Relative Height Estimation using Omnidirectional Images and a Global Appearance Approach

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Abstract: This work presents a height estimation method that uses visual information. This method is based on the global appearance of the scenes. Every omnidirectional scene is described with a global appearance descriptor without any other transformation. This approach is tested with our own image database. This database is generated synthetically based on two different virtual rooms. One of the advantages of generating the images synthetically is that noise or occlusions can be added to test the robustness of the algorithms. This database is formed by a set of omnidirectional images captured from different points of these rooms and at different heights. With these scenes we build the descriptor of each image and we use our method to estimate the relative height of the robot. The experimental results show the effectiveness and the robustness of the method.

1 INTRODUCTION

When a mobile robot has to do a task in an unknown environment, it must carry out two fundamental steps. On one hand, it must create an internal representation of the unknown environment (map) and on the other hand it must be able to estimate its position within the map. The robot uses the information extracted from the environment by the different sensors that it is equipped with. This information is compared with the data stored in the map to estimate the position of the robot. There are many kinds of sensors that provide useful information to the robot, such as touch sensors, encoders, laser or vision sensors.

Vision sensors have properties that make them very useful in mobile robotics. These sensors provide a very rich information from the environment and they have multiple possible configurations. In this work we use the omnidirectional configuration. We can find many previous works that use omnidirectional images in navigation tasks, such as (Winters et al., 2000).

The classic developments in mobile robotics using visual sensors, are based on the extraction and description of some landmarks from the scenes. These landmarks can be either natural or artificial, such as SIFT (Scale-Invariant Feature Transform) (Lowe, 1999) and SURF (Speeded-Up Robust Features) (Bay et al., 2006) descriptors.

More recently some works propose using the global information of the images to create the descriptors. These techniques have demonstrated to be a good option to solve the localization and navigation problems in 2D. (Chang et al., 2010) and (Payá et al., 2010) are two examples of this.

Nowadays, the UAVs (Unmanned Aerial Vehicles) are very popular and versatile platforms that can do several tasks in the field of mobile robotics. Some researchers have faced previously the problem of localization with this platform, such as (Mondragon et al., 2010).

Comparing to previous works, the contribution of this paper is to extend the use of global descriptors based on omnidirectional images to estimate the height of the robot. Furthermore we use the omnidirectional images as the vision sensor provides them, without additional transformations (i.e. we do not convert them to panoramic images because it would suppose an additional computational cost, as shown in (Amorós et al., 2014)). We only build a global-appearance descriptor for each omnidirectional image based on the Radon transform. The procedure to obtain this descriptor is summarized in the following section.

In this research the UAV does not change its inclination with respect to the z axis. It will be able to estimate the relative height between two different positions along this axis. The Figure 6 shows the system scheme that we use in this work, in this scheme

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we can observe the axes directions, the focus of the camera (F) and the focus of the mirror (F').

The experiments with our method have been carried out with our own synthetic image database. This database has been created with two synthetic environments of two different rooms.

The remainder of this paper is structured as follows. Section 2 introduces the method we use to describe global appearance, the Radon transform. Section 3 presents the algorithm we have designed for height estimation. Section 4 describes the image database used in this research. Section 5 presents the experiments and results. At last section 6 outlines the conclusions.

2 GLOBAL-APPEARANCE DESCRIPTORS: RADON TRANSFORM

Methods based on the global appearance of the scenes constitute a robust alternative compared with methods based on landmark extraction. This is because global appearance descriptors represent the environment through high level features that can be interpreted and handled easily.

This section presents the image descriptor we have used to describe the scenes. It is based on global appearance without any segmentation or local landmark extraction.

When designing a new description method, we should take into account several features. This descriptor should have a compression effect in the image information. These should be a correspondence between the distance of two descriptors and the distance of the two positions where the images were captured. The computational cost to calculate and compare them should be low, so that this descriptor can be used in real time. It should provide robustness against noise, illumination changes, occlusions and position changes of the objects in the environment. Furthermore it should have information of the orientation the robot had when it captured the image. In Section 5 we will check if these features are met.

