APPEARANCE-BASED DENSE MAPS CREATION
Comparison of Compression Techniques with Panoramic Images

Luis Payá, Lorenzo Fernández, Óscar Reinoso, Arturo Gil and David Úbeda
Departamento de Ingeniería de Sistemas Industriales, Miguel Hernández University
Avda. de la Universidad s/n. 03202, Elche (Alicante), Spain

Keywords: Robot Mapping, Appearance-based Methods, Omnidirectional Vision, Spatial Localization.

Abstract: The visual information captured by omnidirectional systems is very rich and it may be very useful for a robot to create a map of an environment. This map could be composed of several panoramic images taken from different points of view in the environment, and some geometric relationships between them. To carry out any task, the robot must be able to calculate its position and orientation in the environment, comparing his current visual information with the data stored in the map. In this paper we study and compare some approaches to build the map, using appearance-based methods. The most important factor of these approaches is the kind of information to store in order to minimize the computational cost of the operations. We have carried out an exhaustive experimentation to study the amount of memory each technique requires to build the map, and the time consumption to create it and to carry out the localization process inside it. Also, we have tested the accuracy to compute the position and the orientation of a robot in the environment.

1 INTRODUCTION

When a robot or a team of robots have to carry out a task in an environment, an internal representation of it is usually needed so that the robot can estimate its initial position and orientation and navigate to the target points. Omnidirectional visual systems are a widespread sensor used with this aim due to their low cost and the richness of information they provide. Extensive work has been carried out in this field, using the extraction of some natural or artificial landmarks from the images to build the map and carry out the localization of the robot (Thrun, 2003). However, these processes can be carried out just working with the images as a whole, without extracting landmarks nor salient regions.

These appearance-based approaches are useful when working in unstructured environments where it may be hard to create appropriate models for recognition, and offer a systematic and intuitive way to build the map. Nevertheless, as we do not extract any relevant information from the images, an important problem of such approaches is the high computational cost they suppose.

Different researchers have shown how a manifold representation of the environment using some compression techniques can be used. A widely extended method is PCA (Principal Components Analysis), as (Kröse, 2004) does to create a database using a set of views with a probabilistic approach for the localization inside this database. Conventional PCA methods do not take profit of the amount of information that omnidirectional cameras offer, because they cannot deal with rotations in the plane where the robot moves. (Uenohara, 1998) studied this problem with a set of rotated images, and (Jogan, 2000) applied these concepts to an appearance-based map of an environment. The approach consists in creating an eigenspace that takes into account the possible rotations of each training image, trying to keep a good relationship between amount of memory, time and precision of the map. Other works rely on Fourier Transform to compress the information, as (Menegatti, 2004), that defines the concept of Fourier Signature and presents a method to build the map and localize the robot inside it, or (Rossi, 2008), that uses spherical Fourier transform of the omnidirectional images.

The representation of an environment with appearance-based approaches can be separated in a low-level map, that represents a room with several images and a high-level map, which tries to modelize the spatial relationships between rooms and between rooms and corridors. (Booij, 2007)

Payá L., Fernández L., Reinoso Ó., Gil A. and Úbeda D. (2009).
APPEARANCE-BASED DENSE MAPS CREATION - Comparison of Compression Techniques with Panoramic Images.
In *Proceedings of the 6th International Conference on Informatics in Control, Automation and Robotics - Robotics and Automation*, pages 250-255
DOI: 10.5220/0002210502500255

shows how these concepts can be implemented through a graph representation whose nodes are the images and whose links denote similarity between them and (Vasudevan, 2007) uses a hierarchy of cognitive maps where place cells represent the scenes through a PCA compression and the information provided by a compass is used to compute the connectedness between them. Appearance-based techniques constitute a basis framework to other robotics applications, as in route-following, as (Payá, 2008) shows.

2 REVIEW OF COMPRESSION TECHNIQUES USING OMNIDIRECTIONAL IMAGES

In this section, we outline some techniques to extract the most relevant information from a set of panoramic images, captured from several positions in the environment to map.

