Airborne-SLAM Approaches as Automation Techniques of Air Transportation

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***Abstract*—Simultaneous localization and mapping (SLAM) of unmanned systems has been proposed in last decade for global navigation satellite systems (GNSS) denied environments. In this reseach it is identified in details by detecting SLAM algorithms particularly in air vehicle platforms as a tool for application of an automation strategies from other domains to air transportation or surveillance and navigation applications of data science in aviation besides particle and particle flow filter based SLAM of aerial systems is first stated as well. Regarding to survey consequences the variety of SLAM applications span from parametric filters such as Unscented Kalman Filter, Extended Kalman Filter to nonparametric such as Particle Filter and concerning diversity of vision based approaches that aims up level control and variety of sensors that unmanned vehicles carry a taxonomy is a requirement of better comprehension SLAM performances. Although it is not aimed to compare performance of all SLAM methods for problem of Airborne-SLAM (A-SLAM) navigation the scan of indexed papers suggests that best SLAM algorithm can only be identified in reference to the scenario which differs in environment, platform, vehicle, sensor…etc. and can be used as an transportation tool by combining path planning and other navigation approaches.**

Keywords-Unmanned Aerial Systems, Autonomous Navigation, Airborne SLAM, Extended Kalman Filter, Uncscented Kalman Filter, Particle Filter Based SLAM, GNSS denied Environment

I. INTRODUCTION

Nowadays unmanned systems are everywhere in the life from the entertainment to the decision making platforms such as reconnaissance and surveillance in the military and civilian areas. One of main purposes of unmanned aerial systems (UAS) is autonomous navigation that provides flexible functionality on a stand alone flight operations as well as formation motions. To determine the systems' precise position for successful navigation GNSS are actually preferred as geo location tools in the world with their small drawbacks. Despite being mostly adequate tools for UAS position determination it is needed to find some new manners in environments where for example GPS signal does not exists. In this case both local position and the map of environment is supposed to be determined simultaneously. Simultaneous Localization and Mapping (SLAM) is one of the key issues such as map representation or path planning or navigation in the field of robotic mapping and if SLAM structure is designed for aerial vehicle it is called Airborne Simultaneous Localization and Mapping (A-SLAM). In the context of this study it is proposed as a tool for application of an automation strategies from other domains to air transportation or surveillance and navigation applications of data science in aviation by examining detailed performance of existing SLAM algorithms which might be considered as part of autonomous air transportation.

SLAM was revealed by Smith and Cheesman [1], detailed by Dissanayake, Durrant-Whyte and Bailey [2] and improved by Bailey and White [3-4]. In other studies, structure of the Kalman filter-based SLAM effects of partial observability [5-7], stability [8] and the consistency problem [9,10] were examined to present recommendations for solutions of the SLAM problem whereas Airborne SLAM applications are continued simultaneously [11-13]. It was very important to know the current location for autonomous navigation [14] and the creation of an accurate map. SLAM researches have used parametric filter approaches such as Extended Kalman Filtresi (EKF) and Unscented Kalman Filter (UKF) besides non-parametric methods such as Particle Filter (PF) or their derivatives which seeks better performans [15-22] and based on visiual techniques [23-29]. Among these SLAM researches J.Welle at all (2010) implemented particle based SLAM on robot platform [29]. They performed mapping by using 3D laser scanner on Pioneer P3-AT robot and particle based SLAM by using odometer and laser scanner sensors. The simulation results compatibility with experimental findings is presented in their work. The developed, accelerated or paralel processed filter structures are presented in other researches particularly due to filter structure and real time data process need [30-32]. The SLAM estimation method is generally determined not only but by environment and vehicle type. Former SLAM studies are implemented on territorial or humanoid vehicles [33] so called less complex since it contains less dimensional parameter and applications for marital [34] or aerial platforms [35-40] seeks for error reduction caused by filter structure. Oguz and Temeltas analyzed EKF-based SLAM filter inconsistency for the first time (2013) for Unmanned Air/Aerial Vehicle (UAV) platforms, put forwarded filter inconsistency with its symptoms, performed root-causes analysis and investigate observability of EKF based SLAM structure for detection of inconsistency reasons [41]. The filter observability, stability, consistency has been among other research subjects in last years [42-51]. Julier and Uhlman (2001) indicated that robot position prediciton error become smaller by recursive measurement of robot and lendmark position [52], Castellanos at all (2004) presented filter inconsistency due to linearization error in Kalman Filter based SLAM methods [53], Huang and Disanayake (2007) stated that for consistant prediction filter jacobien should be full rank[54]. Huang, Mourikis and Roumeliotis (2010) at all optimize jacobien matrices by lagrange polynomial method to reduce distortion effect of unobservable subspaces to increase consistency by limiting observability for UKF SLAM of territorial platforms [55]. While sensors such as camera, laser, ultrasonic, RADAR, LİDAR may be used for localizaiton, Hesch at all (2012) used camera and INS data for SLAM of a small UAV [56]. Yang (2012) designed particle filter based SLAM for robots by using ultrasonic sensors [57]. Yang proposed 4 lendmark map building and verification technique with its pros such as accuracy improvement and less complexity. Sub-mapping and loop closure which guarantees to reach starting point in mapping are other research areas [58-69]. Yoona at all (2013) performed real time 3D localization for humanoid robot [70-72] and other researchers worked on real time multi vehicle systems SLAM and navigation [73-82]. In addition to them many more survey on SLAM performans of all kind of methods is recorded recently [83-85]. Qu at all (2011) and Namiski at all (2013) released SLAM analysis and survey studies and Monjazeb at all (2011) compared EKF and Fast SLAM [86], Rigatos (2010) presented technics and cost efficiency comparison of Kalman filter and particle filter of autonomous navigation [87].