We make use of the Radon transform which is described in (Radon, 1917). Previous research demonstrate the efficacy of this descriptor in shape description and segmentation such as (Hoang and Tabbone, 2010) and (Hasegawa and Tabbone, 2011).

The Radon transform in 2D consists of the integral of a 2D function over straight lines (line-integral projections).

This transform is invertible. The inverse Radon transform reconstructs an image from its line-integral projections.

The Radon transform can be defined as:

$$\mathcal{R}\{f(x,y)\} = \lambda_f(p,\phi) = \\ = \iint_{-\infty}^{+\infty} f(x,y)\delta(p - \vec{r}\,\hat{\vec{p}})dxdy \qquad (1)$$

Where $f(x,y)$ is the function to transform. δ is the Dirac delta function ($\delta(x) = 1$ when $x = 0$, and $\delta(x) = 0$ elsewhere). The integration line is specified by the radial vector $\vec{p}$ that is defined by $\vec{p} = \hat{\vec{p}} \cdot p$ where $\hat{\vec{p}}$ is a unitary vector in the direction of $\vec{p}$. p is the $\vec{p}$ module defined by:

$$p = |\vec{p}| \qquad (2)$$

$$p \equiv \alpha \cos\phi + \beta \sin\phi \qquad (3)$$

The line-integral projections evaluated for each azimuth angle, ϕ, produce a 2D polar function, λ_f, that depends on the radial distance p and the azimuth angle ϕ. $\vec{r}$ is a cluster of points which are perpendicular to $\vec{p}$.

The Radon transform calculation of an image $im(x,y)$ along the line $c_1(d,\phi)$ (Figure 1) is given by the following equivalent expression:

$$\mathcal{R}\{im(x,y)\} = \int_{\mathbb{R}} im(x'\cos\phi - y'\sin\phi + y'\cos\phi)ds \qquad (4)$$

where

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\phi & \sin\phi \\ -\sin\phi & \cos\phi \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \qquad (5)$$

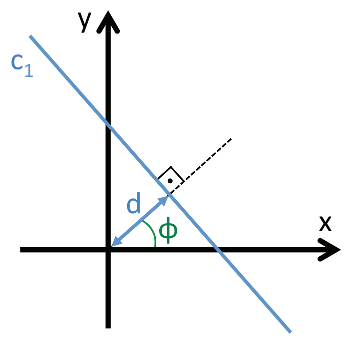
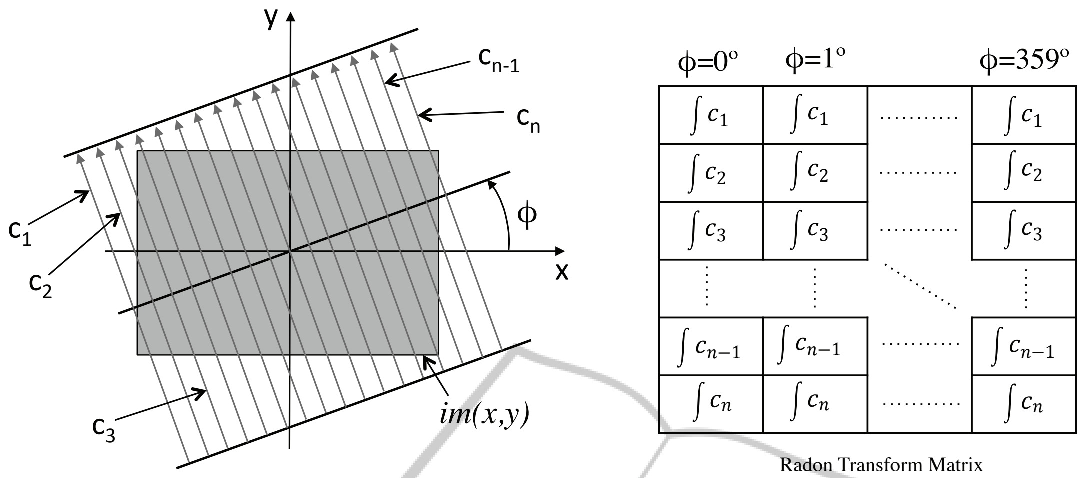


Figure 1: Line parametrization through the origin distance d and the angle between the normal line and the x axis, ϕ.

