Robot Localization by Stochastic Vision Based Device

GECHTER Franck
Equipe MAIA
LORIA UHP NANCY I
BP 239 54506 Vandœuvre Lès Nancy
gechterf@loria.fr

THOMAS Vincent
Equipe MAIA
LORIA UHP NANCY I
BP 239 54506 Vandœuvre Lès Nancy
vthomas@loria.fr

CHARPILLET François
Equipe MAIA
LORIA INRIA
BP 239 54506 Vandœuvre Lès Nancy
charp@loria.fr

ABSTRACT

The localization of a mobile vehicle in a dynamic outdoor environment is a very hard task that requires robust data processing and interpretation. This paper proposes a localization device, based on both image processing and stochastic evaluation. As far it is concerned the data processing task is performed by a vision device that uses a principal component analysis in order to find out the most probable position of the mobile vehicle considering the image acquired. This vision device works in parallel with a stochastic position evaluation that uses Partially Observable Markov Decision Process where the observation probability is conditioned by the results of the vision device. The method developed in this paper seems to give very satisfying results compared with standard methods and particularly neighborhoods based ones.

Keywords: Partially Observable, Markov Decision Processes, Karhunen-Loeve Transform, Principal Component Analysis, Computer Vision, Mobile Vehicle, Robotics.

1. INTRODUCTION

The processing of a large amount of information delivered by multiple acquisition devices is one of the key issue in robotics localization. Moreover, mobile vehicles and robotic applications are prone to drifts on account of the inaccuracy of their sensors and their actuators. Such systems need to take those uncertainties into account to produce an autonomous and reliable robot. The localization device developed in this paper is based on data fusion using both computer vision processing and stochastic position estimation. This method provides an effective and relative low-cost system which can be used in order to ensure a robust navigation.

The localization can be considered as the determination of the position of a mobile vehicle considering the known absolute localization of several beacons. Those ones can be physical such as doorsteps for instance, or artificial such as features extracted from sensors acquisition. Among this localization methods, we can notice stereoscopic vision devices ([4] and [5]). The major drawbacks of the stereoscopic methods are the sensibility of the results considering the calibration phase of the cameras and their computational cost which requires the use of DSP (Digital Signal Processor) in order to obtain real time processing. By contrast, beacons algorithms are low cost and reliable but they require the modification of the environment or the use of other mobile vehicles with a known absolute position.([3]).

In order to overcome these drawbacks, we propose, in this paper, an approach based on a Principal Component Analysis (PCA) or Karhunen-Loeve Transform which is a very low cost classification algorithm already used in face recognition and robotics([1] and [2]). The PCA is divided into a preprocessing stage, that structures the initial database by computing a representation of the environment called the space model, and a recognition stage which uses this model to extract the most probable position of the robot. Even if the results are acceptable in an indoor structured environment, the use of PCA is not accurate enough to be sole the basis of localization system. Indeed, successive recognition tasks can lead to very different estimations of the position due to the sensibility of the Principal Component Analysis to the light exposure variations.

On account of the limitation of the PCA method, the vision algorithm has been enhanced with interpretation and anticipation on the moves of the robot by first using a neighborhood (static or dynamic) and second using a Markov based position estimator. Markov models and particularly Partially Observable Markov Decision Processes (POMDP) have already been widely used in robotics ([6]) especially in robot navigation. The POMDP brings an estimation of the position of the mobile vehicle by taking into account the previous probable positions of the robot, its previous moves considering a transition probability and an observation probability. The originality of the approach developed in this paper is the use of the vision algorithm in order to update the probability of the Markov model.

The following paragraph explains the main key elements of the Principal Component Analysis. Then part 3 describes the use of the topology in order to overcome the main drawbacks of the vision method through the use of two neighborhoods methods based on static and growing neighborhoods. Part 4 explains the use of Markov models in the localization task. And eventually part 5 deals with some experimental results.

