Mobile Robot Localization Under Varying Illumination *

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Abstract

Methods for mobile robot localization that use eigenspaces of panoramic snapshots of the environment are in general sensitive to changes in the illumination of the environment. Therefore, we propose in this paper an approach which achieves a reliable localization under severe illumination conditions by illumination insensitive eigenspaces. The method in question uses gradient filtering of the eigenspaces. The method was tested on images obtained by a mobile robot and, as we show, it outperforms by far the other known methods.

1. Introduction

To enable localization of a mobile robot in an outdoor or indoor environment, a number of methods have been proposed that construct an appearance model of the environment by capturing panoramic views of locations, obtained with an omnidirectional sensor [1, 3, 9]. The model of appearance is predominantly constructed by compressing the set of visual snapshots captured at different locations using PCA, resulting in the *eigenspace representation*, which has been successfully used in many areas of computer vision [6, 8]. With this approach, images captured during the process of learning get represented as points in a low—dimensional *eigenspace*, which is spanned by the principal components of the data - *eigenimages*. Localization can then be performed by a projection of the momentary panoramic view on the eigenspace, followed by a search for the nearest coefficient of the training images.

The eigenspace method was mainly used in a straightforward way of classifying target appearances by projection without accounting for the possible discrepancies between the learned data and the subsequent images that have to be recognized during the localization phase. This can lead to potential problems when we want the robot to be able to estimate its position in a dynamic environment, with changing configurations of moving objects and persons, and with changing illumination conditions. To cope with occlusions from objects, a robust algorithm for the calculation of the eigenimage coefficients was proposed [4, 3].

While this method can also tolerate some artifacts that appear due to the illumination (e.g. specularities or dark shadows), it results in erroneous localization when dealing with global or smooth illumination changes. Some approaches attempt to alleviate the problem of global illumination by a normalization [5]. In the case of occlusions such an approach can not be applied, since normalization is inherently nonrobust. In panoramic images this problem gets even harder, since they depict 360 degrees of the surrounding, which integrates several local lighting conditions. Such a variety clearly cannot be handled by simple normalization.

In this paper we describe a method for mobile robot localization under varying illumination that achieves illumination invariance of the recognition process by convolving the eigenimages with a bank of linear filters. As a starting point we use the method that was presented and tested on object recognition by Bischof et al. [2], and modify it in order to be applicable for the task of mobile robot localization. As we will demonstrate, we achieve excellent results even in severe illumination conditions.

In section 2 we first briefly review the eigenspace method. Then we show how it is possible to calculate the coef-

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ficients of the eigenimage expansion from the filtered eigenimages. This approach is the core of illumination insensitive localization, which is also described in this section. In section 3 we evaluate the method on sets of images obtained by the mobile robot while moving in an indoor environment with changing illumination. We demonstrate, that by applying a filter bank of gradient filters on an eigenspace of panoramic images, we achieve accurate and illumination insensitive localization, compared to the other known approaches. In section 4 we conclude with a discussion.

2. Illumination insensitive eigenspace

A straightforward approach to the problem of illumination in appearance-based learning and recognition is to learn the appearance under all of the possible light conditions [5]. However, an object in the environment can produce so many different images that it is not clear how to sample all of them.

It is therefore better to use a recognition method that exploits image features that are invariant to illumination. As we will show, it is possible to greatly alleviate the sensitivity to illumination by convolving the eigenimages with linear filters in order to remove the illumination artifacts.

In this section we first review the standard eigenspace approach and point out the key problems that arise due to its nonrobustness. Then we review the method that achieves illumination insensitive recognition, as it is described in [2].

Eigenspace based recognition To build the eigenspace, we first represent the images from the training set as image vectors, from which the mean image is subtracted, $\mathbf{x}_i;\ i = 0 \dots N-1$, which form an image matrix $X = \left[\begin{array}{cccc} \mathbf{x}_0 & \mathbf{x}_1 & \dots & \mathbf{x}_{N-1} \end{array}\right],\ X \in \mathbb{R}^{n \times N}$; where n is the number of pixels in the image and N is the number of images. These training images serve as input for the Principal Components Analysis (PCA) algorithm, which results in a set of p *eigenimages* $\mathbf{v}_i,\ i = 1, \dots, p$, that span a low-dimensional *eigenspace*. Eigenimages are selected on the basis of the variance that they represent in the training set. Every original image $\mathbf{x}_i$ can be transformed and represented with a set of coefficients $q_{ij} = \mathbf{x}_i \mathbf{v}_j,\ j = 1, \dots, p$, which represent a point in the eigenspace. That way, every image is approximated as $\tilde{\mathbf{x}}_i = \sum_{i=1}^{p} q_{ij} \mathbf{e}_i$.