When the Radon transform is applied to images, it calculates the image projections along the specified directions through a cluster of line integrals along parallel lines in this direction. The distance between the parallel lines is usually one pixel. The Figure 2(a) shows the integration paths to calculate the Radon



(a) (b)

Figure 2: (a) Integration paths to calculate the Radon transform of the image $im(x,y)$ in the ϕ direction. (b) Radon transform matrix of the image $im(x,y)$.

transform of an image in the ϕ direction, and the Figure 2(b) shows the construction process of the Radon transform.

The Figure 3 a sample black and white image, on the left, and its Radon transform, on the right. Furthermore it shows graphically the process to calculate the Radon transform.

2.1 Radon Transform Properties

The Radon transform has several properties that make it useful in localization tasks using images. These properties are the following:

- Linearity: The Radon transform has the linearity property as the integration operation is a linear function of the integrand:

$$\mathcal{R}\{\alpha f + \beta g\} = \alpha\mathcal{R}\{f\} + \beta\mathcal{R}\{g\} \quad (6)$$

- Shift: The Radon transform is a variant operation to translation. Translation of the two-dimensional function, by a vector $\overrightarrow{r_0} = (x_0, y_0)$, has the translation effect on each projection, this translation is given by a distance $\overrightarrow{r} \cdot (\cos\phi, \sin\phi)$.
- Rotation: If the image is rotated an angle ϕ_o it implies a shift ϕ_0 of the Radon transform along the variable ϕ. (columns shift).
- Scaling: A scaling of f by a factor b implies a scaling of the d coordinate and amplitude by a factor b, and implies a scaling of the Radon transform by a factor $1/b$.

$$\mathcal{R}\left\{f\left(\frac{x}{b}, \frac{y}{b}\right)\right\} = |b|\lambda_f\left(\frac{d}{b}, \phi\right) \quad (7)$$

3 HEIGHT ESTIMATION

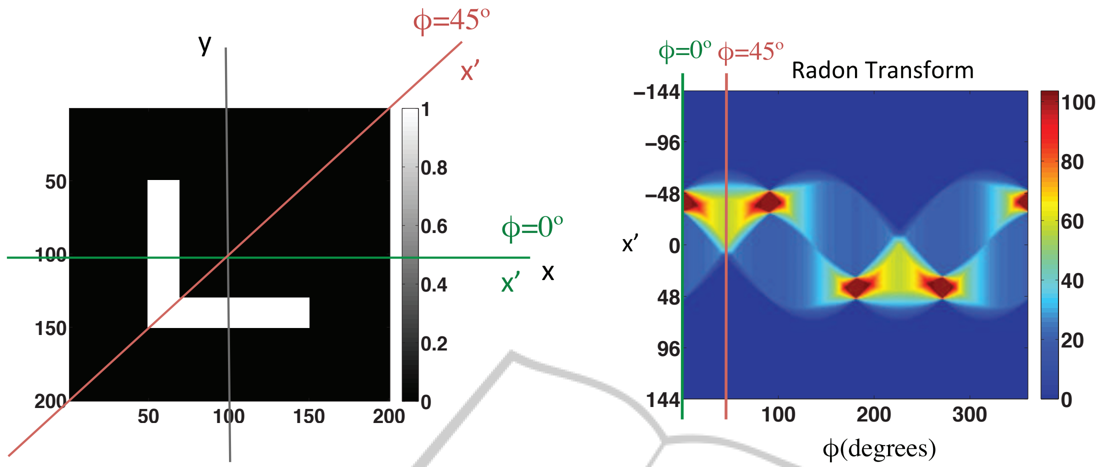
The Radon transform has been used extensively in medical imaging applications and in shape description in scenes. However we have not found any previous application to robot localization and height estimation. In this section, we present a method based on the Radon transform to obtain a topological height estimator. The method provides information of the direction and the magnitude of the vertical displacement of the robot using only omnidirectional images captured by a camera mounted on the robot.

