Improving Covariance Matrix Diagonalization in SLAM of Mobile Robot

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Abstract. Diagonalization of covariance matrix through eigenvalue approach in extended Kalman Filter (EKF)-based simultaneous localization and mapping (SLAM) of mobile robot has been studied, as one of the possible approach in reducing complexity hence computational cost of the system. However, the estimation is seemed to be too optimistic, and further investigation need to be conducted. In this paper, the effect on addition of Pseudo elements in the diagonalization process is investigated. It is evaluated at the updated state covariance matrix of EKF-based SLAM. It is found that the additional of pseudo components in diagonal matrix can improve the covariance matrix and lower the computational complexity. This findings have been proved through simulation.

Keywords: Covariance, Diagonalization, Pseudo.

1 Introduction

Dealing with hazardous environment such as underwater is a challenging job for human. In this situation robot is applied to represent human for surveillance and navigation purpose. Several issues are faced in order to apply the robotic system such as the environment, data association, mapping and localization. These factors cause more problems to be appeared and need more research works to work on. A situation where a mobile robot appoint to inspect a nameless environment and additively design a map of surroundings that it has identified is cater by Simultaneous Localization and Mapping (SLAM). It able to restrict itself on the constructed recursively until its task is achieved. However, this process is susceptible to errors that may be generated from various sources such as the sensors, modeling, system and algorithm[1]-[2].

There are several of filtering method that used by researchers to deal with SLAM problem such as Extended Kalman Filter (EKF)[3], Unscented Kalman Filter (UKF),

H_∞ and Consistence Extended Kalman Filter (CEKF). Some of the filtering method may lead to disadvantage which can cause low optimization performance in SLAM. For example, the Fast-SLAM is said to be the greatest filtering as it tougher than any filtering. Nonetheless this approach needs greater complexity of computational.

In order to solve the problem in SLAM, Extended Kalman Filter is commonly used by researchers because of the simplicity of algorithm[4]. However, each moment when a new landmark is detected the entire covariance matrix in EKF-based SLAM should be updated. This procedure drags lots of mathematical works that may lead to computational cost. The more landmarks are detected; the dimension of covariance matrix will gain twice the number of landmark. In traditional EKF-base SLAM algorithm is known that the cost of O(m^2), a total number of landmarks of the map is m. In realizing the aspect of multiplication operation of landmarks, the used of EKF in big environment is finite. The full covariance structure which is responsive to the effects of linearization errors which build up through time will affected when the landmarks increase.

In search of solution to improve the SLAM performance researchers work very hard to propose various kinds of probabilistic techniques by giving attention on the simplification of the covariance structure. A technique of decorrelation algorithm has been introduced by Guivant and Nebot[5] in order to make the covariance matrix easy. The weakly cross-correlation term in the matrix of covariance will be cancel when subset of the state that is weakly correlated will decorrelate. In order to reduce these couple elements in SLAM which is the storage costs and computational complexity a positive semi definite matrix is added to the covariance matrix. Another technique on reducing a computational cost where an algorithm, also to cancel the weekly cross-correlation has been presented[6]. The RLR (Relative Landmark Representation) has been used to produce a much closer to optimal result generation, using an appropriate map management strategies. The computational and memory requirement of algorithm has been reduced through this implementation. A method of adding a pseudo Positive Semi definite (PsD) namely covariance inflation has been implemented to reduce computational cost[6],[7]-[8]. In this method some minor changes on the covariance matrix has been done in order to decorrelate the system; which lead to low the computational cost.

By the additional of Pseudo noise into the matrix that has been diagonalized using eigenvalue[9] on computational complexity of EKF SLAM the research is conducted to evaluate the performance effects of covariance state update. The performance of covariance is identified throughout the simulation results.

2 Issue of Design

2.1 SLAM in term of Modeling.

The equation of separate time dynamic system is pictured for SLAM are regarding process and consideration model. Whereas the observation model with regard to the mobile robot position represents the measuring of the map options that process model illustrate the movements of the mobile robot. (i.e. method and observation model) of SLAM shows on Fig.1 for each model. For equation that represent SLAM process model from time k to time k + 1 in linear system, is declared as

$$X_{k+1} = F_k X_k + G_k U_k + w_k \tag{1}$$

in which, X_k is expression of the condition of landmarks and mobile robot, F_k represent the state transition matrix, G_k defined the control matrix, U_k pictured the control inputs, and covariance Q characterized w_k along the zero-mean Gaussian process noise.

