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A State of the Art in Simultaneous Localization and Mapping (SLAM) for Unmanned Ariel Vehicle (UAV): A Review

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Abstract – **For the past decade, the main problem that has attracted researchers' attention in aerial robotics is the position estimation or Simultaneous Localization and Mapping (SLAM) of Unmanned Aerial Vehicles (UAVs) where the GPS signal is poor or denied. This article reviews the strengths and weaknesses of existing methods in the field of aerial robotics. There are many different techniques and algorithms that are used to overcome the localization and mapping problem of these UAVs. These techniques and algorithms use different sensors, such as Red Green Blue-Depth (RGB_D), Light Detecting and Ranging (LIDAR), and Ultra-wideband (UWB). The most common technique is used, i.e., probability-based SLAM, which uses two algorithms: Linear Kalman Filter (LKF) and Extended Kalman Filter (EKF). LKF consists of five phases and this algorithm is just used for linear system problems. However, the EKF algorithm is used for non-linear systems. Aerial robots are used to perform many tasks, such as rescue, transportation, search, control, monitoring, and different military operations because of their vast top view. These properties are increasing their demand as compared to human service. In this paper, different techniques for the localization of aerial vehicles are discussed in terms of advantages and disadvantages, practicality and efficiency. This paper enables future researchers to find the suitable SLAM solution based on their problems; either the researcher is dealing with a linear problem or a non-linear problem.**

***Keywords* – EKF, extended Kalman filter, light detecting and range, linear Kalman filter, simultaneously localization and mapping, SLAM, unmanned aerial vehicle.**

I. Introduction

Today, Artificial Intelligence is developing rapidly in the field of aerial robotics. Aerial robotics is used to perform many tasks, such as rescue, remote sensing, disaster response, surveillance, transportation, search, control, monitoring, and different military operations where the performance of humans is impossible because of their vast top view and reachability anywhere. However, there is a problem of aerial vehicles which grasp the attention of researchers and technologists in the position estimation and mapping of aerial vehicles. This problem is mostly called the Simultaneous Localization and Mapping (SLAM) problem. Unmanned Aerial Vehicles (UAVs) should have such a design that works freely in an unknown environment without using previous information about the environment. UAVs should be capable of estimating the position and exploring such areas where normal estimation of the position of things is too difficult and reachability of humans is not possible [1]–[10]. There are various methods and algorithms used to solve these problems of UAV robots, such as low-energy sensors and radio frequency circuitry, Ultra-wideband (UWB) based algorithms, Red Green Blue-Depth (RGB_D) sensors, and Linear Kalman Filter (LKF) and Extended Kalman Filter (EKF) both with SLAM. Low-energy sensors and radio frequency circuitry attract researchers' attention due to availability; this technology uses signals received by the sensors to estimate the position of sensors. Due to its low accuracy in getting information, this technique is not useful. The UWB technique is suitable for short-distance mapping and localization in indoor systems and it is possible to obtain correct data within a few centimetres [11], [12]. The Linear Kalman filter algorithm consists of five phases and is used for linear system problems. The EKF algorithm, in turn, is used for the non-linear system. Fig. 1 shows that landmark-based localization methods are divided into two categories:
1. Relative Localization; 2. Absolute Localization.

Relative localization methodology uses inner sensors, which are odometry and inertial unit of measurement to measure every occurring change in the environment. However, the calculation of error triggered by Wheel Slippage on pulverized vehicles becomes large for long time operations [13]–[16]. On the other hand, absolute localization methodology uses outer sensors for the estimation of the position of the UAV after every little drive of the robot, and the calculation error becomes least or zero [17]–[22].

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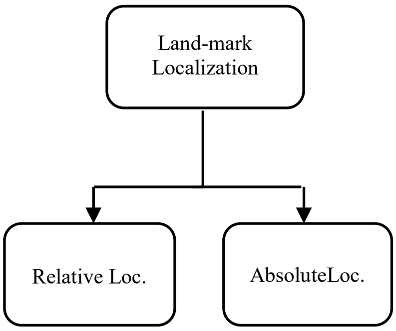

Fig. 1. Classification of land-mark localization.

