely on Discrete Fourier Transform (DTF) methods to get the most relevant information from the images. As an example, Menegatti et al. (2004) define the concept of Fourier Signature and Payá et al. (2009) apply this concept to the construction of appearance-based grid maps. When working with panoramic images captured by an omnidirectional system, the Fourier Signature presents

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rotational ground-plane invariance and concentrates the most relevant information in the low frequency components of the transformed image.

The appearance of an image depends strongly of the lighting conditions of the environment to map. Adini et al. (1997) show the influence of the illumination of the scene in a process of facial recognition. An individual cannot be recognized if there is a substantial change of lighting in the scene. To avoid the problems of illumination variation Murase et al. (1994) use an appearance-based approach. With this aim many views of the object are generated under different lighting conditions. Faraid et al. (1999) show that it is possible to separate the effects of reflections and illumination using ICA (Independent Component Analysis). Other researchers (Bischof et al., 2004) have shown how to mitigate the effects of changing lighting on the appearance of an object, using gradient filter banks. The approach consists in implementing a series of filters before building the linear subspace using PCA. Other works (De Araújo et al., 2006) make use of banks of Homomorphic filters to separate the components of luminance and reflectance. This way it is possible to filter these components separately to reduce significantly the dependence of image appearance with respect to changes in lighting.

Once we have studied the kind of information to store in the database, it is necessary to establish some relationships between the stored location to complete the mapping process. With respect to the mapping problem, the current research can be classified into two approaches: *metric* and *topological*. The first one consists in modelling the environment using a metric map obtained with geometrical accuracy when representing the position of the robot in the map. For example Moravec et al. (1985) describe a sonar-based mapping system developed for mobile robot navigation and Collins et al. (2007) analyse the performance of several established mapping techniques using identical test data. On the other side, topological maps are graphical models of the environment that capture places and their connectivity in a compact form. An example of this method is presented in Menegatti et al. (2004) where a topological map of the environment is obtained by means of the application of a method based on the physics of harmonic oscillators. Also Werner et al. (2009) present a method for topological SLAM (Simultaneous Localization and Mapping) using fast vision techniques. Tully et al. (2009) present a probabilistic method for topological SLAM, solving the topological graph loop-closing problem by means of a tree expansion algorithm and Angeli et al. (2009) develop an incremental topological mapping and localization approach, integrating metrical information from robot odometry. At last, Stimec et al. (2008) present an appearance-based method for path-based map learning by means of a clustering of the PCA features extracted from a set of panoramic images into distinctive visual aspects. Valgren et al. (2008) study how to build a topological map of large indoor and outdoor environments using local features extracted from omnidirectional images and the epipolar constraint, and a clustering method to perform localization more efficiently.

In this paper we present a methodology to built a robust appearance-based topological map under changing lighting conditions and we extend this method to construct the topological map incrementally. The main advantage of our method comparing to batch methods is the possibility of constructing the map in real time while the robot is exploring the environment. Also, as we show throughout the paper, it avoids possible errors in the construction of the map.

The work is structured as follows. Section 2 describes the Fourier transform and its use with omnidirectional images. Section 3 makes a brief review of filtering techniques to remove the dependence on changes in the lighting conditions. Section 4 shows a method for batch topological mapping. Section 5 presents a technique for building topological maps incrementally. In section 6 we show the results of the experiments. Finally, we present the conclusions and future work in section 7.

2. FOURIER SIGNATURE WITH OMNIDIRECTIONAL IMAGES

To date, different description methods have been used in the context of omnidirectional robot vision. In this work, we make use of Fourier-based techniques. When we have an image $f(x,y)$ with N_x rows and N_y columns, we can obtain the most relevant information from the image by means of the Discrete Fourier Transform.

There are several possibilities, such as to implement the 2D Discrete Fourier Transform (Payá et al. 2009) or the Fourier Signature of the panoramic image (Menegatti et al. 2004). The Fourier Signature exploits better the invariance to ground-plane rotations in panoramic images. This transformation consists in expanding each row of the panoramic image $\{a_n\} = \{a_0, a_1, \ldots, a_{N_y-1}\}$ using the Discrete Fourier Transform into the sequence of complex numbers $\{A_n\} = \{A_0, A_1, \ldots, A_{N_y-1}\}$. The most important information is concentrated in the low frequency components of each row, so we can work only with the information from the k first columns in the Signature. Also, this feature presents rotational invariance. It is possible to prove that if each row of the original image is represented by the sequence $\{a_n\}$ and each row of the rotated image by $\{a_{n-q}\}$ (being q the amount of shift), when the Fourier Transform of the shifted sequence is computed, we obtain the same amplitudes A_k than in the non-shifted sequence, and there is only a phase change, proportional to the amount of shift q, (eq.1).

$$\Im\left[\left\{a_{n-q}\right\}\right] = A_k e^{-j\cdot\frac{2\pi qk}{N_y}}; \qquad k = 0,\ldots,N_y - 1 \qquad (1)$$

Thanks to this shift theorem, we can separate the computation of the robot position and the orientation. It is interesting to highlight also that the Fourier Signature is an inherently incremental method (what differs from the PCA Analysis, Kröse et al., 2004).