The method compares an image captured at a determinate height with another image captured at another height. As a result, the relative height between both images must be estimated.

3.1 Compression-expansion of the Radon Transform

The key of the method resides in the differences between the Radon transform of two scenes captured al different heights. If the vertical displacement is upwards, then the objects in the omnidirectional scene tend to move towards the center of the image. This produces that the information in the columns of the Radon transform move towards the center row. And vice-versa, if the displacement is downwards, the information in the columns moves outwards the center row. This effect is related to scaling property of the Radon transform, Equation (7).

This feature produces a characteristic change in the Radon Transform. When the robot moves upwards, the information in the columns of the Radon



(a) (b)

Figure 3: (a) Example image. (b) Radon transform of the example image.

transform tends to move towards the central row (compression effect), and when the robot moves downwards, the information in the columns tends to move outwards the central row (expansion effect). The method we use to estimate the height of the robot, is based on these effects.

The Figure 4 shows an example of this feature, two omnidirectional images captured at different heights ($1m$ and $1.5m$) and their corresponding Radon transforms. In this figure it is possible to observe that in the second image the objects have moved towards the center of the omnidirectional image and the Radon transform presents a "compression" effect with respect the central row.

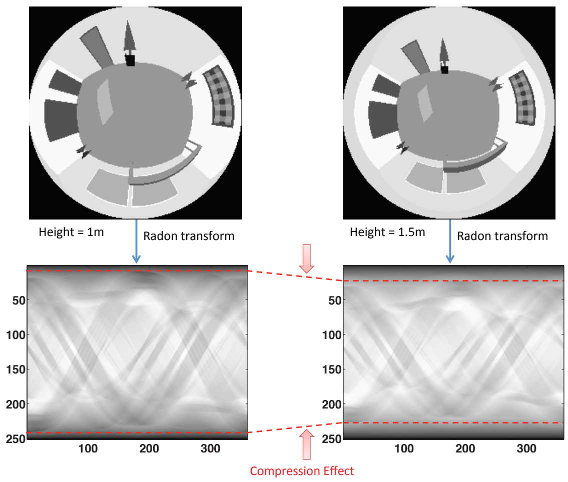


Figure 4: Example of the Radon transform compression.

3.2 POC (Phase Only Correlation)

In this subsection we present the method we use to compare two Radon transforms.

In general, a function in the frequency domain is defined by its magnitude and its phase. Sometimes, only the magnitude is taken into account and the phase information is usually discarded. However, when the magnitude and the phase features are examined in the Fourier domain, it follows that the phase features contain also important information because they reflect the characteristics of patterns in the images.