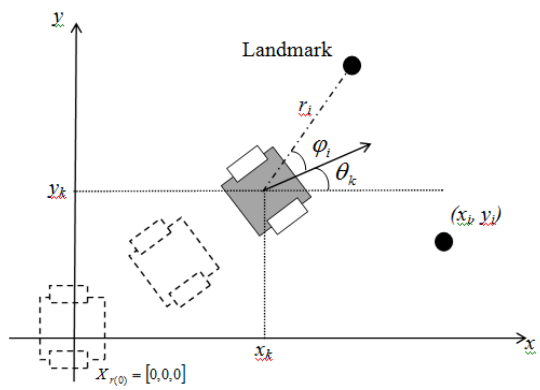

Fig. 1. SLAM model.

Landmarks X_m and robot X_r is a mixed state vector serve as 2D SLAM at time *k* as pursue by the state vector

$$X_k = \begin{bmatrix} X_r \\ X_m \end{bmatrix} = \begin{bmatrix} \theta_k \\ x_k \\ y_k \\ x_i \\ y_i \end{bmatrix} \tag{2}$$

where x_k and y_k pictured the middle location of the mobile robot with allusion to global coordinate frame and the θ_k picture the guidance angle of the mobile robot. Where *m* is number of landmarks and *i*= 1, 2,…, *m* is correlate to the landmark model by the Cartesian coordinate (x_i , y_i),. A model of two-wheel mobile robot is enforced concluded this study. In this study occasionally we express it as robot posture conversely $X_r = [\theta_k \quad x_k \quad y_k]^T$ is practiced to imply the robot position. The kinematic of mobile robot that depict the refine form pictured as $X_{r(k+1)} = f(X_{r(k)}, u_k, \delta\omega, \delta\upsilon)$ and $u_k = [\omega_k \quad \upsilon_k]^T$ in which

$$\begin{aligned} \theta_{k+1} &= \theta_k + (\omega_k + \delta\omega)T \\ x_{k+1} &= x_k + (\upsilon_k + \delta\upsilon)T\cos(\theta_k) \\ y_{k+1} &= y_k + (\upsilon_k + \delta\upsilon)T\sin(\theta_k) \end{aligned} \tag{3}$$

The mobile robot angular acceleration control inputs is pictured ω_k and the mobile robot velocity with pertinent process noises, $\delta\omega$ and $\delta\upsilon$ is produce by υ_k. T picture as the time intermission of one evolution step. As landmarks are counterfeit to be stagnant, For i= 1, 2,…, m is guileless with zero noise are the process model for the landmarks $[x_i, y_i]^T$

$$X_{m(k+1)} = X_{m(k)} \tag{4}$$

Observation model are expressed applying State observation or measurement process

$$z_{(k+1)} = \begin{bmatrix} r_i \\ \phi_i \end{bmatrix} = H_{k+1}X_{k+1} + V_{r_i\phi_i} \tag{5}$$

Where H_k defined the measurement matrix and R define the zero-mean Gaussian noise with covariance matrix $V_{r_i\phi_i}$. The consideration of i^{th} landmark is a range r_i and bearing ϕ_i which displays the connection distance is at time $k+1$, and the attended landmarks is angle of the mobile robot. The sensor in the robot engage with a range sensor are it is counterfeit that and the consideration of the landmark in the situation as well as the conceal on the wheel for vehicle speed analysis is bearing that retain. The range and bearing are pictured as

$$r_i = \sqrt{(y_i - y_{k+1})^2 + (x_i - x_{k+1})^2} + v_{r_i} \tag{6}$$

$$\phi_i = \arctan\left(\frac{y_i - y_{k+1}}{x_i - x_{k+1}}\right) - \theta_{k+1} + v_{\theta_i} \tag{7}$$

where current robot position is $(x_{k+1}, y_{k+1}, \theta_{k+1})$, (x_i, y_i) is position of observed landmark, v_{r_i} and v_{θ_i} are the noises on the analysis

2.2 SLAM Situated on Extended Kalman Filter

To rating the location of mobile robot and landmarks the extended Kalman filter (EKF) is practiced through this study. First, situated on the prior system advice, the state vector is anticipated. Subsequently that applying the measurement data earned from the sensors, the state vector will be predicted. The updated state vector $\hat{X}_k$ and the covariance matrix of the estimation P_k are the concern parameters related. The amplification of prediction and estimation of EKF are certain as pursue.

