# Experimental Validation of a PCA-Based Localization System for Mobile Robots in Unstructured Environments

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***Abstract*— In this paper a new PCA-based positioning sensor and localization system for mobile robots to operate in unstructured environments (e.g. industry, services, domestic, ...) is proposed and experimentally validated. The positioning system resorts to principal component analysis (PCA) of images acquired by a video camera installed onboard, looking upwards to the ceiling. This solution has the advantage that the need of selecting and extracting features is avoided. The principal components of the acquired images are compared with previously registered images, present in a reduced onboard image database and the position measured is fused with odometry data. The optimal estimates of position and slippage are provided by a Kalman filter, with global stable error dynamics. The experimental validation reported in this work focus on the results of a set of exhaustive experiments carried out in a real environment, where the robot travels along straight lines. A small position error estimate was always observed, for arbitrarily long experiments, and slippage was estimated accurately in real time.**

## I. INTRODUCTION

The problem of localization has been a great challenge to the scientific community in the area of mobile robotics; see [6], [3] and the references therein. As happens with persons or animals, for a robot to navigate from a point to another it is of great importance its ability to look at the environment and rapidly answer the following questions: where am I? and what am I facing?

SLAM (Simultaneous Localization And Mapping) is a process by which a mobile robot can build a map of an environment and at the same time to use this map to estimate its localization. In SLAM, both the trajectory of the platform and the localization of all landmarks are estimated online without the need for any a priori knowledge of localization [6], [19]. However, substantial issues remain to be solved in practice. One of the issues that remain open is that of solutions relying on landmarks or on any other features that the robot may sense in the environment, and will subsequently be used for robot localization. In practice, given one environment, there is no guarantee that the same features will be present in the environment on subsequent visits of the robot to the same localization (loop closure problem). For instance, fast corners [24] are a very efficient way to detect features in an image but the number of corners actually found may depend on many tuning parameters and different corners may appear in different images taken from the same localization at different times. Random Sample Consensus (RANSAC) is considered the state of the art technique to keep track of features while disregarding outliers but in practice all these strategies rely on some structure of the environment [2], [16], [7].

This paper follows an alternative approach resorting to Principal Component Analysis (PCA) that actually does not depends on any predefined structure of the environment. Of course, there should always be something to distinguish data acquired in one location to data acquired in another location but no previous assumptions on the predefined structure of the environment needs to be considered. The PCA data analysis corresponds to the computation of the data orthogonal components that will make each dataset different. Hence, the localization is defined based on the PCA of the large amount of data taken from the unstructured environment. Experimental results in 1D are shown, proving the efficacy of the approach.

### A. Current Practices

The use of vision systems for robot localization is very common [22], [21] due to the ability to obtain information about the environment. Many vision systems compute the robot pose (position and attitude) from features of the environment, either from the entire image [11], extracting lines [15], simply getting points of interest [12], [10], or extracting scale-invariant features [17]. The computational complexity of such algorithms to obtain features is not negligible: thus the implementation in real-time systems still demands the search for other approaches of reduced complexity.

Very successful implementations of visual odometry are presented in [21], where a robot was able to localize itself outdoors based on a minimum number of singular points that have to be present in the environment. Although many robots use cameras to look around itself to get its global pose in the environment [23], [10], [14], others use a single camera looking upward [12], [8], [25]. The use of vision from the ceiling has the advantage that images can be considered without scaling, i.e. a 2D image problem results and will be pursued in this work.

### B. PCA-based localization and optimal estimation

Since feature based techniques are computationally heavy, some researchers have been working to find methods to make this process more efficient. To achieve reduced complexity algorithms, the use of PCA in mobile robots for self-localization has been explored [14], [18], [1]. However, all these approaches use front or omnidirectional cameras, causing the algorithms to address problems of occlusion or

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comparison with images in different planes. In [20], PCA was used for terrain reference navigation of underwater vehicles. The PCA-based localization system that we present is this work corresponds to a experimental validation of the one proposed in [20], using a Dubins Car equipped with a video camera looking upwards to the ceiling.

