

VISUAL MAP BUILDING AND LOCALIZATION WITH AN APPEARANCE-BASED APPROACH

Comparisons of Techniques to Extract Information of Panoramic Images

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Abstract: Appearance-based techniques have proved to constitute a robust approach to build a topological map of an environment using just visual information. In this paper, we describe a complete methodology to build appearance-based maps from a set of omnidirectional images captured by a robot along an environment. To extract the most relevant information from the images, we use and compare the performance of several compressing methods. In this analysis we include their invariance against rotations of the robot on the ground plane and small changes in the environment. The main objective consists in building a map that the robot can use in any application where it needs to know its position and orientation within the environment, with minimum memory requirements and computational cost but with a reasonable accuracy. This way, we present both a method to build the map and a method to test its performance in future applications.

1 INTRODUCTION

The applications that require the navigation of a robot through an environment need the use of an internal representation of it. Thanks to it, the robot can estimate its position and orientation regarding the map it has with the information captured by the sensors the robot is equipped with. Omnidirectional visual systems can be stood out due to the richness of the information they provide and their relatively low cost. Classical researches into mobile robots provided with vision systems have focused on the extraction of natural or artificial landmarks from the image to build the map and carry out the localization of the robot (Thrun, 2003). Nevertheless, it is not necessary to extract such kind of landmarks to recognize where the robot is. Instead of this, we can process the image as a whole. These appearance-based approaches are an interesting option when dealing with unstructured environments where it may be hard to find patterns to recognize the scene. With these approaches, the comparisons are made using the whole information of the scenes. As a disadvantage, we have to work with a huge amount of information, thus having a high computational cost, so we need to study compression techniques.

There are several researches that show compression

techniques that can be used. For example, PCA (Principal Components Analysis) is a widely used method that has demonstrated being robust applied to image processing, (Krose et al., 2007). Due to the fact that conventional PCA is not a rotational invariant method, other authors introduced a PCA approach that, although being computationally heavier, takes into account the images with diverse orientations (Jogan and Leonardis, 2000). There are authors that use the Fourier Transform as a generic method to extract the most relevant information of an image. In this field, (Menegatti et al., 2004) defines the Fourier Signature, which is based on the 1D Discrete Fourier Transform of the image rows and gets more robustness dealing with different orientation images. On the other hand, (Dalal and Triggs, 2005) used a method based on the Histogram of Oriented Gradients (HOG) to the pedestrian detection, proving that it could be a useful descriptor for computer vision and image processing using the objects' appearance.

(Paya et al., 2009) present a comparative study of appearance-based techniques. We extend this study, taking into account three different methods: Fourier Signature, PCA over Fourier Signature and HOG.

2 REVIEW OF COMPRESSION TECHNIQUES

In this section we summarize some techniques to extract the most relevant information from a database made up of panoramic images trying to keep the amount of memory to a minimum.

2.1 Fourier-based Techniques

As shown in (Paya et al., 2009) it is possible to represent an image using the Discrete Fourier Transform of each row. Taking profit of the Fourier Transform properties, we just keep the first coefficients to represent each row since the most relevant information concentrates in the low frequency components of the sequence. Moreover, as we are working with omnidirectional images, when the Fourier Transform of each row is computed, another very interesting property appears: rotational invariance. Due to the fact that the rotation of a panoramic image is represented as a shift of its columns, the Fourier Transform component's module will be the same. So, the amplitude of the transforms is the same as the original, and just the phase changes. Therefore, we can find out the relative rotation of two images by comparing its Fourier coefficient phases.

2.2 PCA over Fourier Signature

PCA-based techniques have proved to be a very useful compressing methods. They make possible that, having a set of N images with M pixels each, $\vec{x}^j \in \mathcal{R}^{M \times 1}$, $j = 1 \dots N$, we could transform each image in a feature vector (also named projection of the image) $\vec{p}^j \in \mathcal{R}^{k \times 1}$, $j = 1 \dots N$, being K the PCA features containing the most relevant information of the image, $k \leq N$. However, if we apply PCA directly over the matrix that contains the images, we obtain a database with information just with the orientation of the robot when capturing those images but not for other possible orientations. What we propose in this point is to transform the Fourier Signature components instead of the image, obtaining the compression of rotational invariant information, joining the advantages of PCA and Fourier techniques.