The standard approach to localization is to find the coefficient vector $\mathbf{q}$ of the momentary input image $\mathbf{y}$ by projecting it onto the eigenspace using the dot product $q_i =< \mathbf{y}, \mathbf{e}_i >$, so that $\mathbf{q} = [q_1, \dots, q_p]^T$ is the point in the eigenspace.

If we want the image $\mathbf{y}$ to be recognized as its most similar counterpart in the training set (or in a representation constructed by means of interpolation, see [6]), the corresponding coefficients have to lie close together in the eigenspace. However, in the case when the input image is distorted, either due to occlusion, noise or variation in lighting, the coefficient we get by projecting onto the eigenspace can be arbitrarily erroneous.

It was however shown, that one can also calculate the coefficient vector $\mathbf{q}$ by solving a system of k linear equations on $k \geq p$ points $\mathbf{r} = (r_1, \dots r_k)$

$$y_{r_i} = \sum_{j=1}^{n} q_j e_{jr_i} \quad 1 \leq i \leq k \tag{1}$$

using a robust equation solver and multiple hypotheses [4].

In [3] it was shown how this method can be used to allow robust localization in presence of occlusions. However it does not solve the problem of illumination.

Illumination insensitivity The method presented in [2], takes the computations of parameters one step further. Since Eq. (1) is linear, it also holds that $(f * x)(r) = \sum_{i=1}^{p} q_j (f * e_i)(r)$, where f denotes a filter kernel.

This means that if we convolve both sides with a kernel, the equality still holds. Therefore, we can calculate the coefficients q_i also from the filtered eigenimages, if we filter the input image.

By using a set of linear filters $\mathcal{F}$ we can construct a system of equations

$$(f_s * x)(r) = \sum_{i=1}^{p} q_i (f_s * e_i)(r) \quad s = 1, \dots, q \ . \tag{2}$$

It is now possible to calculate the coefficients $\mathbf{q}$ either by using k points, or using q filter responses at that single point, or a combination of this two.

It is well known from the literature that gradient-based filters are insensitive to illumination variations. By taking a filter bank of gradient filters in several orientations, we can therefore augment the descriptive power of the representation and achieve illumination invariance in the recognition phase.

Illumination invariant localization of a mobile robot can therefore be performed as follows: once the eigenspace is built, we filter the eigenimages by a bank of filters (Fig. 1). Then, for localization, the momentary input image $\mathbf{y}$ from the panoramic camera has to be filtered with the same filters; only after that we retrieve its coefficient vector $\mathbf{q}$ using the robust equation solver. The calculated coefficients are used to infer the momentary location of the robot.

Note that this approach is not the same as constructing the eigenspace from filtered images, as it allows far more flexibility. In fact, once the model is built, we can select the filters and their number according to the momentary illumination conditions, or even run the algorithm on non–filtered images. Moreover, the eigenspace built from filtered images

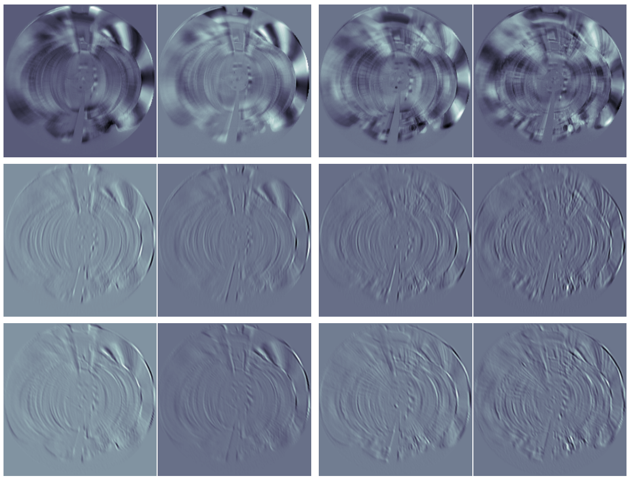


Figure 1. First row shows the first four eigenimages. The consecutive rows show two filter responses for each eigenimage.

is a suboptimal representation due to the small correlation ratio between the transformed images [10].