A. (Update of time) is a Prediction

The state vector at the current k for the estimation certain as

$$\hat{X}_k = \begin{bmatrix} \hat{X}_r & \hat{X}_1 & \hat{X}_2 & \dots & \hat{X}_m \end{bmatrix}^T \tag{8}$$

and the estimation error is P_k for the covariance matrix. (Equations 1 to 4) is linearized as an expension of the Taylor series about $\hat{X}_k$ for the mechanism model and the later predicted state vector $\hat{X}_{k+1}^-$ and error covariance matrix P_{k+1}^- is hence drive to

$$\begin{aligned} \hat{X}_{k+1}^- &= f(X_k, u_k, 0, k) \\ P_{k+1}^- &= \nabla F_X P_k \nabla F_X{}^T + \nabla F_w Q_k \nabla F_w{}^T \end{aligned} \tag{9}$$

spot the Jacobian of f with consideration to X_k is characterized by ∇F_X and the Jacobian with consideration to ω_k is characterized by ∇F_ω the Jacobian with consideration to ω_k. From the Eq. 3 at $\hat{X}_k$ these Jacobians are valued and have the consecutive interpretation:

$$\nabla F_X = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -\omega T \sin\hat{\theta}_k & 1 & 0 & 0 \\ \omega T \cos\hat{\theta}_k & 0 & 1 & 0 \\ 0 & 0 & 0 & I_m \end{bmatrix}, \nabla F_X = \begin{bmatrix} \nabla F_{\gamma\omega} \\ 0_m \end{bmatrix} \tag{10}$$

I_m and 0_m is the aspect and ineffective matrix independently with proper appraisal confide upon the capacity of points of landmark minded although the observe rate is T. The landmarks as they are counterfeit to be stagnant steadily adjacent is no process noise.

B. (Update estimation) is a Updated

The Taylor series advancement about $\hat{X}_{k+1}^-$ the equation of the state vector is linearization of the observation model (Eq. 5) and the update procedure is enclosed for the error covariance matrix. The mobile robot updates its current position proportionate by positioning the observed landmarks beside the convenience of estimation data advice z_{k+1},

$$P_{k+1}^+ = P_{k+1}^- - K_{k+1}(\nabla H_i P_{k+1}^- \nabla H_i{}^T + R_k) K_{k+1}{}^T$$

K_{k+1} is a Kalman gain and has the adherents explanation:

(11)

$$K_{k+1} = P_{k+1}^{-} \nabla H_i^T \left(\nabla H_i P_{k+1}^{-} \nabla H_i^T + R_k \right)^{-1}$$

The Jacobian is characterized by ∇H_i in Eq. 5 with refer to X_k appraise at $\hat{X}_{k+1}^{-}$ and assert as follows:

$$\nabla H_i = \begin{bmatrix} 0 & -\frac{dx}{r} & -\frac{dy}{r} & \frac{dx}{r} & \frac{dy}{r} \\ -1 & \frac{dy}{r^2} & -\frac{dx}{r^2} & -\frac{dy}{r^2} & \frac{dx}{r^2} \end{bmatrix} \quad (12)$$

with

$$dx = \hat{x}_i^{-} - \hat{x}_{k+1}^{\gamma-}, \; dy = \hat{y}_i^{-} - \hat{y}_{k+1}^{\gamma-}, \; r = \sqrt{dx^2 + dy^2} \quad (13)$$

2.3 The Matrix of State Error Covariance

The part of the correlation among two variables is frequently the covariance of two modifications. The correlation theory can be deliberate by the volume of linear dependency among variables. In SLAM, the matrix arrangement between landmarks covariance matrices and the robot position, also not forget about the correlation among landmarks and robot is represent through the state estimate covariance matrix as follows:

$$P = \begin{bmatrix} P_{RR} & P_{RM} \\ P_{RM}^T & P_{MM} \end{bmatrix} \quad (14)$$

For the robot position the covariance matrix related is P_{RR}, while for landmark position the covariance matrix that matches is P_{MM} and also for the cross-correlation among robot and landmarks having their covariance matrix depute by P_{RM} .

