

PROBABILISTIC ROBOTICS: SIMULTANEOUS LOCALIZATION AND MAPPING

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1

Let d the dimension of state space in EKF SLAM, and N the number of landmarks in the map. We have $d = 3N + 3$. The complexity of motion update in EKF SLAM is asymptotically dominated by order d matrix multiplications, so the complexity is $O(d^\omega)$ or equivalently $O(N^\omega)$, where $\omega < 2.3728639$ (cf. [1]). On the other hand, the complexity of EKF algorithm for localization is dominated by the loop over all sensings, which is executed $O(N)$ times and contains a constant number of constant size matrix multiplications / inversions; hence an asymptotic complexity of $O(N)$.

2

A solution to initialize landmarks during bearing-only SLAM can be found in paper [2]; It uses the framework described in [3], [4] to manage relationships between spatial uncertainties. I will give only a summary of the main ideas here and refer the reader to the papers for the details.

In [4], the concept of *approximate transformation* (AT) is defined: it expresses the uncertain relative location of one frame $\mathbf{B} = (X_2, Y_2, \theta_2)$ with respect to another frame $\mathbf{A} = (X_1, Y_1, \theta_1)$. The transformation has a mean and a covariance matrix. Think of it as the pose of the robot or the location of a landmark.

- (i) The ATs can be *compounded*: knowing the AT \mathbf{A} with respect to \mathbf{W} and the AT \mathbf{B} with respect to \mathbf{A} , compute the AT \mathbf{B} with respect to \mathbf{W} , in which case the uncertainty is the sum of the original ones (think of 2 successive motion update in Kalman filter without sensing).
- (ii) The ATs can be *merged*; knowing a first AT \mathbf{A}_1 with respect to \mathbf{W} and a second AT of the same frame \mathbf{A}_2 with respect to \mathbf{W} , compute the AT \mathbf{A} with respect to \mathbf{W} by combining the 2 spatial relationships, in which case the resulting uncertainty is less than both of original uncertainties (think of motion update followed by sensing a known location landmark).

An insightful analogy can be made with series / parallel electric resistances.

Back to the landmark initialization problem: Obviously, a single bearing measurement of a landmark does not allow to determine a location for it (cf. 1). The idea is to accumulate over time evidences of the presence of a new landmark before integrating it in the state variable. We see in figure 2 that potential landmarks location arise at the intersections of measurements from different positions. For each of the intersection, we *compound* the covariance Σ_t of robot uncertain pose at time t with covariance of the measurement Q to get an approximate landmark location $\hookrightarrow \mathcal{N}(\mu, C_1)$. We do it again from location at time $t + 1$ to get another estimate $\hookrightarrow \mathcal{N}(\mu, C_2)$ and then *merge* both estimates (cf. figure 3) to get a clearer position $\mathcal{N}(\mu, C_3)$.

Note that every measurements intersection is not necessarily a landmark, that is why we need to introduce the notion of *persistance*: as the persistence count increases, the certainty that the gaussian corresponds to an actual landmark increases. In figure 4 again estimate is build from measurement intersection $\mathcal{N}(\mu_4, C_4)$. This estimate is close enough (we need to define a distance between Gaussian distributions) from the previous one, so the estimates are merged and persistance count is incremented. When the count reaches a certain threshold, the landmark is appended to state variable and initialized with current estimate's mean and covariance.

