A REAL-TIME ARCHITECTURE FOR LOW-COST VISION BASED ROBOTS NAVIGATION

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Abstract: Artificial vision can be used in many environments such as indoor, outdoor, space, and even in underwater contexts. Most of times, vision based localization requires complex algorithms and hardware resources when related to general environment features. However, the use of simple landmarks can reduce dramatically the cost and the complexity of the recognition system. In typical indoor environments, in particular in offices, ceiling lamps are all of the same type and are placed in a quite regular way. Moreover, they can be easily seen, as generally no obstacles can exist between them and the robot vision system. These peculiarities motivated a study on the possibility of implementing a very low cost localization procedure using a standard onboard webcam. A Kalman filtering approach has been used to fuse vision and odometric data for position estimation, and a navigation architecture, based on a real-time Linux kernel, has been set up to show its reliability and flexibility.

Keywords: Localization, Vision, Mobile Robots.

1. INTRODUCTION

Vision can be added to a localization system for mobile robots in order to reduce odometric errors due to the incremental nature of those sensors. The use of natural or artificial landmarks allows both simple resetting of odometric errors, so that sensors can restart each time with the correct absolute position information (Adam et al., 1999), and more complex sensor fusion algorithms that integrates all available information in a single estimation process (Panzieri et al., 2000).

Among the others, natural landmarks have the interesting features that avoid any change in the work environment. In indoor environments one can find many different reference points and marks that can be interpreted as natural landmarks, e.g. doors, corners, geometry of the floor. In particular in (Martinez et al., 1992) and (Adam et al., 1999) some of the ceiling characterizing elements are suggested as natural landmarks in order to avoid any occlusion problems.

Unfortunately, visual based control schema requires, generally, very complex algorithm and dedicated hardware (Amat et al., 2000). In this paper we have explored the possibility to realize a localization system for a mobile robot using very low cost standard hardware, i.e. a PC with a 40$ webcam.

To this end we have mounted the webcam on the mobile robot focused to the ceiling and used the lamps as reference points. Moreover, we have used a suitable topological representation of the environments, i.e., we represent the environment by means of a graph where each node is a location of interest and the arcs capture the connectivity of the space.

So the localization system uses the information about the position of each lamp to localize the robot on the graph and then inside the environment. Nevertheless, given the repetitive nature of the lamps, the system needs to label and track each lamp in the image sequence in order to avoid any wrong interpretation of the environment. This imposes an upper limit on the robot speed in order to guarantee that each lamp met by the robot on its path appears at least in one webcam image.

Further, the presence of low cost hardware generates some drawbacks. The first of all is due to the limited transfer rate that, in addition to the time consumed by the feature extraction algorithm, generates a considerable time delay in the loop.

Also the poor quality of the image generated by the camera and the optical distortion introduced by its lens system should be taken into account especially when vision is used for precise positioning tasks.

The proposed localization system has been experimentally tested on a mobile robot going through the passageway of the faculty and using ceiling lamps as reference landmarks.

From the software implementation point of view, our interest has been concentrated on GNU/Linux operating system that, compared with Microsoft systems, has the great advantage of being completely OpenSource and based on the Unix system. As all Unix systems, Linux scheduler is *preemptive*, that means a process can always loose the processor utilization when another one has matured a greater priority. Most recent versions of Linux kernel, called Real-Time Linux, introduce the possibility of defining higher priority user tasks and avoid preemption from Kernel routines disabling their interrupts.

2. AN AUGMENTED TOPOLOGICAL MAP APPROACH

It is well known that an effective environment representation for a mobile robot must describe all the essential features necessary for self-localization, motion planning and navigation. Moreover, the robot should be able to extract the features directly from sensory data.

The mapping approaches, i.e., the way the world is represented, that have been proposed in literature can be grouped in two main classes (Borenstain et al., 1996): *metric maps* and *topological maps*. In the metric maps the environment is represented in terms of geometric relations between the objects and a fixed reference frame. On the other hand, in a topological map, only adjacency relations between objects are represented (Dudeck et al., 1991), avoiding metric information as far as possible.