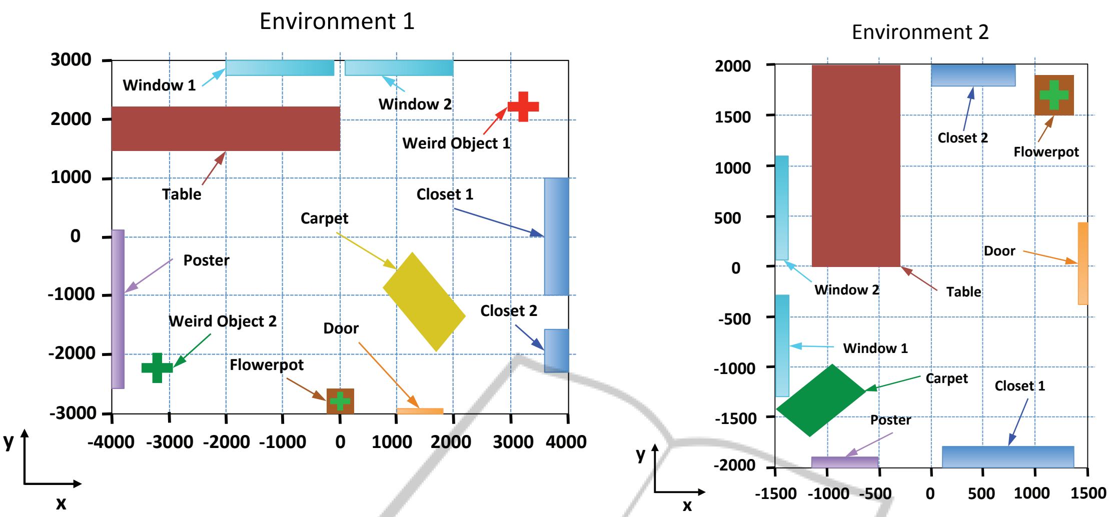
Oppenheim and Lim have demonstrated this by reconstructing images using the full information from the phase with unit magnitude. This shows that the images resemble the originals, in contrast to reconstructing images using the full information from the magnitude with uniform phase(Oppenheim and Lim, 1981).

POC, proposed in (Kuglin and Hines, 1975), is an operation made in the frequency domain that provides a correlation coefficient between two images (Kobayashi et al., 2004). In our case we compare two Radon transforms but this does not affect the POC performance because the Radon transform can be interpreted as an image.

The correspondence between two images $im_1(x,y)$ and $im_2(x,y)$ calculated by POC is given by the following equation:

$$C(x,y) = \mathcal{F}^{-1}\left\{ \frac{\mathbf{IM}_1(u,v) \cdot \mathbf{IM}_2^*(u,v)}{|\mathbf{IM}_1(u,v) \cdot \mathbf{IM}_2^*(u,v)|} \right\} \quad (8)$$

Where $\mathbf{IM}_1$ is the Fourier transform of the image 1 and $\mathbf{IM}_2^*$ is the conjugate of the Fourier transform



(a) (b)

Figure 5: (a) Plane of the environment 1. (b) Plane of the environment 2. (Dimensions in millimeters).

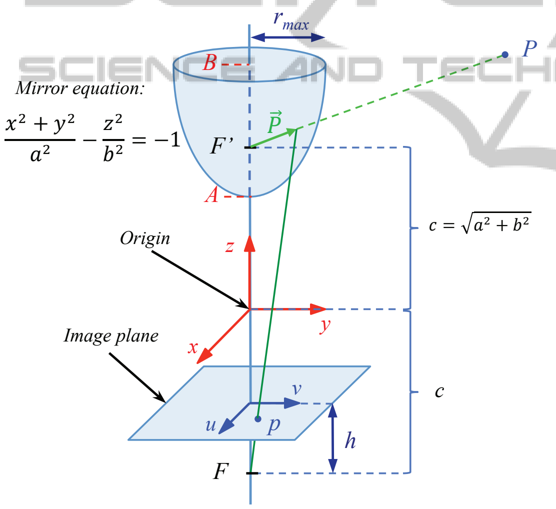


Figure 6: Scheme of the hyperbolic mirror used to capture the synthetic omnidirectional images were built.

os the image 2. $\mathcal{F}^{-1}$ is the inverse Fourier transform operator.

$max\{C(x,y)\}$ is a coefficient that takes values in the interval $[0,1]$ and it measures the similitude between the two images. This measure is invariant under translations in the original image. To estimate the similitude between two images we have used the following expression:

$$dist(im_1, im_2) = 1 - max\{(C(x,y)\} \quad (9)$$

Furthermore, it is possible to estimate the relative displacements between the two images Δ_x and Δ_y along both axes by:

$$(\Delta_x, \Delta_y) = argmax_{(x,y)}\{C(x,y)\} \quad (10)$$

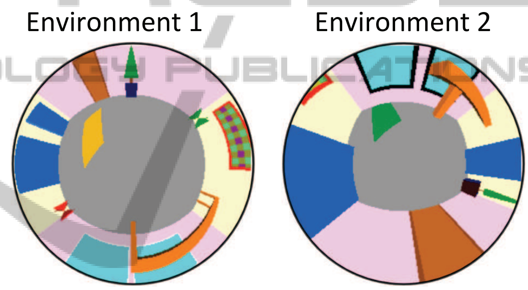


Figure 7: Example of an omnidirectional image of each Environment.