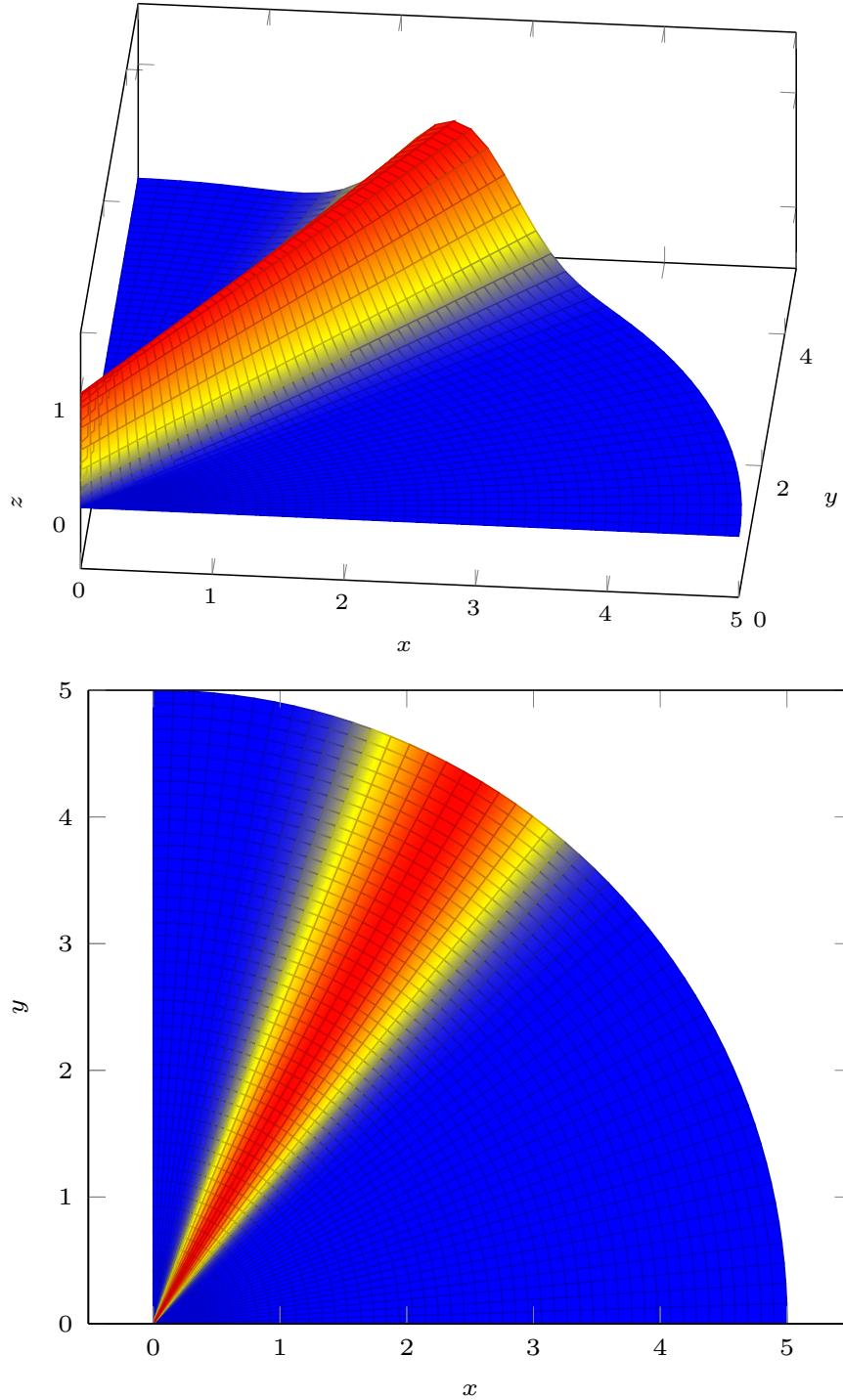


FIGURE 1. scaled probability density of location in robot local frame of a landmark, detected at $\phi = \frac{\pi}{3}$ with noise variance $\sigma^2 = 0.01$

We have seen previously that for a given known landmark k , the r.v. $\pi_k = (z - h(y_t, k))\Psi_k^{-1}(z - h(y_t, k))$ is a chi-squared r.v. if landmark k is the actual target of measurement z ; so we can do a Chi-squared test and decide a threshold α above which the landmark is associated to the measurement (we need to choose a policy to handle incompatibilities); if the measurement cannot be associated to any already known landmark, it is used in above initialization algorithm.

