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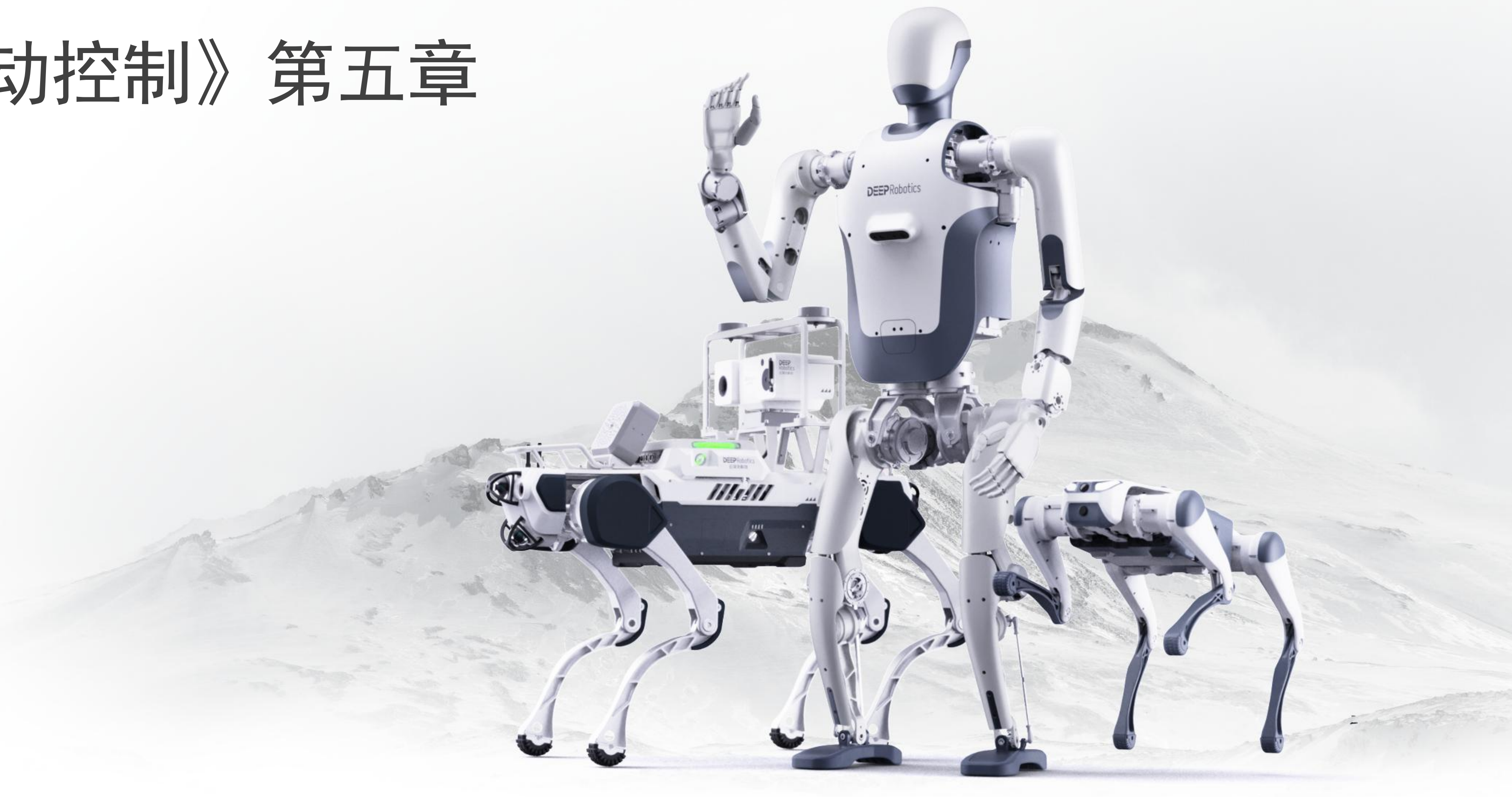