2. SINGLE USE OF THE VISION ALGORITHM

The principles of the PCA

The aim of Principal Component Analysis (or Karhunen-Loeve Transform) is to sort out multidimensional and homogenous data. This sort is made through the determination of the discrimination axis of the data base by computing the covariance matrix of the system. The classification between the elements of the data base is performed by interpreting their weight vectors which are the projections of the elements on the discrimination axes. Consequently, the comparisons aimed at classifying the data are made in the eigenspace of the system by using only the weight vectors. The extend of this method to a set of images requires an adaptation. It has to be assumed that an image can be represented as a point in a n-dimensional space where n is the number of pixels in the image. Considering the principle of the algorithm, the set has to be composed of homogenous images in term of size and gray level range.

This method has the great advantage to make the comparison between the images by taking into account only general properties instead of classical methods, such as stereovision algorithms, that compare with only some key elements of the images. Furthermore, the PCA based algorithm has a very low computational cost, since the comparisons are performed with the weight vectors. This technique seems to be very competitive compared with the standard ones, and thus can be used on a large range of mobile platforms in order to obtain a real time processing even on standard computers.

The algorithm is split into two parts. The first one is the construction of the space model that requires the computation of the covariance matrix of the system and its eigen-elements. Then, the weight vectors of the images are computed by using the eigenvectors matrix. This information (eigenvectors, weight vectors, mean image of the base) is saved as a structured space model. As explained before, the recognition task is performed by using the weight vectors of the images. As a result, the first stage of the recognition is a projection of the unknown image in the eigenspace. Then the unknown weight vector is compared with the weight vectors of the database. It is assumed that the more probable position of the robot corresponds to the nearest image of the initial set.

First tests with a single vision device

The single use of PCA for the localization of a mobile vehicle raises some issues. Indeed, the first idea considered consisted to find in the database the picture whose distance to the image acquired by the camera was the smallest and to assume the state of the robot was the corresponding state. However, such a method didn't take into account the previous estimated state of the robot to evaluate its new pose. It resulted in teleportation phenomena : the localization system allowed the robot to cross the entire environment, in a single time step which was of course not realistic. Besides, a search through the whole database was needed, thus requiring a high amount of time that could be reduced by a search related to the area in which the robot was supposed to be.

The results obtained with this method without any enhancement are acceptable provided the lighting conditions are well controlled. In such a case, the recognition rate is near 36% in a slightly ambiguous environment. By contrast, when the environment is semi opened (i.e. when the light is both natural and artificial), the results sink up to 10%.

3. INCLUDE TOPOLOGY

To improve the system, the next method relies on the introduction of the topology of the environment in the localization algorithm. To this way, each element of the database is tied with a neighborhood of seven images corresponding to the states the vehicle can reach after one of its elementary moves, taking into account that the robot can drift and move away from its trajectory by a small translation or rotation. The estimated state of the robot has to be chosen among the neighborhood centered on the assumed position of the robot. The figure 1 presents such a neighborhood. On this figure, each big square represents a position of the robot and each small square one of its eight possible orientations. The black dot corresponds to the supposed position of the robot. Eventually, gray dots constitute the neighborhood in which the robot is assumed to be.

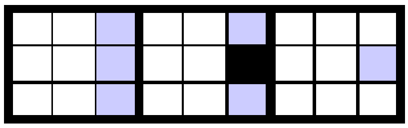

Figure 1: The neighborhood used to force the recognition of the position of the robot.

Unfortunately, since the recognition task forces the estimation, as soon as the vehicle fails to estimate its real pose, the neighborhoods don't include the effective state and the robot is definitively lost. This Method can be improved by the use of dynamical neighborhoods which grow whenever the robot estimates its state is not sure enough or in other words, when the smallest distance between the image perceived and the set of pictures of the neighborhood is above a certain threshold.

Nevertheless, this algorithm is not flawless. Indeed, it is based on a threshold value, which has a big influence on the results and the way this factor is determined is the real weakness of the growing neighborhood method : the distance criterion under which the robot considers it is lost, is currently empirically tuned requiring a lot of manipulations to be adapted to the environment.