II. DISCUSSIONS

A. *Definitions:*

Body Plane

The center of body plane system of UAV is gravity center and X,Y,Z directions are as follows. The concentricity of body plane with UAV means that it remains constant as UAV moves as shown in Fig 1.

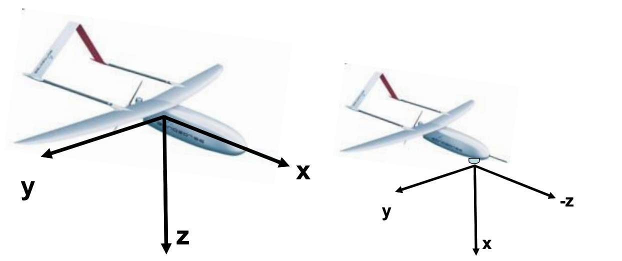

Figure 1.UAV Coordinate System – Body Frame (right) and Sensor Frame (left)

The usage goal of body plane which is also defined as UAV coordinate systems is to provide definition of target or lendmark with regard to UAV and linear or inertial movement measurements on UAV.

Navigation Plane

It is a coordinate system that has center at the center of the earth and its X,Y,Z direction points north, east and the center of earth respectively. It refers the same plane of the body plane at the beginning of the navigation and regarded as stable referencing to the earth that provides navigation according to the origin.

Euler Angles

It is a necessity of angular transformation to describe a coordinate system with respect to the other. If one is navigation plane and the other one is body plane this transformation is able to prescribed by Euler Angles Transformation in which θ, ve ψ is pitch,yaw, roll respectively as shown in Fig 2.

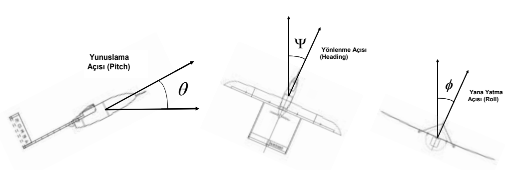

Figure 2. UAV Angle Planes

B. *Kinematic model of an unmanned air vehicle*

Investigating kinematic model of UAV for the structure of A-SLAM includes the transformation of the body frame motions of air vehicle to the navigation frame plays important role since the global mapping of the environment requires air vehicle equation of motion to the global frame. Euler angle transformations can be used for this purpose. The air vehicle body frame accelerations of the directional navigation and angular rates are transferred to navigation frame, the position of the air vehicle is calculated in navigation frame. The general equation generated during this process is expressed as the kinematic equation of the air vehicle. The matrix expression obtained by the transfer of directional acceleration to navigation frame of air vehicles is;

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} \cos\theta\cos\Psi & \cos\Psi\sin\theta\sin\phi - \cos\phi\sin\Psi & \cos\Psi\sin\theta\cos\phi + \sin\phi\sin\Psi \\ \cos\theta\sin\Psi & \cos\phi\cos\Psi + \sin\theta\sin\phi\sin\Psi & -\sin\phi\cos\Psi + \sin\theta\cos\phi\sin\Psi \\ -\sin\theta & \cos\theta\sin\phi & \cos\theta\cos\phi \end{bmatrix} . \begin{bmatrix} u \\ v \\ w \end{bmatrix} \quad (1)$$

The transformation matrix of angular rates from body frame to navigating frame is;

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\Psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi\sec\theta & \cos\phi\sec\theta \end{bmatrix} . \begin{bmatrix} p \\ q \\ r \end{bmatrix} \quad (2)$$

These two matrix equation is referred as the kinematic model of air vehicle. The vector [u,v,w] is directional acceleration in body frame and [p,q,r] is angular rates of body frame. At this point it may provide some background to introduce a couple of dynamics of aerial systems.

III. METHODS

A. *Extended Kalman Filter Based Airborne SLAM (EKF A-SLAM)*

Kalman filter is a recursive state estimation method used for a linear state-space systems modeled. The Kalman Filter mathematics;

$$x(k+1) = Ax(k) + Bu(k) + v(k)$$
$$z(k) = Hx(k) + \omega(k) \quad (3)$$

are state-space model and measurement model respectively in which A, B, H are state, input and observation matrices; x(k) state-space; u(k) input and z(k) observation or measurement data; v(k) represents process noise with covariance Q; ω(k) measurement noise with covariance R as well. Kalman filter uses both prediction and update steps in which it makes state prediction at time k for time k+1 as;

$$\hat{x}(k+1|k) = Ax(k|k) + Bu(k) \quad (4)$$

and covariance prediciton as

$$\hat{P}(k+1|k) = AP(k|k)A^T + Q \quad (5)$$

At update steps right after finding kalman gain (KG) the state and covariance updates are performed with reference to KG which is;

$$W(k+1) = \hat{P}(k+1|k).H^T(H.\hat{P}(k+1|k)H^T + R)^{-1} \quad (6)$$

State and covariance update according to measurement and KG respectively is;

$$x(k+1|k+1) = \hat{x}(k+1|k) + W(k+1).(z(k+1) - H.\hat{x}(k+1|k))$$
$$P(k+1|k+1) = (I - W(k+1).H).\hat{P}(k+1|k) \quad (7)$$