2.1 PCA-based Techniques

When we have a set of N images with M pixels each, $\vec{x}^j \in \Re^{Mx1};\ j = 1 \ldots N$, each image can be transformed in a feature vector (also named 'projection' of the image) $\vec{p}^j \in \Re^{Kx1};\ j = 1 \ldots N$, being K the PCA features containing the most relevant information of the image, $K \le N$ (Kirby, 2000). The PCA transformation can be computed from SVD of the covariance matrix C of the data matrix, X that contains all the training images arranged in columns (with the mean subtracted). If V is the matrix containing the K principal eigenvectors and P is the reduced data of size K x N, the dimensionality reduction is done by $P = V^T \cdot X$, where the columns of P are the projections of the training images, $\vec{p}^j$.

However, the database built in this way contains information only for the orientation the robot had when capturing each image but not for all the possible orientations on each point. (Jogan, 2000) presents a methodology to include this orientation information but acquiring just one image per position. When we work with panoramic images, we can artificially rotate them by just shifting the rows. This way, from every image $\vec{x}^j \in \Re^{Mx1};\ j = 1 \ldots N$ we can build a submatrix $\mathbf{X}^j \in \Re^{MxQ}$ where the first column is the original image, and the rest of them are the shifted versions of the original one, with a $2\pi/Q$ rotation between them.

When having a set of N training images, the data matrix is composed of N blocks, and the covariance matrix has the following form:

$$\mathbf{X} = \left[\mathbf{X}^1 \middle| \mathbf{X}^2 \middle| \ldots \middle| \mathbf{X}^N\right]$$
$$\Rightarrow \quad C = X^T X = \begin{bmatrix} X^{11} & X^{12} & \ldots & X^{1N} \\ X^{21} & X^{22} & \ldots & X^{2N} \\ \vdots & \vdots & \ddots & \vdots \\ X^{N1} & X^{N2} & \ldots & X^{NN} \end{bmatrix} \tag{1}$$

Where $\mathbf{X}^{ik} \in \Re^{QxQ}$ are circulant blocks. The eigenvectors of a general circulant matrix are the Q basis vectors from the Fourier matrix (Ueonara, 1998):

$$\vec{\omega}_i = \begin{bmatrix} 1 & \gamma^i & \gamma^{2i} & \ldots & \gamma^{(Q-1)i} \end{bmatrix}^T$$
$$i = 0, \ldots, Q, \quad \gamma = e^{-2\pi j/Q}, \quad j = \sqrt{-1} \tag{2}$$

This property allows us to compute the eigenvectors without necessity of performing the SVD decomposition of C (this would be a computationally very expensive process). This problem can be solved by carrying out Q decompositions of order N. The eigenvectors of C shall be found among vectors of the form:

$$\vec{v}_i = \left[\alpha_i^1 \vec{\omega}_i^T, \alpha_i^2 \vec{\omega}_i^T, \ldots, \alpha_i^N \vec{\omega}_i^T\right]^T, i = 0, \ldots, N \tag{3}$$

where $\vec{\alpha}_i = \left[\alpha_i^1, \alpha_i^2, \ldots, \alpha_i^N\right]^T, i = 0, \ldots, N$ are the eigenvectors of the following matrix:

$$\Lambda = \begin{bmatrix} \lambda_i^{11} & \lambda_i^{12} & \ldots & \lambda_i^{1N} \\ \lambda_i^{21} & \lambda_i^{22} & \ldots & \lambda_i^{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_i^{N1} & \lambda_i^{N2} & \ldots & \lambda_i^{NN} \end{bmatrix} \tag{4}$$

where λ_i^{jk} is an eigenvalue of X^{jk} corresponding to the eigenvector $\vec{\omega}_i$. As the matrix Λ has N eigenvectors, if we repeat this process for every $\vec{\omega}_i$ we can obtain $Q \cdot N$ linearly independent eigenvectors of C.