Beyond the problems of image processing for self-localization, another challenge is to deal with the fusion of the PCA-based position with the odometry data that is given by the robot kinematics. Mobile robot kinematics (e.g. Dubins car) are in general non linear. This fact prevents the direct use of a Kalman Filter, which is a linear optimal estimator. To tackle this problem, many localization systems use the Extended Kalman Filter (EKF) with well characterized optimality and stability limitations. Even though it can give a reasonable performance, the EKF may diverge in consequence of wrong linearisation or sensor noise.

For the purpose of this paper, the Dubins Car model is restricted to one-dimensional movement, thus avoiding the non-linear model issues mentioned above. Moreover, the filter also estimates the slippage that is eventually present in the reality. Many researchers tend to neglect slippage: our approach addresses the problem explicitly. As slippage is inevitable, we append a state to our model to express the slippage explicitly. The filter estimates both slippage and robot localization. Furthermore, the optimal estimate is achieved, under the assumption that disturbance noise can be modelled by Gaussian distributions, with global stable error dynamics can be obtained (see [20], where however no experimental results are given). Further work will be carried out in the near future to deal with 2D operation of the Dubins car resorting to the recent results that can be found in [4].

### C. Advantages and drawbacks

The proposed PCA-based position sensor and localization estimation has the following advantages:

- The robot is able to self-locate in an indoor environment, only with onboard sensors (no external sensors or landmarks are required);
- The algorithm is fast, thus it consumes very few computational resources;
- The database of images stored onboard the mobile robot is of reduced size, when compared with the total number of images considered;
- The memory to allocate for the database storage is flexible and related with the required positioning error accuracy;
- No hypothesis is made about specific features in the environment: thus this system can operate in an unstructured environment where the only requirement is that images must be different in each location;
- Under Gaussian assumption for the disturbances, the localization system estimates in real time the position and slippage with global stable error dynamics.

Some of the limitations for the proposed approach include:

- The robots should work in buildings with ceilings where rich information can be found (e.g. building-related systems such as HVAC, electrical and security systems, etc.);
- The ceilings should be static: the system cannot be used outdoors as the sky is far from static and changes randomly;
- The system is formulated in a digital discretised version as well as the PCA approach pursued.

A general limitation of all vision-based systems is their sensitivity relative to lighting conditions.

This paper is organized as follows: in section II, the principal component analysis technique is introduced in detail. In section III, the mobile robot kinematics model is presented and section IV a set of experimental results are reported to validate and assess the performance of the proposed PCA-based positioning sensor and localization system, resorting to a Kalman filter. Conclusions and future work are presented in section V.

## II. PRINCIPAL COMPONENT ANALYSIS

In this section the fundamentals of the positioning system proposed in this work will be introduced. The proposed methodology resorts to optimal signal processing techniques, namely PCA, based on the Karhunen-Loève (KL) transform to obtain a nonlinear positioning sensor. Considering all linear transformations, PCA allows for the optimal approximation to a stochastic signal in the least squares sense. Furthermore, it is a well known signal expansion technique with uncorrelated coefficients for dimensionality reduction. These features make the KL transform interesting for many signal processing applications such as data compression, image and voice processing, data mining, exploratory data analysis, pattern recognition and time series prediction. For a thorough introduction to this topic and a number of state of the art applications see [13].

Consider a set of $M$ stochastic signals $\mathbf{x}_i \in \mathbb{R}^N$, $i = 1, \ldots, M$, each corresponding to the stacked version of an image acquired with the video camera installed onboard the mobile robot and represented as a column vector with mean $\mathbf{m}_x = \frac{1}{M}\sum_{i=1}^{M}\mathbf{x}_i$. The purpose of the KL transform is to find an orthogonal basis to decompose a stochastic signal $\mathbf{x}$, from the same original space, to be computed as $\mathbf{x} = \mathbf{U}\mathbf{v} + \mathbf{m}_x$, where vector $\mathbf{v} \in \mathbb{R}^N$ is the projection of $\mathbf{x}$ in the basis, i.e. $\mathbf{v} = \mathbf{U}^T(\mathbf{x} - \mathbf{m}_x)$. Matrix $\mathbf{U} = [\mathbf{u}_1\, \mathbf{u}_2 \ldots \mathbf{u}_N]$ should be composed by the $N$ orthogonal column vectors of the basis, verifying the eigenvalue problem

$$\mathbf{R}_{xx}\mathbf{u}_j = \lambda_j \mathbf{u}_j, \;\; j = 1, ..., N, \tag{1}$$

where $\mathbf{R}_{xx}$ is the covariance matrix, computed from the set of $M$ experiments using

$$\mathbf{R}_{xx} = \frac{1}{M-1}\sum_{i=1}^{M}(\mathbf{x}_i - \mathbf{m}_x)(\mathbf{x}_i - \mathbf{m}_x)^T. \tag{2}$$