The state vector used in nonlinear system model consist of UAV state vector which is made up of position (x,y,z), velocity (Vx,Vy,Vz) ve Euler angles (Φ roll, θ pitch, heading) and map vector that is constituted of position of each lendmark (xL,yL,zL) whereas the length of the vector is 3xn (n:number of lendmark)

$$x(k) = \begin{bmatrix} x_{UAV} \\ x_{MAP} \end{bmatrix} \quad (8)$$

EKF is a kalman filter used in nonlinear systems that predicts the next state with respect to the prior state and measurement state. It is comprised of prediction and update steps such as in Kalman Filter. The state space model used in the filter is;

$$x(k+1) = f(x(k), u(k), v(k)) \quad (9)$$

In state space model state vector at k+1 depends on state vector at k and input data. Lendmark position has distance and angle values in polar coordinates as in measurement model and transformation of sensor plane to coordinate plane is made by transformation matrices. Measurement model depends on UAV positon at and presented as;

$$z(k) = h(x(k), \omega(k)) \quad (10)$$

where v(k) and w(k) represents zero mean white noise. The state space model in excpilicit form;

$$f_{uav}=\begin{bmatrix}P^n(k)\\V^n(k)\\\Psi^n(k)\end{bmatrix}=\begin{bmatrix}P^n(k-1)+\Delta t*V^n(k-1)\\V^n(k-1)+\Delta t*T_b^n(k-1)*f^b(k)]\\\Psi^n(k-1)+\Delta t*E_b^n(k-1)*w^b(k)\end{bmatrix}+\begin{bmatrix}w_{P^n}\\w_{V^n}\\w_{\Psi^n}\end{bmatrix} \quad (11)$$

The state vector is derived from UAV kinematic equations and made up of position (x,y,z), directional velocity (Vx,Vy,Vz) ve Euler angles (Φ roll, θ pitch,   heading). It is crucial to decide of the observed lendmark is whether in map or not.

Consequently in GNSS denied enviroment EKF based SLAM filter simulation for a UAV model for some time indicated us that it is possible to determine UAV position and position error stayed in acceptable level but it my not be so in long distance motion because error accumulation of Kalman based filters that may be unreliable out of 2σ trust limit.

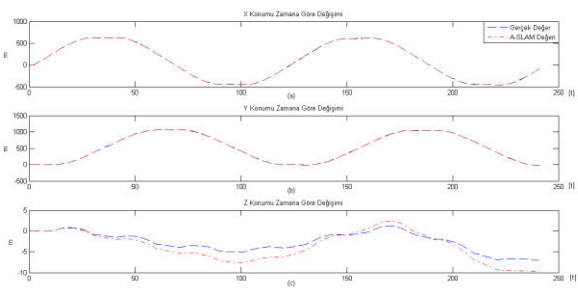

Figure 3. (Extended Kalman Filter based A-SLAM) UAV Position Error

B. *Unscented Kalman Filter Based Airborne SLAM (UKF A-SLAM)*

UKF Filter first introduced by Julier and Uhlmann is a filter structure consist of prediction and update or correction steps such as EKF except only difference usage of jacobien matrices which comes from derivatives and is used for non linear systems linearization in EKF but not in UKF. 2n+1 points are obtained by addition of uncertainty limits or covariances in normal distribution to previous UAV position vector in the UKF structure and system model predicts next position using these points and get some kind of average of them which is applied to the observation model in same manner before prediction.

Nonlinear system and observation model first and second moments (average and variance) are:

$$\bar{x}=E[x],\sum\nolimits_x[(x-\bar{x})(x-\bar{x})^T]$$
$$\bar{z}=E[z],\sum\nolimits_x[(z-\bar{z})(z-\bar{z})^T] \quad (12)$$

2n+1 (n:state space dimension) sigma point (χ^k) is chosen for each state variable as

$$\chi^0=\bar{x}$$
$$\chi^k=\bar{x}\pm\left[\sqrt{(n+\lambda)\sum\nolimits_x}\right]_k \qquad for \quad k=1,\ldots,n \quad (13)$$

where λ is proportion factor and weighing factors for each sigma point is;

$$W_0=\frac{\lambda}{n+\lambda}$$
$$W_k=\frac{\lambda}{2(n+\lambda)} \quad 0<k\le 2n \quad (14)$$

weighing factors for covariance matrix is;

$$W_0=\frac{\lambda}{n+\lambda}+1-\alpha^2+\beta$$
$$W_k=\frac{\lambda}{2(n+\lambda)} \quad 1<k\le 2n \quad (15)$$

Then predicition step is performed in which previous positon of 2n+1 sigma point, average and covariance prediction as:

$$\chi^k(t+1|t)=f(\chi^k(t|t),u(t))$$
$$\hat{x}(t+1|t)=\sum_{i=1}^{2n+1}W_i\chi^i(t+1|t)$$
$$P(t+1|t)=\sum_{i=1}^{2n+1}W_i[(\chi^i(t+1|t)-\hat{x}(t+1|t)).(\chi^i(t+1|t)-\hat{x}(t+1|t))^T] \quad (16)$$

Observation prediction average using observation predictions and weighing factors;

$$Z_i(t+1|t)=h(\chi^i(t+1|t))$$
$$\hat{z}(t+1|t)=\sum_{i=1}^{2n+1}W_iZ_i(t+1|t) \quad (17)$$