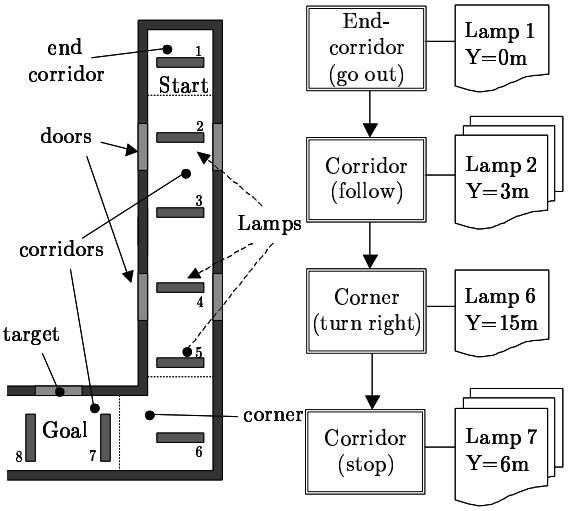

Fig. 1. Topological map

Metric maps and topological maps are two different representations of the same environment: as a consequence, they exhibit complementary rather than opposite properties. Metric maps are adequate to represent sensor delivered metric information and are necessary in the implementation of metric algorithms like shortest path. Unfortunately, this kind of representation is space consuming, often unsuitable for global planning and sensitive to odometric errors (Thrun, 1999).

On the other side topological maps produce more abstract representations than a metric one. The environment can be synthetically described by a graph where nodes represent basic features (*topological nodes*) and arcs gives information on connections between them. Topological maps can be effectively used for symbolic planning in particular when considering long displacements, but they are unusable in the presence of tasks which call for accurate robot positioning.

To exploit the best of both approaches the authors in (Fabrizi et al., 2000) have suggested to put additional metric information in nodes as tags of particular interest related to the natural landmarks included in the node itself.

In particular, this approach has been successfully applied for the representation of office-like environments: this kind of indoor environment is usually structured with standard elements like corridors, T-junctions, corners, and end-corridor, and very often a navigation task can be expressed as a sequence of places defining a path inside the environment such as “follow the corridor and turn right at the first corner”. So one has a graph representation as high-level view of the environment (useful for the integration of the system in an artificial intelligence framework), and, at the same time, metric information about length of the

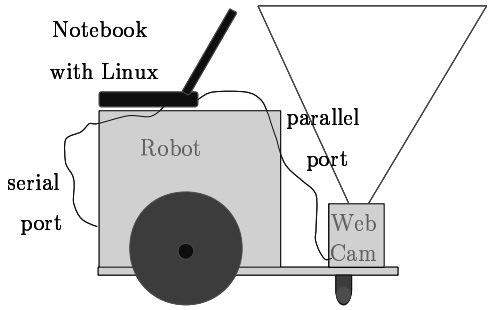

Fig. 2. Robotic system

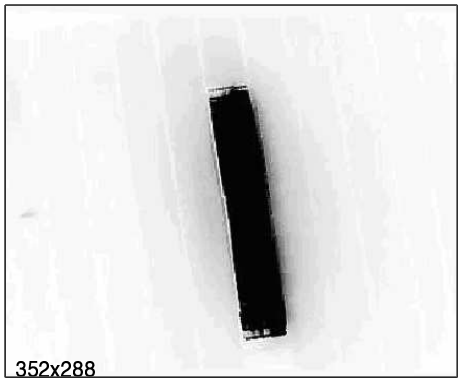

Fig. 3. A negative image of a lamp on the ceiling

corridor, number of left and right doors, number of lamps in the ceiling and possibly their relative distance.

Unfortunately, the extraction of some of the features mentioned before from a webcam image may be a very time-consuming task. For example the process of recognizing the shape of a corner or a T-junction using an image can be extremely hard and, perhaps, more simple sensors, like sonar or laser ones, can give better and faster results. The computational burden can be dramatically reduced if the extraction procedure is focused on particular landmarks as the lamps in the ceiling which can be easily extracted ((Martinez et al., 1992; Adam et al., 1999)). Indeed, they are well visible, easy to identify inside the image, generally all of the same type and placed in a quite regular pattern.

Limiting vision system to identify only the lamps in the ceiling imposes to the graph the inclusion in the *topological nodes* of a labeled sequence of landmark tags associated to the lamps. Nodes are used to decide the correct navigational behavior (follow corridor, turn right at corner) and eventually to perform an approximate localization; tags are employed to refine the localization process.

An example of the adopted representation is shown in Fig. 1 where the planned path from *Start* to *Goal* assumes that the robot *goes out* of the end-corridor, *follows* a corridor, *turns right* at the corner and find the *Goal* in the next corridor. Once finished this high-level motion, the target location (a door) can be reached with a fine motion.