Assuming that the eigenvalues are ordered, i.e. $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_N$, the choice of the first $n \ll N$ principal components leads to an approximation to the stochastic signals given by the ratio on the covariances associated with the components, i.e. $\sum_n \lambda_n / \sum_N \lambda_N$. In many applications, where stochastic multidimensional signals are the key to overcome the problem at hand, this approximation can constitute a large dimensional reduction and thus a computational complexity reduction.

The advantages of PCA are threefold: i) it is an optimal (in terms of mean squared error) linear scheme for compressing a set of high dimensional vectors into a set of lower dimensional vectors; ii) the model parameters can be computed directly from the data (by diagonalising the ensemble covariance); and iii) given the model parameters, projection into and from the bases are computationally inexpensive operations, $\sim \mathcal{O}(nN)$. These advantages suit our problem especially, as the computation power, energy and data storage onboard should be kept as reduced as possible to augment the operation interval and reduce the cost of the systems onboard.

Assume that scenario in the area of indoor mobile robotics (e.g. industrial automation or robotic office applications), where a navigation system to be installed on one or more mobile robots must be developed and operated. In this scenario it is considered that there is data available allowing to develop a positioning system that recognizes the actual position of the robot in real time. The steps to implement a PCA-based positioning sensor using this visual data will be outlined next.

Prior to the deployment of the robots, the visual data of the area under consideration should be partitioned in *mosaics* with fixed dimensions $N_x$ by $N_y$. After reorganizing this two-dimensional data in vector form, e.g. stacking the columns, a set of $M$ stochastic signals $\mathbf{x}_i \in \mathbb{R}^N$, $N = N_x N_y$ results. The number of signals $M$ to be considered depends on the mission scenario and on mosaic overlapping. The KL transform can be computed, using (1)–(2); the eigenvalues must be ordered; and the number $n$ of the principal components to be used should be selected, according with the required level of approximation.

The following data should be recorded for later use:

1) the data ensemble mean $\mathbf{m}_x$;
2) the matrix transformation with $n$ eigenvectors

$$\mathbf{U}_n = [\mathbf{u}_1 \ \ldots \ \mathbf{u}_n]; \tag{3}$$

3) the projection on the selected basis of all the mosaics, computed using

$$\mathbf{v}_i = \mathbf{U}_n^T(\mathbf{x}_i - \mathbf{m}_x), \ i = 1, \ldots, M; \tag{4}$$

4) the coordinates of the center of the mosaics

$$(x_i, y_i), \ i = 1, \ldots, M. \tag{5}$$

During the mission, at the time instants $t_k = Lk$ (where $L$ is a positive integer), the acquired images will constitute the input signal $\mathbf{x}$ to the PCA positioning system. The following tasks should be performed:

a) compute the projection of the signal $\mathbf{x}$ into the basis, using

$$\mathbf{v} = \mathbf{U}_n^T(\mathbf{x} - \mathbf{m}_x); \tag{6}$$

b) given an estimate of the current horizontal coordinates of the robot position $\hat{x}$ and $\hat{y}$, provided by the navigation system, search on a given neighborhood $\delta$ the mosaic that verifies

$$\forall_i \|[\hat{x}\ \hat{y}]^T - [x_i\ y_i]^T\|_2 < \delta, \ r_{\text{PCA}} = \min_i \ \|\mathbf{v} - \mathbf{v}_i\|_2; \tag{7}$$

c) given the mosaic $i$ which is closest to the present input, its center coordinates $(x_i, y_i)$ will be selected as the $x_m$ and $y_m$ measurements.

