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Simultaneous Localization and Mapping: Issues and Approaches

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***Abstract*– Nowadays, with technological advances in the science of robotics, We've seen building the robots to work autonomously in other planets, under seas and oceans and each unknown environments. Considering that the robots do not have any information about the environment, should have the ability to build environment map on the move and also estimate its location on that map correctly. This action is called Simultaneous Localization and Mapping (SLAM). Mapping is to obtain a model of the robot environment, and localization is to estimate the position of robot in obtained map. For building map, we need to acknowledge about location of robot and for localization we need to map (chicken and egg problem), so the SLAM is a hard and famous problem in robotic word. In this study, we will explain related issues and parameters that are necessary for investigate and work on the SLAM problem.**

***Index Terms*– Simultaneous Localization and Mapping, SLAM and Robots**

I. INTRODUCTION

NECESSITY of determining the position of the robot and knowing the position of the required objects on the map in unknown environments such as underwater, other planets and the remaining areas of natural disasters, leads to the development of efficient algorithms for Simultaneous Localization And Mapping (SLAM) in the past three decades.

The robots for their duties need to identify their surroundings and estimate their location with high precision. Because robot doesn't have any information about environment that is enter in there; so starts to construct a map and find its location in that with using of its odometer and sensor data. In simultaneous localization and mapping(SLAM); the mobile robot catches the data from environment with own sensors then interprets them and after building a appropriate map, determine its location in that map [1], [2], [3].

Due to the name of problem; we have two key words: mapping and localization. but in SLAM problem, apart from localization and mapping issue, we have many effective factors like sensors uncertainty, loop closing, correspondence issue, time complexity, memory complexity, dynamic environment etc. in this paper we will review these parameters. After this section we will study the kinds of map in section II and in section III we will review the some effective parameters in localization and mapping and at section IV we will introduce some tools and methods that are using in SLAM solutions [1], [4].

II. MODEL OF MAP IN ROBOTIC

Maps are often used for guidance and localization, so for mapping; robots must be equipped with several sensors. Sensors that are commonly used for this work are Sonar sensors for measure the distance, laser, radar, infrared, touch sensors, GPS, camera etc. It should be noted that all the sensors have at least a bitty of measurement error and also most sensors have a limited operating range so because of these limitations, robot for building the map should move in environment and use of sophisticated methods.

In general, in different types of robotics applications, four methods are used for representation of environment map: metric map, topologic map, conceptual map and cognitive map [5].

A. Metric Map

Metric map shows a scaled display of the environment. One of metric maps is occupancy grid that represented the environment with a discrete network of cells. The cell is occupied by an obstacle or is empty and is considered as vacuity. This method is used especially when the mobile robot is equipped with distance sensors like sonar because map update is easier. Each cell has a counter that increases when the distance sensor return a value for it, and decrease when measurement passes it. The important weakness of this solution is using high memory [1], [6], [7].

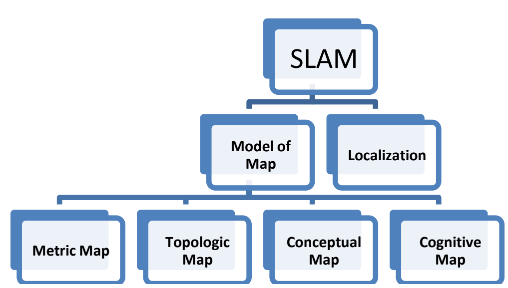

Figure 1: Kinds of Map in SLAM

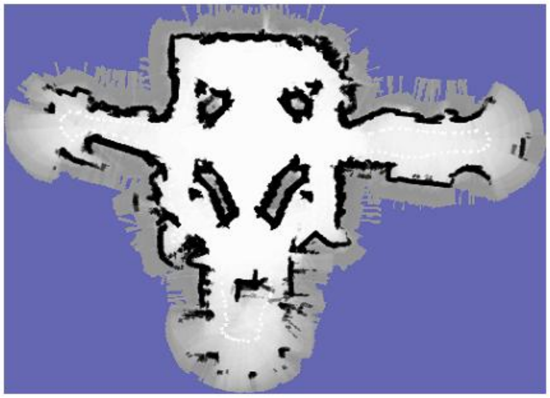

Figure 2: Occupancy grid as a metric map that in this model the map is represented with discrete network a of cells that each cell is occupied by an obstacle or is empty and is considered as vacuity

B. Topologic Map

In topologic maps; avoid to the environment geometric measurements and instead, emphasizes the characteristics of an environment that is effective in robot localization. In the general case, the topological map is a graph of nodes and links. The nodes show the important places in environment and links show the contiguity of nodes. When a link connects two nodes means that the robot can move directly between those two places. The feature of topologic maps is simplify of maps and their uses [6], [8], [9].

