A Review of Learning-Based SLAM Approaches of Autonomous Unmanned Vehicles (AUV)

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Abdul Rauf, M Jehanzeb Irshad, Zubair Mehmood, Muhammad Wasif, Javaid Aslam, Sajjad Miran*

Department of Electrical Engineering, University of Gujrat, Pakistan.

* Corresponding Author: sajjad.miran@uog.edu.pk

ABSTRACT

Artificial Intelligence (AI) is becoming a hot topic in the field of robotic research in the last few decades. Autonomous Unmanned Vehicles (AUV) are being used for different tasks like rescue, search, monitoring, aerial operations as well as underwater operations even AUV can aid where human reachability is impossible. Localization, tracking, and mapping are fundamentals of an autonomous system. The main problem of AUV, which attracts researchers, is the simultaneous localization and mapping, where no external positioning source is available like GPS. There are many proposed techniques and algorithms which can be used to solve this problem of AUV like GPS (Global Positioning System), Motion Capture System (MCS), Visual System, etc. with limitations. Some probabilistic solutions like Graph SLAM, EKF based SALM, and Fast SLAM are also available for this problem. EKF based SLAM is used for the non-linear model but has different issues (like inconsistency) when the map becomes large and complex. It does not work well with the non-Gaussian distribution. Fast SLAM algorithm is used with the non-Gaussian distribution. It can provide high speed computation and good accuracy but has issues during the resampling processes like particle depletion and degeneracy. On the other hand, Graph based SLAM can deal with large and complex maps and can process a large number of landmarks accurately and it can perform much better than EKF and Fast SLAM.

Keywords: Autonomous Unmanned Vehicle; SLAM; Graph SLAM; Fast SLAM; EKF SLAM.

INTRODUCTION

Artificial Intelligence (AI) has become the most focusing and discussed topic in the field of robotics in the last two decades. It is upbringing a great turn in the field of research and has the power to change the upcoming era. Autonomous Unmanned Vehicles (AUV) are being utilized to perform different tasks like equipment transportation, researching, rescue, agricultural and military spy operations as well as underwater operations. AUVs can operate everywhere, even where humans cannot have access easily. The main problem of AUV which captures the researcher's attention is its navigation and build up map of an unstructured environment at the same time. This problem is mostly called Simultaneously Localization and Mapping (SLAM) [1-6].

Localization, tracking, and mapping are fundamentals of an autonomous system. Many solutions are available for them like GPS, Motion Capture System (MCS), visual system, etc. They have limitations due to environmental effects, time consumption, labors requirements as well as computational cost [7].

A clear difference should be made between the localization of the robot and its navigation. Localization is how a robot localizes itself within a map accurately. However, navigation is how well a robot locates itself and guides from one point to another [8].

The main problem of AUV is to operate and localize itself as well as develop a map of its surrounding at the same time in such an environment where no external source of information is available like GPS etc. It is a difficult job for AUV.

SLAM techniques are divided into two groups based on probability i.e., online, and offline SLAM techniques. The offline technique includes Graph SLAM, Smoothing and Mapping (SAM) [9] and the online technique includes EKF SLAM and Fast SLAM [10].

In this paper, we discussed both offline and online techniques and compared them based on their advantages and disadvantages as well as compared them based on distance error. The focus of this paper is to elaborate the better on SLAM technique for the ease of researchers based on their comparison in all aspects.

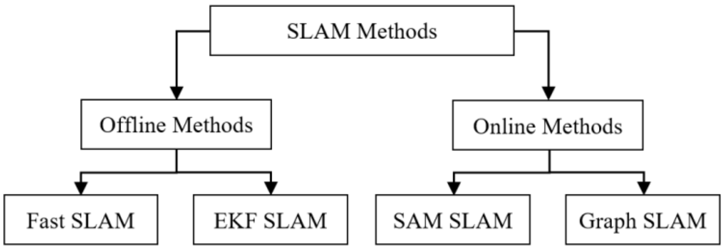

Figure 1. Probability based classification of SLAM methods

METHODS

Different Techniques uses to solve the challenges of Localization of AUV.

1. Graph based SLAM

Graph based SLAM approach consists of two main things i.e., Nodes and Edges. Nodes are the points that describe the poses or position of Autonomous Unmanned Vehicles. And edges are the connection lines between two consecutive nodes which represent the constraint equations labeled as the distribution probability over the relative position of the poses of AUV [11].