The combination of both relative and absolute localization methods is used widely to minimise the localization error by using Kalman filters (Linear & extended Kalman filters) [23]–[25]. UAV robots have integrated odometry sensors that need sport by using other techniques or approaches such as GPS. However, GPS fails indoor due to its limitation and it can easily be lost by weather conditions or, in other words, it depends on weather conditions [26]–[28].

II. Literature Review

A. Ultra-wideband Based Algorithm Approach

UWB sensor-based algorithm consists of two main steps. Firstly, the position estimation data are obtained by UWB sensors and after that the 3D conservation map is refined with position estimation data. In step 2, optimization of estimated position of UAV and UWB sensors is done.

Step 1: RO Map & Localization

The main aim of this step is to gather the data about the position of UWB sensors and then use the data to compute the 3D Map of aerial vehicles. This step is called RO-SLAM. Different algorithms are used for RO-SLAM based on two things, i.e., timing filtering and probabilistic framework. Fat-SLAM is a method that presents better outcomes than others based on EKF and UKF algorithms [29]. It does not protect the relationship between milestones of the guide in those applications where it may exist on the map. Nevertheless, it has a drawback that it significantly reduces the optimization of the estimated UAV position. To overcome this problem, a group of methods is proposed to estimate the position of UAV robots using singular value deterioration (SVD) [30]. However, these approaches assume the estimated measurements of all sensors at all robot positions [31].

Problem Definition

A robot trajectory is denoted by N number of poses as $X = \{x_1, x_2, x_3, \ldots x_N\}$ and the position of UWB is represented by $B = \{b_j\}$ where j = 1, 2, 3,….M. Each UAV robot pose is denoted by $x_{1,} = [x_{i,} y_{i,}, z_i, \Psi_i] b$ and every position of UWB sensor is denoted by $b_j = [b_{xj}, b_{yj}, b_{zj}]t$. These observations are combined to compute $d_{ij} = [x_i. b_j]$ that is called Euclidean distance. The main aim of RO-SLAM is to compute the X and B flight of the robot and the position of UWB sensors, respectively. The result of X and B can be computed by the following expression (1):

$$\underset{\{X,B\}}{\arg min} [\textstyle\sum_{i=1}^{N} . \sum_{j=1}^{M} C_{ij} (\left\| x_i - b_j \right\| - d_{ij})^2]. \tag{1}$$

There, c_{ij} is a variable which equals 1 if measurement takes from robot pose to sensor positions and otherwise it is equal to 0. The restrictions can be overwhelmed by adding the odometrical term into (1). Thus, (1) becomes:

$$\underset{\{X,B\}}{\arg min} [\textstyle\sum_{i=1}^{N} (E(x_i, x_{i-1}) + \sum_{j=1}^{M} C_{ij} (\left\| x_i - b_j \right\| - d_{ij})^2)] \tag{2}$$

In (2) $E(x_i, x_{i-1})$ is a squared error among x_i and x_{i-1} states.

Optimization

If the data set about robots are already known, then the result can be obtained straightforwardly from (2) by simply adding values. If the data are unknown, then the value of B (positions of sensors) is initialized randomly and the process chooses the right one.

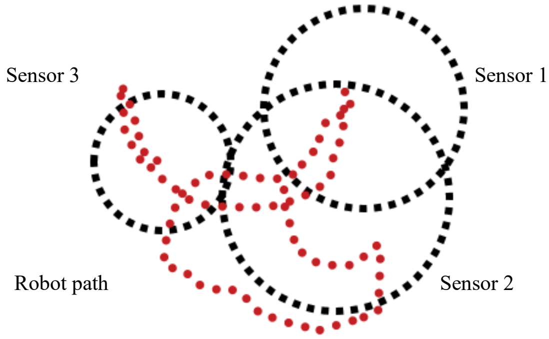

Fig. 2. Orthogonal view of multiple hypothesis of robot and three UWB positions.

Instead, the parameter of the UWB sensor pose is recalculated. Therefore, many values of the estimate should be taken into the optimizer [32]. In this way, when UAVs perform a slight movement and obtain position xi gets the first run estimate value d_{ij} to jth sensor. Hight of the sensor in the circle is d_{z_i}. This process creates several hypotheses by sampling the circle and allowing the optimizer to choose a value that is better among all.