3. FILTERING TECHNIQUES USING PANORAMIC IMAGES

Depending on the lighting conditions of the environment, the appearance of an object in an image can vary strongly. It is therefore necessary to implement a mechanism that allows us to work independently of the lighting conditions of the environment.

Several researchers have studied how to get invariance with respect to the illumination of the scene in object recognition tasks. We have separated the different methods in two fields. The first one concerns the application of a bank of gradient (first derivative) or Laplacian (second derivative) filters. The second one consists in performing a Homomorphic filtering of the image separating the luminance from the reflectance component and thereby to control the influence of each component separately.

3.1 Edge detector

The main advantage of using a representation of the image edges resides mainly in the fact that we obtain a compact representation and that, in most cases, it is insensitive to changes in the lighting on the objects of the image.

An edge detection filtering can be carried out through the Prewitt gradient filter, based on the estimation of the modulus of the gradient using two masks of size 3x3 (h_1 in the x-axis and h_2 in the y-axis):

$$h_1 = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \quad h_2 = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \tag{2}$$

An evolution of the Prewitt Filter is the Sobel Filter that, apart from estimating the value of the modulus of the gradient, produces a smoothing of the image that may be beneficial, given the noisy behaviour that present the estimations based on the derivation of the image:

$$h_1 = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad h_2 = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{3}$$

The Laplacian of Gaussian operator is another method for detecting edges, which combines the effect of a Gaussian smoothing with the improvement in the location of the edge (null values in the second derivative). In this case it is only necessary to apply a mask:

$$h_2 = \begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix} \tag{4}$$

3.2 Homomorphic filter

A Homomorphic Filter can separate the components of luminance and reflectance of an image (Gonzalez et al., 1993). Thus it is possible to build a filter for each component separately, so we can control the influence of each component on the image appearance. It is possible to separate the luminance component from the reflectance component by computing the natural logarithm of the image:

$$\begin{aligned} f(x,y) &= i(x,y) \times r(x,y) \\ z(x,y) &= \ln(f(x,y)) \\ z(x,y) &= \ln(i(x,y)) + \ln(r(x,y)) \end{aligned} \tag{5}$$

Where $f(x,y)$ corresponds to the panoramic image that can be expressed as a multiplication of the luminance of the image $i(x,y)$ and the reflectance $r(x,y)$ components. Once the components are separated, we apply the 2D Discrete Fourier Transform. It is at this point that we can filter the image in the frequency domain:

$$\begin{aligned} \Im(z(x,y)) &= \Im(\ln(i(x,y))) + \Im(\ln(r(x,y))) \\ \Im(z'(x,y)) &= \Im(z(x,y)) \cdot \mathrm{H}(u,v) \end{aligned} \tag{6}$$

Where $\mathrm{H}(u,v)$ is the filter transfer function in the frequency domain. It will be necessary to perform the inverse process to obtain the filtered image in the spatial domain.

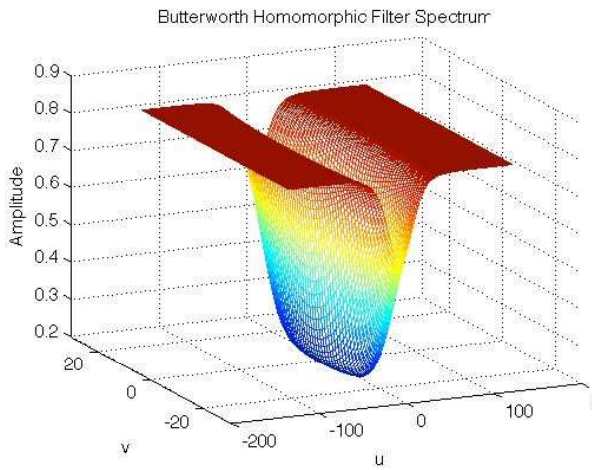

Fig. 1. Amplitude transfer function of a Homomorphic filter.

The low frequency components are associated with the illumination of the image and the high frequency ones with the reflectance of the image. So, to reduce the effects of changes in the illumination of the image, we apply a high pass filter constructed from a low pass filter, for the size of images we work with (56x256):

$$\begin{aligned} \mathrm{H}'_{hp}(u,v) &= 1 - \mathrm{H}_{lp}(u,v) \\ \mathrm{H}_{hp}(u,v) &= (\alpha_h - \alpha_l) \cdot \mathrm{H}'_{hp}(u,v) + \alpha_l \end{aligned} \tag{7}$$

Where $\mathrm{H}_{lp}(u,v)$ is the low pass filter transfer function in the frequency domain, α_h and α_l correspond to the maximum and minimum value of Homomorphic filter and $\mathrm{H}_{hp}(u,v)$ is the high pass filter transfer function in the frequency domain. We have used two families of filters, Butterworth and Gaussian. Fig. 1 shows the Homomorfic Filter Transfer Function from a Butterworth filter. The transfer functions are as follows:

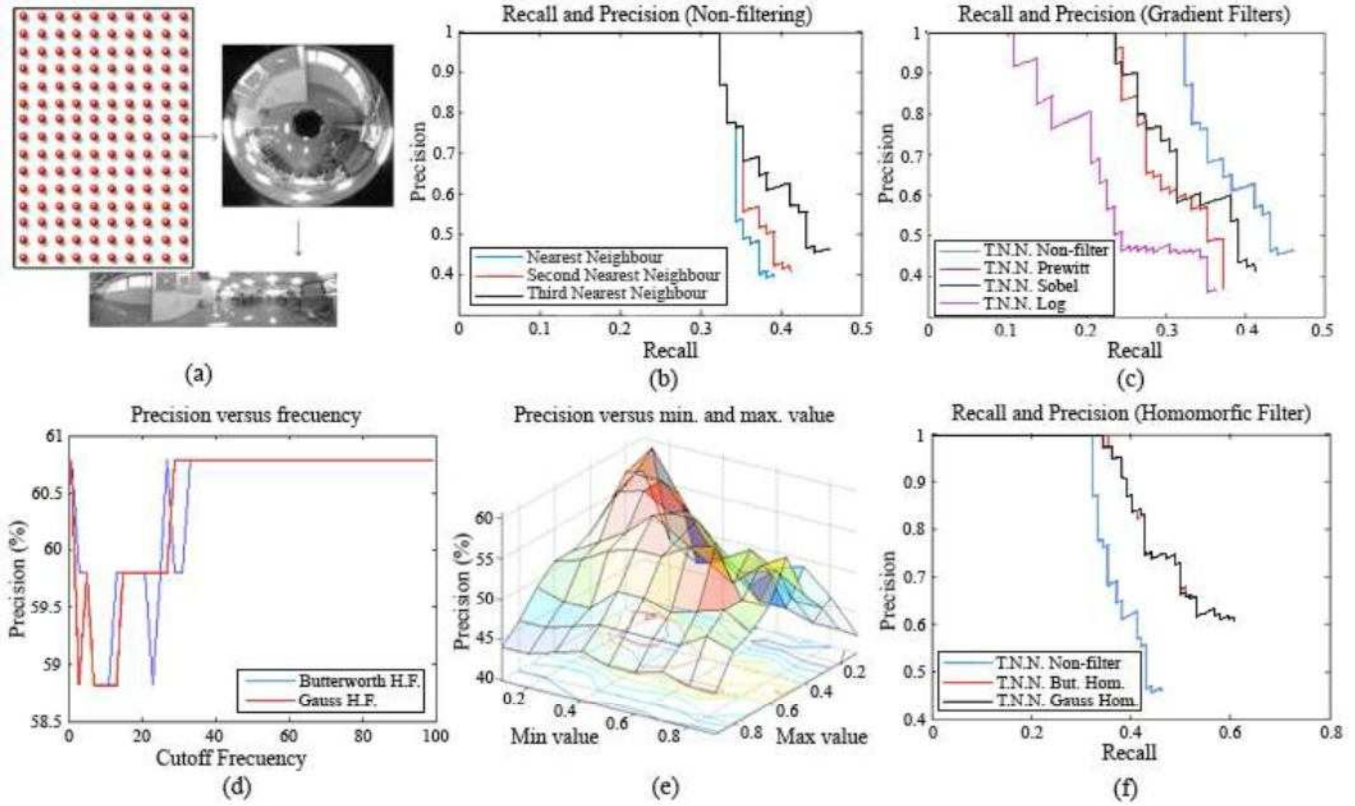

Fig. 2. (a) Grid of test images, and omnidirectional and panoramic images sample, (b) Precision versus Recall localization without filtering, (c) Precision versus Recall localization using Gradient Filters, (d) Precision in terms of frequency of the filters, (e) Precision in terms of maximum and minimum value of the filter, (f) Precision versus Recall localization using Homomorphic Filters.

$$
\begin{aligned}
D(u,v) &= \left(u^2+v^2\right)^{1/2} \\
\mathrm{H}_{Butt}(u,v) &= \frac{1}{1+\left[D(u,v)/D_0\right]^{2n}} \\
\mathrm{H}_{Gauss}(u,v) &= \exp\left(-\left[D(u,v)/D_0\right]^{2}\right)
\end{aligned}
\tag{8}
$$

Where $D(u,v)$ is the distance to the origin in the frequency domain, D_0 is the filter cut-off frequency to construct the low pass filter and n is the order of the filter.

3.3 Filtering techniques experiments

To test the robustness of the filtering methods we have built several maps. With this aim, we have captured several omnidirectional image sets in several predefined grids with different shapes and number of images, both in unstructured indoor environments (two laboratories and an office) and in structured indoor environments (two corridors and a hall). The most relevant features are shown in table 1. We can see a grid example on Fig. 2 (a).