The relation $\mathbf{f}$ between $r_{\text{PCA}}$ and the positioning sensor error covariance $\mathbf{R}$ (observation noise) to be used in the $\mathcal{H}_2$ estimation problem

$$\mathbf{R} = \mathbf{f}\, r_{\text{PCA}} \tag{8}$$

will be chosen according to the chosen environment. Note that the image-based PCA positioning system described above can be straightforwardly extended to incorporate data from other sensors installed onboard mobile robots such as magnetometers and range information from time-of-flight cameras or structured-light 3D scanners (e.g. Microsoft Kinect).

## III. MODEL

The experimental validation of the proposed positioning system was performed resorting to a low cost mobile robotic platform [5], with the configuration of a Dubins car. This platform has a PC laptop that controls the motors through a closed loop motor controller connected by a USB and has a webcam pointing upwards to the ceiling (see figure 1). The low replication cost for these platforms will be instrumental during the future tasks envisioned relying on cooperation and multi-agent systems (mentioned among future work in section V).

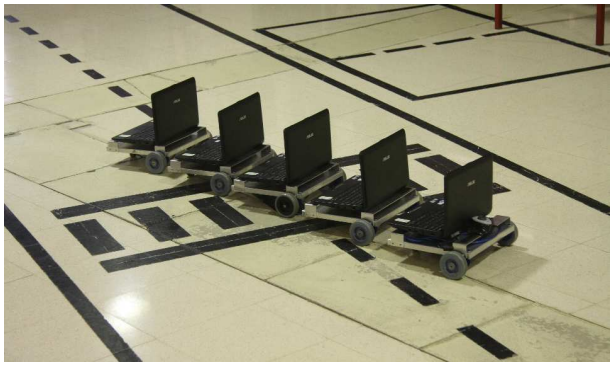

Fig. 1. Mobile robot platforms used for experimental validation

The mobile robot kinematic model that describes the movement in a straight line (1D) is

$$\dot{x} = u + b + \mu_1 \tag{9}$$

$$\dot{b} = 0 + \mu_2 \tag{10}$$

considering the following assumptions:

- the slippage velocity is constant or slowly varying (i.e. $\dot{b} = 0$);
- the noise in the actuation (motors are in closed loop) and the slippage velocity are assumed as zero-mean uncorrelated white Gaussian noise, $\mu_i \sim N(0, \sigma_i^2)$.

Expressing the model dynamics in a state-space system with $\mathbf{x} = [x\ b]^T$,

$$\dot{\mathbf{x}} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \mathbf{x} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \tag{11}$$

$$y = [1\ 0]\, \mathbf{x} + \gamma \tag{12}$$

The output of this system $y$ is the positioning sensor measurement described in the previous section. Since the position estimator is processed in a digital processor, the discrete model is obtained assuming that the vehicle velocity $u$ is constant (zero order hold assumption) between two consecutive processing times, resulting

$$\mathbf{x}(k+1) = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \mathbf{x}(k) + \begin{bmatrix} T \\ 0 \end{bmatrix} u(k) + \begin{bmatrix} T & T^2/2 \\ 0 & T \end{bmatrix} \mu(k) \tag{13}$$

$$y(k) = [1\ 0]\, \mathbf{x}(k) + \gamma(k) \tag{14}$$

The design of a linear time-invariant Kalman filter for the underlying model described above is by now classic and the reader is referred to [9].

## IV. EXPERIMENTAL RESULTS

The mobile robot self-localization methodology proposed in this work is tested for the aforementioned mobile robot travelling along a 3 m length straight line. Ceiling images are captured with a constant distance and referenced, allowing for the creation of the PCA eigenspace (the image database referred in the previous sections of the paper) to capture the principal components of the environment. To create the eigenspace, gray scale images with 320 by240 pixels are subsampled $(1:25)$ and transformed into vectors, $\mathbf{x}_i \in \mathbb{R}^N$, $i = 1, \ldots, M$, where $M$ stands for the number of images and $N$ stands for the number of pixels of each image. (Notice that since this is a 1D experiment only one coordinate is necessary, along the direction of movement.)

