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Robot Localization by Particle Filter using Visual Database

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Abstract - One of the major problems in robotics is to recognize the robots position with respect to a given environment. More recently researchers have begun to exploit the structural properties of robotic domains that have led to great success. A general solution for such problem is the implementation of particle filters. The particle filter is more efficient than any other tracking algorithm because this mechanism follows Bayesian estimation rule of conditional probability propagation. In this paper we would like to present an approach to improvise the particle filter algorithm using SIFT pattern recognition technique and image database processing to obtain unimodal uncertainty for effective position tracking.

Keywords - Particle Filter, SIFT, Monte Carlo, Fast SLAM.

I. INTRODUCTION

One of the key developments in robotics is the development of probabilistic techniques for global localization. Most of the research focused on planning and control in a fully deterministic environment. Brooks proposed a method of control directly based on the sensor behavior [1]. Since the robot localization was never certain this method was typical. Later most of the models started making use of imperfect models and statistical distribution of sensor data to solve the problem. Traced back to 1960 probabilistic laws and Bayesian networks were used to integrate imperfect models and imperfect sensors. Many recently related field employ probabilistic techniques for perception and decision making [2, 3, 4].

A general solution of such probabilistic decision model was Particle Filter algorithm. They comprise a broad family of Monte Carlo algorithms for approximate inference in partially observable Markov Chains. Early successes of Particle Filter implementation can be seen in [5]. Particle filter mainly solved 2 main problems, global localization [6] and kidnapped robot, in which the robot has to recover its pose under global uncertainty. A sincere approach was made by Sebastian Thrun for Particle Filter implementation in robotics [7].

However the application of particle filters to robotics is not without caveats. Some factors arise from the fact that however detailed the probabilistic model may be, it shall still be wrong. Hence to overcome these problems much high probabilistic based decisions has to be made. One such way would be the use of pattern recognition and image data analysis of map scenes. In this paper our main motive is to provide an efficient

method to improve robot localization problem by the use of SIFT pattern recognition implemented through particle filters. We would see that such method would lead to much quicker and efficient unimodal solution for robot localization. This would lead to more accurate solution of the position of the robot in a given environment by rejecting the uncertainties in particle filter. The organization of the paper is as follows: Section 2 deals with the Particle filter algorithm. SIFT pattern recognition is explained in Section 3. Various database and map models and their analysis are dealt in Section 4. Overall algorithm is discussed in Section 5. Finally Section 6 deals with the Conclusion and Future work. A block diagram of the entire algorithm is shown below.

Fig. 1 : Block Diagram of robot localization by Implementation of Pattern Recognition in Particle Filter.

II. PARTICLE FILTER ALGORITHM

One of the major problems with the robot in real time system is the robot localization problem. Localization is the ability of the robot to locate itself in space. Efforts have been made throughout the years to solve the localization problem rather than using GPS devices in robot where margin of error is high (of orders of 10 meters). Objective of implementing successful localization demands the need to reduce the margin of error up to two to three centimeters. To every point or state space there is an associated probability. Posterior probability function is the best representation of robots current belief. This has led to increase in robustness of mobile robot and localization problem with a given map to be solved. [7]

Fast SLAM, a particle filter algorithm has been used, because of its capability to solve the high dimension localization problem in real time. Particle filters are approximate technique for calculating the posteriors in partially observable controllable Markov chains with discrete time.

The most basic version of particle filter is given by the following algorithm.

- Initialization: At time $t=0$, N particles are drawn according to $p(x_0)$, which is the probability distribution of initial state x_0 as shown in.
- Recursion: At time $t>0$, generate the particle x_t according to probabilistic law $p(x_t|u_t, x_{t-1})$ (also referred to as actuation model) where u_t is the control asserted in the interval $(t-1, t)$. The state in Markov chain is not observable. So one can measure z_t which is the stochastic projection of true state x_t generated from the probabilistic law $p(z_t|x_t)$ (also referred to as measurement model).

Bayes filters [9] provide the solution to recover posterior distribution over the state x_t at any time t .

In the context of localization Particle filters are commonly known as Monte Carlo localization (MCL). MCL is basically inspired by condensation algorithm, a particle filter that gained popularity in computer vision [10].

Fig 2 describes the working of Monte Carlo Localization. In Fig 2(a) robots position along with global uncertainty state or state of maximum confusion is shown. In Fig 2 (b) after condensation of particles an intermediate state is shown. Fig 2 (c) shows the final state where robot has successfully localized itself eliminating confusion. MCL has also been made temporarily more persistent by clustering particles and using different sampling rate for different clusters.