Table 1. Relevant physical parameters of the image sets

Set	Size x	Size y	Resolution	Grid step
Lab. 1	10	15	56x256 pixels	30 cm
Lab. 2	10	20	56x256 pixels	50 cm
Office	6	8	56x256 pixels	50 cm
Hall	12	9	56x256 pixels	10 cm
Corr. 1	22	10	56x256 pixels	10 cm
Corr. 2	35	10	56x256 pixels	10 cm

To perform the filtering techniques experiments, we have used these grids and we have taken several sets with test images each, taken at different times of day and under different conditions of illumination (Fig. 3). In our experimental setup we used the test images to carry out a localization process within the previously created maps. We used the Euclidean distance between Fourier Signatures as a classificator. To compare the different methods of filtering we use *Recall and Precision* charts (Gil et al., 2009). The parameters are defined as follows:

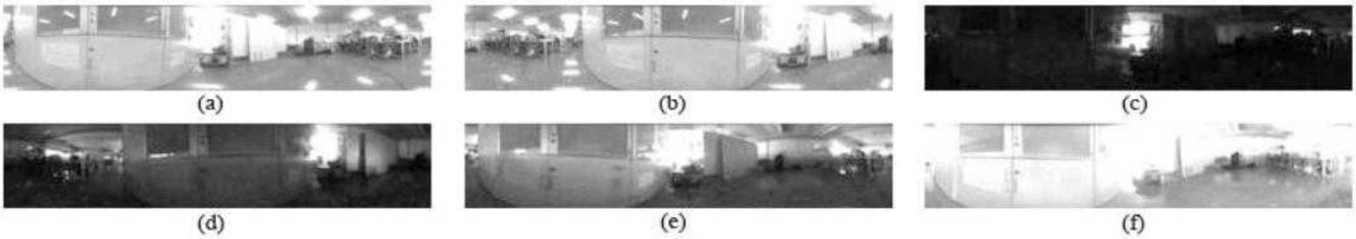

Fig. 3: (a) Test 1 (9:00, artificial light), (b) Test 2 (9:00, artificial light, 90 degrees rotation), (c) Test 3 (18:00, no light), (d) Test 4 (11:00, natural light, 90 degrees rotation), (e) Test 5 (13:00, daylight) and (f) Test 6 (16:00, daylight).

$$recall = \frac{\#\,correct\ matches\ retrieved}{\#\,total\ correct\ matches} \qquad precission = \frac{\#\,correct\ matches\ retrieved}{\#\,matches\ retrieved} \tag{9}$$

For the data association we use the minimum Euclidean distance, through the descriptors Nearest Neighbor (N.N.), Second Nearest Neighbor (S.N.N.) and Third Nearest Neighbor (T.N.N.). Fig. 2 (b) shows the results obtained when we perform a localization process without prior filtering. We can observe the improvement that occurs when we use the descriptor T.N.N.

In Fig. 2 (c) we can observe how worse results are obtained when we apply gradient-based filters. It reduces the accuracy of a 46.08% (no filter) to 41.18% (Sobel), a 37.25% (Prewitt), or at worst a 36.27% (Laplacian).

When working with Homomorphic filters the parameters of filters need to be previously adjusted. The behaviour of Homomorphic filter built using a Butterworth filter depends mainly on the cutoff frequency, the order of the filter and the maximum and minimum values of the filter. When we get the filter from a Gaussian filter, the most important parameters are the cutoff frequency and maximum and minimum values of the filter. As we can see in Fig. 2 (d) and Fig. 2 (e), both filters are more dependent on the maximum and minimum values, than on the cutoff frequency.

After exhaustive tests, the optimal parameters are a cutoff frequency of 50Hz, 3rd order Butterworth filter, homomorphic filter maximum value equal to 0.21 and minimum value equal to 0.20. Fig. 2 (f) shows how the accuracy in the localization within the map can be improved by means of a previous homomorphic filtering of the images. The accuracy in localization has increased from 46.08% (with no filter) to 60.78 % (with the homomorphic filter). We can also see how the results obtained with the Gaussian filter are almost identical to those obtained using the Butterworth filter.

4. TOPOLOGICAL MAPPING

To have a topological map from the environment, once we have constructed the database from the filtered Fourier Signatures of the grid images, it is necessary to estimate the geometric relationships between them. With this goal we use a graph model whose nodes represent positions and links represent the connectivity between them.

4.1 Mass-spring-damper model

The topological map is a graph whose nodes correspond to distinct locations in the environment and whose edges model the neighboring relations between the nodes. We have captured the image grid by teleoperating the robot through the environment to create the map. Once we have all the images, we have first implemented a method that allows us to create a topological map from them, without having into account the storage order. The method must be capable of ordering the captures and situating them in the corresponding place of the topological map.