2.3 Histogram of Oriented Gradient

The Histogram of Oriented Gradient descriptors (HOG) (Dalal and Triggs, 2005) are based on the orientation of the gradient in local areas of an image. Basically it consist in computing the orientation binning of the image by dividing it in cells, and creating the

histogram of each cell, obtaining module and orientation of each pixel. The histogram is computed based on the gradient orientation of the pixels within the cell, weighted with the corresponding module value. An omnidirectional image contains the same pixels in a row although the image is rotated, but in a different order. So, if we calculate the histogram of cells with the same width as the image, we obtain an array of rotational invariant characteristics.

However, to know the relative orientation between two rotated images vertical windows are used, with the same height of the window, being able to vary its width and application distance. Ordering the histograms of these windows in a different way, we obtain the same results as calculating the histogram of a rotated image with an angle proportional to the distance between windows. That also will determine the accuracy in orientation computation.

3 LOCALIZATION AND ORIENTATION RECOVERING

In this section, we measure the goodness of each algorithm by assessing the results of calculating the pose of the robot with a new image compared to a map created previously. All the functions and simulations have been made using Matlab R2008b under Max OS X. The maps have been made up of images belonging to a database got from Technique Faculty of Bielefeld University (Moeller et al., 2007). They were collected in three living spaces under realistic illumination conditions. All of them are structured in a 10x10 cm rectangular grid. The images were captured with an omnidirectional camera, and later converted into panoramic ones with 41x256 pixel size. The number of images that compose the database varies depending on the experiment, since, in order to assess the robustness of the algorithms, the distance between the images of the grid we take will be expanded. In the results shown in this paper, the grid used is 20x20cm, with 204 images.

The test images used to carry out the experiments is made up of all the available images in the database, with 15 artificial rotations of each one (every 22.5°). 11,936 images altogether. Because the pose includes the position and orientation of the robot, both are studied separately. Position is studied with recall and precision measurement (Gil et al., 2009). Each chart shows the information about if a correct location is in the Nearest Neighbour (N.N.), i. e., if it is the first result selected, or between Second or Third Nearest Neighbours (S.N.N or T.N.N). Regarding the rotation, we represent the results accuracy in bar graphs

depending on how much they differ from the correct ones. If the experiment error is bigger than ± 10 degrees, it is considered as a fail and not taken into account.

3.1 Fourier Signature Technique

The map obtained with Fourier Signature is represented with two matrices: the module and the phase of the Fourier Coefficients. With the module matrix we can estimate the position of the robot by calculating the Euclidean distance of the power spectrum of that image with the spectra of the map stored, whereas the phase vector associated to the most similar image retrieved is used to compute the orientation of the robot regarding the map created previously.

Figure 1 (a),(b),(c) show recall and precision measures. We can see that when we take more coefficients, the location is better, but there is a limit where it is not interesting to raise the number of elements we take because the results do not improve. The phase accuracy (Figure 1(d)) also improves when more coefficients are used to compute the angle, although is quite constant when we take 8 or more components. It can be stressed that with just 2 components (Figure 1(a)) we have 96 percent accuracy when we study the Nearest Neighbour, and almost 100 percent when we keep the three Nearest Neighbours.

3.2 PCA over Fourier Signature

After applying PCA over Fourier Signature module matrix, we obtain another matrix containing the main eigenvectors selected, and the projection of the map images onto the space made up with that vectors. These are used to calculate the position of the robot. On the other hand, we keep the phase matrix of Fourier Signature directly to estimate the orientation. To know where the robot is, first the Fourier Signature of the current position image must be computed. After selecting the corresponding coefficients of each row, we project the vector of modules onto the eigenspace, and find the most similar image through Euclidean distance. When the position is known, the phase is calculated the same way than when we do not apply PCA since the phase matrix is not modified.

As we can see in Figure 1(e),(f),(g),(h), if we are looking for a high accuracy in the localization task, it is required a high number of PCA eigenvectors, what means losing the advantages of applying this method. Moreover, in the majority of the experiments, the number of Fourier coefficients we need is bigger than when we do not use PCA, incrementing the memory used. Phase results are not included be-

cause the results are exactly the same as showed in Figure 1(d) since its calculation method does not vary.

3.3 Histogram of Oriented Gradient

When a new image arrives, we need to calculate its histogram of oriented gradient using cells with the same size of those we used to build the map. So, the time needed to find the pose of the robot varies depending on both vertical and horizontal cells we use. To find the location of the robot the horizontal cell information is used, whereas to compute the phase we need the vertical cells. In both cases, the information is found by calculating the Euclidean distance between the histogram of the new image and the stored ones in the map. The recall-precision charts (Figure 1(i),(j),(k)) shows that the more windows to divide the image, the better accuracy we obtain. However, it is not a notably difference between the cases. Regarding the orientation (fig 1(l)), although the results are good, it can be stressed that, when the window application distance is greater than 2 pixels, the results are like binary variables, appearing just cases with zero gap, or failures, which is to say that the error is zero or greater than 10 degrees.