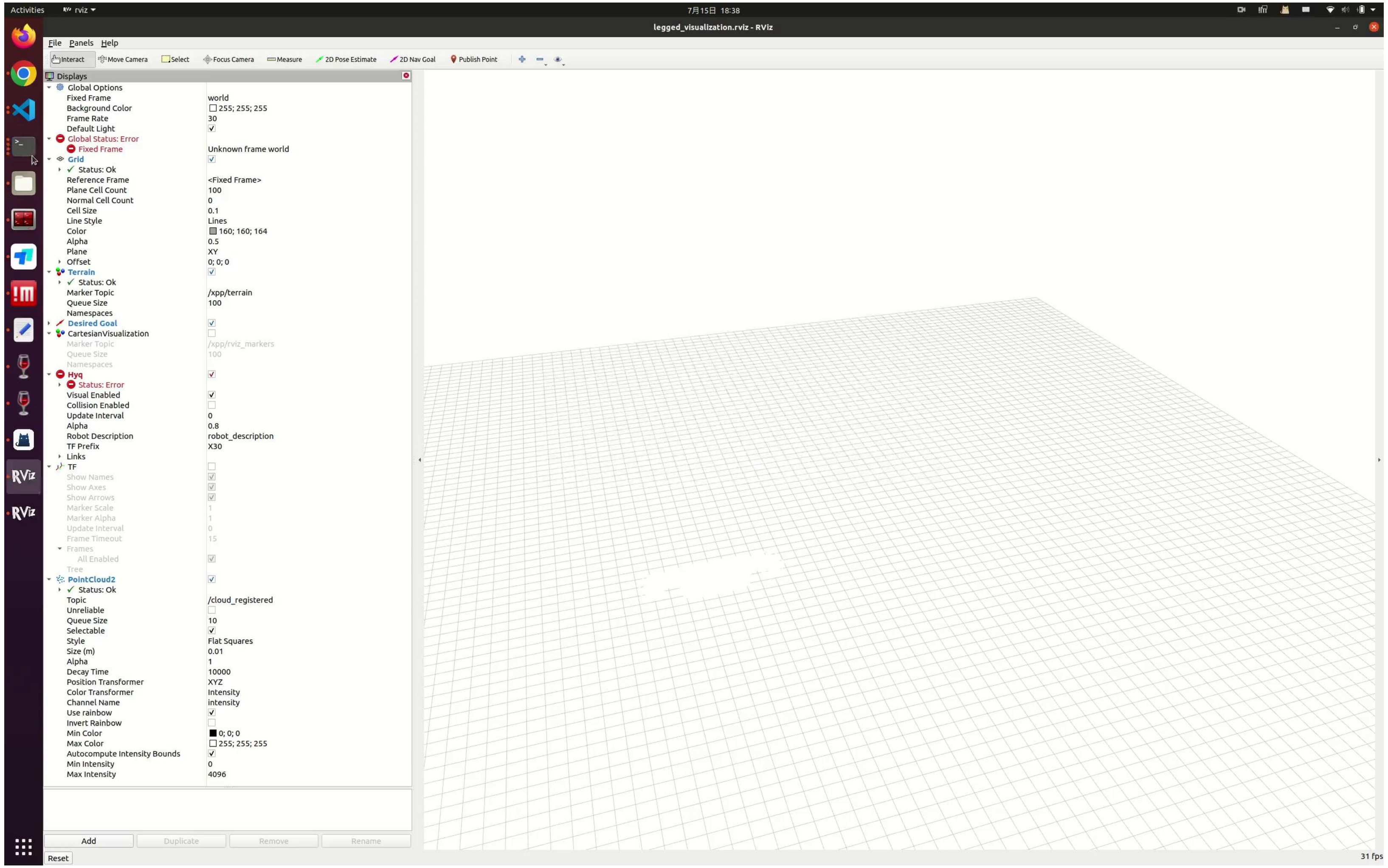
《足式机器人运动控制》第五章