To do this we make use of a method based on Hooke's law and Newton's second law, known as mass-spring-damper system (Menegatti et al., 2004). Fig. 4 shows an example of the physical principle to build the map. Each particle P_i is an image and the springs S_{ij} connecting the particles together represent the distances between images. Each particle of the system will be connected with other particles (with all of the nearest). To calculate the lengths of the springs of the system we use the Euclidean Distance between the Fourier Signature of stored images. When we let the system to evolve freely, it is expected to tend to a similar topology comparing to the real system.

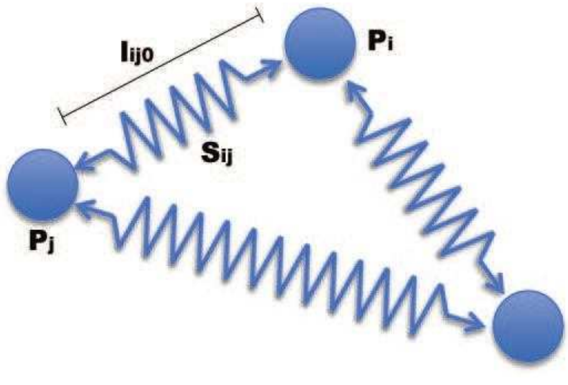

Fig. 4. Spring model for topological map.

To construct the mass-spring-damper system we have taken into account the following system of forces:

$$\begin{aligned}
&\vec{F}_i = \sum_{S_{ij}\in S}\left(-k_{ij}\cdot(l_{ij0}-l_{ij})-\kappa_{ij}\cdot(v_i-v_j)\right)\\
&\vec{a}_i = \vec{F}_i / m_i \rightarrow \dot{\vec{v}}_i = \vec{a}_i \rightarrow \dot{\vec{r}}_i = \vec{v}_i\\
&\vec{r}_i(t+\Delta T) = \vec{r}_i(t)+\vec{v}_i(t)\cdot\Delta T + 1/2\cdot\vec{a}_i(t)\cdot\Delta T^2\\
&\vec{v}_i(t+\Delta T) = \vec{v}_i(t)+\vec{a}_i(t)\cdot\Delta T
\end{aligned} \tag{10}$$

Where the first equation corresponds to Hooke's Harmonic Oscillator Law and depends both on the length of the spring l_{ij} and on the difference of velocities where k_{ij} is the elastic and κ_{ij} the damping constant. The second expression refers to Newton's second law and allows us to obtain the system motion equations from the force $\vec{F}_i$ provided by the Hooke's law and the mass m_i of the particle. To simplify the system we have used the same mass value for all particles. This value is equal to 1. Finally the last two equations show how to calculate the position $\vec{r}_i$ and velocity $\vec{v}_i$ of every particle of the system at each iteration.

It is interesting to highlight the importance of the parameter ΔT in the system relaxation time and in the final result. If ΔT takes a too large value, the system is very unstable and therefore it will be difficult to reach the steady-state. By contrast, if a too small value is chosen, it will take too long to reach the rest. This is the reason why we have achieved a compromise between speed and stability. To do this we set a maximum number of steps s_{tot} and we let ΔT be dependent on it:

$$\Delta T = \xi\cdot(1-\frac{s}{s_{tot}}) \tag{11}$$

Where s corresponds to the number of steps until a given time and ξ is a constant.

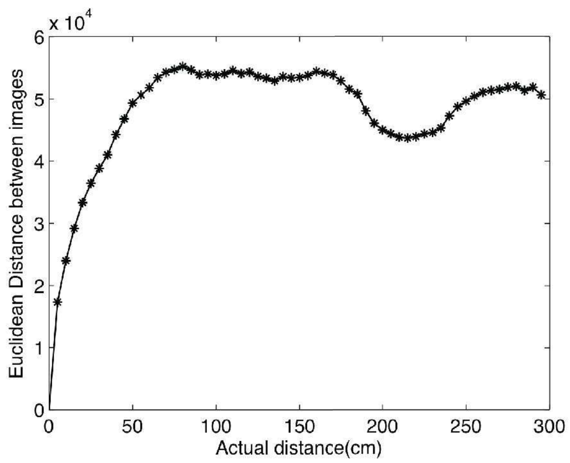

Fig. 5. Euclidean distance between the Fourier Signature of the images versus real geometric distance between the points where images were captured.

Another issue to consider is the value of the elastic constant k_{ij} of each spring system. As we can observe in Fig. 5, the Euclidean distance between the Fourier Signatures behaves approximately linear in the surroundings of the point where the image was captured, but this linearity disappears as we move away from it. To solve the problem we have taken elastic constants dependent on Euclidean distance L_2^{ij} between the Fourier projections.

5. INCREMENTAL TOPOLOGICAL MAPPING

One of the main problems we find when constructing a topological map from the stored database resides in the fact that the computational cost increases exponentially with the number of images captured, due to the growing number of forces on each particle of the mass-spring-damper system. Also we need to have all the images stored in the database to create the topological map, so it is only possible to build it in an offline process, once all the images have been captured.

To avoid this problem, it is interesting to exploit the benefits offered by working with the Fourier Signature. One of the most important features is the fact that the Fourier Signature is an inherently incremental method. Thus we can build the topological map incrementally and also in real time.