The error connected with the assumption of the state of the robot and the allusion point shows the covariance matrix points In SLAM. The errors and uncertainties of estimation can be monitoring either raise or decrease, in which they stand for the certainty and firmness of the appraisal through the covariance matrix information. As a result, it is extremely important to explore the behavior of the covariance matrix as it commits important issue in SLAM.

Proposition 1: The amount of the uncertainty ellipsoid associated with the state estimate, which indicate the total uncertainty of that particular state estimation is measure of the determinant of the error covariance matrix[10].

In SLAM, the dimension of the state error covariance matrix is $(3 + 2m)^2$, where landmarks represented by *m.* While the robot identifies the latest landmark in its territory, the content of the state error covariance will be expended. The matrix of SLAM's state error covariance produces in Eq.15. Through the matrix of state error covariance, the changing of the erroneous and the uncertainties could be attended in order to preserve the quality of estimation. Better estimation shows the smaller value of covariance. A situation where the covariance value of prediction is dramatically tiny than the real value the estimation illustrate a deception, but at the same time the covariance shows smaller value, this phenomena is called an optimistic estimation. In EKF-based SLAM this becomes one of important aspect to take attention for the estimation works.

$$\begin{bmatrix} P_{\theta\theta} & P_{\theta x} & P_{\theta y} & P_{\theta m_{1,x}} & P_{\theta m_{1,y}} & \cdots\cdots & P_{\theta m_{n,x}} & P_{\theta m_{n,y}} \\ P_{x\theta} & P_{xx} & P_{xy} & P_{xm_{1,x}} & P_{xm_{1,y}} & \cdots\cdots & P_{xm_{n,x}} & P_{xm_{n,y}} \\ P_{y\theta} & P_{yx} & P_{yy} & P_{ym_{1,x}} & P_{ym_{1,y}} & \cdots\cdots & P_{ym_{n,x}} & P_{ym_{n,y}} \\ P_{m_{1,x}\theta} & P_{m_{1,x}x} & P_{m_{1,x}y} & P_{m_{1,x}m_{1,x}} & P_{m_{1,x}m_{1,y}} & \cdots\cdots & P_{m_{1,x}m_{n,x}} & P_{m_{1,x}m_{n,y}} \\ P_{m_{1,y}\theta} & P_{m_{1,y}x} & P_{m_{1,y}y} & P_{m_{1,y}m_{1,x}} & P_{m_{1,y}m_{1,y}} & \cdots\cdots & P_{m_{1,y}m_{n,x}} & P_{m_{1,y}m_{n,y}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \cdots\cdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \cdots\cdots & \vdots & \vdots \\ P_{m_{n,x}\theta} & P_{m_{n,x}x} & P_{m_{n,x}y} & P_{m_{n,x}m_{1,x}} & P_{m_{n,x}m_{1,y}} & \cdots\cdots & P_{m_{n,x}m_{n,x}} & P_{m_{n,x}m_{n,y}} \\ P_{m_{n,y}\theta} & P_{m_{n,y}x} & P_{m_{n,y}y} & P_{m_{n,y}m_{1,x}} & P_{m_{n,y}m_{1,y}} & \cdots\cdots & P_{m_{n,y}m_{n,x}} & P_{m_{n,y}m_{n,y}} \end{bmatrix} \tag{15}$$

3 Matrix Diagonalization

Diagonal matrix is a matrix that during which the highest and bottom components area unit all null. The ingredients of diagonal components might replenish maybe with price or conjointly null. For a $n \times n$ matrix is alleged to be square matrix if it explicit as

Let the elements of $D = (d_{i,j})$

$$(d_{i,j}) = 0 \text{ if } i \neq j \forall i, j \in \{1,2,...,n\} \tag{16}$$

Wherever simply diagonal components area unit involved, the multiplication step of the matrix is simpler for a diagonal matrix and this need a lower computational cost and can create the operation faster if applied in SLAM.