Innovation (measurement) covariance and correlation matrices are

$$S(t+1|t)=\sum_{i=1}^{2n+1}W_i[(Z_i(t+1|t)-\hat{z}(t+1|t)).(Z_i(t+1|t)-\hat{z}(t+1|t))^T$$
$$P_{x,z}(t+1|t)=\sum_{i=1}^{2n+1}W_i[(\chi^i(t+1|t)-\hat{x}(t+1|t)).(Z_i(t+1|t)-\hat{z}(t+1|t))^T \quad (18)$$

In update step, values emerges from prediction step is updated by correlation and innovation matrices gotten by measurements, where Kalman gain, state update and updated covariances using correlation matrices are;

$$K(t)=P_{x,z}(t+1|t).P_{x,z}(t+1|t)^T$$
$$\hat{x}(t+1|t+1)=\hat{x}(t+1|t)-K(t)(z(t)-\hat{z}(t+1|t))$$
$$P(t+1|t+1)=P(t+1|t)-K(t)S(t+1|t)K^T(t) \quad (19)$$

The next position is calculated using below and so on. It is aimed to reduce filter based error and increase of consistency by this way in some researches. Since UAV kinematic and dynamic models are nonlinear, SLAM that use EKF and UKF which has derivation errors because of linearization through jacobien matrices for state prediction yield error production.

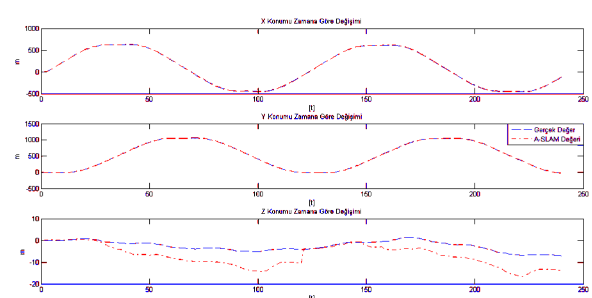

Figure 4. UAV Position Variation in Unscented Kalman Filter based A-SLAM

UKF based SLAM has transcendence for derivation error reduction over others owing to reference results which states prosperous determination of vehicle and lendmark position without prior map information but has some problem about consistency for long distance navigation problems. It is needed to conduct consistency and observability analysis which might be stemmed from unobservable subspaces.

C. Particle Filter Based Airborne SLAM (PF A-SLAM)

Particle filters are a set of on-line posterior density estimation algorithms that estimate the posterior density of the non or linear state-space by directly implementing the Bayesian recursion equations and by using sampling with a set of particles to represent the posterior density. It provide a well-established methodology for generating samples from the required distribution without requiring assumptions about the state-space model or the state distributions.

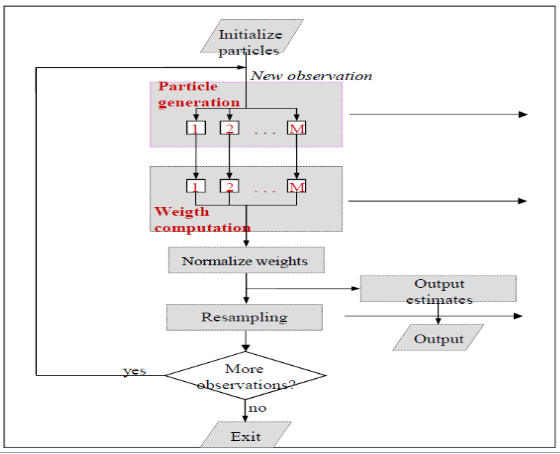

Figure 5. Particle Filter Algorithm

The samples from the distribution are represented by a set of particles; each particle has a weight assigned to it that represents the probability of that particle being sampled from the probability density function. Particle filters in which the objective is to estimate the posterior density of the state variables given the observation variables are a set of on-line posterior density estimation algorithms that is performed for non or linear state-space by directly implementing the Bayesian recursion equations and by using sampling with a set of particles to represent the posterior density. It provide a well-established methodology for generating samples from the required distribution without requiring assumptions about the state-space model or the state distributions. The samples from the distribution are represented by a set of particles; each particle has a assigned weight that represents the probability of particle being sampled from the probability density function (PDF). The weight degeneracy or disparity are issues that all but one of the importance weights are close to zero or else to solve for which one should perform resampling step in which particles with smaller weights are replaced by new particles in the proximity of the particles with higher weights. The observable variables and the dynamical system describing the evolution of the state variables are related to the hidden variables (state-process) by some functional form that is known probabilistically. In this research for particle filter application sequential importance resampling (SIR) which approximates the filtering distribution by a weighted set of P particles and state space equations used.