3. Robot localization — Experimental Results

We have extensively evaluated the proposed method on sequences of images acquired by a mobile robot using a panoramic camera setup with a hyperbolic mirror. The set of training images was generated by moving the robot on a straight 4 meter long path through the laboratory. Pictures were taken at positions 10cm apart from each other, yielding a total number of 40 images. All images were acquired under constant lighting conditions. These training images were represented in an eigenspace of dimension 10, which serves as our appearance model of the environment. Seven sets of test images each consisting of 40 images were produced by moving the robot on the same path as in the training case. This time the illumination conditions were changed for every set. In addition, in 4 sets, occlusions in the images were caused by people walking through the room. In Figure 2 we depict examples of the training images and test images.

Choosing the filters To achieve insensitivity against the changes in the illumination we convolve the eigenimages and test images with a bank of linear gradient-based filters. In particular, we have chosen a set of six steerable filters [7]. It is important to note that it is always possible to change the set of linear filters, even when the model is completely built. Fig. 1 depicts the first four eigenimages filtered with the two of the six derivative filters.

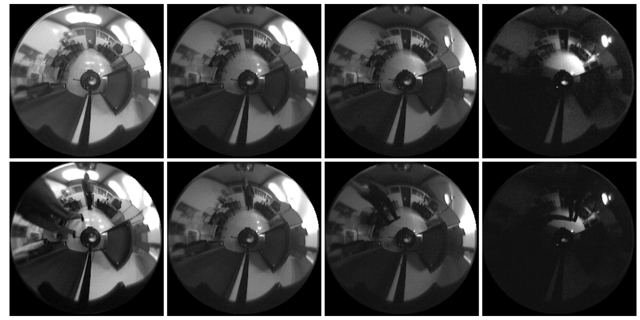


Figure 2. Upper row, from left to right: Training set images and test sets 1 to 3 with changing illumination. Lower row: Test sets 4 to 7 with occlusions.

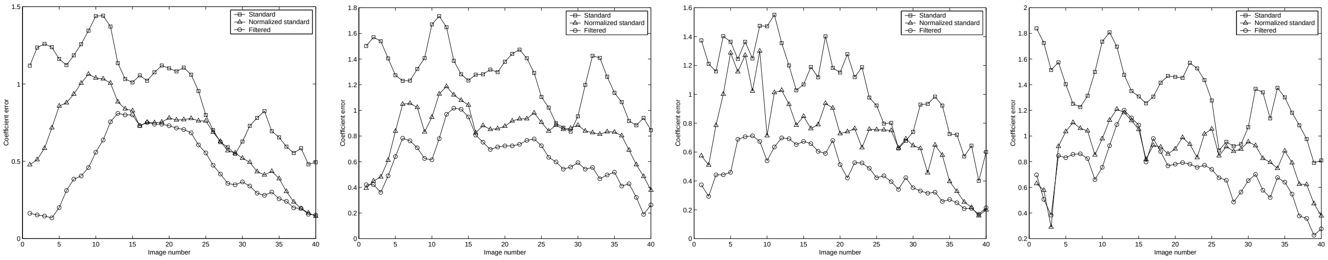
Evaluation of the retrieved coefficients To have a systematic performance evaluation we compared the performance of the filtered eigenspace with two other approaches: the standard approach, in which images are projected on the non-filtered eigenspace, and the normalized standard PCA approach, in which the eigenspace is built from training images normalized to unit vector length in order to account for global illumination changes. In the latter approach, the test images also have to be normalized before the projection.

To compensate for the changes in global illumination which represent the additive factor of illumination variability, we applied a distance measure based on the angle between coefficient vectors for the search of the nearest coefficients in the eigenspace. In other words, once we have determined the eigenspace coefficients of an image, we find its corresponding point in the eigenspace by choosing the coefficient vector of the training image with the smallest angle.

In Fig. 3 we compare the angular coefficient error for the test sets with severe illumination changes (set 2 and 3) and the corresponding occluded test sets. The results for all 7 test sets are shown in Table 1. These experiments demonstrate that our approach consistently performs better for all illumination conditions, for the test set without occlusions and for the test sets with occluded images.