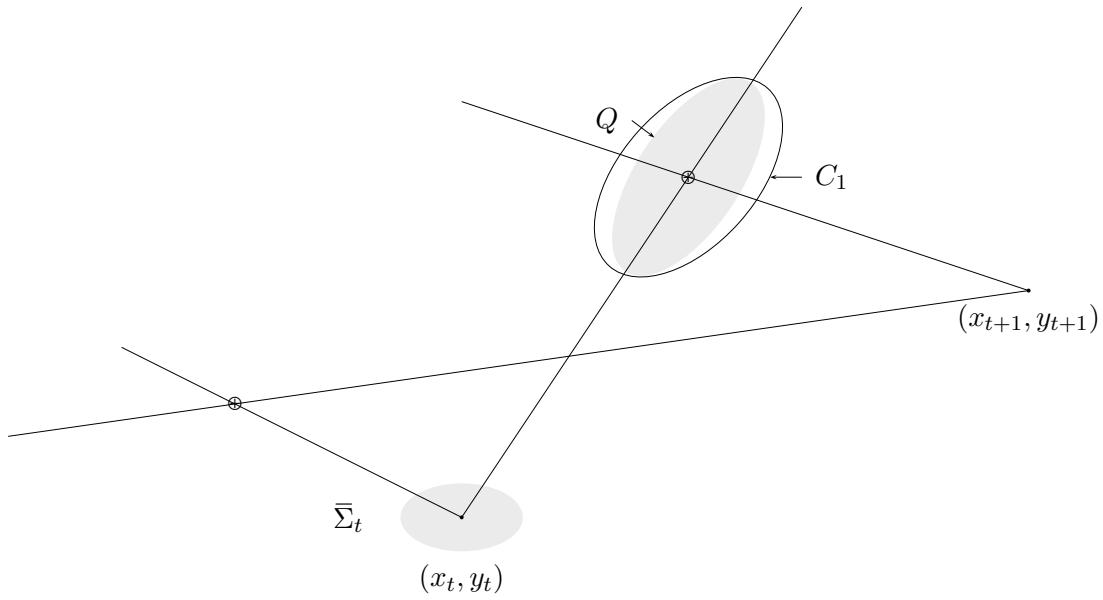


FIGURE 2. Uncertainty of the robot pose is compounded with noise uncertainty to estimate landmark position

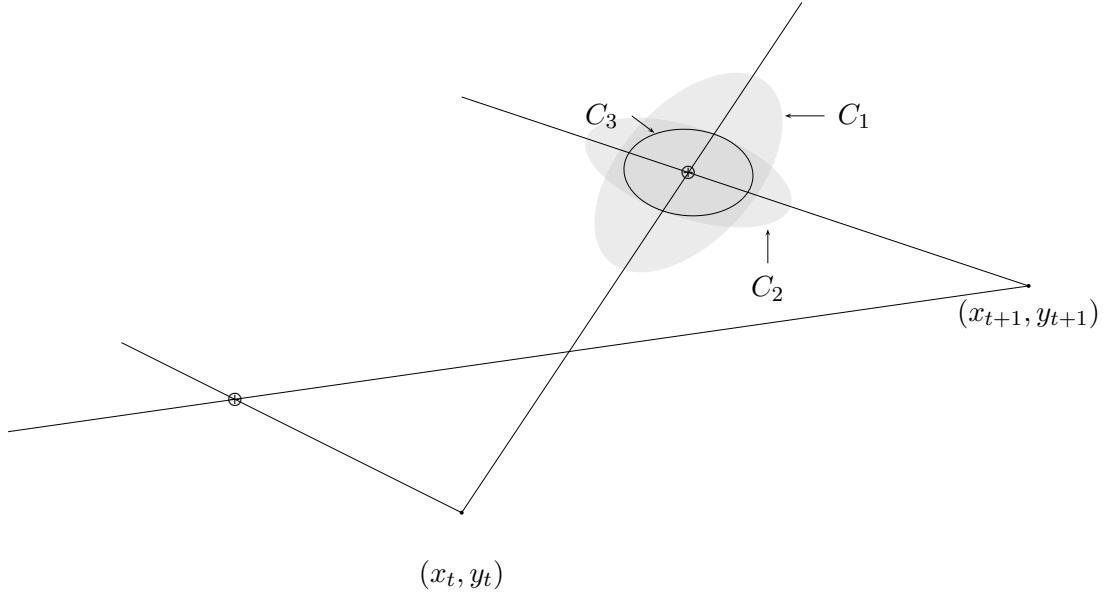


FIGURE 3. Merging of estimates from 2 different positions

3

First we review the matrix

$$F_{x,j} = \begin{bmatrix} 1 & 0 & 0 & \overbrace{0 \dots 0}^{3j-3} & 0 & 0 & 0 & \overbrace{0 \dots 0}^{3N-3j} \\ 0 & 1 & 0 & 0 \dots 0 & 0 & 0 & 0 & 0 \dots 0 \\ 0 & 0 & 1 & 0 \dots 0 & 0 & 0 & 0 & 0 \dots 0 \\ 0 & 0 & 0 & 0 \dots 0 & 1 & 0 & 0 & 0 \dots 0 \\ 0 & 0 & 0 & 0 \dots 0 & 0 & 1 & 0 & 0 \dots 0 \\ 0 & 0 & 0 & 0 \dots 0 & 0 & 0 & 1 & 0 \dots 0 \end{bmatrix}$$