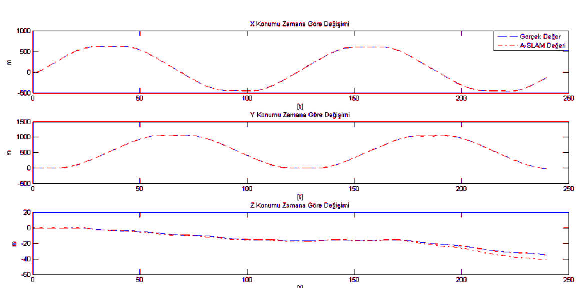

Figure 6. UAV Position Error in Particle Filter based A-SLAM

IV. CONCLUSION AND FUTURE WORK

In conclusion it may be stated that in GNSS denied environments unmanned systems need to localize itself and built the map around. In addition what if a path planning or tracking for a mission is needed. Since this reseach seeks to detect SLAM algorithms in details particularly in air vehicle platforms as a tool for application of an automation strategies from other domains to air transportation or surveillance and navigation applications of data science in aviation and it is also important to state that particle filter based SLAM implementation of aerial systems is first introduced during the research. In a certain scenario EKF, UKF and particle filter based Airborne SLAM performances according to process time and average error is analyzed and recursive calculations give superiority of particle filter in some circumstance whereas of other filters in some other conditions. Particle number is such critical that if it is small the process time become small but average position error remains a bit higher or if it is larger it is visa versa. When taking into considerations of particle numbers variety from 5 through 1000 although tradeoff between particle numbers and process time or error system produced is obvious best number should be around 50 or 100 below and under which time or fault excession occurs. It is seen as another vital comment that particle filter takes a state for example x position of UAV as initial value (prior probability) and produces n number probable candidate particle around it in each prediction and correction (update) cycle before iterations which require to jump between distinct probable positions that is sometimes very challenging for a UAV. Due to simulation results with greater lendmark number and model complexity scenarios regarding to problem UKF and EKF gives more faulty results in shorter time while particle filter based approaches gives more accurate but slower results and for this reason modified methods particularly using paralel architecture such as modified and gpu accelerated methods has some preeminence over others additionally real-time compatible methods may be preferred rather than off-line ones if hardware allows. Regarding to survey consequences the variety of SLAM applications span from parametric filters such as Unscented Kalman Filter, Extended Kalman Filter to nonparametric such as Particle Filter and concerning diversity of vision based approaches that aims up level control and variety of sensors that unmanned vehicles carry a taxonomy is a requirement of better comprehension SLAM performances. Although it is not aimed to compare performance of all SLAM methods for problem of Airborne-SLAM (A-SLAM) navigation the scan of indexed papers suggests that best SLAM algorithm can only be identified in reference to the scenario which differs in environment, platform, vehicle, sensor…etc. and can be used as an transportation tool by combining path planning and other navigation approaches.

SLAM methods with its prosperious background in last decade and potential future solutions might be considered as localization, mapping, tracking, navigation, planning and also all with others as part of an air transportation access in the near future. As a future work it is currently being extended algortihms to analize particle flow filter based A-SLAM for the first time in the literature which is suppose to put forward mathematics, algorithms and filter analysis comparatively as particle filter based A-SLAM techniques in its part.

REFERENCES

[1] R.Smith and P.Cheesman, On the Representation Of Spatial Uncertainty, Int. J. Robot. Res., Vol. 5, No. 4, pp. 56–68, 1987

[2] G.Dissanayake, H.F.Durrant-Whyte and T. Bailey, A Computationally Efficient Solution to the Simultaneous Localisation and Map Building (SLAM) Problem, ICRA, 2000

[3] Tim Bailey and Hugh Durrant-Whyte, Simultaneous Localization and Mapping (SLAM): Part I The Essential Algorithms., IEEE Robotics and Automation Magazine, 2006

[4] Tim Bailey and Hugh Durrant-Whyte, Simultaneous Localisation and Mapping (SLAM): Part II State of the Art., IEEE Robotics and Automation Magazine, September 2006

[5] J.Andrade-Cetto, and A.Sanfeliu, The Effects of Partial Observability in SLAM, IEEE Int. Conf. Robot. Automat., New Orleans, pp.397-402, 2004

[6] M.Bryson, and S.Sukkarieh, Observability Analysis and Active Control for Airborne SLAM, IEEE Transaction on Aerospace and Electronic Systems, Vol.44, No.4, pp.261-280, 2008

[7] G.P.Huang, N.Trawny, A.I.Mourikis and S.I.Roumeliotis, Observability-based consistent EKF estimators for multi-robot cooperative localization, Autonomous Robots, Volume 30, Number 1, pp. 99-122, 2011

[8] T.Vidal-Calleja, J.Andrade-Cetto and A.Sanfeliu, Conditional for Suboptimal Filter Stability in SLAM, IEEE Inernational Conferance on Intelligent Robots and Systems, Sendai Japan, 2004

[9] T.Bailey, J.Nieto, J.Guivant, M.Stevens and E.Nebot, Consistency of the EKF-SLAM Algorithm, IROS'06 IEEE/RSJ International Conference on Intelligent Robots and Systems, Beijing, China, 2006

[10] J.A.Castellanos, J.Neira, J.Tardos, Limits to The Consistency of EKF-Based SLAM, IAV2004 5th IFAC Symp. on Intelligent Autonomous Vehicles, 2004

[11] J.Kim and S.Sukkarieh, Airborne Simultaneous Localisation and Map Building, IEEE Int. Conf. Robot. Automat., Taipei Taiwan, 2003

[12] J.Kim, S.Sukkarieh, S.Wishart, Real-Time Navigation, Guidance and Control of a UAV Using Low-Cost Sensors, International Conferance of Field and Service Robotics, Yamanashi, Japan, pp.95-100, 2003

[13] J.Kim, S.Sukkarieh, Autonomous Airborne Navigation in Unknown Terrain Environments, IEEE Transaction on Aerospace and Electronic Systems, Vol.40, No.3, pp.1031-1044, 2004

[14] S.Kurnaz, O.Cetin, Autonomous Navigation and Landing Tasks for Fixed Wing Small Unmanned Aerial Vehicles, Acta Polytechnica Hungarica Vol. 7, No. 1, 2010

[15] AntSLAM: Global Map Optization Using Swarm Intelligence in Non-Static Environments, R.Iser, F.M.Wahl, IEEE International Conference on Robotics and Automation, 2010