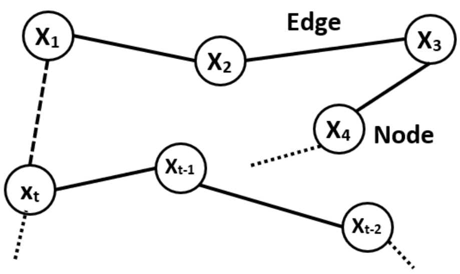

Figure 2. Graph based SLAM representation

Circles are labeled as nodes and black lines show edges with the connection between two consecutive poses. Dotted lines are used for connections between two different poses. Two types of information are used in Graph-based SLAM for making graph edges [12]. The Graph-Based SLAM is an optimization-based approach that is a graphical representation of the Bayes Theorem and is widely used to solve the SLAM problem of AUV. To show the interrelationship of landmarks in the map and the pose of the robot, it uses matrix form. We can easily find the minimum cost for the trajectory between robot location and the landmarks after building up the matrix form [13][14]. We can use the equation to find out the minimum cost.

$$E(x,m) = \sum_{ij} e_{ij}(x,m)^T \Omega_{ij}(x,m) \tag{1}$$

In the above equation, E is the minimum cost function. x, m and e_{ij} represent the pose of the robot, landmarks, and error function respectively. Error functions calculate the distance between the location of the landmark and the estimated position of the robot. These poses and landmarks have some information represented by Ω_{ij}. At the end, to find the best estimated trajectory of the AUV, find the optimal value. The optimal value is the smallest value of minimum cost function E(x,m) which we find from equation 1 [15].

$$(x^*, m^*) = argmin\ E(x,m) \tag{2}$$

Graph based SLAM has the information about robot poses and landmarks in the form of matrix which help to estimate the best trajectory for AUV by finding minimum cost function value with high accuracy. It can deal with high dynamic environments and can process a large area as well. It has a high computational cost which makes it a more expensive approach [14].

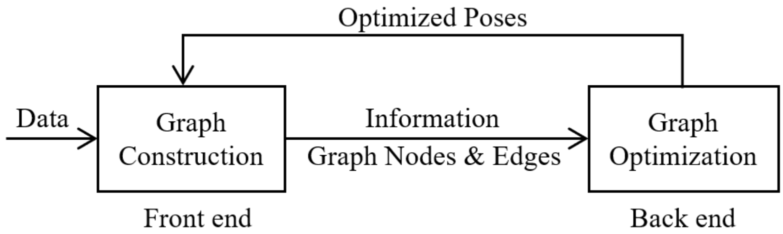

Figure 3. Block diagram of Graph based SLAM approach

2. EKF based SLAM

Many approaches are used being to solve the SLAM problem currently, but the most common and popular among them is Extended Kalman Filter based SLAM (EKF SLAM) [16][17][18].

It is the extended version of the Kalman filter which is used to deal with non-linear models. EKF consists of two models:

i. Motion Model

ii. Observational Model

The motion model is a model which describes the motion of the autonomous unmanned vehicles and can mathematically be explained as:

$$p(x_t|x_{t-1},u_t), x_t = f(x_{t-1},u_t) + \omega_t \qquad (3)$$

In the above equation, $f(x_{t-1},u_t)$ are robot's kinematics. x_t, u_t and ω_t is the position of the robot's control inputs and disturbance in motion of robots respectively.

The observational model describes the observational representation taken from the sensors and its mathematical formula is:

$$p(z_t|x_t,m), z_t = h(x_t,m) + v_t \qquad (4)$$

Where $h(x_t,m)$ describes the geometrical model of the observations taken by the sensors. v_t and z_t are the observational error and sensor measurements, respectively. The detailed information about EKF is available at [19].

To localize the robot in the map at time 't' with all measurements z_t and control inputs u_t, we need to find out the joint posterior distribution. Calculate the covariance and mean of the measured posterior distributions which help the EKF to find out the convergence points w.r.t the uncertainty of the landmarks [18]. These convergence points are useful in finding out correct loop closure and work as a re-localization function towards corrected landmarks.