We observe that multiplying on the right any 6-columns matrix by $F_{x,j}$ has the effect to insert $3j - 3$ null columns between columns 3 and 4 and $3N - 3j$ null columns on the end so that we end

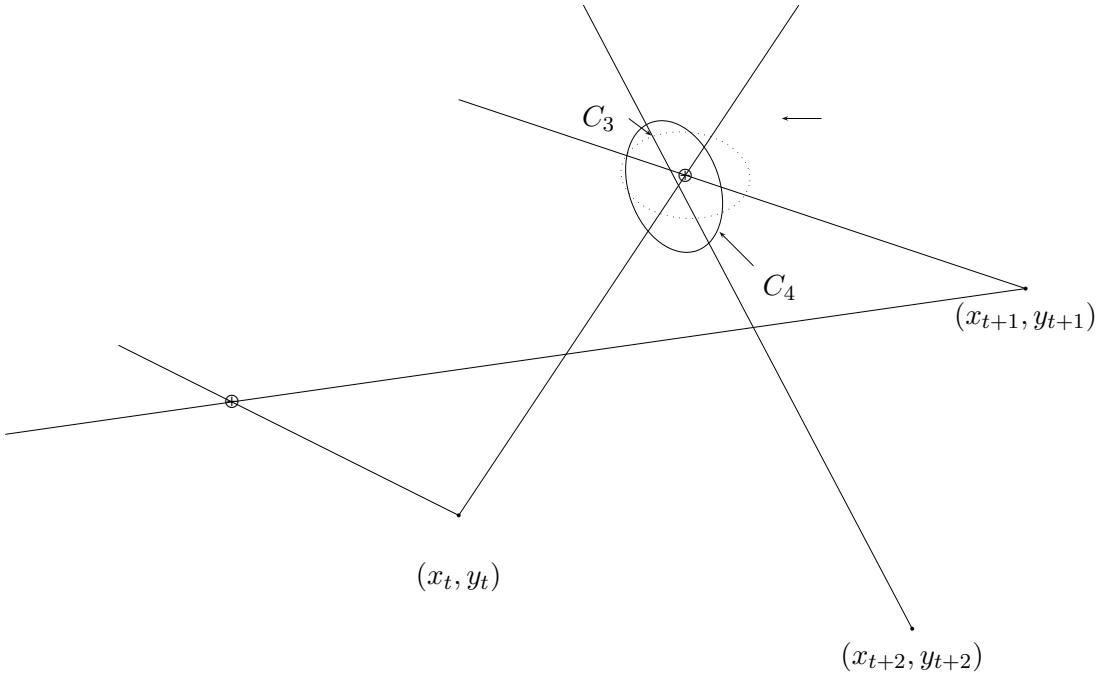


FIGURE 4. Persistance count of landmark is increased when seen again at a later stage

with a matrix with $3N + 3$ columns. Similarly, multiplying on the left any 6-rows matrix by $F_{x,j}^T$ has the effect to insert $3j - 3$ null rows between rows 3 and 4 and $3N - 3j$ null rows on the end so that we end with a matrix with $3N + 3$ rows.

Remember we have initialized the covariance matrix of the state with equation (10.9):

$$\Sigma_0 = \begin{bmatrix} 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \infty & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \dots & \infty \end{bmatrix}$$

Note that in this context ∞ actually means huge number so that $0 \times \infty = 0$. We write the covariance matrix Σ_t of by block:

$$\Sigma_t = \begin{bmatrix} \Sigma_t^X & \dots & [\Sigma_t^{X,k}]^T & \dots \\ \vdots & \ddots & \vdots & \dots \\ \Sigma_t^{X,k} & \dots & \Sigma_t^k & \dots \\ \vdots & \dots & \vdots & \ddots \end{bmatrix}$$

where $\Sigma_t^{X,k}$ is the cross-covariance between the landmark number k and the robot pose (index X).