[16] Simultaneous Localisation and Mapping Using Extended Kalman Filter, S.Yavuz, Z.Kurt, M.S.Biçer, IEEE 17th Signal Processing and Communications Applications Conference, April 2009

[17] Recasting SLAM-Towards Improving Efficiency and Platform Independency, J.H.Kim, S.Sukkarieh, Robotic Research STAR 15, pp.399-408, 2005

[18] Simultaneous Mapping and Localization with Sparse Extended Information Filters, S.Thrun, Y.Liu, D.Koller, A.Ng, Z.Ghahramani, H.Durrant-Whyte, International Journal of Robotics Research, Vol 23, pp.693-716, 2004

[19] Simultaneous Mapping and Localization with Sparse Extended Information Filters; Theory and Initial Results, S.Thrun, S.Sukkarieh, Robotics and Autonomous Systems, Vol 55, pp.62-71, 2007

[20] Mobile robot navigation based on interactive SLAM with an intelligent space , Hashikawa, F. ; Morioka, K.,8th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), 2011

[21] Autonomous Airborne Navigation in Unknown Terrain Environments, J.Kim, S.Sukkarieh, IEEE Transaction on Aerospace and Electronic Systems, Vol.40, No.3, pp.1031-1044, 2004

[22] An Omni-directional vSLAM based on spherical camera model and 3D modeling 10th World , Guofeng Tong ; Zizhang Wu ; NingLong Weng ; Wenbo Hou,Congress on Intelligent Control and Automation (WCICA), 2012

[23] Mobile robot localization using odometry and kinect sensor , Ganganath, N. ; Leung, H.,IEEE International Conference on Emerging Signal Processing Applications (ESPA), 2012

[24] A video tracking algorithm for UAV based on differential evolution particle filter , Han Yu; Wang Longsheng ; Yu Yunzhi,31st Chinese Control Conference (CCC), 2012

[25] Sparse optical flow regularization for real-time visual tracking , Spruyt, V. ; Ledda, A. ; Philips, W.,IEEE International Conference on Multimedia and Expo (ICME), 2013

[26] Scene matching based EKF-SLAM visual navigation , Li Yaojun ; Pan Quan ; Zhao Chunhui ; Yang Feng, 31st Chinese Publication Control Conference (CCC), Page(s): 5094-5099, 2012

[27] Autonomous Flight in GPS-Denied Environments Using Monocular Vision and Inertial Sensors, Allen D. Wu, Eric N. Johnson, Michael Kaess, Frank and Girish Chowdhary, Journal Of Aerospace Informatıon Systems Vol. 10, No. 4, April 2013

[28] Unmanned Aerial Vehicle Localization Based on Monocular Vision and Online Mosaicking, A New Mapping Framework, F.Caballero, L.Merino, J.Ferruz, A.Ollero, J Intel Robot Systems, Vol 55, pp. 323-343, 2009

[29] J.Welle, D.Schulz,T.Bachran ve A.B.Cremers,"Optimization Techniques for Laser-Based 3D Particle Filter SLAM", IEEE Internatonal Conference on Robotics and Automation,Alaska,USA, May 2010

[30] Mobile robot parallel PF-SLAM based on OpenMP , Songmin Jia ; Xiaolin Yin ; Xiuzhi Li,IEEE International Conference on Robotics and Biomimetics (ROBIO), 2012

[31] Distributed parallel processing of mobile robot PF-SLAM , Xiuzhi Li ; Songmin Jia; Ke Wang ; Xiaolin Yin, International Conference on Automatic Control and Artificial Intelligence ACAI 2012,

[32] CUDA accelerated robot localization and mapping , Haiyang Zhang, Fred Martin, IEEE International Conference on Technologies for Practical Robot Applications (TePRA), 22-23 April 2013,Woburn, MA

[33] Real-time 3D simultaneous localization and map-building for a dynamic walking humanoid robot,Sukjune Yoona, Seungyong Hyunga, Minhyung Leea, Kyung Shik Roha, SungHwan Ahna, Andrew Geeb, Pished Bunnunb, Andrew Calwayb & Waterio W. Mayol-Cuevasb, Advanced Robotics Volume 27, Issue 10, pages 759-772, 2013

[34] A Hybrid SLAM Representation for Dynamic Marine Environments, C.Bibby, I.Reid, IEEE International Conference on Robotics and Automation, 2010

[35] Implementation of a 4D fast SLAM including volumetric sum of the UAV , Aditya, A.,Sixth International Conference on Sensing Technology (ICST), 2012

[36] Overview on simultaneous localization and mapping for uninhabited aerial vehicle vision 30th , Wang Xi-Bin ; Zhao Guo-Rong ; Pan Shuang,Chinese Control Conference (CCC), 2011

[37] Monocular visual SLAM for small UAVs in GPS-denied environments , Chaolei Wang ; Tianmiao Wang ; Jianhong Liang ; Yang Chen ; Yicheng Zhang ; Cong Wang,IEEE International Conference on Robotics and Biomimetics (ROBIO), 2012

[38] Unscented FastSLAM for UAV, Shi Jianli ; Pan Shuang ; Wu Yugiang ; Wang Xibin, International Conference on Computer Science and Network Technology (ICCSNT), 2011

[39] 6DoF SLAM aided GNSS/INS Navigation in GNSS Denied and Unknown Environments, J.Kim, S.Sukkarieh, Journal of Global Positioning Systems, Vol.4, No.1-2, pp.120-128, 2005