4. MARKOV MODELS

MDP and POMDP models

In order to avoid the requirement of parameters that has to be evaluated through experiments, a localization estimator of the robot has been developed. Contrary to the previous methods which were only looking for possible states without further information, this method consists to evaluate recursively the probability distribution among the positions of the entire environment for the vehicle to attain a specific state considering the moves it has undertaken. In order to estimate the probability for the vehicle to be in a particular state, the algorithm presented in this paper is inspired by Simmons and Koenig method ([6]) and is based on Markov models.

A Markov Decision Process (MDP) is a probabilistic automaton : a start state and a given action could lead to different states according to a probability distribution. A Markov model is specified as:

- S, a finite set of states : in our case, those states are the different poses of the robot
- A, a finite set of actions that can be executed in each state : " go forward ", " turn left ", " turn right " for our robot
- T[s'|s,a], a probability distribution.

The Matrix T which gives the probability for the system, making a known action **a**, from a known state **s**, to arrive in the state **s'** determines the result of all the actions undertaken. One of the key characteristic of systems ruled by MDP, is that they must constantly have knowledge of their true state, which is the purpose of our application, by an accurate and complete perception of their environment. That is why, MDP not fitting our goal, a generalization of Markov Decision Process is required: POMDP (Partially Observable Markov Decision Process). Henceforth, the real state of the system is not known but the robot can have some belief about its real pose : it could now make observations and gathers clues in order to guess its state. A POMDP consists of :

- A MDP (a set of states S, a set of actions A and a probability distribution T)
- O, a set of observations.
- P[o s], the probability distribution of observing o in state s.

This model furnishes estimations, called "belief states", of the real pose of the robot. Those belief states B(t,s) contain the probability at each step **t**, for each state **s**, to be the effective state of the vehicle. They are assessed by taking into account the action taken by the robot, the observation made and the former probability distribution, thus, considering the history of the robot's moves. This is the aim of the following equation :

$$B(t,s)=K\times(\sum_{s'\in S}T(s,s',a)\times B(t-1,s'))\times P(o,s)$$

Equation 1

First step: Using a Pseudo-MDP based method.

Markov models can be used as an assistant for the recognition system : from the actions the vehicle has made and the knowledge of its starting state, it will furnish to the recognition system a neighborhood which contains the effective state of the robot. From this consideration, a "Pseudo-Markov Decision Process " is used to evaluate iteratively the possible positions of the robot in the entire environment without taking the information it can perceive into account. The expression of the new evolution law is then reduced to the below equation.

$$B(t,s)=K\times\sum_{s'\in S}T(s,s',a)\times B(t-1,s')$$

Equation 2

From a known belief states, equal to 0 in everywhere except in the robot's starting state, the system evaluates step by step belief states at time t. The real pose of the robot is assumed to be among the states whose belief state is high (a threshold has been set, under which the state is not taken into account for the recognition task), forcing the estimated pose to be included in this set of states. At first, results are promising because it reduces the search with the certainty the true pose of the robot is still among the considered states. However, in the long run, due to the absence of recalibration by extracting information from the environment perceived, belief states become uniform and the recognition task tend to search in the whole database.

Second step: Using a POMDP based method

Nevertheless, the algorithm presented in the previous chapter can be improved by adding a feedback loop. Henceforth, the results of the image processing module are used as observations to perform an efficient recalibration of the robot. In order to link this distance to observations in a POMDP, the law of update of the belief state has to be modified on the basis of the following consideration: if the distance between the image acquired by the camera and the image of the database corresponding to the state s is short, the robot has great chance to be in the corresponding state and the probability for **s** to be the effective state, or , in other words, the belief state of state **s**, must be reinforced. On the contrary, if the distance is high, the same probability should drop. To that way, the probability of observation **o** (P(o,s)) has been replaced by a coefficient proportional to the inverse of the distance between the image perceived and the image associated to the state **s** of the vehicle.

$$Bt(s) = K \times \left(\sum_{s' \in S} T(s,s',a) \times B_{t-1}(s') \right) \times \frac{1}{d(u,s)}$$