On the way, the robot can always refine its localization using landmarks (lamps) that are associated to each topological node but only a low precision is required. Note that its odometry should be able to correctly label each lamp and to handle abnormal situation (e.g., when a lamp is out of order). Near the target the estimated position must be refined to correctly approach the target.

It is important to stress that during the motion, the localization system use odometric information for a rough prediction of the landmark positions.

3. VISION BASED LOCALIZATION

3.1 *Image acquisition*

The vision system used in this work has a camera-on-board configuration (see the Fig. 2). The low cost webcam mounted on the mobile robot is based on the VLSI vision chipset ("CPiA"), and it is connected to a notebook running Linux through the parallel port. For a better description of the frame format used by the webcam and the Linux driver adopted (CPiA-Linux-driver1.5), the reader can refer to (Panzieri *et.al*, 2001).

Accurate calibration of cameras is a crucial step for applications that involve quantitative measurements, such as the geometrical and the dimensional ones (Weng et al., 1992). Webcam lens aberrations must be evaluated and corrected. Using a low cost, wide angle camera this procedure become even more important. In this work we only consider camera distortion, which is related to the position of image points in the image plane, but not directly to the image quality, because we only use geometrical information in our localization system (see below). Moreover, we consider as accurately known the position of the camera in the robot frame. Calibration matrices are calculated and used as in (Panzieri *et. al*, 2001) where more details can be found.

3.2 *Lamps recognition*

After the calibration step the algorithm proceeds analyzing the image. Remember that typical image processing algorithms use complex strategies to reduce the computational burden and good public domain implementation are quite common on the world-wide web.

First, a three search of all connected components is performed comparing, for each pixel, the luminance information Y with a threshold: if the pixel luminance exceeds the threshold then is considered, otherwise is neglected.

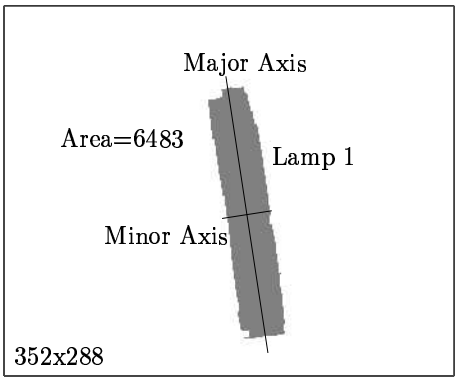

Fig. 4. Major and minor axes, center of mass and labeling

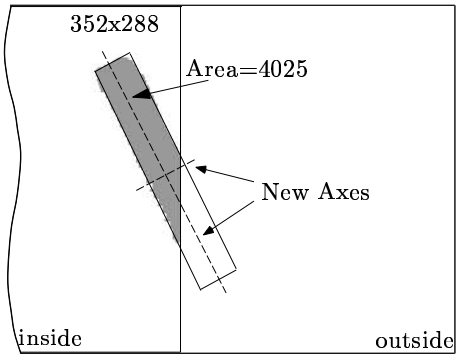

Fig. 5. Completing partial view

After this scanning, more than one connected component are usually retrieved. Sometimes reflections can produce small connected components that can be discriminated evaluating their area. Our lamps produce an image that is around 6300 pixels; we suppose to have lamps only if the area is greater then 3500 pixels. From the area we also know how much of the lamp is in the viewing window and how much is left out. After that, to better the quality of the image the morphological operators of erosion and dilation are applied to reduce fringes caused by small reflection along borders of the lamp. This effect is more evident when lamps are far from the center of the image and the light reaches the camera after reflecting on the common metallic grids that are always set over the luminescent elements.

At this point we deduce the robot position and orientation using the lamps configuration in the image plane. To do this we compute the center of gravity (CoG) and the orientation of each lamp (see Fig. 4 obtained from the analysis of Fig. 3).

With this procedure, the system is able to recognize when a new lamp appears in the image and when the lamp disappear from it. Using the odometry (on a short range) a new incoming lamp is labeled and its CoG and orientation is calculated. To correctly use these measures the system needs a good estimate of those quantities and this is not possible when only a partial view is available.

Due to the limited view of the camera some problems may occur when only a partial view of a lamp is available. This forced us to develop a recovery algorithm able to complete the missing area and correctly estimate CoG and orientation. In Fig. 5 the result of this procedure, based on the knowledge of the reconstructing shape, is shown. The procedure is performed only when the visible area is greater then 4000 pixels. The algorithm uses edges found in the area and tries to interpolate them with a least square method. The reliability of such process is not extremely high but the information retrieved is a valued one in any case.