Let us assume that hypotheses are denoted by H and for jth sensors, it will be H_j, then the UWB sensor parameter will become

$$b_j = [b_{j1}, b_{j2}, b_{j3}, \ldots.., b_j H_j] \tag{3-a}$$

and for each sensor position hypotheses will be:

$$b_{jk} = [b_{xjk}, b_{yjk}, b_{zj}]t. \tag{3-b}$$

The parameter b_{zj} stays the same because it is known. Let us recall (2) and reparametrize it:

$$\underset{\{X,B\}}{\arg min} [\textstyle\sum_{i=1}^{N} (E(x_i, x_{i-1}) + \sum_{j=1}^{M} \frac{1}{H_j} \sum_{k=1}^{H_j} C_{ij} (\left\| x_i - b_{jk} \right\| - d_{ij})^2). \tag{4}$$

Initialization

Now the values of UAV robot pose xi and the position of sensors b_j will be initialized by odometry values and hypotheses, respectively. Thus, it gets the value of d_{ij} from UWB sensors for the first time then we use the current position of the UAV robot by the following equations:

$$b_{xjk} = x_i + d_{ij}\cos(2\pi(k-1)/H_j); \quad (5)$$

$$b_{yjk} = y_i + d_{ij}\sin(2\pi(k-1)/H_j); \quad (6)$$

$$b_{zjk} = b_{zj}. \quad (7)$$

Step2: Calculation of Map and Position

The result obtained in the first step includes the data about the robot and UWB estimated position. If the motion of a robot is much stronger, it lets the optimizer remove uncertainty from trajectory and position [33]. Thus, it will assemble the single solution and all hypotheses find at the same position, having good gauss data about UWB sensors and path of the movement of robot, then it can use automatically loop closing method for those techniques which are based on RGB-D, such as VPR or SM. In this paper, the SM process is executed for all poses of robots. In a close loop, the data of sensor point-cloud pci for x_i pose and p_{cj} for x_j pose are given, then matching process creates the transformation which aligns both points in a better way. Usually, this type of transformation is used as a constraint between the information matrix associated with the pose and poses of the robot, which converts the importance of constraints into a non-linear optimization approach [34]. In this entire process of transformation, all point clouds are transformed into a global frame of reference according to connected pose pc_i^g and error among these cloud points is calculated. Thus, (2) becomes:

$$\underset{\{X,B\}}{\arg min} \left[\sum_{i=1}^{N}\left(E(x_i, x_{i-1}) + \sum_{l=1}^{p_i} D(pc_i^g, pc_l^g\right) + \sum_{j=1}^{M} C_{ij}(\left\|x_i - b_j\right\| - d_{ij})^2)\right]. \quad (8)$$

The calculation of $D\left(pc_i^g, pc_l^g\right)$ could have significant cost if this calculation involves large cloud points. It is necessary to calculate the matching between cloud points at every time; thus, this process slows down the optimization. Therefore, the assuming value of poses for optimization is not so far away from the final estimation in the RO-SLAM step. Hence, $D\left(pc_i^g, pc_l^g\right)$ needs to be recalculated because the association is known.

B. KF and EKF Approach

Kalman filter (KF) approach uses a linear system that is why it is known as linear Kalman filter. Linear Kalman filter consists of five phases:

1) Absolute measurement of motionless robot (AMOML);
2) Absolute measurement of moving robot (AMOM);
3) Relative measurement of motionless robot (RMOML);
4) Relative measurement of moving robot (RMOM);
5) Relative measurement of moving robot/while the position of robot is not detected.

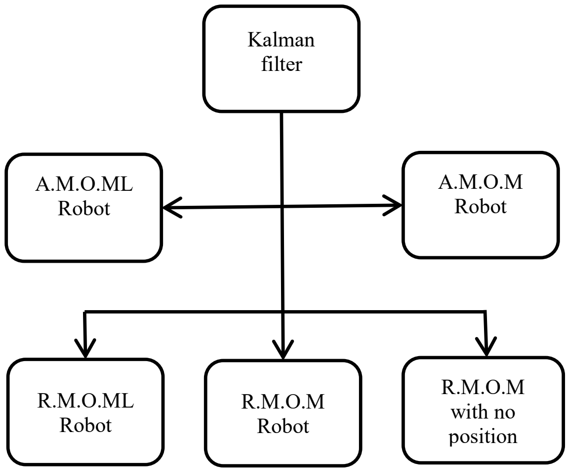

Fig. 3. Phases of Kalman filter.