Equation 3

As it is highlighted by the experimental results, this Markov based localization system is more efficient for locating our robot. This fact can be explained by the following points. At first, because belief states at time t are updated from belief states at time t-1, the system bears in mind the information it can extract from history. Thus, even if the system failed to estimate rightly the effective state of the robot, it can nevertheless be assumed that the belief state corresponding to the true state of the mobile vehicle is high and that, after the next time step, it is highly probable the new image perceived will allow the system to clear up the ambiguity. Besides, this method permits to avoid the "sensor aliasing" problem : in a uniform indoor environment, two states can generate nearby observation. It is then quite difficult, from sole observation to determine where the robot might be. Our system takes the information contained in the history of the moves, kept throughout the belief state into account and merges it with the results obtained by the image processing module. So, if probabilities of observation are similar, the system will more rely on history to determine where the vehicle might be. Eventually, like in the previous method, it is also possible to lead the search in the database, accelerating the task by reducing the extent of the search.

As it appears in experimental results, the system we have developed is characterized by its robustness. The robot, even if it is totally lost in the environment, can be located in few steps.

5. IMPROVE THE SYSTEM BY ADDING NEW DEVICES

To enhance this already robust system, a second video device whose axis is perpendicular to the translation axis of the robot has been added as it is depicted in [1]. This new camera furnishes a new amount of information non correlated to the information acquired by the first one. The vehicle gathers more hints to evaluate where it might be. That is why its estimation should be more efficient and accurate. Besides, it is easy to include these new information in the Markov model by considering new observation : henceforth, it consists in a couple of distances. The first distance is furnished by the PCA module applied on the image obtained by the first camera, the second is the result of the same module but applied to the image acquired by the second camera. The product of the inverses of the distances has now the role of probabilities of observation for our model. Moreover POMDP take into account the relevancy of a piece of information. Indeed, when information is not pertinent, the distribution of probabilities of observation tends to be uniform and belief states are thus not highly modified by it. On the contrary, when information is relevant, few states will be highly reinforced. Ultimately, the new data can be processed by the existing PCA module and , because the environment is the same, the database is still adapted, thus requiring no additional development.

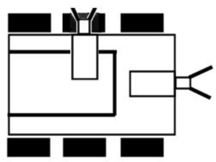

Figure 2 : The position of the two cameras

Images provided by this new camera improves the efficiency of our localization system. Especially when the robot goes forward, since a small movement leads to an important modification of the picture acquired by the second camera. For example, it is particularly pertinent when the robot advances in a long corridor.

6. EXPERIMENTAL RESULTS

The test base

The test area is an 18-squared meter area with a lot of windows and a high reflective ground (fig 3 presents some pictures of the test area). Moreover, the lighting condition are not controlled because it depends on the sun exposure. This environment can be considered to be semi-opened (i.e. it is structured as an indoor environment but the lighting condition are similar to outdoor).

The test area has been divided into squared state (1 meter by 1 meter) tied each with 8 sub states that correspond to the eight natural orientations.

Figure 3 : Some pictures of the test base

In order to perform the test, a second base (144 pictures) has been constructed with other lighting condition and shift position compared with the previous database.

Comparison of the four methods

The tests were made by using a simulation program that takes into account the inaccuracy of the effectors of the mobile vehicle(i.e. actions are made at each step and their result is determined by a transition probability computed from data from various real robots). We performed the same sequence for the four methods by counting the number of failures in the position estimation and the number of good recalibrations of the robot after the loose of the real position at the previous step. The figure 4 shows the rate of bad estimations obtained by the neighborhoods methods (static and growing neighborhoods) and by the Markov based method (with one or two cameras).