4 CONCLUSIONS

This work has focused on the comparison of different appearance-based algorithms applied to the creation of a dense map of a real environment, using omnidirectional images. We have presented three different methods to compress the information in the map. All of them have demonstrated to be valid to carry out the estimation of the pose of a robot inside the map. Fourier Signature has proved to be the most efficient method since taking few components per row we obtain good results. No advantages have been found in applying PCA to the Fourier signature, since in order to have good results it is needed to keep the great majority of the eigenvectors obtained and more Fourier coefficients. In both cases the orientation accuracy depends just on the number of Fourier components, and the error in its estimation is less than or equal to 5 degrees is the great majority of simulations. Regarding HOG, results demonstrate it is a robust method in localization task, having slightly worse results than Fourier algorithm ones. However the orientations computing is less effective due to fact that the degrees are sampled depending the number of windows we use, determining that way its accuracy. This paper shows again the wide range of possibilities of appearance-based methods applied to mo-

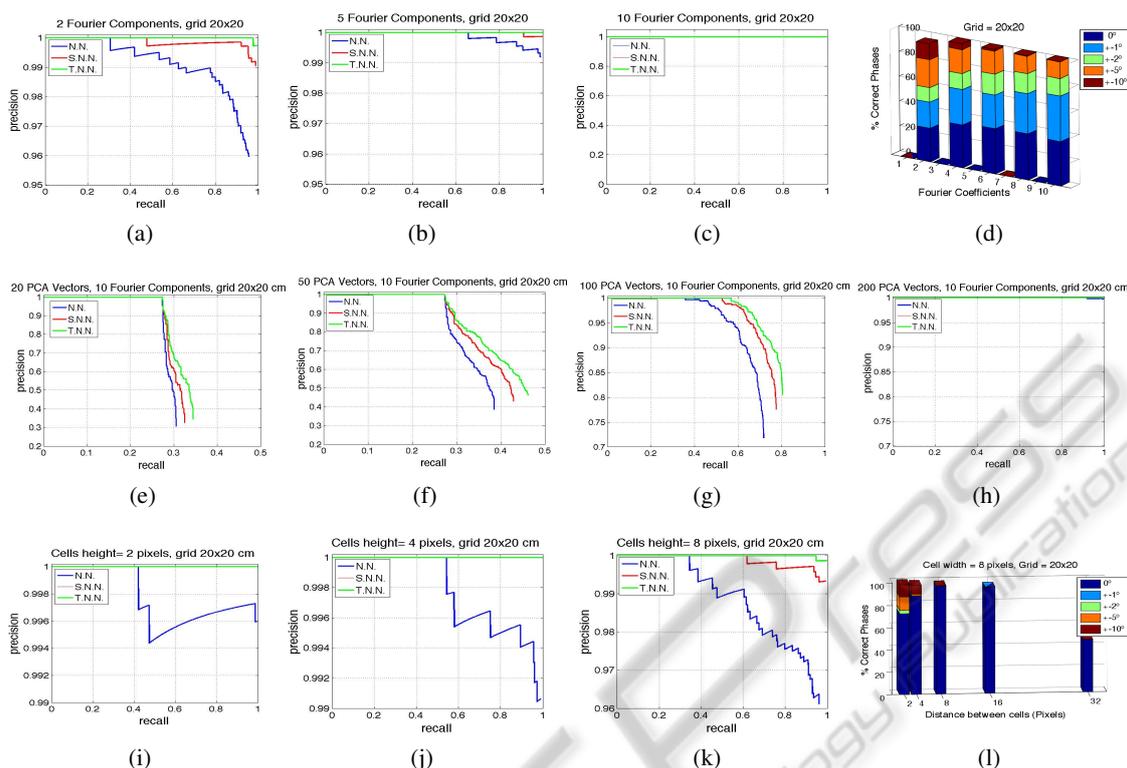


Figure 1: (a), (b), (c) Recall-Precision charts with N.N., S.N.N. and T.N.N and (d) phase accuracy using Fourier Signature varying number of components. (e), (f), (g), (h) Recall-Precision charts with N.N., S.N.N. and T.N.N using PCA over Fourier Signature varying number of PCA vectors. (i), (j), (k) Recall-Precision charts with N.N., S.N.N. and T.N.N and (l) phase accuracy using HOG varying horizontal window's height.

mobile robotics, and its promising results encourage us to continue studying them in depth, looking for new available techniques or improving the robustness to illumination changes for them.

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