The covariances to be used in the Kalman Filter design were considered as constant and were obtained considering $\mathbf{Q} = \mathbf{Q}(k)$ and $\mathbf{R} = \mathbf{R}(k)$ as the covariance error in the actuation and the pose estimator, respectively. The value of $\mathbf{Q} = 4.1 \times 10^{-6}$ m$^2$ was obtained measuring the covariance error of the robot motion along one predefined path. The value of $\mathbf{R} = 6.8 \times 10^{-3}$ m$^2$ was obtained measuring the covariance error of the pose estimator (position given by the PCA positioning sensor) when the robot moves along one path with images in the eigenspace. This process and sensor noises lead to a Kalman filter gain $\mathbf{K} = [0.0429\ 0.0188]^T$.

To study the PCA positioning sensor performance, 31 ceiling images (with a distance of 0.1 m) were captured with the mobile robot travelling with a constant velocity of 0.125 m/s along the straight line, as mentioned above. The images have been subsampled with a step of 5 pixels in width and height to reduce the amount of processing data $(1:25)$. Analysing the eigenvalues and selecting components that explain the variability of the images in an excess of 80%, results on an eigenspace (image database) of 4 eigenvectors.

### A. Monte Carlo Performance Tests

To assess the mobile robot self-localization methodology proposed, a Monte Carlo test composed of 10 experiments as described above has been repeated. Images were captured at 20 Hz and the PCA-based positioning sensor was acquired; figure 2 gives the localization results obtained in one of those experiments. The results show that the PCA algorithm provides a good approximation to the real robot localization. However, some discontinuities in the acquired robot position are observed. Anyway, the deviations observed in instants

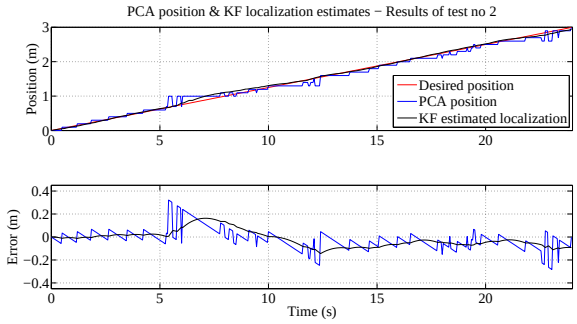


Fig. 2. Results of PCA-based positioning sensor and localization estimates from Kalman filter

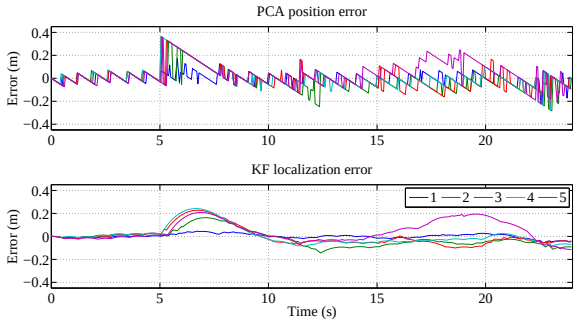


Fig. 3. Localization errors of tests along a straight line

6 s, 13 s and 22 s are due to disturbances. It is important to remark that the results from the Kalman filter smooth out the position errors present in the PCA-based positioning sensor. The estimated errors for 5 experiments are depicted in figure 3.

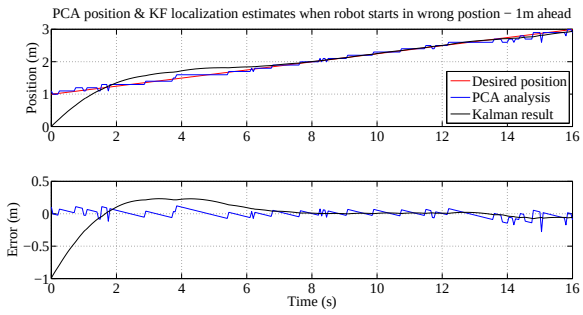


Fig. 4. Results of positioning system when the robot starts 1 m ahead of the usual position

### B. Stability Validation

A second test was performed to assess the positioning system global stability when the initial position coordinates do not match the robot real initial position. Thus it is possible to check that the estimator is able to correct the initial position error, as predicted by the stability properties of the Kalman filter. In this case, the robot was placed 1 m ahead of the usual initial position. An Extended Kalman filter could easily diverge under such experimental conditions. The eigenspace was again created with a distance between

acquire images of 0.1 m (same 31 images as in the previous set of tests) and the results show that the positioning system needs less than 1.5 s to provide an accurate estimate of the mobile robot localization. Considering that the robot moves at a constant velocity of 1.5 m/s, the positioning system is able to identify the mobile robot real position at the same time that the second image is captured to the eigenspace (figure 4).