This technique uses linear approximation which is related to positions and covariance matrices of error for the determination of the estimation of prior condition for the generation of an estimate of posterior [35]. The following equation explains the dynamic and measurement model system, which is used for the estimation purpose [35].

YN+1=f (YN, BN, CN) (9)

DN+1=h (YN, EN) (10)

YN+1/N=FN×YN/N (11)

LN+1/N=FN×LN/N×FNT+AN×QN×ANT (12)

GN+1=LN+1/N×HNT[HN+1×LN+1/N×HN+1T+RN]−1 (13)

YN+1/N+1=YN+1/N+GN+1[DN+1−HN+1×YN+1/N] (14)

LN+1/N+1=[I−GN+1×HN+1]×LN+1/N (15)

TABLE I
TABLE OF NOTATIONS

Symbol	Name
YN	Present state
YN−1	Prior state
QN	Covariance estimation matrix
RN	Covariance observation matrix
YN+1	Predictable state vector
LN+1/N	Covariance matrix
Q	Process matrix of noise
R	Measurement matrix noise
CN ~N (0, QN)	Noise of process
EN ~ N (0. RN)	Noise of observation

N+1	Instantaneous time
DN+1	Predictable measurement vector
∇Fx, ∇Fu	Matrices of Jacobian for function f
V	Velocity
L	Landmark position
JF	State equation of Jacobian
GN+1	Kalman gain
YN+1/N+1	Updated estimation
LN+1/N+1	Updated covariance
H	Measurement Jacobian
dt	Universal time
T	Time
t	Initial value of time
LN	New covariance matrix

These seven equations are based on the Kalman filter method. Eqs. (9)–(10) are used for conjunction; for the generalization of prior state and covariance error of equivalent, (11) and (12) are used, respectively. The Kalman gain can be obtained by using (13) and state approx. & covariance error by (14)–(15).

It is known that the KF approach is used for a linear system but sometimes it can be used for a non-linear system by taking the first-order partial derivative, calculation of H_{k+1} factor, and nonlinear system (Fk matrices linearized).

2) Extended Kalman Filter Approach

EKF approach is a technique used for non-linear systems.

EKF SLAM for UAV robot is executed in identified field with a significant value. In this paper, two mathematical models are represented:

The EKF state

Model of observation that is described by equations:

YN+1=f [YN, BN, CN]; (16)

DN+1=h [YN+1, EN+1], (17)

where CN, EN+1, YN+1, BN, and DN+1 represent the noise that occurs during operation, the noise of observation, predictable state vector at time N+1, known input BN assumptive all noise to be CN, and the predictable measurement vector at the time instant N+1, respectively [36].

This approach is divided into two stages:

initial stage $Y_{N+1;}$

predication stage $L_{N+1/N.}$

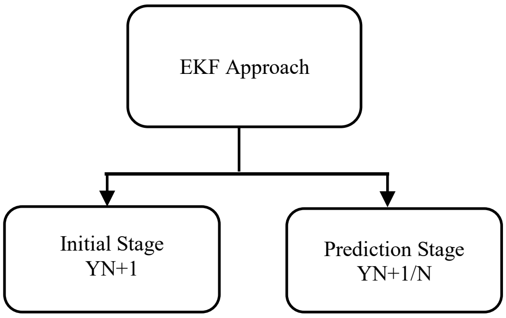

Fig. 4. Stages of EKF approach.