Fig. 2(a) : Initial State

Fig. 2(b) : Intermediate state

Fig. 2(c) : Final State.

One of the main problems encountered in particle filters is the poor performance in higher dimension spaces because the number of particles needed to populate a state space increases exponentially with dimension of state space. As this article deals with localization in higher dimension space, the problems concerning the higher dimension space needs to be considered. The localization error can occur because of errors in the environmental features of the map and data association problem of determining whether two

environment features, observed at different points in time, correspond to the same physical feature in the environment. Also all applications require real time processing [7].

The resulting estimation is described as a problem of jointly estimating a time-variant robot pose x_t and time invariant location of N features denoted, y_1 to y_n :

$$\begin{aligned} p(x_t, y_1, \dots, y_N | z^t, u^t) \\ = \text{const.} \cdot p(z_t | x_t) \int p(x_t | u_t, x_{t-1}) \\ p(x_{t-1}, y_1, \dots, y_N | z^{t-1}, u^{t-1}) dx_{t-1} \end{aligned} \quad (1)$$

This integration involves only the robot pose x_t and not the variables $y_1 \dots y_n$.

A particle filter algorithm, Fast SLAM, is used as it overcomes the problems associated with high dimensional space. Also it exploits the fact that robot may only observe a finite number of features at any point of time. The use of particle filter opens the door to solution of data association problem. Fast SLAM makes it possible to sample over data associations rather than simply assuming that the most likely association is correct. FastSLAM can also incorporate negative information that is, not seeing a feature that the robot expects to see. This is achieved by modifying the importance factors of individual particles accordingly.[7]

III. SIFT

Since robot localization requires accurate pattern matching results, SIFT algorithm was chosen for this purpose. Scale Invariant Feature Transform (SIFT)[8] algorithm developed by David Lowe is proven as efficient method in Object recognition leading to very satisfying results due to invariance to translation, rotation, partial illumination changes and affine or 3D projection. The SIFT features share a number of properties in common with the responses of neurons in Inferior Temporal cortex in primate vision [1].

The SIFT approach firstly identifies the key locations in scale space by locating local maxima or minima of Difference of Gaussian function. These points are used to generate the feature vectors describing image region sampled relative to its scale space co-ordinates. These features are invariant to local variations by blurring image gradient locations. A 2D Gaussian function (1) is used for blurring the image.

$$g(x) = (1/\sqrt{(2\pi\sigma)}) \cdot \exp(-(x^2)/(\sigma^2)) \quad (2)$$

Where σ is the standard deviation of the Gaussian distribution.

The feature vectors are called SIFT key points. These key points are used in indexing to identify candidate object models. The keys which match are identified through hash table. When at least 3 to 4 keys agree, there is a strong evidence of a match. Fig 3 depicts the key points identified by SIFT algorithm. The red markings are the key points found by SIFT in the image.

There are variety of benefits of using SIFT algorithm over other methods.

- SIFT performs an accurate pattern match due to large number of features under consideration.
- The algorithm is Scale, Rotation, Illumination and View point invariant.
- Due to requirement of less number of key points for recognition purpose, the solution is highly redundant and can sustain substantial occlusion.

Fig. 3. (a) : Key points of input image 1

Fig. 3 (b) : Key points of input image 2.

Fig 4 shows the matched key points of input images 1 and 2. These key points are marked green for reference. A probability analysis is carried out based on the number of matched points with the database (explained in section 3). The result of the matching technique is shown in Fig 5. Also a table describing the stability of SIFT algorithm is shown in Table 1.

Fig. 4. (a) : Matched Key points of input image 1

Fig. 4. (b) : Matched key points of input image 2.

Fig. 5. (a) : Matched Database image1 vs. input image1.

Fig. 5.(b) : Matched Database image2 vs. input image2.

TABLE I. Table describing the stability of SIFT transform

Sl. No.	Key Stability to image Transformations		
	Image transformation	Match %	Ori %
A	Increase Contrast by 1.3	89.0	86.6
B	Decrease Intensity by 0.3	88.5	85.9
C	Scale by 0.7	85.1	80.3
D	Stretch by 1.3	83.5	76.1
E	Add 10% pixel noise	90.3	88.4

IV. SELECTION OF MAP MODEL AND DATABASE IMAGES

The very first task of the project is to provide a model of robot environment generally referred to as Map Model for robot to locate itself. The robot locates or knows its position with respect to this map. Also database images has to be supplied for SIFT recognition and Particle Filter analysis. Now the main challenge is to select specific database images for recognition purpose in a given Map. The following subtopics deal with the Map model and selection of database images in a given Map.