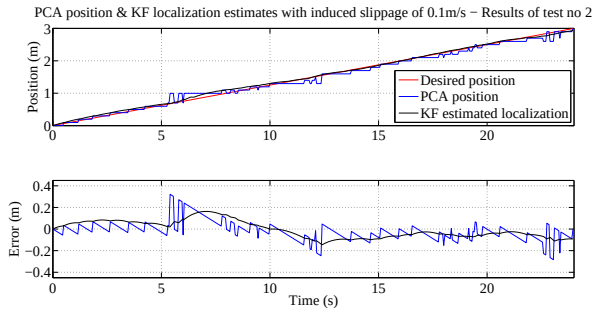


Fig. 5. Results of the positioning system when the robot moves with a slip velocity of 0.1 m/s

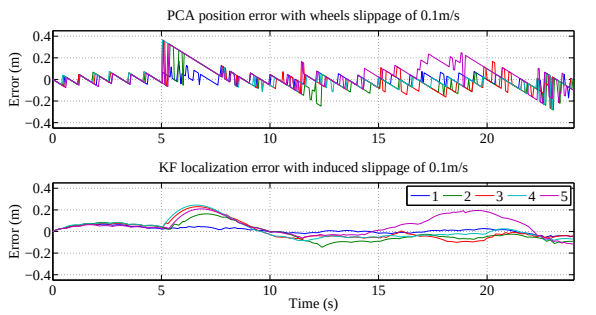


Fig. 6. Error of positioning system when the robot moves with a slip velocity of 0.1 m/s

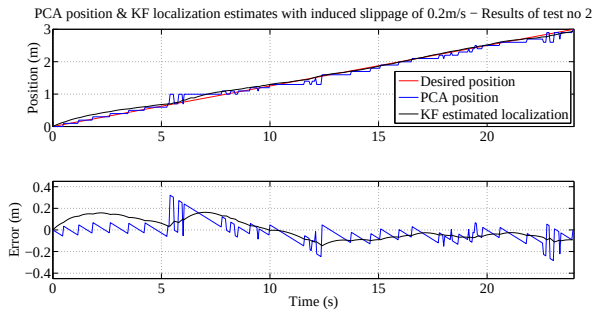


Fig. 7. Results of the positioning system when the robot moves with a slip velocity of 0.2 m/s

## C. Real-time Slippage Estimation

As a further assessment of the localization system performance, a set of tests have been conducted considering that the mobile robot experiences a constant, artificially imposed, wheel slippage. Two tests are reported considering that the mobile robot travels with a slippage in the wheels, that leads

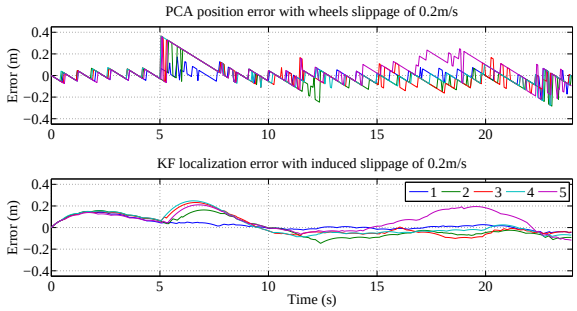


Fig. 8. Error of positioning system when the robot moves with a slip velocity of 0.2 m/s

to a constant velocity below 0.1 m/s and 0.2 m/s, respectively in figures 5 and 7, relative to the commanded velocity. The estimation errors are depicted respectively in figures 6 and 8. Results show that the localization system is able to accurately estimate the mobile robot real position in all situations. The Kalman filter estimates present initial higher errors for higher values of slippage (above 0.2 m/s). After a transient of about 5 s (see figure 9), the localization system is able to estimate and correct the wheels slippage in real-time and the results obtained in the remaining of the experiments have similar performance as the ones obtained in the experiments without slippage.