2.2 Fourier-based Techniques

2.2.1 2D Discrete Fourier Transform

When we have an image $f(x,y)$ with N_y rows and N_x columns, the 2D discrete Fourier Transform is defined through:

$$\Im[f(x,y)] = F(u,v) = \\ = \frac{1}{N_y}\sum_{x=0}^{N_x-1}\sum_{y=0}^{N_y-1} f(x,y)\cdot e^{-2\pi j\left(\frac{ux}{N_x}+\frac{vy}{N_y}\right)} \quad (5)$$

$$u = 0,\ldots,N_x-1, v = 0,\ldots,N_y-1$$

The components of the transformed image are complex numbers so it can be split in two matrices, one with the modules (power spectrum) and other with the angles. The most relevant information in the Fourier domain concentrates in the low frequency components. Furthermore, removing high frequency information can lead to an improvement in localization because these components are more affected by noise. Another interesting property when we work with panoramic images is the rotational invariance, which is reflected in the shift theorem:

$$\Im[f(x-x_0, y-y_0)] = F(u,v)\cdot e^{-2\pi j\cdot\left(\frac{ux_0}{N_x}+\frac{vy_0}{N_y}\right)} \quad (6)$$

$$u = 0,\ldots,N_x-1, v = 0,\ldots,N_y-1$$

According to this property, the power spectrum of the rotated image remains the same of the original image and only a change in the phase of the components of the transformed image is produced, whose value depends on the shift on the x-axis (x_0) and the y-axis (y_0). It means that when two images are acquired from close points of the environment but with different headings for the robot, then, the power spectrum is very similar, and studying the difference in phases we could estimate the angle between the two orientations, using eq. (6).

2.2.2 Fourier Signature of the Image

If we work with panoramic images, we can use another Fourier-based compact representation that takes profit of the shift theorem applied to panoramic images (Menegatti, 2004). It 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 $\{A_n\} = \{A_0, A_1, \ldots, A_{N_y-1}\}$.

This Fourier Signature presents the same properties as the 2D Fourier Transform. The most relevant information concentrates in the low frequency components of each row, and it presents rotational invariance. However, it exploits better this invariance to ground-plane rotations in panoramic images. These rotations lead to two panoramic images which are the same but shifted along the horizontal axis (fig. 1). Each row of the first image can be represented with the sequence $\{a_n\}$ and each row of the second image will be the sequence $\{a_{n-q}\}$, being q the amount of shift, that is proportional to the relative rotation between images. The rotational invariance is deducted from the shift theorem, which can be expressed as:

$$\Im[\{a_{n-q}\}] = A_k e^{-j\frac{2\pi qk}{N_y}}; \qquad k = 0, \ldots, N_y - 1 \quad (7)$$

where $\Im[\{a_{n-q}\}]$ is the Fourier Transform of the shifted sequence, and A_k are the components of the Fourier Transform of the non-shifted sequence. According to this expression, the amplitude of the Fourier Transform of the shifted image is the same as the original transform and there is only a phase change, proportional to the amount of shift q.

Figure 1: A robot rotation on the ground plane produces a shift in the panoramic image captured.

3 MAP BUILDING

To carry out the experiments, we have captured a set of omnidirectional images on a pre-defined 40x40 cm grid in an indoor environment, including an unstructured room (a laboratory) and a structured one (a corridor). We work with panoramic images with size 56x256 pixels. Once we have all the panoramic images, we have used the compression methods exposed in the previous section. Fig. 2(a) shows a bird's eye view of the grid used to take the images and two examples of panoramic images.

Before using the compression methods, a normalisation and a filtering process have been carried out to make the map robust to changes in illumination. There have been significant differences when using each one of the compression methods, regarding the elapsed time and the amount of memory the map takes up once it is built.