If we use Radon transforms instead of images, the value Δ_x is equal to the relative orientation of the robot when capturing the two images.

This way, POC is able to compare two images independently on the orientation and it is also able to estimate this change in orientation.

3.3 Height Estimation Method

The height estimation method is based on the concepts described in the previous two subsections. It is invariant to rotation with respect to the z axis thanks to the use of POC to compare the Radon transforms. The method works as follows.

The robot takes an omnidirectional image from its first position and saves its Radon transform. Then the robot moves upwards or downwards, captures a new omnidirectional image and saves its Radon transform.

The next step consists in detecting the height difference between the images. Since it produces a compression effect in the Radon transform with respect to the central row, our procedure consists in applying a

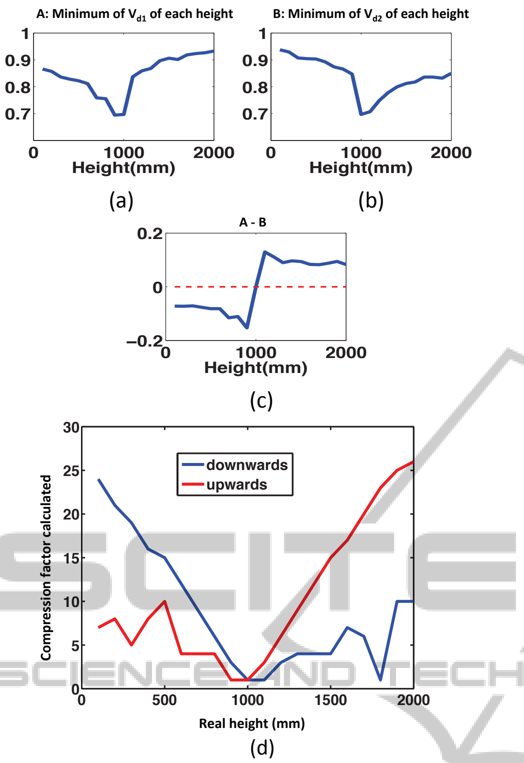


Figure 8: Minimum of the vectors (a) V_{d1}(case 1) and (b) V_{d2}(case 2). (c) Difference between (a) and (b). (d) a' factor which is proportional to the real relative height between each image and the test image. This example is in the environment 1 with the following position: $x = 0$ mm and $y = 0$ mm.

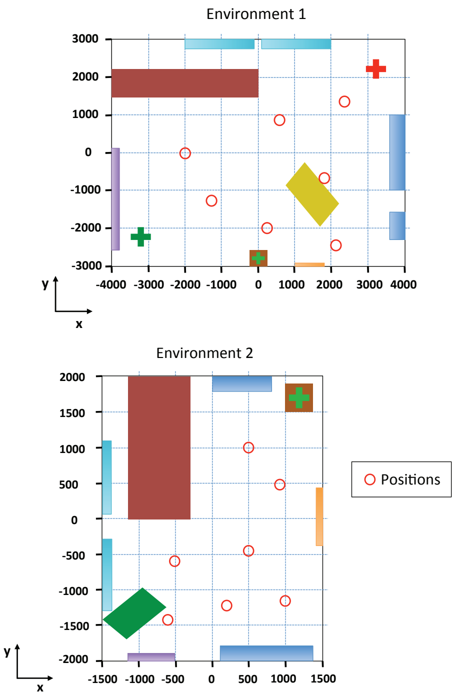


Figure 9: Positions of the test images in each Environment.

scale factor a to each column of the first Radon transform and comparing the result with the second Radon transform using POC. Then, the distance is obtained using Equation (9). This step is repeated increasing the compression factor a in each step, until the compression does not make sense, because the transform has no relevant information. In this moment the robot has a vector of distance values V_d calculated with POC, each element of the vector corresponds to one value of the compression factor a. The a factor, that has produced the minimum of the vector of distances V_d, is a magnitude proportional to the relative height, a'.