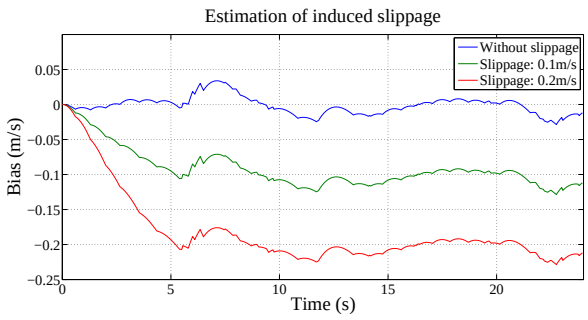


Fig. 9. Results of bias in Kalman Filter for different wheels slippery velocity

## D. Preliminary PCA Performance Assessment

PCA has a number of parameters that must be selected prior to the deployment of the positioning and localization system. A trade-off will always be found relating the number of images in the database (eigenspace size) and the accuracy of the positioning sensor proposed. A preliminary study on the impact of changing these parameters will be reported in this section. The results from a set of tests where the image acquisition step varies in the interval [0.05 0.4] m, i.e. using between 61 and 8 images, respectively, were performed creating different eigenspaces. Hence, the mobile robot positioning system performance has been tested considering an increase between the eigenspace points used (Table I).

Results show that the PCA positioning system with Kalman Filter were able to identify the correct mobile robot position based on ceiling captured images, even when the distance between knowledge points is increased, reducing the number of images in the eigenspace (figure 10). For a

TABLE I

PCA POSITIONING SENSOR AND LOCALIZATION SYSTEM WITH DIFFERENT IMAGE ACQUISITION STEPS

| Distance between images (m) | Sample time (s) | Number of images in PCA | PCA localization $\overline{\sigma^2}$ (m$^2$) | PCA with a Kalman Filter $\overline{\sigma^2}$ (m$^2$) |
|---|---|---|---|---|
| 0.05 | 0.4 | 61 | 0.00545 | 0.00380 |
| 0.1 | 0.8 | 31 | 0.00683 | 0.00436 |
| 0.2 | 1.6 | 16 | 0.01063 | 0.00525 |
| 0.3 | 2.4 | 11 | 0.01360 | 0.00341 |
| 0.4 | 3.2 | 8 | 0.06428 | 0.03844 |

distance between frames up to 0.3 m, results show that the position error is small, not exceeding 0.15 m. For longer distances between frames, e.g. 0.4 m, the position estimate accuracy degrades gracefully. However, even in this case, the error is below 0.4 m, which allows to conclude that the error is less than the granularity associated with the image acquisition intervals.

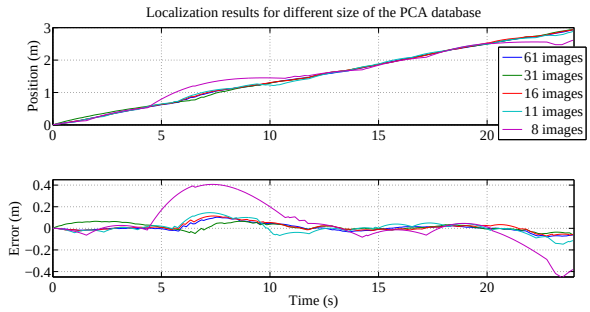


Fig. 10. Results of PCA together with a Kalman Filter

## V. CONCLUSIONS

A new positioning sensor and a localization system for mobile robots to operate in unstructured environments is proposed and experimentally validated along a straight line (1D). The positioning sensor resorts to PCA, from the images acquired by a video camera installed onboard, looking upwards to the ceiling. Several tests were performed namely: i) Monte Carlo performance study, ii) global stability validation, iii) real-time slippage estimation, and iv) PCA performance assessment. All tests were successful and allow to conclude that the proposed approach can be useful in a number of mobile robotic applications.

This paper represents the initial step towards a multi-agent system based architecture where a large set of mobile robots will be able to cooperate to perform navigation and formation tasks, featuring obstacle avoidance, human interaction and search and rescue activities. For that purpose, the next step taken was to consider the robots in 2D. Currently, the theoretical part of 2D version has been developed, resorting to a set of recent results reported in [4], and will be subject to intensive validation tests in the near future.

## ACKNOWLEDGMENTS

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