4. KALMAN BASED DATA FUSION

At the end of the image processing phase, estimated position and orientation values are available. This process can be repeated with a rate that in general depends on the frames acquisition hardware and on the complexity of algorithms performed. With a low cost hardware this is limited to few images per second and in the experiments that we present this rate is only one frame per second. On the other contrary the algorithm that controls the motion of the robot is performed with a higher rate and needs an estimate of the full state (position, orientation, and their derivatives) at each sampling time; even if no lamps are in the view of the webcam. Then, the estimate must be obtained merging odometry, always available, with vision data. This can be done by means of an Extended Kalman Filter. The only drawback is that a delay exists between the frame acquisition instant and the time in which geometrical data becomes available to the filter. The solution adopted, like in (Panzieri et al., 2000), was to preserve in a buffer some past state values and odometric data and, each time a new frame (relative to time t_f) is processed, go back with the filtering algorithm to $t = t_f$, include the geometrical data in its evaluation, and then propagate to the actual instant the state estimate using the odometric data previously stored.

4.1 *State prediction*

In designing the Kalman Filter, the following points must be taken into account:

- the measures provided by the webcam are noisy, but do not grow with the traveled path;
- the vision system accuracy is correlated to the robot velocity;
- a delay of about 1 sec arises for computations and communications.

The prediction equation are simply obtained by the unicycle kinematic model. Define the vector state as the robot configuration, $X_k = (x_k, y_k, \phi_k)$ and the input $U_k = (\Delta S_k, \Delta R_k)$ as the vehicle displacement and rotation along the trajectory in the k-sampling interval. The inertial prediction is then:

$$\hat{X}_{k+1/k} = f(\hat{X}_k, U_k) = \\ = \begin{bmatrix} \hat{x}_k + \Delta S_k \cos\left(\phi_k + \frac{\Delta R_k}{2}\right) \\ \hat{y}_k + \Delta S_k \sin\left(\phi_k + \frac{\Delta R_k}{2}\right) \\ \hat{\phi}_k + \Delta R_k \end{bmatrix} \quad (1)$$

The model inputs are computed using encoder data as follows. The robot displacement is measured from right end left encoder readings that give respctively the values ΔS_k^r and ΔS_k^l as

$$\Delta S_k = \frac{\Delta S_k^r + \Delta S_k^l}{2}. \quad (2)$$

The platform rotation is estimated as

$$\Delta S_k = \frac{\Delta S_k^r + \Delta S_k^l}{2a}. \quad (3)$$

where a is the semiaxis length.

The covariance matrix associated with the prediction error is written as

$$P_{k+1|k} = J_f^X \left(X_{k+1|k}, U_k\right) \cdot P_k \cdot J_f^X \left(X_{k+1|k}, U_k\right)^T + Q(U_k) \quad (4)$$

where $J_{fk}^U(\cdot)$ is the Jacobian matrix of $f(\cdot)$ with the respect to $\hat{X}_k$, P_k is the covariance matrix at time istant t_k and $Q(U_k)$ is given by

$$Q(U_k) = J_{f_k}^U(U_k) \cdot C \cdot J_{f_k}^U(U_k)^T \quad (5)$$

The (5) show that $Q(U_k)$ is the projection of the noise affecting the inputs on the state.

4.2 *Observation prediction*

The observation prediction is given by the vector

$$\hat{Z}_{k+1} = \hat{X}_{k+1/k} \quad (6)$$

The innovation term and the associated covariance, being $\hat{Z}_{k+1}$ the measured output from the webcam, are computed as

$$V_{k+1} = Z_{k+1} - \hat{Z}_{k+1} \quad (7)$$

$$S_{k+1} = J_h^X(\hat{X}_{k+1/k})\, P_{k+1/k}\, (J_h^X(\hat{X}_{k+1/k}))^T + R_{k+1} \quad (8)$$

where $J_h^{k+1}(\cdot)$ is the Jacobian matrix of $h(\cdot)$ respect to $\hat{X}_{k+1/k}$. The first term used to compute S_{k+1} represents the uncertainty on the observation due to the uncertainty on the inertial prediction. The second term is the observation noise covariance matrix.