EKF based SLAM can linearize the non-linear model, mostly AUV's has non-linear model due to the dynamic environment and also has the ability of good loop closure detection which is used to monitor the robot when it revisits the same landmark. Without good loop closure, an error will occur in robot pose estimation. The advantage is that it has a large piece of work but as the map becomes large and complex, EKF will not work properly. Different kinds of problems may occur like inconsistency, low speed performance, and make issues in convergence.

3. Fast / Practical based SLAM

Particle filter-based SLAM is called Fast SLAM. It is considered a widely used approach for the solution of SLAM of AUVs. Fast SLAM is used for the robotic signal control and is also used for path finding, search methods as well as sampling of new poses for AUV. In data association issues for non-linear models, the Fast SLAM can behave much better than extended Kalman filter-based SLAM (EKF-SLAM) [20][21][22].

EKF based SLAM algorithm uses probabilistic model which obeys Gaussian distribution, but a lot of new algorithms are now available which uses non-Gaussian distribution. Fast SLAM is one of them which uses non-Gaussian distribution. It is the combination of two filters i.e. Particle Filter and Extended Kalman Filter [19]. It divides the SLAM problem into two parts as localization problem and map problem. Particle Filter and EKF are used to solve localization problems and map problems, respectively.

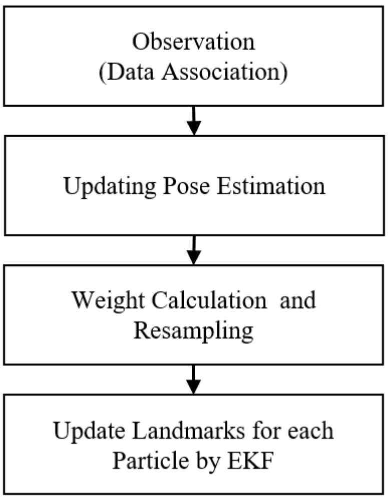

Figure 4. Flow chart of Fast SLAM algorithm

A. Localization Problem:

The localization problem involves different steps to estimate the correct location of the robot.

i. Sampling new poses of robots:

In this step, estimate the new samples of robot poses by finding posterior probability.

$$X_t^i \sim p(X_t | X_{1:t-1}^i, \mu_{1:t}, z_{1:t}, d_{1:t}) \quad (5)$$

It is not possible to find direct samples from equation (5) due to nonlinear data, so it needs first order linearization for sampling.

ii. Weight Calculation:

After sampling, calculate the weights of each sample or particle because there is some difference present between estimated probability and real probability [23]. To calculate the weights, use the following formula:

$$\text{Particle weight} = \frac{\text{Target Distributaion}}{\text{Proposal Distribution}} \quad (6)$$

iii. Resampling:

After calculating the weights of particles, it needs a resampling process. In this process, calculated weight is compared with the effective number of samples $N_{\text{effective}}$. If the effective number of sample values is greater than particle weight, then resampling is required.

$$N_{\text{effective}} = \frac{1}{\sum_{\mathrm{i=1}}^{\mathrm{M}} (\text{particle weight})^2} \quad (7)$$

B. Map Problem:

After doing all the above steps, landmark estimation is required to solve the map problem.

i. Estimation of Landmark:

The landmark estimation process depends on two main things i.e., observational information and newly estimated poses of the robot. After the estimation of new poses of robots, EKF is used to update the estimation of landmarks for each particle [24][25]. It doesn't need any specific distribution or Gaussian distribution like EKF and has the capability to deal with non-Gaussian distribution [26][27]. Fast SLAM processed each particle through EKF which makes it capable to process more landmarks and giving better accuracy in data association. It suffers from particle depletion and degeneracy problems etc.

DISCUSSION

In this section, we compare above discussed SLAM methods based on their advantages, disadvantages, and distance error.

Figure 5 shows the average distance error of EKF, Fast, and Graph SLAM is 0.73m, 0.658m, and 0.52m, respectively [28][12]. The distance error of Graph SLAM is lesser than other discussed methods which shows that Graph based SLAM is better rather than EKF and Fast SLAM as shown in Figure 6-8.