YN+1=f (YN, CN+1) + ∇Fx × (YN − YN/N). (18)

LN+1/N =∇Fx ×LN/N×∇FTx+∇Fu×QN ×∇FTu. (19)

∇Fu and ∇Fx are both Jacobean matrices. *B* and *F* are the state equations written below:

$$B=\begin{bmatrix} dt\ \times\cos(x(3)) & 0 \\ dt\ \times\cos(x(3)) & 0 \\ 0 & dt \end{bmatrix}; \tag{20}$$

$$F=\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{21}$$

The Jacobean state equation will be as follows:

$$\mathrm{JF}=\begin{bmatrix} 0 & 0 & -\mathrm{dt}\times \mathrm{u}(1)\times\sin(\mathrm{x}(3)) \\ 0 & 0 & \mathrm{dt}\times \mathrm{u}(1)\times\cos(\mathrm{x}(3)) \\ 0 & 0 & 0 \end{bmatrix}. \tag{22}$$

Initialization of Jacobian G is the following:

$$\mathrm{G}=\begin{bmatrix} -\sqrt{\delta(1)} & -\sqrt{\delta(2)} & 0 & \sqrt{\delta(1)} & \sqrt{\delta(2)} \\ \delta(2) & -\delta(1) & -1 & -\delta(2) & \delta(1) \end{bmatrix}. \tag{23}$$

Updating an observation phase, the model of observation DN+1 at YN+1/N can be represented as follows:

DN+1=h(YN+1/N)+HN+1×(YN+1/N−YN+1) (24)

For the KF update phase, the KF gain is found using the formula:

GN+1 = LN+1/N×HT N+1×[HN+1×LN+1/N ×HTN+1+RN]–1; (25)

GN+1/N+1=YN+1/N+GN+1×[DN+1−HN+1×YN+1/N]. (26)

If the value of DN is known, then EKF analyses the matrix of Kalman gain to obtain the value of YN and update the error matrix of the state. For updating step, the above equations become:

YN = YN + GN × [DN −h(YN)]; (27)

LN = [I −GN ×HN] ×LN. (28)

The updated LN+1/N+1 is denoted as:

LN+1/N+1= [I −GN+1×HN+1] ×LN+1/N. (29)

III. Critical Analysis

These all equations are used in both approaches KF & EKF. EKF has one disadvantage, i.e., the noise in its measurements is not perfectly removed, then the robot will deviate from its route, which gives inconsistency in the result.

In this section, the comparison of all discussed approaches is shown in tabular forms. Table II shows the properties and limitations of UWB, KF, and EKF techniques. Table III shows the sampling time of these techniques. These comparisons show the clear advantages of EKF techniques over other existing techniques; EKF based approach can deal with non-linear models, exhibits good loop closure, and is suitable for long-distance rather than UWB and KF based approaches, which are only capable of dealing with short-distance and linear models, respectively.

TABLE II

Comparison of SLAM Techniques Based on Advantages and Disadvantages [37]

Sr. No.	Techniques	Properties	Limitations
1	UWB	• It deals only with indoor problems • It is suitable for short distance	• Work well within limited range, such as few centimetres to a meter only (not suitable for long distances) • It has computational cost too high
2	KF	• It deals with indoor as well as outdoor problems • It is suitable for different distances • Less computational cost	• It does not deal with nonlinear models • It does not deal with complex environment
3	EKF	• Deals with both linear and nonlinear models • Less computational cost • Loop closure efficient • Suitable for different distances	• It has noise and inconsistency problems when it deals with a large or complex map

TABLE III

Comparison of SLAM Approaches Based on Sampling [38], [39]

Sr. No.	Techniques	Sampling time
1	EKF Based SLAM	0.2 s
2	UWB Based SLAM	0.3 s
3	KF Based SLAM	0.3 s

IV. Conclusion

In this paper, a comparative study has been carried out between different approaches for the localization of UAVs. These techniques have their strengths and weaknesses. During the study, it has been observed that the UWB approach is limited for indoor tasks and a short distance of few centimetres to a meter. It gives satisfactory results; however, in a complex environment, it does not get proper information about the position estimation of the robot. To improve the results, RGB-D sensors are used. However, these sensors are too costly as compared to UWB. KF technique is commonly used for linear systems to estimate the position and mapping. It has five distinct phases. This technique is limited to linear systems and does not work for non-linear systems.

The EKF approach is used for both linear and nonlinear systems. It simply linearizes all nonlinear system models and accurately evaluates the UAV robot position. Results show that EKF SLAM is better than KF due to accuracy, practicality, and efficiency. Although it has a problem when the noise in its measurements is not perfectly removed, the robot deviates from its route. Future work in the direction of noise reduction techniques for unbiased location estimation is recommended.

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