We now restate measurement update line 23 of EKF SLAM:

$$\begin{aligned} \mu_t &= \bar{\mu}_t + K_t^i(z_t^i - \hat{z}_t^{j(i)}) \\ \Leftrightarrow \mu_t &= \bar{\mu}_t + \bar{\Sigma}_t [H_t^{j(i)}]^T \Psi_{j(i)}^{-1} (z_t^i - \hat{z}_t^{j(i)}) \\ \Leftrightarrow \mu_t &= \bar{\mu}_t + \bar{\Sigma}_t F_{x,j(i)}^T h_t^{j(i)} \Psi_{j(i)}^{-1} (z_t^i - \hat{z}_t^{j(i)}) \end{aligned}$$

By the previous remarks, a little thought show that if the lines / columns related to landmark k have not changed since initialization ($\forall j \neq k, \Sigma_t^{j,k} = 0$ and $\Sigma_t^k = \begin{bmatrix} \infty & 0 & 0 \\ 0 & \infty & 0 \\ 0 & 0 & \infty \end{bmatrix}$) and if $j(i) \neq k$, the position estimate of landmark k is left untouched by the update. If we also consider covariance update:

$$\begin{aligned} \Sigma_t &= (I - K_t^i H_t^{j(i)}) \bar{\Sigma}_t \\ \Leftrightarrow \Sigma_t &= (I - \bar{\Sigma}_t [H_t^{j(i)}]^T \Psi_{j(i)}^{-1} H_t^{j(i)}) \bar{\Sigma}_t \\ \Leftrightarrow \Sigma_t &= \bar{\Sigma}_t - \bar{\Sigma}_t [H_t^{j(i)}]^T \Psi_{j(i)}^{-1} H_t^{j(i)} \bar{\Sigma}_t \\ \Leftrightarrow \Sigma_t &= \bar{\Sigma}_t - \bar{\Sigma}_t F_{x,j(i)}^T h_t^{j(i)} \Psi_{j(i)}^{-1} h_t^{j(i)} F_{x,j(i)} \bar{\Sigma}_t \end{aligned}$$

we can also see that if $j(i) \neq k$, the lines / columns in covariance matrix related to landmark k stay untouched. By applying same kind of reasoning on motion update, we can assert that as long as a given landmark has not been observed, the corresponding lines / columns in both μ and Σ keep their initial values during the execution of the algorithm; this was expected since the cross covariances being set to 0 initially, updating robot and others landmarks locations should not affect the landmark.

Turning now to what happens when the landmark $k = j(i)$ is observed for the first time, the mean is updated line 9 of the EKF SLAM algorithm:

$$\begin{aligned} \begin{bmatrix} \bar{\mu}_{k,x} \\ \bar{\mu}_{k,y} \\ \bar{\mu}_{k,s} \end{bmatrix} &= \begin{bmatrix} \bar{\mu}_{t,x} \\ \bar{\mu}_{t,y} \\ s_t^i \end{bmatrix} + r_t^i \begin{bmatrix} \cos(\phi_t^i + \bar{\mu}_{t,\theta}) \\ \sin(\phi_t^i + \bar{\mu}_{t,\theta}) \\ 0 \end{bmatrix} \\ &= [h_m^t]^{-1}(z_t^i) \end{aligned}$$

where

$$h_m^t = h(y_t, .) : \begin{bmatrix} m_x \\ m_y \\ m_s \end{bmatrix} \mapsto h(y_t, \begin{bmatrix} m_x \\ m_y \\ m_s \end{bmatrix}) = \begin{bmatrix} \sqrt{(m_x - x_t)^2 + (m_y - y_t)^2} \\ \text{atan2}(m_y - y_t, m_x - x_t) - \theta_t \\ m_s \end{bmatrix}$$

this is indeed the best guess of the location we can make from the measurement z_t^i alone. The position is subsequently updated line 23 by:

$$\mu_t = \bar{\mu}_t + K_t^i (z_t^i - \hat{z}_t^k) \quad \textcircled{1}$$

where

$$\begin{aligned} K_t^i &= \bar{\Sigma}_t [H_t^k]^T \Psi_k^{-1} \\ &= \bar{\Sigma}_t F_{x,k}^T [h_t^k]^T \Psi_k^{-1} \end{aligned}$$