The problem in this point is that the robot does not know the translation direction (upwards or downwards). If the translation is upwards the second Radon transform suffers a compression but if the translation is downwards then the first Radon transform is the one that suffers a compression.

To take this problem into account:

Firstly, the robot compresses gradually the first Radon transform and carries out the method described in the foregoing paragraph, to obtain the a' factor, but in this case the robot also has to save the minimum magnitude d_{min} in the vector of distances V_d. This case would be the correct one if the robot was moved upwards

Secondly, the robot repeats the process compressing the second image. This case would be the correct case if the robot was moved downwards.

Finally, the robot has two factors: a'_1 from the first case and a'_2 from the second case, and it has two d_{min} distances: d_{min1} and d_{min2}. The minimum between d_{min1} and d_{min2} determines which is the correct case.

At the end of the process the robot has a magnitude a' proportional to the vertical displacement and, depending or the correct case, the displacement has been upwards (case 1) or downwards (case 2).

4 IMAGE DATABASE

In order to check the performance of the proposed technique, we have created two virtual environments which represent two different rooms. In these environments it is possible to create an omnidirectional image from any position. The Figure 5 shows a scheme of both environments.

The omnidirectional images have 250x250 pixels and they have been created using the hyperbolic mirror which is described in Figure 6. The parameters used in the mirror equation are $a = 40$ and $b = 160$.

Several images have been captured in both environments. In each environment several positions have