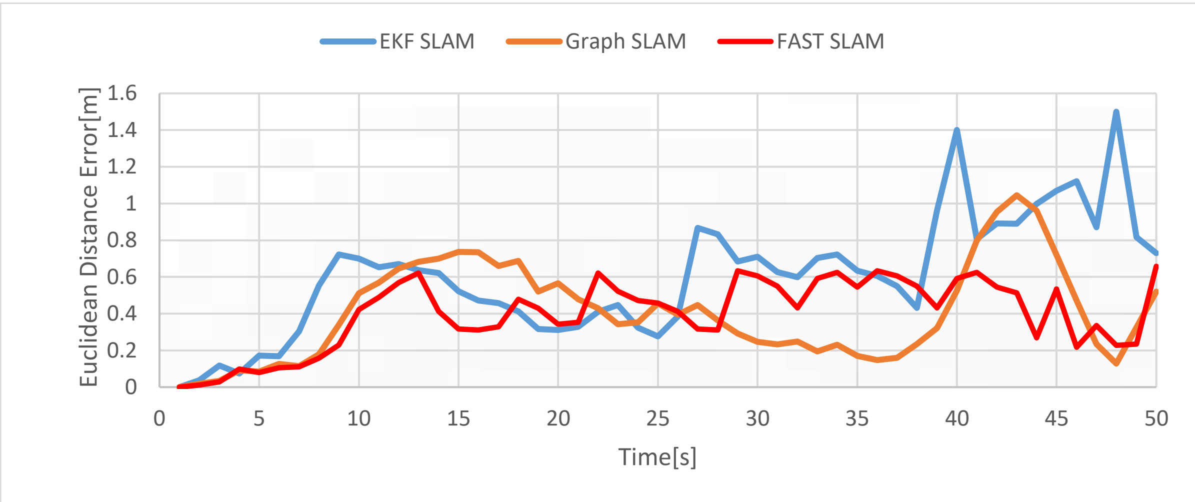

Figure 5: Comparison of EKF, Fast SLAM, and Graph SLAM based on distance error

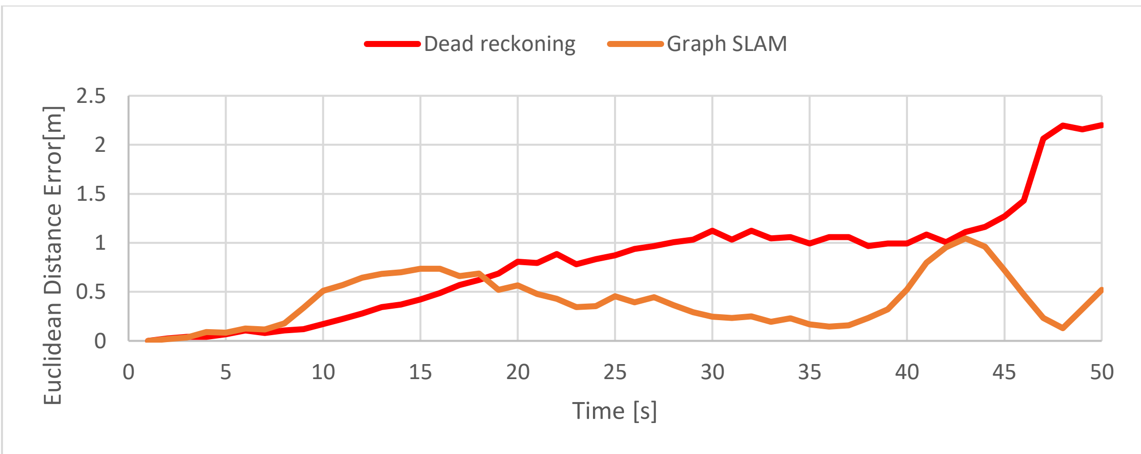

Figure 6: Distance error results of Graph SLAM compared with dead reckoning

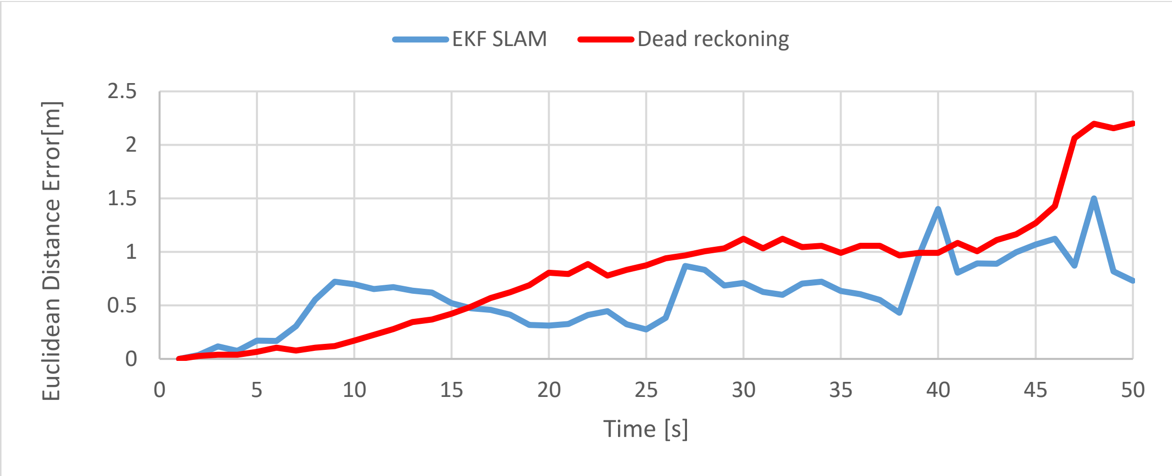

Figure 7: Distance error results of EKF SLAM compared with dead reckoning

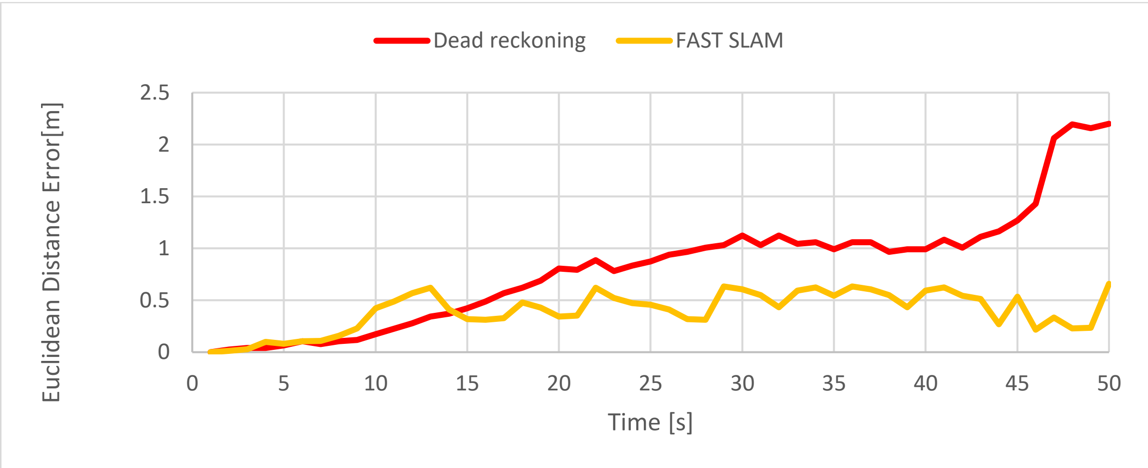

Figure 8: Distance error results of Fast SLAM compared with dead reckoning

The summary of the advantages and disadvantages of SLAM methods is explained in table 1.

It is clear from Table 1 that Graph SLAM has advantages over EKF and Fast SLAM.

Table 1. Summary of advantages and disadvantages of SLAM methods

	Methods	**Advantages**	**Disadvantages**
1	Graph SLAM	High Accuracy Ability to perform with consistency. Able to deal with large maps and can estimate landmarks accurately.	High computational cost.
2	EKF SLAM	Deals with nonlinear models of AUV's Provide efficient Loop closure Suitable for dynamic environments and different ranges of distances	Issues e.g., inconsistency occur when it deals with large and complex maps [29]. Doesn't deal with non-Gaussian distribution.
3	Fast SLAM	Able to deal with non-Gaussian distribution High computational speed.	Particle depletion problem during the sampling process.

Data association accuracy.	Degeneracy problems.

CONCLUSION

In this paper, we have discussed probability-based SLAM techniques to find a suitable method for the solution of the SLAM problem. Different properties are discussed to compare the methods. Graphs and comparison table show that Graph based SLAM is much better than EKF and Fast SLAM. The distance error of Graph based SLAM, EKF, and Fast SLAM is 0.73m, 0.52m, and 0658m, respectively. Graph SLAM has the ability to deal with large and complex maps, non-Gaussian distribution as well as it performs well in dynamic environments with consistency. On the other hand, EKF and Fast SLAM have the issues of large maps, particle depletion problems, and degeneracy problems, respectively.

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