We have

$$\begin{aligned}
F_{x,k}^T [h_t^k]^T &= F_{x,k}^T \begin{bmatrix} J_{(\bar{\mu}_X, \bar{\mu}_k)}^X & J_{(\bar{\mu}_X, \bar{\mu}_k)}^m \end{bmatrix}^T \\
&= F_{x,k}^T \begin{bmatrix} [J_{(\bar{\mu}_X, \bar{\mu}_k)}^X]^T \\ [J_{(\bar{\mu}_X, \bar{\mu}_k)}^m]^T \end{bmatrix} \\
&= \begin{bmatrix} A^T & \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \\ B^T & \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \end{bmatrix} \left. \right\} \begin{array}{l} 3 \\ 3k-3 \\ 3 \\ 3N-3k \end{array}
\end{aligned}$$

where $A = J_{(\bar{\mu}_X, \bar{\mu}_k)}^X$ and $B = J_{(\bar{\mu}_X, \bar{\mu}_k)}^m$ are the Jacobians at current position of measurement function h , respectively with respects to robot's and landmark's positions. Then,

$$\begin{aligned}
\bar{\Sigma}_t F_{x,k}^T [h_t^k]^T &= \begin{bmatrix} \bar{\Sigma}_t^X & \dots & 0 & \dots \\ \vdots & \ddots & \vdots & \dots \\ 0 & \dots & \bar{\Sigma}_0^k & \dots \\ \vdots & \underbrace{\dots}_{3} & \underbrace{\dots}_{3k-3} & \underbrace{\dots}_{3N-3k} \end{bmatrix} \begin{bmatrix} A^T & \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \\ B^T & \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \end{bmatrix} \\
&= \begin{bmatrix} \bar{\Sigma}_t^X A^T \\ \bar{\Sigma}_t^{X,1} A^T \\ \vdots \\ \bar{\Sigma}_t^{X,k-1} A^T \\ \Sigma_0^k B^T \\ \bar{\Sigma}_t^{X,k+1} A^T \\ \vdots \\ \bar{\Sigma}_t^{X,N} A^T \end{bmatrix} \quad \textcircled{2}
\end{aligned}$$

Also,

$$\begin{aligned} H_t^k &= h_t^k F_{x,k} \\ &= \begin{bmatrix} & 0 & \dots & 0 & & 0 & \dots & 0 \\ A & 0 & \dots & 0 & B & 0 & \dots & 0 \\ & 0 & \dots & 0 & & 0 & \dots & 0 \end{bmatrix} \end{aligned}$$

so that

$$\begin{aligned} \Psi_k &= H_t^k \bar{\Sigma}_t [H_t^k]^T + Q_t \\ &= A \bar{\Sigma}_t^X A^T + B \Sigma_0^k B^T + Q_t \end{aligned}$$

Now we can assume $\Sigma_0^k = C \times I_3$, where C is a huge positive constant. Assuming also BB^T is (symmetric positive) definite (this is equivalent to assume B itself is nonsingular),

$$\begin{aligned} \Psi_k &= A \bar{\Sigma}_t^X A^T + CBB^T + Q_t \\ &= [I_3 + \underbrace{\frac{1}{C} (A \bar{\Sigma}_t^X A^T + Q_t) (BB^T)^{-1}}_N] CBB^T \end{aligned}$$

We have given a proof in chapter 7 for the existence and formula of the inverse of $I_3 - M$ when $\|M\| < 1$:

$$(I_3 + \frac{1}{C} N)^{-1} = \sum_{n=0}^{+\infty} \frac{(-1)^n}{C^n} N^n$$

with a norm such that $\left\| \frac{(-1)^n}{C^n} N^n \right\| \leq \left\| \frac{1}{C} N \right\|^n$, we write to first order:

$$\begin{aligned} (I_3 + \frac{1}{C} N)^{-1} &\underset{C \rightarrow +\infty}{=} I_3 - \frac{1}{C} N + o(\left\| \frac{1}{C} \right\|) \\ &\approx I_3 - \frac{1}{C} N \end{aligned}$$

so

$$\begin{aligned} \Psi_k^{-1} &= \frac{1}{C} (BB^T)^{-1} (I_3 - \frac{1}{C} N) \\ &= \frac{1}{C} (BB^T)^{-1} (I_3 - \frac{1}{C} N) \\ \Psi_k^{-1} &= (BB^T)^{-1} (\frac{1}{C} I_3 - \frac{1}{C^2} N) \quad \text{③} \end{aligned}$$

Multiplying ② and ③, and restricting to order 0 in $\frac{1}{C}$ (we discard terms in $\frac{1}{C}$ and smaller),

$$\begin{aligned} \bar{\Sigma}_t [H_t^k]^T \Psi_k^{-1} &= \begin{bmatrix} 0 \\ \vdots \\ 0 \\ B^T (BB^T)^{-1} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} 0 \\ \vdots \\ 0 \\ B^{-1} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \end{aligned}$$