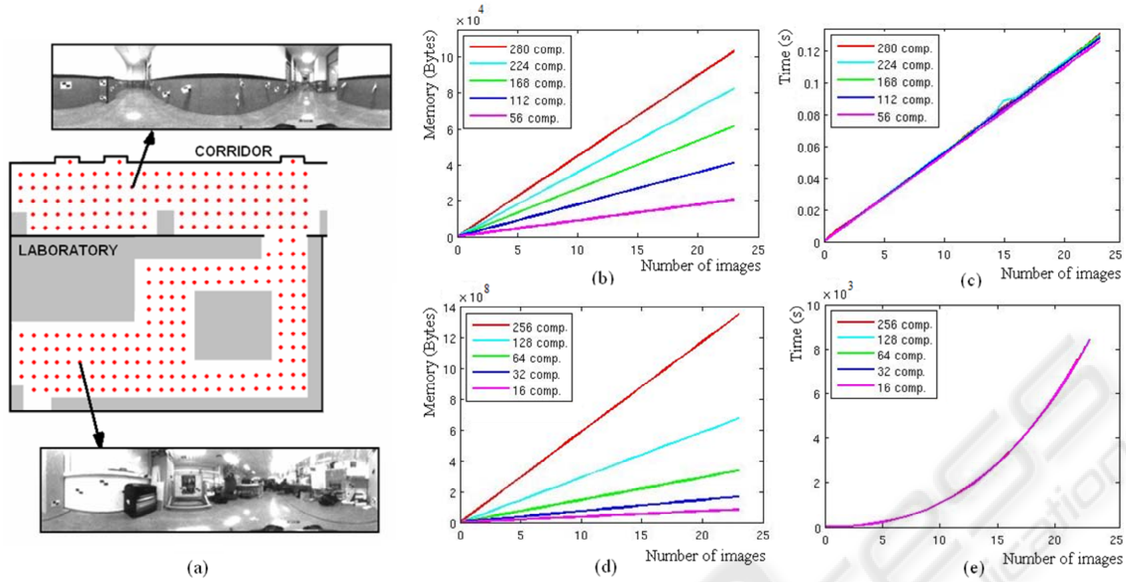


Figure 2: (a) Grid used to capture the training set of images, (b) amount of memory taken up and (c) time elapsed to build the map with the Fourier-based approaches, (d) amount of memory and (e) time elapsed with the PCA-based approach.

Fig. 2(b) shows the amount of memory the map constructed takes up, depending on the number of images in the map, and the number of Fourier Components we retain (those of lower frequency). When we work with the Fourier Signature, taking 224 components implies we retain 4 Fourier Components per row (56 rows in the image). In the case of 2D Fourier transform, 224 components means we take the firs 7 rows and 32 columns (where the main information is concentrated).

Fig. 2(c) shows the elapsed time to build the database, depending on the number of images in the map and the number of Fourier components we retain. The time elapsed is very similar when we use the Fourier Signature and the 2D Fourier Transform. On the other hand, fig. 2(d) and 2(e) show the results when using the PCA compression technique for spinning images. Fig 2(d) shows the amount of memory required. The PCA map is composed of the matrix $V \in C^{KxM}$, which contains the K main eigenvectors and the projections of the training images $\vec{p}_j \in C^{Kx1};\ j = 1 \ldots N$.

Although the training images have been artificially rotated to add the orientation information in the database, it is not necessary to store the projections of all the rotated images but only the projections of one image per training position. This is due to the fact that a rotation in the image results in the change of angle of the PCA coefficients of this image, but not in the module. So, if we have the coefficients for one representative viewpoint, the coefficients of the rotated images can automatically be generated through a rotation in the complex plane. So the module of the projections can be used to compute the position of the robot, and the phase is useful to know the orientation. Anyway, as we can see on fig. 2, PCA is a computationally more expensive process comparing to Fourier Transform.

4 LOCALIZATION AND ORIENTATION RECOVERING

To test the validity of the previous maps, the robot has captured several test images in some half-way points among those stored in the map. We have captured two sets of test images, the first one, at the same time we took the training set and the second one a few days later, in different times of the day (with varying illumination conditions) and with changes in the position of some objects. The objective is to compute the position and orientation of the robot when it took the test images, just using the visual information in the maps.

4.1 PCA-based Techniques

The PCA map is made up of the matrix $V \in C^{KxM}$, which contains the K main eigenvectors and the projections of the training images $\vec{p}^{\,j} \in C^{Kx1}$ (one per position, as explained in the previous section), that have been decomposed in two vectors, $\vec{p}_m^{\,j} \in R^{Kx1}$ containing the modules of the components of the projections and $\vec{p}_{ph}^{\,j} \in R^{Kx1}$ containing the phases.