5.1 Incremental mass-spring-damper model

To build the incremental topological map we have used an adaptation of the system used in the previous section to construct the batch topological map. When we build the map incrementally we have several options. When a new image arrives, we can relax the whole system of particles or otherwise we can relax only the new particle with respect to other particles that are already in the system. After several experiments we reached the conclusion that the best option was a compromise between both of them. Every time we add a new particle to the system we allow this particle to relax while maintaining the position of other particles fixed. Once the particle is at rest, the whole system relaxes. In this way the system compensates the nonlinearity that occurs in the Euclidean distance as we move away from the new particle.

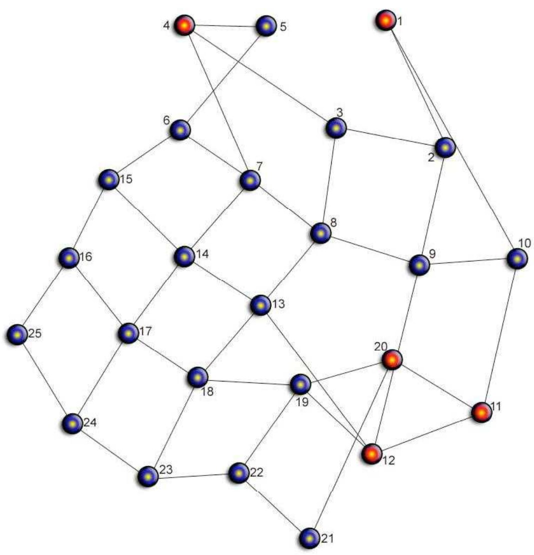

Fig. 6. False minimum in a square grid of 5x5 images for batch topological mapping.