This shows that measurement update ① updates only landmark k position with:

$$\begin{aligned} \mu_k &= \bar{\mu}_k + B^{-1}(z_t^i - \hat{z}_t^k) \\ &= \bar{\mu}_k + B^{-1}(\underbrace{h(y_t, \bar{\mu}_k) - h(y_t, \bar{\mu}_k)}_{=0}) \\ \mu_k &= \begin{bmatrix} \bar{\mu}_{t,x} \\ \bar{\mu}_{t,y} \\ s_t^i \end{bmatrix} + r_t^i \begin{bmatrix} \cos(\phi_t^i + \bar{\mu}_{t,\theta}) \\ \sin(\phi_t^i + \bar{\mu}_{t,\theta}) \\ 0 \end{bmatrix} \quad ④ \end{aligned}$$

Line 24 of the algorithm, covariance is updated with

$$\begin{aligned} \Sigma_t &= (I - K_t^i H_t^i) \bar{\Sigma}_t \\ &= \bar{\Sigma}_t - K_t^i H_t^k \bar{\Sigma}_t \end{aligned}$$

$$\begin{aligned}
& K_t^i H_t^k \bar{\Sigma}_t \\
&= \bar{\Sigma}_t [H_t^k]^T \Psi_k^{-1} H_t^k \bar{\Sigma}_t \\
&= \left[\begin{array}{c} \bar{\Sigma}_t^X A^T \\ \bar{\Sigma}_t^{X,1} A^T \\ \vdots \\ \bar{\Sigma}_t^{X,k-1} A^T \\ CB^T \\ \bar{\Sigma}_t^{X,k+1} A^T \\ \vdots \\ \bar{\Sigma}_t^{X,N} A^T \end{array} \right] (BB^T)^{-1} \left(\frac{1}{C} I_3 - \frac{1}{C^2} N \right) \left[\begin{array}{cccccc} A \bar{\Sigma}_t^X & A \bar{\Sigma}_t^{X,1} & \dots & A \bar{\Sigma}_t^{X,k-1} & CB & \dots & A \bar{\Sigma}_t^{X,N} \end{array} \right] \\
&\underset{C \rightarrow +\infty}{\approx} \left[\begin{array}{cccccc} 0 & \dots & 0 & \bar{\Sigma}_t^X A^T [B^T]^{-1} & 0 & \dots \\ \vdots & \ddots & \vdots & \bar{\Sigma}_t^{X,1} A^T [B^T]^{-1} & \vdots & \dots \\ 0 & \dots & 0 & \vdots & 0 & \dots \\ B^{-1} A \bar{\Sigma}_t^X & \dots & B^{-1} A \bar{\Sigma}_t^{X,k-1} & CI_3 - B^{-1} NB & B^{-1} A \bar{\Sigma}_t^{X,k+1} & \dots \\ 0 & \dots & 0 & \bar{\Sigma}_t^{X,k+1} A^T [B^T]^{-1} & 0 & \dots \\ \vdots & & \vdots & \vdots & \vdots & \ddots \\ 0 & \dots & 0 & \bar{\Sigma}_t^{X,N} A^T [B^T]^{-1} & 0 & \dots \end{array} \right]
\end{aligned}$$

to order 0 in $\frac{1}{C}$, with

$$\begin{aligned}
B^{-1} NB &= B^{-1} (A \bar{\Sigma}_t^X A^T + Q_t) (BB^T)^{-1} B \\
&= B^{-1} (A \bar{\Sigma}_t^X A^T + Q_t) [B^T]^{-1} \quad \textcircled{5}
\end{aligned}$$

The latter expression should be familiar: it is the compound of independant uncertainties of robot position and measurement, transformed back to landmark position frame. Besides,

$$\begin{aligned}
z_t^i &= h(\bar{\mu}_t, k) + A(\bar{X}_t - \mu_t) + B(X^k - \mu_k) + \underbrace{\xi^k}_{\hookrightarrow \mathcal{N}(0, Q_t)} \\
\Rightarrow z_t^i (X^j - \mu_j)^T &= h(\bar{\mu}_t, k) (X^j - \mu_j)^T + A(\bar{X}_t - \mu_t) (X^j - \mu_j)^T + B(X^k - \mu_k) (X^j - \mu_j)^T + \xi^k (X^j - \mu_j)^T
\end{aligned}$$

Taking the expectancy of this relation and since we can assume if $k \neq j$ that ξ^k and X_j are independant, we verify

$$\begin{aligned}
&\Rightarrow 0 = A \bar{\Sigma}_t^{X,j} + B \Sigma^{k,j} + 0 \\
&\Rightarrow B \Sigma^{k,j} = -A \bar{\Sigma}_t^{X,j} \\
&\Leftrightarrow \Sigma^{k,j} = -B^{-1} A \bar{\Sigma}_t^{X,j} \quad \textcircled{6}
\end{aligned}$$

which is indeed also the result we obtained with matrix calculus.