Actually the webcam neasures are available at a slower rate and some delay. This problem has been worked around as follows: when the webcam information are not available, the Kalman filter is not executed and the position estimation is given by the odometric prediction. As the estimations proceed, all the input and state values are stored together with a time stamp. When the webcam measures became available the nearest time stamp is searched for and the above equations are applied. In this way the past state is corrected. From that instant on, the EKF is executed again using the stored measures and the new state estimations.

4.3 *Extended Kalman Filter*

The Extended Kalman Filter is used to correct the inertial configuration estimate on the basis of the validated observations. Particularly, the final configuration estimate is obtained as

$$\hat{X}_{k+1} = \hat{X}_{k+1/k} + K_{k+1}[Z_{k+1} - \hat{Z}_{k+1}] \quad (9)$$

where K_{k+1} is the Kalman gain matrix

$$K_{k+1} = P_{k+1/k}(J_h^X(\hat{X}_{k+1/k}))^T S_{k+1}^{-1}. \quad (10)$$

The covariance associated with the final configuration estimate $\hat{X}_{k+1}$ is given by

$$P_{k+1} = P_{k+1/k} - K_{k+1}\, S_{k+1}\, K_{k+1}^T. \quad (11)$$

5. EXPERIMENTAL RESULTS

The proposed algorithm has been tested using the mobile robot super M.A.R.I.O., a Creative webcam II and a Notebook (Pentium II 366MHz). The mobile platform is a unicycle robot built in our Department having a front castor and two fixed wheels on the same axle actuated by two independent motors. The robot sensory system is composed by two incremental encoders mounted on the two motors and connected to the on board robot mini-computer where runs the low-level control algorithm. The high-level control algorithm runs on the Notebook, connected to the on-board PC through the serial port. The webcam is mounted on the robot focused to the ceiling (see Fig. 2). The distance between the vision system and the landmarks (rectangular lamps) is about 2.50m, so each pixel is about 8mm at the 356×288 resolution and about 16mm at the 176×144 resolution.

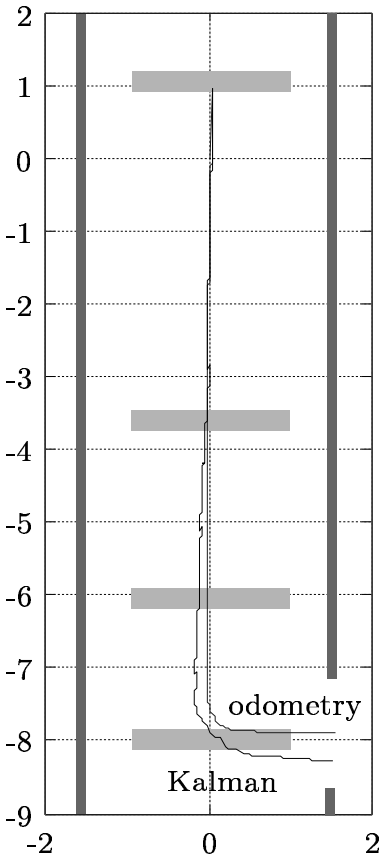

Fig. 6. Odometric and Filtered position

In Fig. 6 a path traveled by the mobile platform is shown. Four lamps are met before turning left into a door. In this very initial experiment (this section will be extended in the final version), the feedback has been closed around the odometry and the initial position has been manually set. A left-turn has been programmed in front of the door and the path labeled as *odometry* is the precise odometric result of the control algorithm executed. The path labeled as *Kalman* is the trajectory computed by the Kalman Filter and the one that has been actually followed by the robot. About 108 frames have been captured (one for each second), and 50% of them have given no information because black. In Fig. 7 the norm of the state covariance has been reported showing how, during the odometric navigation (no lamps in view), it slowly increases meaning that uncertainty on robot position and orientation becomes greater. Once a lamp is again in the field of the webcam, uncertainty is brought back to a value that depends on the visual sensor precision.

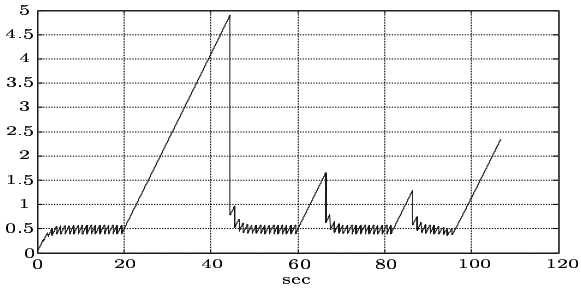

Fig. 7. Norm of covariance along path

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