$n \times n$ square matrix is A . It's believed that there be gift variety and a column matrix B with dimension of specified

$$AB = \lambda B$$

λ is outline as an eigenvalue of A with the matching eigenvector B,. Then A is diagonalizable to a matrix D. For every $n \ x \ n$ matrix there'll typically be n number of eigenvalues, during which the eigenvalues may be actual, complex or the be join of reciprocally numbers.

Definition 1: *Let A be a n x n square matrix and D is a diagonal matrix in which its diagonal elements are the eigenvalues of A, such as follows:*

$$D = \begin{bmatrix} \lambda_1 & 0 & 0 & 0 \\ 0 & \lambda_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & \lambda_n \end{bmatrix}$$

(17)

The subsequent relationship between matrix A and matrix D there exists ac

$$\det(A) = \det(D)$$
$$norm(A) = norm(D) \tag{18}$$

The behavior of the diagonal matrix given by Eq.18 thus pertaining to Proposition 1, the diagonalisation over eigenvalues could also be one in every of the choice techniques to minimize the computational cost of SLAM based on EKF is the chance exists that. The method was conjointly motivated by the sooner works of [5] and [11] that chiefly investigated and mentioned concerning the diagonalization of the modernize state covariance matrix.

3.1 Covariance Matrix Diagonalization by means EKF-based SLAM

Through simulation analysis, the investigation of diagonalization of covariance matrix on estimation performance is examined. In order to minimize the computational cost, the multiplication steps in the covariance calculation have to be simpler and it becomes the goal of this study. The diagonal elements involve in multiplication of a matrix with a diagonal matrix that it is much quicker and simpler. This has been approved through matrix diagonalization using eigenvalue [9]. However, through the simulation, the covariance behaves unusual, where the covariance matrix decrease quickly and it is too slightly compared to the normal covariance. It is said to be an optimistic estimation phenomenon as mentioned in Section 2.3. We then proposed a method of adding pseudo namely covariance inflation as an approach to overcome the phenomena and to reduce the computational cost. We believe that using this approach the optimistic estimation can be escaped and immedietly actualizing the reduction of cost computational for EKF SLAM problem.

3.2 Covariance expansion by methods for Decorrelation

Additional pseudo noise approach in the system by covariance inflation is means of decorrelation. The mathematical description for the covariance inflation for convenience to be express. For EKF, supplementary of pseudo noise ΔP to the EKF algorithm result in

$$P_{k+1}^{+} = P_{k+1}^{-} - K_{k+1}(\nabla H_i P_{k+1}^{-} \nabla H_i^{T} + R_k) K_{k+1}^{T} + \Delta P_k \tag{19}$$

By referring covariance inflation, for $d > 0$ to 2-D realizations

$$\Delta P_k = \begin{bmatrix} dP^{12} & -P^{12} \\ -P^{21} & \dfrac{P^{12}}{2d} \end{bmatrix} \tag{20}$$

To guide a lower value of the covariance matrix P_k, ΔP_k is select. Further details are explain in[11]. To unwrap commonly the analytical measure of ΔP, this paper is

(21)

presented precisely in[11]-[12]and can be spread in EKF. A PsD covariance matrix is inclined through for each update,

$$P_{k+1} = P_k + \Delta P_k$$

The covarience is combined by Pseudo noise ΔP_k . It is presumed that for the later modernize

$$\begin{aligned} P_{k+2} &= P_{k+1} + \Delta P_{k+1} \\ &= (P_k + \Delta P_k) + \Delta P_{k+1} \\ &= P_k + \Delta P_k + \Delta P_{k+1} \\ &= P_k + n\Delta P_k \end{aligned} \tag{22}$$

This study involves some modification on covariance matrix where the delta P is added in order to reduce the optimistic problem as stated in[13]. Based on two case studies, the study has been organized:

(1) Diagonalization using eigenvalue [13] on estimated covariance for both (robot and landmarks).

(2) Diagonalization using eigenvalue with additional of delta P on Estimated covariance for both (robot and landmarks).

Using the function stated as follows for the case study 1, the eigenvalue of estimated covariance is first calculated:

$$\lambda_n = eig\,(P_{k+1}^{+}) \tag{23}$$

Where the estimated covariance is represented (P_{k+1}^{+}) and the eigenvalue is represented λ_n. Using the next function the diagonal matrix will be build stated as follows:

$$P_{(D),k+1}^{+} = diag\,(\lambda_n) \tag{24}$$

where $P_{(D),k+1}^{+} = diag\,(\lambda_n)$ is a diagonal matrix that built from eigenvalue.