In conclusion, we have proven that the EKF SLAM presented in the book is equivalent to:

- (i) start with a state including only robot pose.
- (ii) each time a new landmark is found, augment the state variable using formulas ④, ⑤, ⑥ to initialize mean and covariances matrices related to the landmark.

4

Let ε the event “the landmark exists”, $\neg\varepsilon$ the complementary event. The odds form of probability of existence is

$$\begin{aligned} \frac{p(\varepsilon | z_{1:t})}{p(\neg\varepsilon | z_{1:t})} &= \frac{p(\varepsilon \cap z_t | z_{1:t-1})}{p(z_t | z_{1:t-1})} \times \frac{p(z_t | z_{1:t-1})}{p(\neg\varepsilon \cap z_t | z_{1:t-1})} \\ &= \frac{p(\varepsilon \cap z_t | z_{1:t-1})}{p(\neg\varepsilon \cap z_t | z_{1:t-1})} \\ &= \frac{p(z_t | \varepsilon, z_{1:t-1})p(\varepsilon | z_{1:t-1})}{p(z_t | \neg\varepsilon, z_{1:t-1})p(\neg\varepsilon | z_{1:t-1})} \\ &= \frac{p(z_t | \varepsilon)p(\varepsilon | z_{1:t-1})}{p(z_t | \neg\varepsilon)p(\neg\varepsilon | z_{1:t-1})} \end{aligned}$$

where we have assumed that, conditioned on ε or $\neg\varepsilon$, the measurement z_t is independant of past measurements $z_{1:t-1}$. In log-odds form :

$$\log\left(\frac{p(\varepsilon | z_{1:t})}{p(\neg\varepsilon | z_{1:t})}\right) = \log\left(\frac{p(z_t | \varepsilon)}{p(z_t | \neg\varepsilon)}\right) + \log\left(\frac{p(\varepsilon | z_{1:t-1})}{p(\neg\varepsilon | z_{1:t-1})}\right)$$

The probabilities $p(z_t | \varepsilon)$ and $p(z_t | \neg\varepsilon)$ can be computed with measurement model; We can inverse the model with :

$$\log\left(\frac{p(\varepsilon | z_{1:t})}{p(\neg\varepsilon | z_{1:t})}\right) = \log\left(\frac{p(\varepsilon | z_t)}{p(\neg\varepsilon | z_t)}\right) - \log\left(\frac{p(\varepsilon)}{p(\neg\varepsilon)}\right) + \log\left(\frac{p(\varepsilon | z_{1:t-1})}{p(\neg\varepsilon | z_{1:t-1})}\right)$$

7

The ideas for using occupancy grids in SLAM are developed in articles [5], [6], [7] and [8]. Local occupancy grids are built from sensors readings as explained in chapter 9; the same occupancy grid can be constructed from multiple sensors, or each sensor reading is used to built its own occupancy grid and the probabilistic evidences are combined at a later stage. The key is then to integrate the local occupancy grid V_R with a global map M_G ; There is two different policies to take the robot position uncertainty (AT \tilde{R}) relatively to the world frame:

- (i) In *world-based mapping*, the local map is first blurred (convolution operation $\tilde{\otimes}$) due to robot position uncertainty, then fused ($\tilde{\oplus}$) with the global map. In this point of view, with robot position increasing with times, the newer observations are less sharp than past ones. $M_G \leftarrow M_G \tilde{\oplus} (V_R \tilde{\otimes} \tilde{R})$
- (ii) In *robot-based mapping*, the global map is first blurred due to robot position uncertainty, then fused with the local map. In this point of view, the newer observations are sharper than past ones. $M_G \leftarrow V_R \tilde{\oplus} (M_G \tilde{\otimes} \tilde{R})$

The uncertainty due to robot motion can be reduced using some map matching mechanism, or landmarks. See the articles for the details.

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