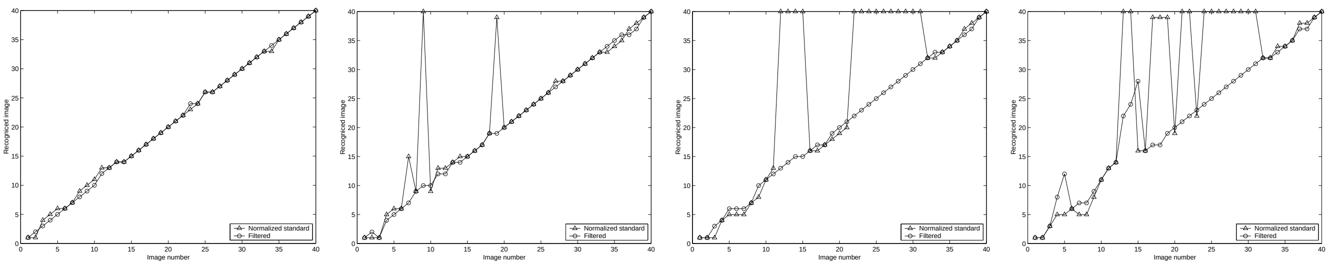
Table 1. Average angular coefficient error.

Set	1	2	3	4	5	6	7
Std.	0.62	0.96	1.26	0.38	0.77	1.05	1.33
Nor.	0.37	0.66	0.84	0.35	0.50	0.73	0.89
Flt.	0.19	0.45	0.63	0.26	0.33	0.47	0.72



Test set 2 Test set 3 Test set 6 Test set 7

Figure 3. Comparison of the coefficient errors for severe illumination conditions.



Test set 2 Test set 6 Test set 3 Test set 7

Figure 4. Place recognition for non-occluded and occluded images under identical illumination.

Table 2. Average localization error (cm).

Set	1	2	3	4	5	6	7
Std.	7	48.7	74.8	2.5	13.5	57.8	108.0
Nor.	1.5	3.3	65.0	0.8	3.3	19.0	68.3
Flt.	0	1.3	4.0	0.5	1.8	2.3	14.0

Evaluation of the location recognition The graphs in Fig. 4 illustrate the performance of localization of the mobile robot. Every deviation from the diagonal means an error in the recognition of the momentary position. We omitted the results of the standard approach, since its performance was consistently worse than the performance of the depicted methods. For a full comparison of all tested methods on all test sets, see Table 2. It is evident that our method clearly outperforms both the standard and the standard approach with normalization.

4. Conclusion

In this contribution we described an eigenspace–based method for mobile robot localization under varying illumination, which performs illumination invariant recognition based on filtering of the eigenimages. As our experiments show, the method outperforms the other known methods. Furthermore, it does not require a special model for the purpose, since the invariance achieved is inherent in the recognition method itself. This allows for extreme flexibility; note that we can easily combine the method with the robust approach to the retrieval of parameters that copes with occlusion [2].

References

[1] H. Aihara, N. Iwasa, N. Yokoya, and H. Takemura. Memory-based self-localisation using omnidirectional images. *14th ICPR*, pages 297–299. IEEE Computer Society, 1998.

[2] H. Bischof, H. Wildenauer, and A. Leonardis. Illumination insensitive eigenspaces. In *ICCV01*, pages I: 233–238, 2001.

[3] M. Jogan and A. Leonardis. Robust localization using panoramic view-based recognition. In *15th ICPR*, volume 4, pages 136–139, 2000.

[4] A. Leonardis and H. Bischof. Robust recognition using eigenimages. *CVIU*, 78(1):99–118, 2000.

[5] H. Murase and S. K. Nayar. Illumination planning for object recognition using parametric eigenspaces. *IEEE Trans PAMI*, (12):1219–1227, 1994.

[6] S. K. Nayar, S. A. Nene, and H. Murase. Subspace methods for robot vision. *IEEE Trans RA*, 12(5):750–758, 1996.

[7] E. Simoncelli and H. Farid. Steerable wedge filters for local orientation analysis. In *IEEE Trans IP*, pp. 1–15, 1996.

[8] M. Turk and A. Pentland. Face recognition using eigenfaces. In *CVPR91*, pages 586–591, 1991.

[9] N. Winters, J. Gaspar, G. Lacey, and J. Santos-Victor. Omnidirectional vision for robot navigation. In *IEEE Workshop on Omnidirectional Vision*, pages 21–28, 2000.

[10] A. Yilmaz and M. Gokmen. Eigenhill vs. eigenface and eigenedge. *Pattern Recognition*, 34(1):181–184, 2001.