For the case study 2 the equation of (23) and (24) is applied again but for this time the pseudo elements added after the diagonal matrix is build. The function involve as follows:

$$P_{(D,new),k+1}^{+} = P_{(D),k+1}^{+} + \Delta P$$

where $P_{(D,new),k+1}^{+}$ is the new diagonal matrix after adding pseudo and ΔP is a pseudo noise.

The performances of the proposed method are analyzed using the two cases mentioned above.

4 Results of Simulation and discussions

In Section 3, the simulation analysis for two cases of contrasting diagonalization technique as defined and the pattern of the estimation and covariance matrix of EKF-based SLAM are presented to examine.

The estimation of the mobile robot position and landmarks under normal condition depicted in Fig.2. With constant speed, the simulation time for the mobile robot is 300s and the landmarks for every cycle of motion continuously detects. The covariance ellipses represent the uncertainties of the estimation. The smaller ellipse size, show the better estimation.

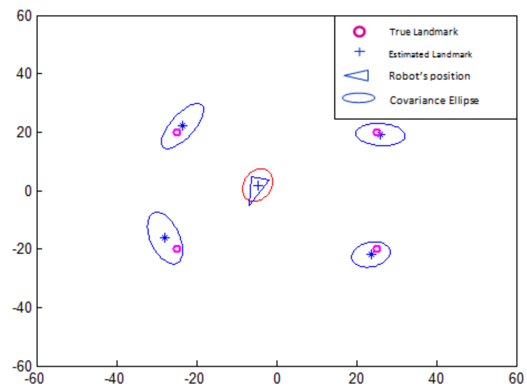

Fig. 2. Under normal condition for position estimation and covariance.

By applying the same parameters, the simulation for two case studies as stated in Section 3 are conducted. Fig.3 shows the behavior of covariance through estimation for the first case, while the result of second case study is depicted in Fig.4. The estimation of landmark and mobile robot position is available when the entire covariance is diagonalized through the technique define in previous section. However,the estimation regulate some decent errors.

The covariance behaves uncommon for case 1, where the covariance decrease suddenly and it is too small compared the the normal covariance as shown in Fig.2. This illustrates the optimistic estimation as describe in Section 2.3 of this paper. However for case 2, after adding the pseudo elements in the estimation, the covariance ellipses shows some value and it can be seen in Fig4. It shows that the robot able to do estimation where the robot is not lost within its environment. This shows that by adding the pseudo elements into diagonalization through finding eigenvalue, the optimistic value of covariance matrix can be corrected.

Table 1 depicts the comparison of processing time of all cases. Eigenvalue (case 1) was begin to be quickest amid all cases regarding 8.82% quicker than normal condition when diagonalization of cavarience matrix through finding. Also concluded regarding 7.69% for case 2 then the regular condition, eventhough the covariance matrix diagonalizing process need extra procedure. Moreover, case 2 produce better covariance ellipse where the optimistic estimation as explain in Section 2.3 can be corrected.

Table 1. Time processing for cases involved.

Covariance type	Simulation time (s)	Total processing time (s)	Percentage of processing time reduction (%)
Normal	300	91.7468	
Case 1	300	83.6527	8.82
Case 2	300	84.6911	7.69

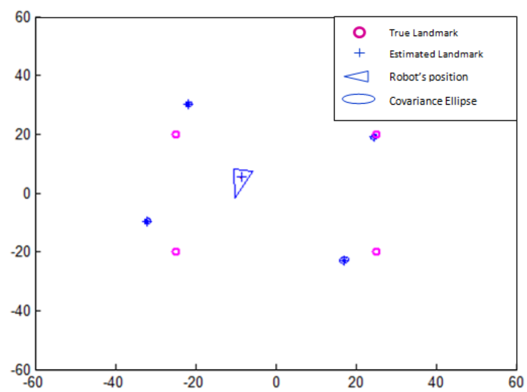

Fig. 3. Estimation of the state and covariance behavior of case one.