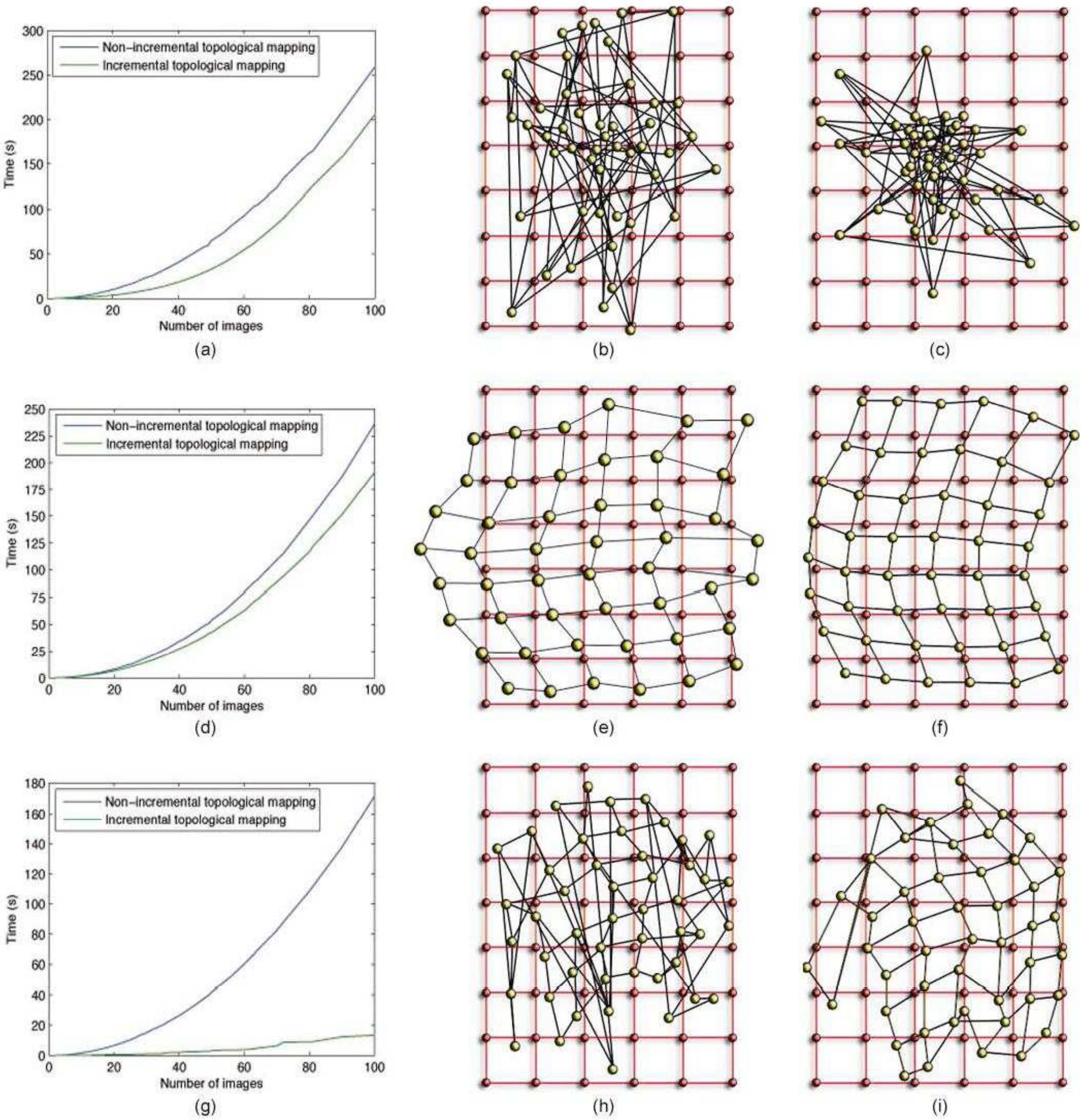

Fig. 7. (a) Time elapsed to build a non-incremental topological map (blue line) and an incremental topological map (green line), (b) comparison between the real map (red circles) and the topological map obtained by the non-incremental method (yellow circles), (c) comparison between the real topological map (red circles) and the topological map obtained by the incremental method (yellow circles), for ξ equal 0.5. (d), (e) and (f) show the same results for ξ equal 0.1 and (g), (h) and (i) for ξ equal 0.01.

Building incrementally the topological map, besides providing the benefits mentioned above, provides a very important advantage to the system: it behaves more stably and does not produce false minima in the relaxation of the system. Fig. 6 shows an example of a false minimum in a square grid of 5x5 images for batch topological mapping. False minima are a common problem in structured environments where visual appearance of far points may be similar (visual aliasing).

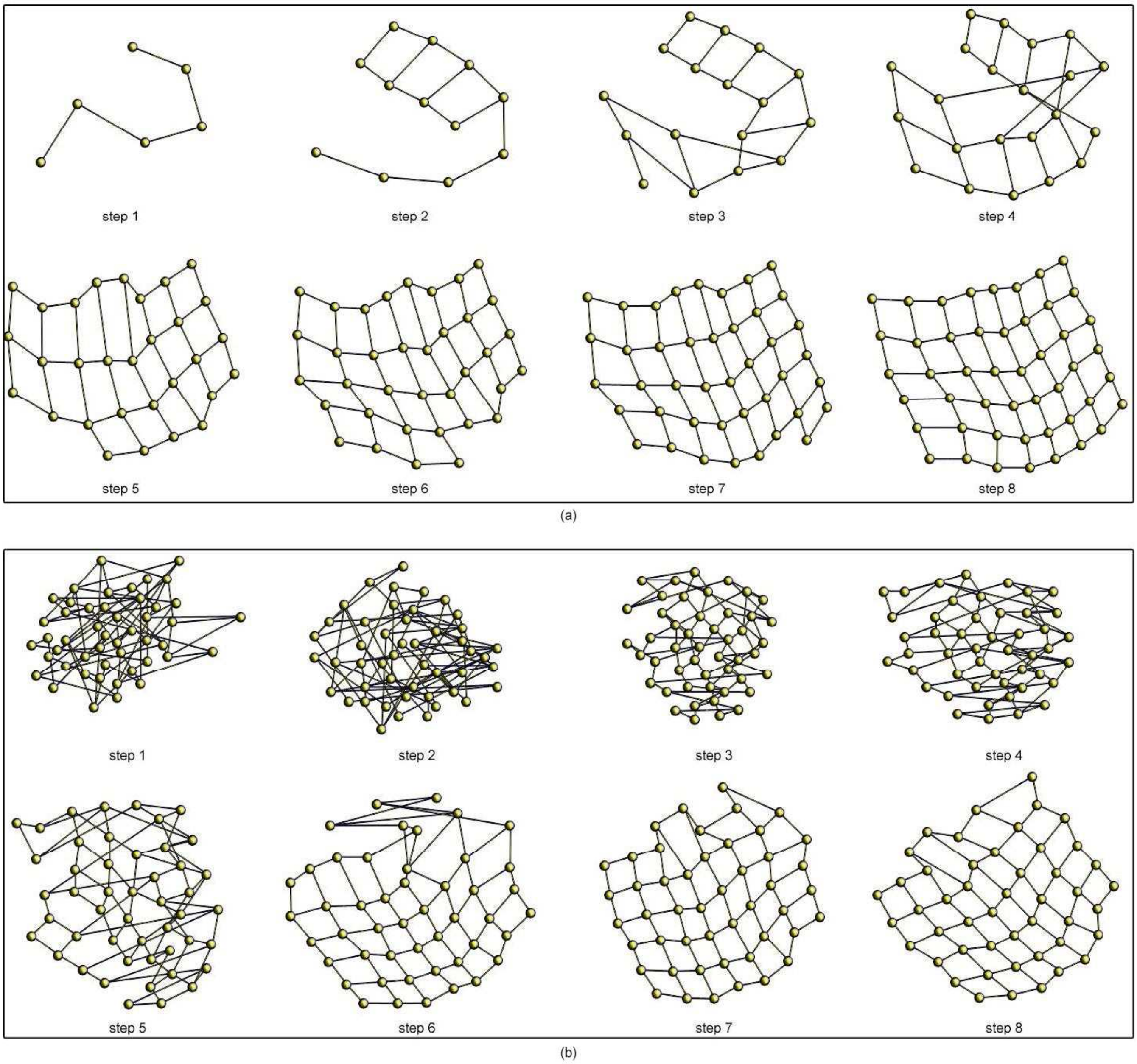

Fig. 8. (a) Example of the incremental topological mapping process with optimized parameters, (b) Example of the batch topological mapping process with optimized parameters.