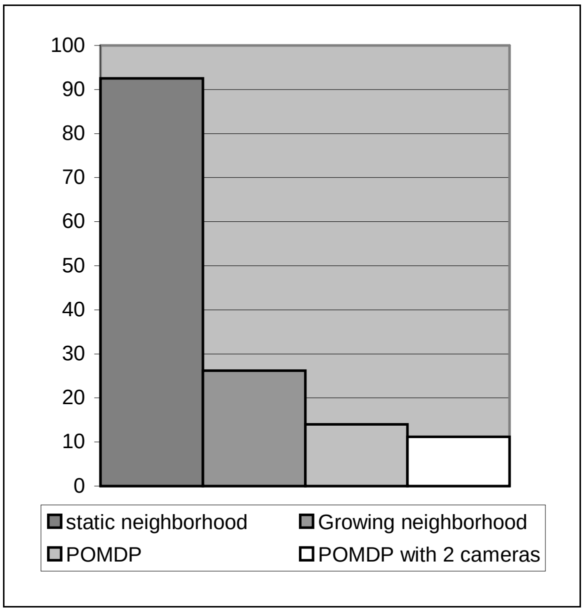

Figure 4 : Rate of bad estimations

The results obtained after the first test point out a small bad rate estimation for the POMDP method with both one and two cameras. (10% better for the two-camera method). The static neighborhood method shows very bad results whereas the growing neighborhoods ones are still acceptable.

The figure 5 presents the efficiency of the four methods. The efficiency is computed by making a comparison between the rate of bad estimation and the number of recalibration success.

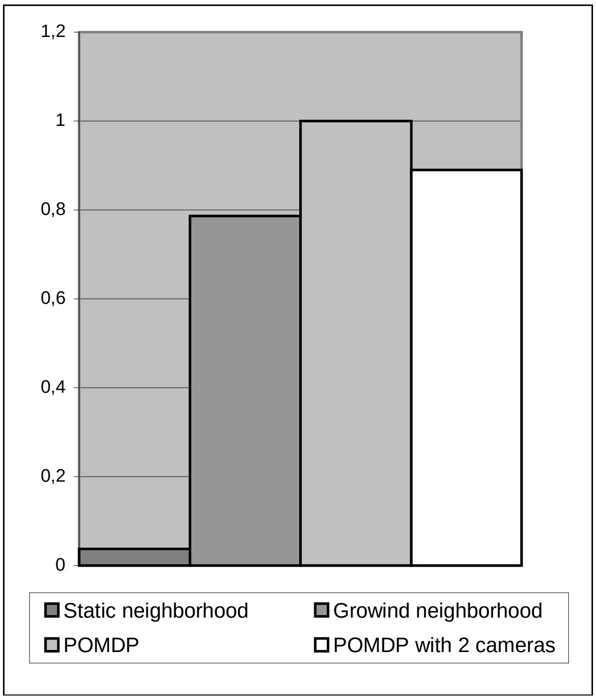

Figure 5 : Efficiency of the different methods

Even if the growing neighborhoods method and the POMDP based methods are similar for the results presented in this section, the first method is less reliable. Indeed, the Markov-based method are not tied to empirical threshold, thus allowing a better adaptation skill in various environments.

Eventually, the addition of a second camera is encouraging since the system is then less prone to failures in estimating the pose of the vehicle. The drop of the "efficiency” of the last system can first seem intriguing but can be explained. Indeed, a robot with two cameras fails to estimate its effective state when the situation is intricate, it is, then, more difficult for the system to recover the pose of the vehicle

7. CONCLUSION

We succeeded in developing a new powerful algorithm whose goal was to recognize the location of a mobile robot in a structured environment. The main advantages are, on the one hand its low cost at both software and hardware levels and, on the other hand, its largely satisfying success rate. The on-line recognition process is very competitive compared to the current algorithms. Moreover, the use of cameras to determine the pose of the robot allows to consider an exploitation of the algorithm in parallel with other vision modules like stereovision module for instance. Furthermore, the processing time of this method makes it possible for its use on low power mobile platform.

Considering the good results of the Markov based approach, further research will be performed. It can consist to improve the Markov model. For now, we have focused on the inverse function, but it might be interesting to study different adapted functions to link the observation to the results of the PCA. We can also imagine to modify the image processing module : the use of "incremental PCA", which constructs and structures its own database of images, adding a new picture whenever the vehicle observes an image corresponding to a state that has not been yet explored, seems to be promising. It would allow to avoid the requirement of a preliminary database of images meant to be representative of the environment which was the main drawback of the algorithm we have presented.

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