A. Map Model:

For global localization of a robot in its given environment a Map of the environment is provided which is the reference for the robot to localize itself. Initially if the robot is left in this environment in a random point, it shall have no clue about its position. Certain points are marked which confirms the position of the robot to its given environment. A map of a street area in New York is shown in Fig 6. The numbers marked in red boxes corresponds to the respective database images in those positions. In this case 1 corresponds to database image1 and 2 for Database image2 respectively (shown in Fig7).

Fig. 6 : Map Model describing the position of Database Images.

B. Database Model:

The selection of database images is a tricky task as images have to be chosen such that they are less repetitive or unique in the environment. Map model of Fig 6 shows 5 varied locations of different database images. These database images are shown in Fig 7. Marking “1” in Fig 6 corresponds to Database image 1 in Fig 7 (a). Similarly “2” for Database image 2 and so on. These images are stored in the memory for matching purpose. Every time the robot views an image it compares that image with these predefined database images. Once the comparison is matched, the location can then be tracked with respect to the position of that image placed in the map. Hence the database images selected should be static images/scenes/figures etc. It should be noted that presence of same object in more than one place shall lead to slight uncertainty but still maintaining its efficiency.

Fig. 7 (a) : Database Image

Fig.7(b) : Database image 2

V. ALGORITHM DESCRIPTION

Initially suppose the robot is left in a random position in the given environment, the main task is to search for the images in the surroundings which are similar to database images. But at the same time robot

has to continue its locomotion in a particular direction according to particle filter algorithm with equal probability distribution at every point. The following processes are carried out:

A. Image Acquisition and processing:

The initial stage of the algorithm is the acquisition of the input images through the camera. Once these images are acquired they are then smoothened using a Gaussian function to reduce the noise in the images as real time images are more subject to noise. It is then filtered using a median mask. Once these processes are completed the image is ready for further pattern matching algorithm.

B. Object Recognition and Probability Analysis:

Once the image is smoothened it is then tested for key points matching through SIFT algorithm as described in Section 3. Suppose if the input image is recognized with the database image the probability distribution of the entire map is drastically changed as the robot recognizes its position in the given environment. A second case would be if there are similar images in the Map model, the particle probability would be concentrated more in those areas where these images are present. For example consider the database image of trees. In Fig 6 it can be seen that trees are mostly present at the right most side of the map and in few other places. Hence this would give a probability distribution such that more particles are present near the tree part either in the rightmost side or in other places with much probability at the right side. Further the position can be determined only after observing upcoming images.

Fig 8 depicts the process of the algorithm as the robot moves initially in a random location in the given environment. In Fig 8(a) the robot is left in a initial unknown position. It can be seen that the probability distribution in this case is over the entire map as the probability of robot being in every place is same. Now as the robot moves forward the particle probabilities starts getting concentrated at only some particular positions. This is shown in Fig 8(b). Further in Fig 8(c) it can be seen that once the robot is closer to the image points where the object is recognized with the database image there is a drastic change in the probability distribution according to the posterior function. It can be seen that the particles are more concentrated at one position after the robot comes nearer to the data base points in the map. Like this the robot gets to know its present position in the environment. Now it shall be able to achieve its destination according the user requirement.

Fig. 8 (a) : Initial position of the robot and its particle distribution.

Fig. 8 (b) : Particle distribution as the robot moves ahead.

Fig. 8(c) : Particle distribution as the robot recognizes the object.

VI. CONCLUSION

In this paper we have presented a Fast SLAM particle filter approach with visual database recognition for enhancement of robot localization techniques.

Particle filters have always been applied for localization on small scale. Recently, advancement variants of particle filters have provided new solutions to challenging higher dimension problems. These approaches use representations expressed by conditional independence.

The main idea was to develop a mechanism for robot localization in an unknown environment. This technique is more valid in real time environment but the only disadvantage would be in the matter of computation time when a large number of database images have to be matched. However this could be overcome by using certain AI techniques for image classifiers. In future we would like to enhance this technique by investigating 3 D models using stereo vision analysis.

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