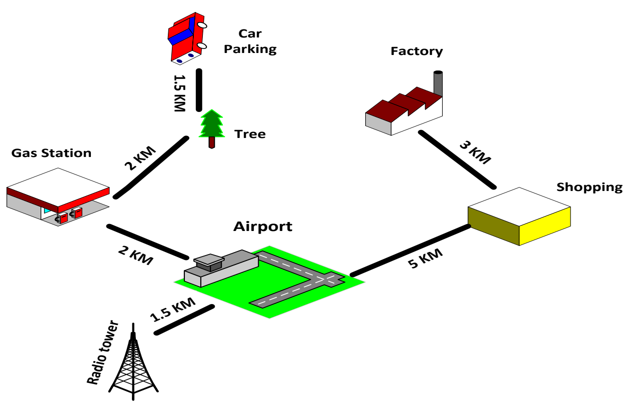

Figure 3: Topologic map: a graph of nodes(locations in the environment) and links(contiguity of nodes)

C. Conceptual Map

In this approach, Galindo and his colleagues are trying to equip the robot with organizing and representing knowledge. These two knowledge will be related through the anchoring. This work connect the symbols (like bed-1 in Figure 4) to special data that refers to the same physical entity in environment. The Figure 4 shows the mentioned structure well [10].

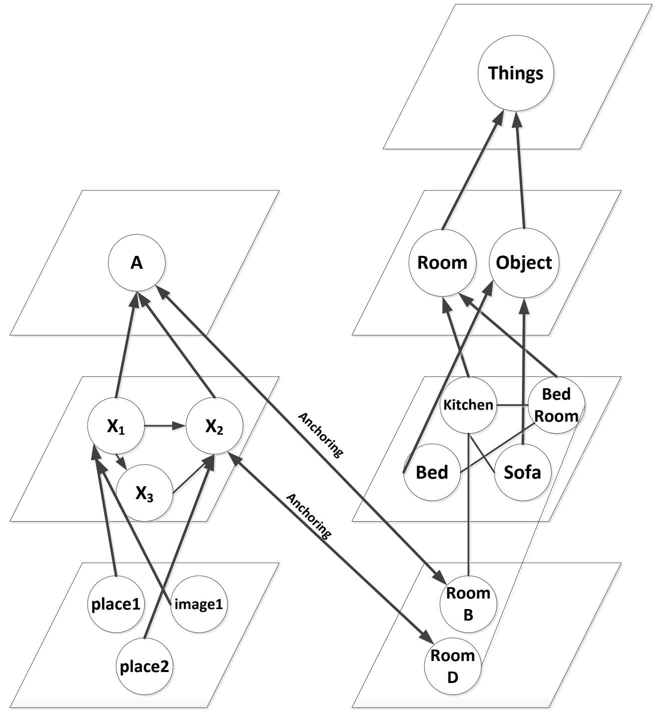

Figure 4: the hierarchical structure for conceptual map. in left side; the geometric information collected by the robot and right side is semantic Information

D. Cognitive Map

In cognitive map, a model will be presented that intelligent robot, understand the environment map like humans. Thus based on it, act like humans. In these maps, model is presented based on anatomy and function of the human brain. Actually is a biological model of the human brain for map building [1], [11].

III. EFFECTIVE PARAMETERS IN SLAM

There are some important and effective parameters in investigation of SLAM problem that is necessary studying those before addressing the main issue. Some of these are useful for suggested solutions evaluating.

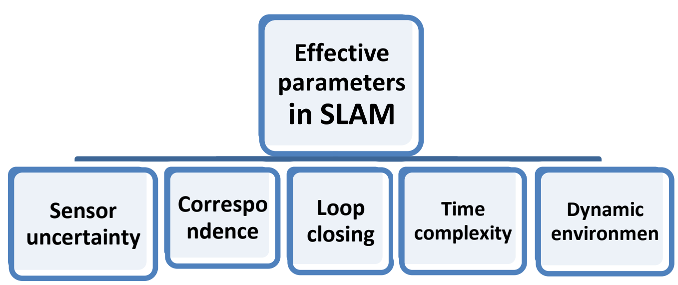

Figure 5: Effective parameters in SLAM

A. Sensor Uncertainty

All sensors have a small amount of error, due to the accumulation of these errors, whatever the robot knows about environment is polluted with correlated error [1], [12]. Elimination of these errors is an important step in building a map successfully. The following reasons can be named as sensors uncertainty:

- ✓ Restriction of incoming: the most of robot's receive range is limited in a small distances from around the robot. So makes sense the farther distances with more error.
- ✓ Sensor fault: data obtained from the sensor may be polluted with noise and in some cases the error distribution is unknown.
- ✓ Mistake/Slip: Unfortunately the robot movement is not always accurate. A little slip in time will cause big problems for robot for example existence a small pebble in a robot path may be cause of the overall change in the obtained map [12], [13].