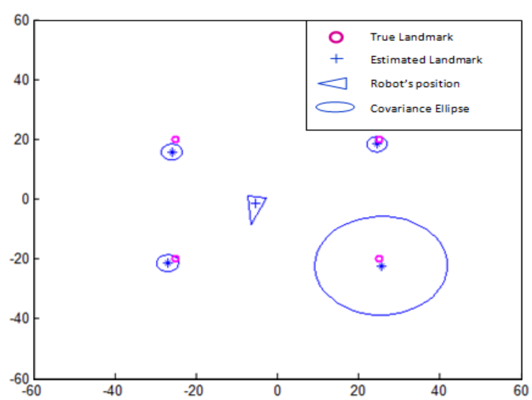

Fig. 4. Estimation of the state and covariance behavior of case two.

5 Conclusion

The investigation of EKF based SLAM achievements in the environment of diagonalized covariance are produced through this paper. Through eigenvalue the covariance matrix have been diagonalized in Case 1, whereas just in case 2, a pseudo parts is added into the technique mention just in case 1. Based on simulation result Case 1 complete the quickest estimation compared to the normal condition and Case 2. Additionally, it absolutely was identified that Case 2 produces better estimation than Case 1 wherever the errorneous seems to be less and the covariance ellipse appeared and might correct the optimistic estimation that mention in Section 2.3.

References

1. He H, Wang K, and Sun L.: A SLAM algorithm of fused EKF and Particle filter. In: 2018 WRC Symposium on Advanced Robotics and Automation. WRC SARA 2018 - Proceeding, Dec. 2018, pp. 249–254 (2018).
2. Zhang Y, Zhang T, and Huang S.: Comparison of EKF based SLAM and optimization based SLAM algorithms. In: Proceedings of the 13th IEEE Conference on Industrial Electronics and Applications, ICIEA 2018, Jun. 2018, pp. 1308–1313 (2018).
3. Ullah I, Su X, Zhang X, and Choi D.: Simultaneous Localization and Mapping Based on Kalman Filter and Extended Kalman Filter. Wirel. Commun. Mob. Comput., vol. 2020. (2020).
4. Todoran H G and Bader M.: Extended kalman filter (EKF)-based local SLAM in dynamic environments: A framework. In: Advances in Intelligent Systems and Computing, 2016, vol. 371, pp. 459–469 (2016).
5. Guivant J E and Nebot E. M.: Solving computational and memory requirements of feature-based simultaneous localization and mapping algorithms. IEEE Trans. Robot. Autom., vol. 19, no. 4, pp. 749–755 (2003).
6. Guivant J and Nebot E..: Improving computational and memory requirements of simultaneous localization and map building algorithms. In: Proceedings - IEEE International Conference on Robotics and Automation, 2002, vol. 3, pp. 2731–2736 (2002).
7. Ahmad H and Namerikawa T.: Feasibility study of partial observability in H∞ filtering for robot localization and mapping problem.: In: Proceedings of the 2010 American Control Conference, Jun. 2010, pp. 3980–3985 (2010).
8. Ahmad H, Othman N, Saari M, Ramli M, Mazlan M, Namerikawa T.: A hypothesis of state covariance decorrelation effects to partial observability SLAM. Indonesian Journal of Electrical Engineering and Computer Science (2019), vol 14(2), pp. 588-596(2019).
9. Othman N. A and Ahmad H.: Examining the eigenvalues effect to the computational cost in mobile robot simultaneous localization and mapping. Comput. Electr. Eng., vol. 56, pp. 659–673. (2016).
10. Gamini Dissanayake M W M, Newman P, Clark S, Durrant-Whyte H F, and Csorba M.: A solution to the simultaneous localization and map building (SLAM) problem. In: IEEE Trans. Robot. Autom., vol. 17, no. 3, pp. 229–241 (2001).
11. Andrade-Cetto J and Sanfeliu A.: The Effects of Partial Observability in SLAM. Robot. Autom. (ICRA), 2004 IEEE Int. Conf., pp. 397-402 Vol.1, (2004).
12. Vidal-Calleja T, Andrade-Cetto J, and Sanfeliu A.: Conditions for suboptimal filter stability in SLAM. In: 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2004, vol. 1, pp. 27–32,(2004).
13. Julier S J.: The Stability of Covariance Inflation Methods for SLAM. In: IEEE International Conference on Intelligent Robots and Systems, 2003, vol. 3, pp. 2749–2754 (2003).