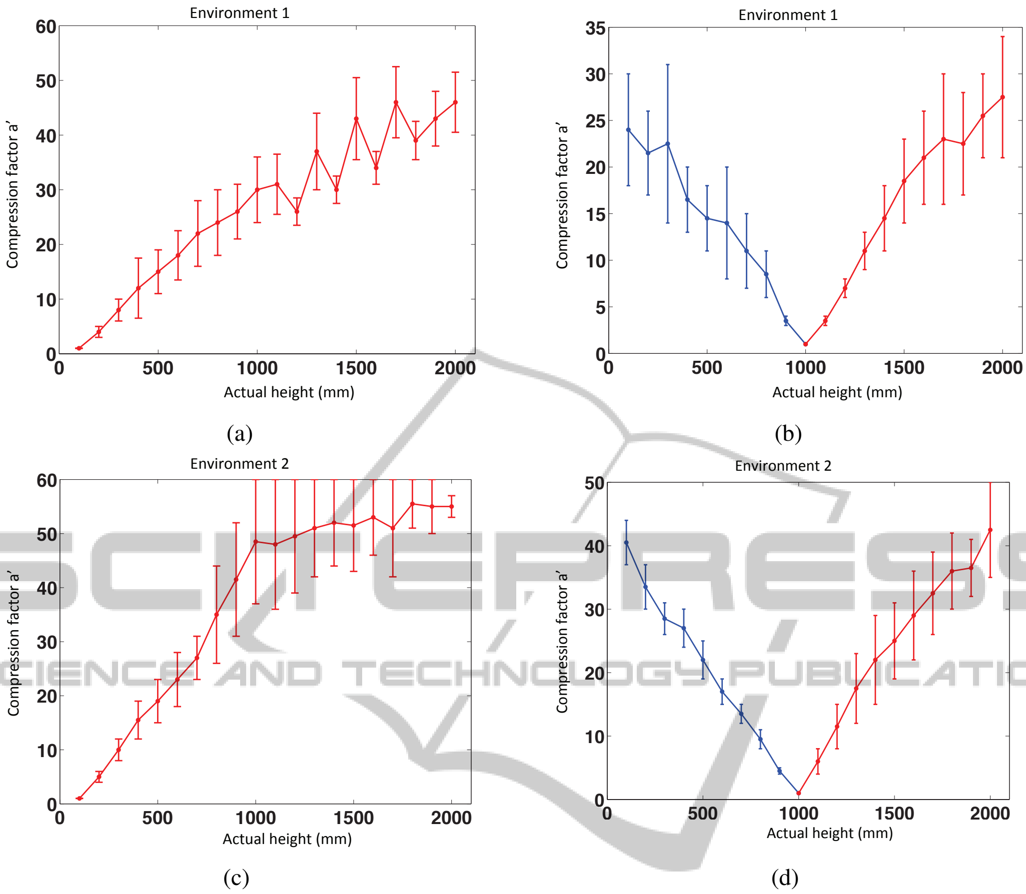


Figure 10: (a) Experiments in the environment 1 with the reference image at height=100 mm. (b) Experiments in the environment 1 with the reference image at 1000 mm. (c) Experiments in the environment 2 with the reference image at 100 mm. (d) Experiments in the environment 2 with the reference image at 1000 mm.

been chosen on the floor and a set of images above these positions were captured to carry out the experiments. The minimum height is 100 mm, and the maximum 2000 mm, with a step of 100 mm. In the Figure 4 there is an example of two different images at different heights. And the Figure 7 shows one omnidirectional image of each environment.

5 EXPERIMENTS AND RESULTS

In this section the results of the experiments with our height estimation method are shown. As exposed in section 3, one of the necessary steps is to differentiate the direction of the translation (upwards or downwards). To distinguish this, it is necessary to calculate the difference between both values: $min(V_{d1}) - min(V_{d2})$. This difference determines which minimum is the lowest and it determines which is the correct direction (upwards or downwards). The Figure 8 shows an example of this. In this figure we take the image captured at 1000 mm as reference. The Figure 8(a) and the Figure 8(b) show the minimum of the vectors V_{d1}(case 1) and V_{d2}(case 2). The Figure 8(c) shows the difference between both vectors. If the difference is negative, the correct case is the case 1 and if the difference is positive, the correct case is the case 2. In Figure 8(d) the a' factor is represented for each height in both cases (case 1: downwards and case 2: upwards). This factor is proportional to the real relative height between each image and the reference image. As we can observe in Figure 8(c), the correct case for heights lower than 1000 mm is the case 1 (downwards) and for heights higher than 1000 mm is the case 2 (upwards). This determines that in Figure 8(d) the blue line to the left of 1000 mm indicates the translation magnitude downwards the reference image and the red line to the right of 1000 mm indicates the translation magnitude upwards the reference image. We can observe that the functions are quite linear.

The Figure 8 is a specific example to show the method steps. To demonstrate the correct performance of our method we have done a whole set of experiments in both virtual environments at different positions. The Figure 9 shows the positions where the images were captured in each environment to carry out the experiments. We use a total of 14 positions with 20 images in each position.

In the Figure 10, the results of these experiments can be observed. The red line shows the magnitude of translation upwards and the blue line shows the magnitude of translation downwards. We can observe that these experiments demonstrate that the method is very linear for values of relative height around 1 meter.

6 CONCLUSIONS

In this work a method to estimate the height of the robot has been presented. This method uses omnidirectional images and transforms them with the Radon transform to make the descriptors of each image. Furthermore it compares the descriptors and finally estimates the relative height of the robot. Taking into account the changes that Radon transforms of scenes suffer when the robot changes its height.

The experiments included in this paper use our own image database created synthetically from two different environments. The results demonstrate that the method is able to estimate the relative height between two images with robustness and linearity.

The method is invariant to rotation with respect to the floor plane because the POC comparison is invariant to shifts of the Radon transform.

The results of this work encourage us to continue this research line. It will be interesting to do the experiments with real images and also with images which have noise, occlusions or changes in lighting conditions. Furthermore we think that the study of movements in 6 degrees of freedom will be interesting to investigate.

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