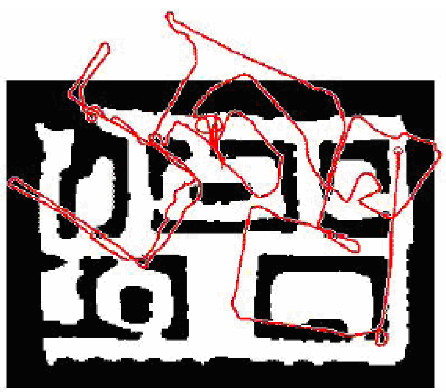

Figure 6: The black episodes is real map and red lines are mapping data based on odometer movements(uncorrected) that has a much error

B. Correspondence Issue

Another issue in mapping is correspondence, that sometimes is called data relation. This issue will determine that; are sensor measurements at different times related to the same physical object or no? the Figure 7 shows an example of this issue. At the end of the loop, the robot must decide that what is its position in map that is previously made [1].

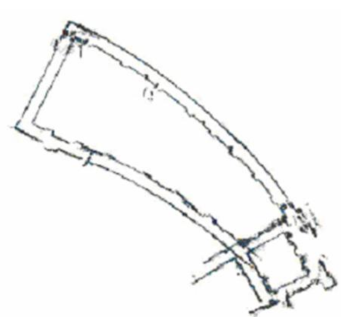

Figure 7: One of correspondence is where the robot moves in a loop

C. Loop Closing

This issue performs after correspondence recognition. This case is shown in Figure 8. At the end of the loop, the robot must decide that what is its position in map that is previously made. It is therefore difficult because during the closing loop may accumulated error be too high. Other this issue's difficulties is; map and location assumptions will grows exponentially [14], [15].

Figure 8: an example of closing the loop; (a) is a map with using of laser and odometer. (b) is the map after closing the loop

D. Time Complexity (Computational Complexity)

The algorithm which is implemented on a autonomous mobile robot should be performer real time, because in many uses of these robots, the time is very important and robot should works fast [2].

E. Dynamic Environment

This is one the raised problems in SLAM. The environment may be change dynamically like remaining areas after the earthquake may deforms during the robot moving. This issue can make two hypotheses for the robot: first, the environment has changed. Second, robot has entered in a new place(where previously has not been) [1].

IV. TOOLS OR METHODS FOR USING IN SLAM

There are some common basic methods or tools that are used in most of SLAM solutions individually or in hybrid form. In this section we will review these tools .

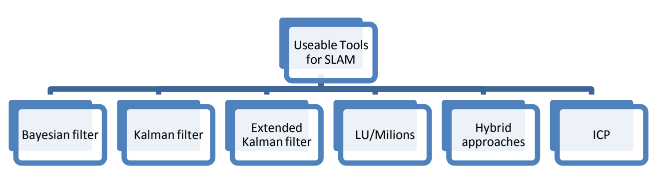

Figure 9: SLAM Tools and Methods

A. Bayesian Filter

We can say all of successfull solutions in field of map building in mobile robots, are using of probabilities approaches. Of course according to sensors uncertainty and the extant noises in sensors, this subject is provable [1], [16], [17]. The basic principle in probabilities solutions is bayesian rule in Equation 1.

$$P(x|d) = \eta P(d|x) P(x) \quad (1)$$

Suppose we have d and we want catch probability of quantity of x , bayesian rule or bayesian filter says that we can catch this probability with multiple two phrase: P(d|x) and P(x) coefficient of η is a normalizer.

In the procedure of mapping in mobile robots, data are obtained during the time and by robot measurements, thus this data are in two categories: values that are measured by sensors and values that are measured by robot controls like odometer. So this data are used for definition of probability.

The bayesian filter can be used for mobile robots state determination in Equation 2.

$$P(x_t|z^t,u^t)=\eta P(z_t|x_t) \quad (2)$$

$$\int P(x_t\,|u_t,x_{t-1})\,P(x_{t-1}|z^{t-1},u^{t-1})\,dx_{t-1}$$

$$\int P(x_t\,|u_t,x_{t-1})P(x_{t-1}|z^{t-1},u^{t-1})dx_{t-1}$$

In Equation 1, x depicts the state of robot, z is data from sensor, u is control data and t is an index for time [12], [18].