[40] Real-Time Implementation of Airborne Inertial-SLAM, J.Kim, S.Sukkarieh, Robotics and Autonomous Systems, Vol 55, pp.62-71, 2007

[41] Extended Kalman Filter Based Airborne Simultaneous Localization And Mapping, A.E. Oguz , H. Temeltas,, Journal of Aeronautics and Space Technologies, Vol.6, No.2, pp.69-74, 2013

[42] The Effect of Partial Observality When Building Fully Correlated Maps, J.Andrade-Cetto, A.Sanfeliu, IEEE Transaction on Robotics, Vol.21, No.4, pp. 771-777, August 2005

[43] Conditional for Suboptimal Filter Stability, T.Vidal-Calleja, J.Andrade-Cetto and A.Sanfeliu, IEEE Inernational Conferance on Intelligent Robots and Systems, 2004

[44] The Effect of Partial Observability in SLAM, J.Andrade-Cetto, A.Sanfeliu, IEEE Conferance on Robotics & Automation, New Orleans, April 2004

[45] Estimator Stability Analysis in SLAM, T.Vidal-Calleja, J.Andrade-Cetto, A.Sanfeliu, IAV2004 5th IFAC Symp. on Intelligent Autonomous Vehicles, 2004

[46] Convergence and consistency analysis for FastSLAM, Liang Zhang ; Xu-jiong Meng ; Yao-wu Chen, IEEE Intelligent Vehicles Symposium, 2009

[47] Consistency of the EKF-SLAM Algorithm, T.Bailey, J.Nieto, J.Guivant, M.Stevens, E.Nebot, International Conference on Intelligent Robots and Systems, October 2006

[48] Convergence Analysis for Extended Kalman Fitler based SLAM, S.Huang, G.Disanayake, IEEE International Conference on Robotics and Automation Beijing, China, May 2006

[49] Analysis and Improvement of the Consistency of Extended Kalman Filter based SLAM, G.Huang, A.I. Mourikis, S.I.Roumeliotis, IEEE International Conference on Robotics and Automation pp.473-479, 2008

[50] A First-Estimates Jacobian EKF for Improving SLAM Consistency, G.Huang, A.I. Mourikis, S.I.Roumeliotis, 11th International Symposium on Experimental Robotics, 2008

[51] Generalized Analysis and Improvement of the Consistency of EKF-based SLAM, G.Huang, A.I. Mourikis, S.I.Roumeliotis, Technical Report, MARS Lab, University of Minnesota, 2008

[52] Simultaneous Localisation and Map Building Using Split Covariance Intersectio, S.J.Julier, J.K.Uhlman, International Conference on Intelligent Robots and Systems, November 2001

[53] Limits to the Consistency of EKF-Based SLAM, J.A.Castellanos, J.Neira, J.D.Tardos, IAV2004 5th IFAC Symp. on Intelligent Autonomous Vehicles, 2004

[54] Convergence and Consistency Analysis for Extended Kalman Filter based SLAM, S.Huang, G.Disanayake, IEEE Transactions on Robotics Vol.23, No.5, pp.1036-1049, 2007

[55] Observability-based Rules for Designing Consistent EKF SLAM Estimators, G.P.Huang, A.I.Mourikis, S.I.Roumeliotis, The International Journal of Robotics Research, Vol.29, No.5, pp. 502-528, April 2010

[56] "On The Consistency Analyzing of A-SLAM for UAVs navigating in GNSS Denied Environment", A.E.Oguz, H.Temeltas, Acta Polytechnica Hungarica Vol.10, No.4, pp.119-132, 2013Robust Airborne 3D Visual Simultaneous Localization and Mapping with Observability and Consistency Analysis, A.Nemra, N.Aouf, J Intel Robot Systems, Vol 55, pp. 345-376, 2009

[57] Observability-constrained Vision-aided Inertial Navigation, Hesch, J.A. Dimitrios, G.K. Bowman, S.L. ve Roumeliotis, S.I. Technical Report, MARS Lab, University of Minnesota, 2012

[58] Efficient particle filter algorithm for ultrasonic sensor-based 2D range-only simultaneous localisation and mapping application , Yang, P.,IET JOURNALS & MAGAZINES, Wireless Sensor Systems, IET Volume: 2 , Issue: 4, Page(s): 394- 401, 2012

[59] Robocentric map joining: Improving the consistency of EKF-SLAM, J.Castellanos, R.Martinez-Cantin, J.D. Tardos, J. Neira, Robotics and Autonomous Systems, Vol 55, pp.21-29, 2007

[60] Dynamic map building for an autonomous mobile robot, J.Leonard, H.Durrant-Whyte, I.Cox, The International Journal of Robotics Research, Vol.11, No.4, pp. 286–298, 1992

[61] The SPmap: A probabilistic framework for simultaneous localization and map building ,J.A.Castellanos, J.M.M.Montiel, J.Neira, J.D.Tardos, IEEE Transactions on Robotics Automation., Vol.15, No.5, pp.948–953, 1999

[62] Robust Mapping And Localization in Indoor Environments Using Sonar Data, J.D.Tardos, J.Neira, P.Newman, J.Leonard, International Journal Robotics Research, Vol.21, No.4, pp.311–330, 2002

[63] Hierarchical SLAM: Real-Time Accurate Mapping of Large Environments, C.Estrada, J.Neira, J.D.TardosIEEE Transactions on Robotics, 2005