6. EXPERIMENTAL RESULTS

In this section the results obtained from topological mapping experiments are presented. To perform the experiments we have used several sets of omnidirectional images with different topologies, varying the shape, the number of images and the distance between them (Table 1). Once we have obtained all the omnidirectional scenes, we have transformed them to panoramic images, we have filtered them (Homomorphic filter) and we have obtained the corresponding Fourier signature.

To calculate the distance for each spring of the mass-spring-damper system we have used the Euclidean distance L_2 between the main harmonics in the Fourier Signature of each image. As Payá et al. (2009) shows, it is desirable to reject the harmonics in the upper spectrum of the Fourier signature, thus we work only with the first 16 harmonics of each row of Fourier Signature.

Time consumption is used as a parameter to compare the two methods of topological mapping. Moreover, we have used the time constant ξ to check the dependence of both methods regarding the time to build the map and the accuracy of the resulting map. Taking it into account, we have compared different topologies obtained for each grid of images using both methods.

On Fig. 7 (a), (d) and (g) we can observe how, when we construct the topological map using the batch method, the computing time increases exponentially with the number of images because it increases the number of neighbors for each image and therefore a greater number of forces in the mass-spring-damper system must be computed at each iteration. On the other hand when we use the incremental method we observe that the time grows to a lesser extent. As we increase ξ, the computation times grow, but as we can observe on Fig. 7 (b), (c), (e), (f), (h) and (i), when we use too high or too low values for ξ, the shape obtained does not represent the real shape of the map. That is why we must reach a compromise between the computation times versus the accuracy of the shape obtained comparing to the real shape.

As we can see on Fig. 7 (e) and Fig. 7 (f), with our method we can obtain a topological map that represents the shape of the real map of the environment by tuning correctly the value of ξ. Fig. 7 (e) shows the topological map obtained by applying batch topological mapping and Fig. 7 (f) shows the topological map obtained by applying incremental topological mapping. The Incremental approach, apart from improving computing time, allows us to obtain a topological map that approximates better the topology of the real map of the environment. We must also take into consideration that during the course of the experiments, when we used the batch method often false minimum appeared. However, by building the topological map incrementally a correct topological map was always obtained. Finally we can see on Fig. 8 an example of both methods with optimized parameters for proper operation. Fig. 8 (a) shows some intermediate steps of the incremental topological mapping process, once the process concluded, the shape obtained is similar to the actual shape. Furthermore, we can see how thanks to the way the map grows, the possible false minima are corrected when we add new images. When we use are a batch topological mapping method (Fig. 8 (b)) until the last step we do not get a similar shape to the actual shape of the map.

7. CONCLUSIONS AND FUTURE WORK

The purpose of this paper is to show how it is possible to construct a topological map of the environment from a set of omnidirectional images (views) obtained on a grid within the environment using only the appearance of each omnidirectional image without extracting neither salient points nor regions or information from the robot odometry.

We have built the database by applying a compression process to the visual information to reduce the computational cost. To obtain a robust map against lighting changes in the environment, we have performed a study of different techniques to filter this dependence. Finally we have decided to apply a Homomorphic filter to panoramic images. To compress the information we have used the Fourier Signature due the fact that it presents a good performance in terms of amount of memory and computation time needed to build the database and it is also invariant to ground-plane rotations and an inherently incremental method.

We have presented two methods for the creation of a robust topological map of the real environment. As shown, the application of the first method (batch mapping) allows us to obtain a topological map of the environment that in most cases corresponds roughly with its actual shape, but sometimes erroneous topologies are presented. On the other hand, applying an incremental topological mapping allow us to obtain a topological map of the environment that in all cases corresponds roughly with the actual shape and also reduces the computation time compared to the previous method. The second method also allows us to build the map online, while the robot is exploring the environment.

This work opens the door to new applications of appearance-based methods in mobile robotics. As we have shown, the topological map created is robust against changes of lighting conditions, and permits us to know the actual topology of the map. If we know the topology of the environment and we know which node is the robot situated in, we will be able to create an algorithm that allows the robot to reach the objective points travelling the shortest path.

We are currently studying the possibility of using appearance-based Monte Carlo localization and mapping methods as well as appearance-based SLAM methods.

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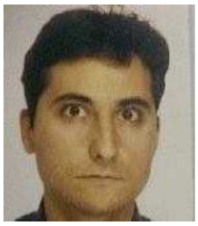

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