Because our target is calculate of map and state of robot simultaneously, thus x is Include the map and location. The map is shown with m and location with s:

$$P(s_t,m_t|z^t,u^t)=$$

$$\eta P(z_t|s_t,m_t) \iint P(s_t\,,m_t|u_t,s_{t-1},m_{t-1})P(s_{t-1},m_{t-1}|z^{t-1},u^{t-1})ds_{t-1}dm_{t-1} \quad (3)$$

of course If it is assumed that the environment is static, the t will be removed from m, and also if If it is assumed that the location is independent from map, the Equation 3 becomes as below:

$$P(s_t,m|z^t,u^t)=\eta P(z_t|s_t,m)\int P\left(s_t\middle|u_t,s_{t-1}\right)P\left(s_{t-1},m\middle|z^{t-1},u^{t-1}\right)ds_{t-1} \quad (4)$$

B. Kalman Filter (KF)

One of the best and widely used approach in map building is the approach based on kalman filter. The solutions based on kalman filter are improving and enhancing from middle of 80's up to now. Kalman algorithm for the first time was introduced by kalman and quickly its High potential was Identified, but until 1988 was not used for representation of a complete environment (Welch and Bishop 1995) (Thrun 2003) [1], [18], [19].

Actually kalman filter is same with bayesian filter whereas kalman filter shows probability estimate with Gaussian Distribution. As you know, Gaussian distribution is a uni-modal (single peak) distribution that is very good represented its behaviour with some simple parameters. In the map building issue, this distribution shows as a vector (x). this vector include the robot map and its location:

$$x_t = (s_t, m)^T \quad (5)$$

This vector is called, state vector.

If we assume that the environment is two-dimensional (this is mostly), we can display the location of robot with three parameter: place in x axis–place in y axis and robot orientation. Also some features are used for description map. with these assumptions, the state vector becomes as Eauation 6:

$$x_t = (s_{x,t}, s_{y,t}, s_{\theta,t}, m_{1,x,t}, m_{1,y,t}, \dots, m_{k,x,t}m_{k,y,t})^T \quad (6)$$

The dimension of this vector is 2k+3 , the k is number of features that are used in map. $m_{k,x,t}$ in this equation is location of k th feature in estimated map.

In the mapping issue, kalman filter is based on three assumptions: 1- the function of the next state is linear with a cumulative noise 2- the robot cognitive model must has this specifications 3- the initial uncertainty must be Gaussian. Linearity of the next state, means: the robot location and map at the time t be depend to robot location and map at the time t-1 and also depend to control data. This assumption is true about map; because our assumption is that the map is fixed, but about the robot location; it is depend to last location and control data nonlinearly. So we need estimate this nonlinear behaviour for compatibility with above assumption [20], [21].

C. Extended Kalman Filter (EKF)

Another solution (in kalman filter) used linear function obtained from Taylor series expansion for robot moving model estimation. These solution named as extended kalman filter [1]. The result of this linearization is that; we can illustrate the state changes in form of a linear function with Gaussian noise:

$$P(x|u,x')=Ax'+Bu+\varepsilon_{control} \quad (7)$$

In above equation, A and B are two matrix that do linearization of last state and control data to new state and ε is normal distribution and zero average measurement's noise.

Actually the number of used features is between tens and maximum several hundred. The most costly action in kalman filter's update is multiple of matrixes. some approaches with dividing the problem to multi minor problems, have ability to work with more features.

The important limitation of approaches based on kalman filter is Gaussian noise assumption. To clarify this limitation, please assume we have two non-difference landmarks that lead to multimodal distribution on robot possible positions; that is in paradox with Gaussian uni-modal distribution. This limitation leads to special changes in implementation of these solutions (based on KF). Due to this limitation, implementation of these procedures need to some landmarks (features) that are easily differentiable, it means that they have completely different specifications or they have acceptable distance. Error in detection of features in these solutions will lead to failure in map building procedure, so for avoidance of this event; is forced to ignore many measured data by its sensors, and work with a few features. The obtained maps contain only these location information, so seriously is confronted with shortage of geometric information of environment [22], [23], [24].

D. Lu/Milios Solution

This solution is partly a new and improved solution based on kalman filter. This approach is composed of two phases: in first phase, the secondary probabilities are calculated with kalman filter and in second phase, the measured values of different measurements are mixed together. In this approach correspondence between measurements is done through maximum Likelihood estimation. Also with repetition of these two phase, the correspondence is obtained. The Lu/Milios solution mostly is worked with laser sensors [1].