To compute the location where the robot took each test image, we have to project the test image $\vec{x}^i \in R^{Mx1}$ onto the eigenspace, $\vec{p}^{\,i} = V^T \cdot \vec{x}^i \in C^{Kx1}$. Then, we compute the vector of modules $\vec{p}_m^{\,i} \in R^{Kx1}$ and compare it with all the vectors $\vec{p}_m^{\,j}$ stored in the map. The criterion used is the Euclidean distance. The corresponding position of the robot is extracted as the best matching. Once this position is known, we make use of the phases vector $\vec{p}_{ph}^{\,i}$ to compute the orientation of the robot.

Table 1 shows the results we have obtained when computing the position and the orientation when the training set is taken over a 30x30 cm grid and table 2 shows the same results for an 40x40 cm grid, depending on the number of eigenvectors (*K*) we retain. In these tables, p_1 is the probability that the best match is the actually nearest image (geometrically), p_2 is the probability that the best match is one of the two actually nearest images, and p_3 is the probability it is one of the three nearest images. At last, e_θ is the average error in the orientation estimation.

Table 1: Accuracy in the estimation of the position and orientation with PCA methods. 30x30 cm grid training set.

K	p_1	p_2	p_3	e_θ
112	81.8	96.7	97.1	3.21º
224	82.6	96.8	98.8	2.89º
448	87.2	96.8	98.8	5.29º

Table 2: Accuracy in the estimation of the position and orientation with PCA methods. 40x40 cm grid training set.

K	p_1	p_2	p_3	e_θ
112	96.3	97.1	98.4	8.07º
224	96.7	97.5	99.3	5.95º
448	97.9	98.8	99.5	4.79º

Fig. 3(a) shows the time taken up by this method to compute the position and orientation, depending of the number of images stored in the map, and the number of eigenvectors.

4.2 Fourier-based Techniques

To compute the position and orientation of the robot for each test image, we compute the Fourier Transform (with the two methods described in the previous section) and then, we compute the Euclidean distance of the power spectrum of the test image with the spectra stored in the map. The best match is taken as the current position of the robot.

On the other hand, the orientation is computed with eq. (6), when we work with 2D Discrete Fourier Transform (assuming $y_0 = 0$) and with the expression (7), when we work with the Fourier Signature. We obtain a different angle per row so we have to compute the average angle. Tables 3 and 4 show the accuracy we obtain in position and orientation estimation with the Fourier methods.

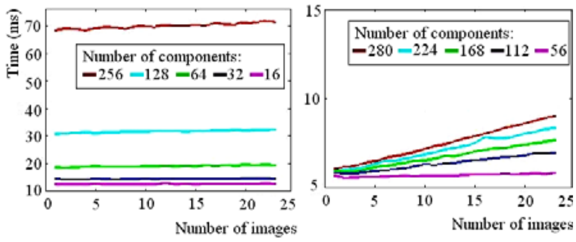
Table 3: Accuracy in the estimation of the position and orientation. Fourier methods. 30x30 cm grid training set.

K	p_1	p_2	p_3	e_θ
2x56	76.5	94.6	96.3	3.13º
4x56	78.5	95.5	97.5	3.04º
8x56	83.9	97.4	98.4	2.91º
16x56	85.5	98.4	98.4	2.89º

Table 4: Accuracy in the estimation of the position and orientation. Fourier methods. 40x40 cm grid training set.

K	p_1	p_2	p_3	e_θ
2x56	94.2	96.7	97.2	4.36
4x56	94.6	97.5	98.3	4.35
8x56	96.7	98.8	100	4.40
16x56	97.5	99.6	100	4.37

Fig. 3(b) shows the time elapsed since the robot captures the omnidirectional image until the position and orientation of the robot are obtained, depending on the number of images stored in the map and the number of Fourier components we retain. This approach clearly outperforms the PCA methods in accuracy and time consumption.



(a) (b)

Figure 3: Time consumption to compute position and orientation with (a) PCA and (b) Fourier methods.

5 CONCLUSIONS

In this work, we have exposed the principles of the creation of a dense map of a real environment, using omnidirectional images and appearance-based methods. We have presented three different methods to compress the information in the map. The mathematical properties of these methods together with the rich information the omnidirectional images pick up from the environment permit the robot to compute its position and orientation into the map.