[64] Optimal local map size for EKF-based SLAM, L.M.Paz, J.Neira, IROS'06 IEEE/RSJ International Conference on Intelligent Robots and Systems, Beijing, China, 2006

[65] EKF SLAM updates in O(n) with Divide and Conquer SLAM, L.M.Paz, P.Jensfelt, J.D.Tardos, J.Neira, ICRA'07 IEEE International Conference on Robotics and Automation, , April 2007

[66] Hierarchical Optimization on Manifolds for Online 2D and 3D Mapping, G.Grisetti, R.Kümmerle, C.Stachniss, U.Frese, C.Hertzberg, IEEE International Conference on Robotics and Automation, 2010

[67] Mapping large scale environments by combining Particle Filter and Information Filter, Mohan, M. ; MadhavaKrishna, K., 11th International Conference on Control Automation Robotics & Vision (ICARCV), 2010

[68] Autonomous Exploration and Mapping of Abandoned Mines, S.Thurn, S.Thayer, W.Whittaker, C.Baker, W.Burgard, D.Ferguson, D.Hahnel, M.Montemerlo, A.Morris, Z.Omohundro, C.Reverte, IEEE Robotics and Automation Magazine, 2004

[69] Multisensors Fusion for Simultaneous Localization and Map Building, J.A.Castellanos, J.Neira, J.D.Tardos, IEEE Transaction on Robotics and Automation, Vol.17, No.6, pp. 908-914, December 2001

[70] A Real-time SLAM Algorithm with Optical Flow based Motion Extraction for Autonomous Robot Navigation, O.Şencan, M.Turanlı, H.Temeltaş, S.Kurnaz, S.Bogosyan, International Unmanned Vehicles Workshop UVW2010, 2010

[71] Real-Time Navigation, Guidance and Control of a UAV Using Low-Cost Sensors, J.Kim, S.Sukkarieh, S.Wishart, International Conferance of Field and Service Robotics, Yamanashi, Japan, pp.95-100, 2003

[72] Optimization of the Simultaneous Localization and Map Building Algorithm for Real Time Implementation, J.Guivant, E.Nebot, IEEE Transaction on Robotics and Automation, Vol.17, No.3, pp. 242-257, 2013

[73] Extending Bayesian RFS SLAM to multi-vehicle SLAM , Moratuwage, D. ; Ba-Ngu Vo ; Danwei Wang ; Han Wang,12th International Conference on Control Automation Robotics & Vision (ICARCV), 2012

[74] Simulation Research on Multi-Robot SLAM of Information Filter, Shan Shan Li, Ya Hong Xu, Xiao Long Xu, Ning Hui Zhu, Advances in Mechatronics and Control Engineering Applied Mechanics and Materials (Volumes 278 280), January 2013

[75] Rao-Blackwellized Particle Filters multi robot SLAM with unknown initial correspondences and limited communication, Carlone, L. ; Ng, M.K. ; Jingjing Du ; Bona, B. ; Indri, M., IEEE International Conference on Robotics and Automation (ICRA), 2010

[76] Simulation Research on Multi-Robot SLAM of Information Filter, Shan Shan Li, Ya Hong Xu, Xiao Long Xu, Ning Hui Zhu, Advances in Mechatronics and Control Engineering Applied Mechanics and Materials (Vomarinelumes 278 280), January 2013

[77] Multi-robot Simultaneous Localization and Mapping using Particle Filters, Andrew Howard, , Localization and Mapping Using Only a Rotating FMCW Radar Sensor, Damien Vivet , Paul Checchin; and Roland Chapuis, Internaional Journal of Robotics Research Sensors, 13, 4527-4552, 2013

[78] Multı-Robot Fast SLAM For Large Domains, C.Koperski, AFIT Master Thesis, Marc 2007

[79] Cooperative vSLAM based on UAV application , Xiaodong Li ; Aouf, N.,IEEE International Conference on Robotics and Biomimetics (ROBIO), 2012

[80] Architectures for Cooperative Airborne Simultaneous Localisation and Mapping, M.Bryson, S.Sukkarieh, J Intel Robot Systems, Vol 55, pp. 267-297, 2009

[81] Experimental Research on Cooperative vSLAM for UAVs , Xiaodong Li ; Aouf, N.,Fifth International Conference on Computational Intelligence Communication Systems and Networks (CICSyN), 2013

[82] Just-in-time cooperative simultaneous localization and mapping, Martin, A. ; Emami, M.R., 11th International Conference on Control Automation Robotics & Vision (ICARCV), 2010

[83] An overview of Robot SLAM problem , Liping Qu ; Hongjian Wang,International Conference on Consumer Electronics, Communications and Networks (CECNet), 2011

[84] An Analysis of Simultaneous Localization and Mapping (SLAM) Algorithms, Naminski, Megan R., Honors Projects.Paper 29., 2013

[85] A comparative study on active SLAM and autonomous exploration with Particle Filters, Du J.; Carlone, L. ; Kaouk Ng, M. ; Bona, B. ; Indri, M.,IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), 2011

[86] Autonomous navigation among large number of nearby landmarks using FastSLAM and EKF-SLAM - A comparative study , Monjazeb, A. ; Sasiadek, J.Z. ; Necsulescu, D.,16th International Conference on Methods and Models in Automation and Robotics (MMAR), 2011

[87] Technical Analysis and Implementation Cost Assessment of Sigma-Point Kalman Filtering and Particle Filtering in Autonomous Navigation Systems, Rigatos, G.G., IEEE 71st Vehicular Technology Conference (VTC 2010-Spring), 2010