In practice it has been shown that this solution has ability of building map with unknown correspondent data(some data with unknown correspondence), but using of maximum Likelihood estimation for probability leads to some limitation. In this approach if the initial estimation has little error; this solution performs very good but if initial error was more than 2 meter (for example in map building of circle environment); this solution cannot work well. Also this solution for covariance, needs to frequent passing and gathering of information, thus this solution is not a real time approach. The full of errors data in this solution leads to failure in map building procedure whereas in other solution based on kalman filter; the error data leads to building map with error (not failure in building map) [25].

E. Hybrid Approaches

There are other solutions for a robot building map that mix secondary probability with a maximum likelihood estimation. One famous of these solutions is the Incremental Maximum Likelihood. It can be said that it is a subsidiary version of the Kalman filter solution. The main idea of this solution is that: the robot builds only one map incrementally with obtaining data from sensors and without following of reminder uncertainty. The main reason for the popularity of this method its simplicity. Mathematically language, It can be said the main idea is that; A series of maps with the maximum likelihood are generated alongside of a series of Pose Estimation with the maximum likelihood [26], [27]. Map and position in time t are generated based on map and position in time t-1 and marginal border maximization. This operation is shown in equation 8:

$$(m_t^*, s_t^*) = \\ arg\ \max_{m_t, s_t} P(z_t|s_t, m_t)\, P(s_t, m_t|u_t, s_{t-1}^*, m_{t-1}^*) \qquad (8)$$

The above equation directly use of a Bayesian filter with know of before robot position and map assumption. In practice, it is enough to do the searching between the robot position environment. As a result, for determine location of s_t^* (that it maximizes the next marginal border) needs to only one search in robot positions environment at the times that arrive new data. Like the kalman method, this solution also build map real time, with this difference that in this approach uncertainties are not stable (are not considered). Of course despite of the reason for popularity, this is a big weakness for this solution because due to the Ignoring the uncertainties, cannot modify the previous information with new information. It shows itself when for example the robot is moving in a circular path. For loop closing, this method works badly. Because of the Ignoring the uncertainties; measurement errors increase too much that leads to incompatibility and this approach is unable to solving this problem [28], [29].

Some hybrid solutions solve this problem with generation of an explicit model of uncertainty during the map building. For example; some successful methods solve this problem with adding a part to maximum likelihood. This solutions Addition to using of previous solutions for map building, generate a probability distribution based on Bayesian filter for robot positions. Actually with this approach (that keeps the uncertainties), in faced with cases like circular path and much errors, we can resolve the incompatibility. Nevertheless, the hybrid solutions have many basic weaknesses. These methods don't have ability to deal with uncertainties inside environmental. For example if multiple nested loops exist in the environment, this method will fail. With a strict view, it can be said that these methods are not real time because the time complexity in circular environment is directly proportional to the size of the loop. So these methods in huge issues are unable to building map in real time. However these solutions have good behaviour in office-building type environments and build exact map in real time [29], [30], [31].

F. Iterative Closest Point (ICP) Algorithm

The ICP algorithm since its introduction, has been attention in robotic applications. This algorithm objective is; finding the transformations between reference point cloud and data point cloud, by minimize the dimensions of point's error. This algorithm has a good performance if it has good reference point otherwise will stick in local minimum. The Figure 10 shows the overall procedure:

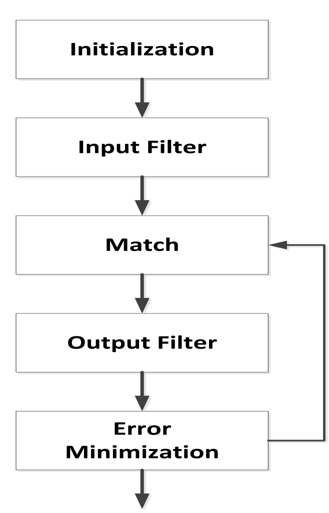

Figure 10: The overall ICP algorithm procedure

The ICP algorithm is used in robotic world as a Scan Matching algorithm. The speed of this algorithm is very good and it is used in online SLAM algorithm [32], [33].

V. CONCLUSION

Since the simultaneous localization and mapping (SLAM) is a hard problem in the robotic world; study and work on that is a few hard. So for better realize of that some basic acknowledges are needed and usefull. In this paper, we have presented a review of issues and effective parameters in SLAM and we summarized the kinds of map in robotic and also we have presented tools and methods used for solving the SLAM problem.

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