The Fourier Transform method (both the 2D Discrete Fourier Transform and the Fourier Signature) has proved to be a good method to compress the information comparing to PCA regarding both the time and the amount of memory, and the accuracy in position and orientation estimation. Another important property is that the Fourier Transform is an inherently incremental method. When we work with PCA, we need to have all the training images available before carrying out the compression so this method cannot be applied to tasks that require an incremental process (e.g. a SLAM algorithm where the information of the new location must be added to the map while the robot is moving around the environment). The Fourier Transform does not present this disadvantage because the compression of each image is carried out independently. These properties make it applicable to future tasks where the robots have to add new information to the map and localize themselves in real time.

This work opens the door to new applications of the appearance-based methods in mobile robotics. As we have shown, the main problem these methods present is the high requirements of memory and computation time to build the database and make the necessary comparisons to compute the position and orientation of the robot. Once we have studied in deep some methods to compress the information and separate the calculation of position and orientation, the next step should be to test their robustness to changes in illumination and in the position of some objects in the scene. Also, their robustness and simplicity make them applicable to the creation of more sophisticated maps, where we have no information of the position the robot had when he took the training images.

ACKNOWLEDGEMENTS

This work has been supported by the Spanish government through the project DPI2007-61197. ‘Sistemas de percepción visual móvil y cooperativo como soporte para la realización de tareas con redes de robots’.

REFERENCES

Artac, M.; Jogan, M. & Leonardis, A., 2002. Mobile Robot Localization Using an Incremental Eigenspace Model, In *Proceedings of IEEE International Conference on Robotics and Automation*, Washington, USA, pp. 1205-1030, IEEE.

Booij, O., Terwijn, B., Zivkovic, Z., Kröse, B., 2007. Navigation using an Appearance Based Topological Map. In *IEEE International Conference on Robotics and Automation*, pp. 3297-3932 IEEE Press, New York.

Jogan, M., Leonardis, A., 2000. Robust Localization Using Eigenspace of Spinning-Images. In *Proc. IEEE Workshop on Omnidirectional Vision*, Hilton Head Island, USA, pp. 37-44, IEEE.

Kirby, M., 2000. *Geometric data analysis. An empirical approach to dimensionality reduction and the study of patterns*, Wiley Interscience.

Kröse, B., Bunschoten, R., Hagen, S., Terwijn, B. Vlassis, N., 2004. Household robots: Look and learn. In *IEEE Robotics & Automation magazine*. Vol. 11, No. 4, pp. 45-52.

Menegatti, E.; Maeda, T. Ishiguro, H., 2004. Image-based memory for robot navigation using properties of omnidirectional images. In *Robotics and Autonomous Systems*. Vol. 47, No. 4, pp. 251-276.

Payá, L., Reinoso, O., Gil, A., Sogorb. J., 2008. Multi-robot route following using omnidirectional vision and appearance-based representation of the environment. In *Lecture Notes in Artificial Intelligence. Hybrid Artificial Intelligence Systems*, Vol. 5271, pp. 680-687 Springer.

Rossi, F., Ranganathan, A., Dellaert, F., Menegatti, E., 2008. Toward topological localization with spherical Fourier transform and uncalibrated camera. In *Proc. Int. Conf. on Simulation, Modeling and Programming for Autonomous Robots*. Venice (Italy), pp. 319-330.

Thrun, S., 2003. Robotic Mapping: A Survey, In *Exploring Artificial Intelligence in the New Milenium*, pp. 1-35, Morgan Kaufmann Publishers, San Francisco, USA.

Ueonara, M., Kanade, T, 1998. Optimal approximation of uniformly rotated images: relationship between Karhunen-Loeve expansion and Discrete Cosine Transform. In *IEEE Transactions on Image Processing*. Vol. 7, No. 1, pp. 116-119.

Vasudevan, S., Gächter, S., Nguyen, V., Siegwart, R., 2007. Cognitive maps for mobile robots – an object based approach. In *Robotics and Autonomous Systems*. Vol. 55, No. 1, pp. 359-371.