状态估计



状态估计



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File Panels Help
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Fixed Frame world
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Frame Rate 30
Default Light
Global Status: Error
Fixed Frame Unknown frame world
Grid
Status: Ok
Reference Frame <Fixed Frame>
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Normal Cell Count 0
Cell Size 0.1
Line Style Lines
Color 160; 160; 164
Alpha 0.5
Plane XY
Offset 0; 0; 0
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Namespaces
Desired Goal
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Namespaces
Hyq
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Collision Enabled
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Alpha 0.8
Robot Description robot_description
TF Prefix X30
Links
TF
Show Names
Show Axes
Show Arrows
Marker Scale 1
Marker Alpha 1
Update Interval 0
Frame Timeout 15
Frames
All Enabled
Tree
PointCloud2
Status: Ok
Topic /cloud_registered
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Queue Size 10
Selectable
Style Flat Squares
Size (m) 0.01
Alpha 1
Decay Time 10000
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Color Transformer Intensity
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Use rainbow
Invert Rainbow
Min Color 0; 0; 0
Max Color 255; 255; 255
Autocompute Intensity Bounds
Min Intensity 0
Max Intensity 4096
Add Duplicate Remove Rename
Reset
31 fps

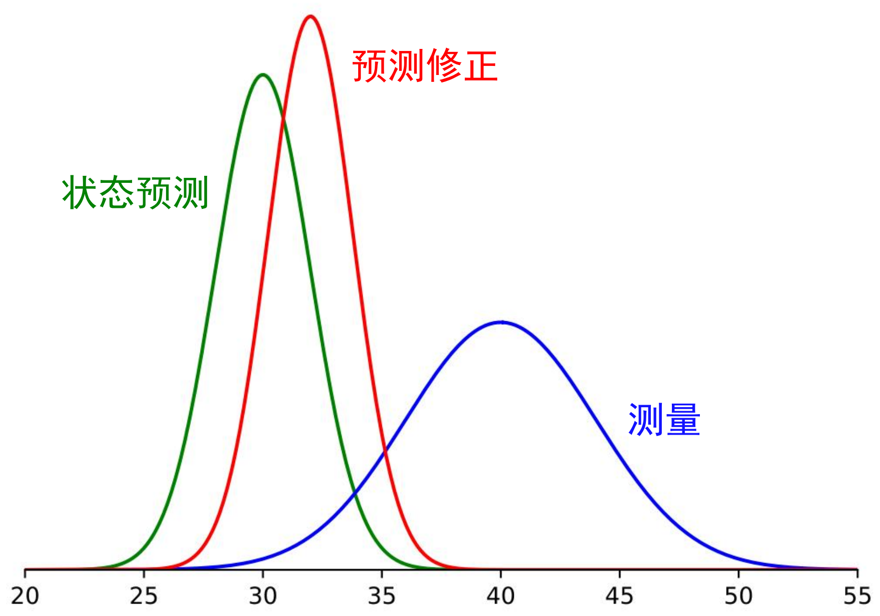
目录

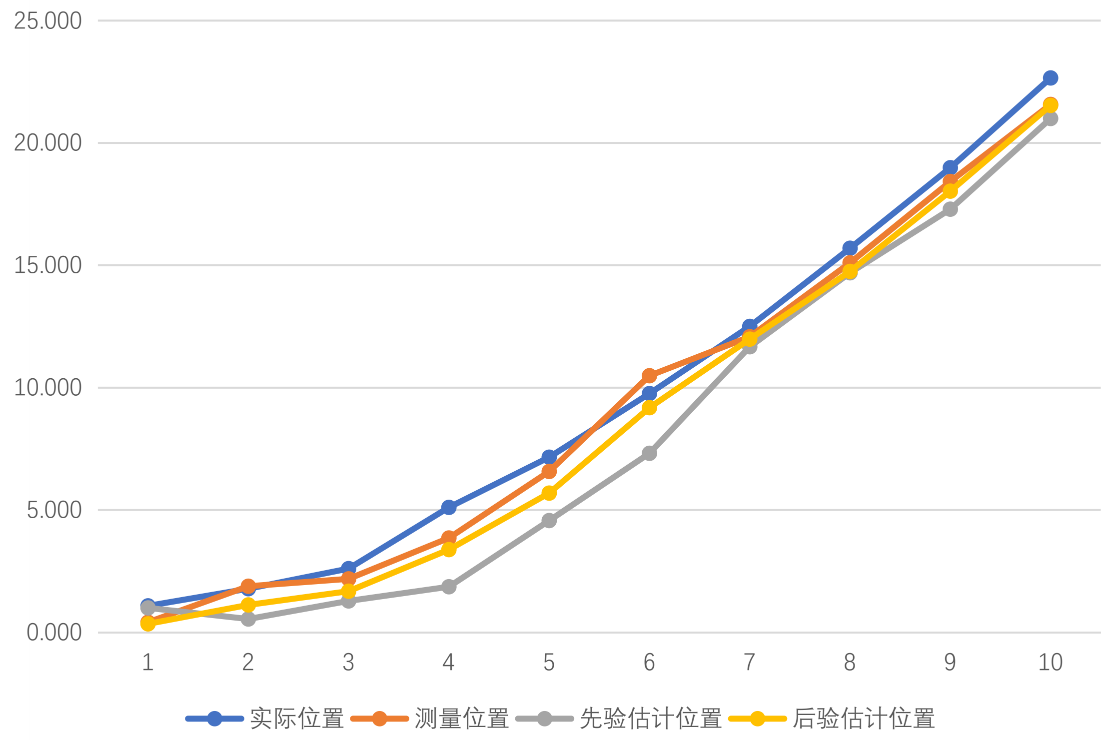
卡尔曼滤波

卡尔曼滤波器（Kalman Filter）

卡尔曼滤波器（Kalman filter）是一种利用线性系统状态方程，通过系统输入输出观测数据，对系统状态进行最优估计的算法。由于观测数据中包括系统中的噪声和干扰的影响，所以最优估计也可看作是滤波过程。

卡尔曼滤波会根据各测量方差已知的量在不同时间下的值，考虑各时间下的联合分布，再产生对未知变量的估计，因此会比只以单一测量量为基础的估计方式要准。





卡尔曼滤波

卡尔曼滤波器

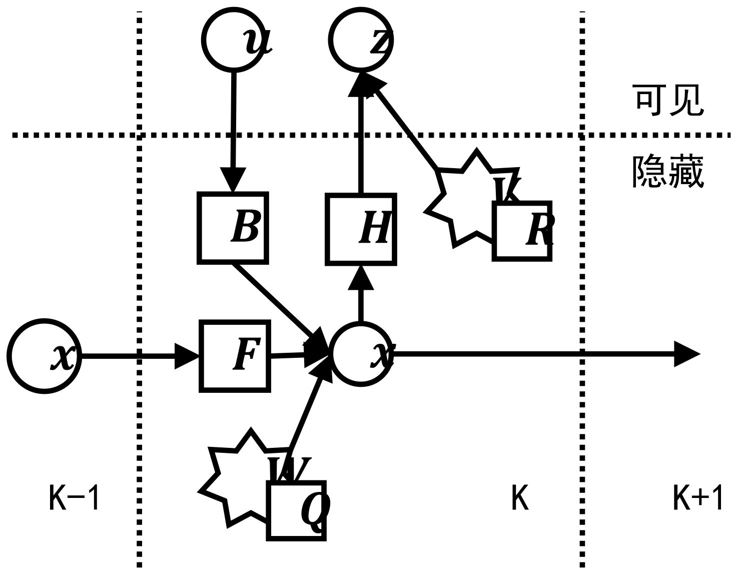
动态系统的基本模型：离散控制过程的系统

- 过程模型：用线性随机微分方程（Linear Stochastic Difference Equation）来描述：$\boldsymbol{x_k} = \boldsymbol{F} \cdot \boldsymbol{x_{k-1}} + \boldsymbol{B} \cdot \boldsymbol{u_k} + \boldsymbol{w_k}$
- 系统观测模型：$\boldsymbol{z_k} = \boldsymbol{H} \cdot \boldsymbol{x_k} + \boldsymbol{v_k}$
- $\boldsymbol{w_k} \sim \boldsymbol{N}(0,\ \boldsymbol{Q_k}), \boldsymbol{Q_k}$过程噪声的协方差矩阵
- $\boldsymbol{v_k} \sim \boldsymbol{N}(0,\ \boldsymbol{R_k}), \boldsymbol{R_k}$过程噪声的协方差矩阵

卡尔曼滤波器的状态由以下两个变量表示：

- $\hat{\boldsymbol{x}}_{k|k}$，在时刻$k$的状态的估计；
- $\boldsymbol{P}_{k|k}$，后验估计误差协方差矩阵，度量估计值的精确程度。

卡尔曼滤波器的操作包括两个阶段：**预测与更新**。



卡尔曼滤波

- 利用状态转移方程可以得到预测状态$\hat{x}_{k|k-1} = F_k\hat{x}_{k-1|k-1} + B_k u_k$
- 算出测量的参差$y_k = z_k - H_k\hat{x}_{k|k-1}$，$y_k$衡量的是测量值和预测值的偏差
- 后验估计$\hat{x}_{k|k}$为：$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left(z_k - H_k\hat{x}_{k|k-1}\right)$，其中$K_k$就是卡尔曼增益

目标：寻找$\boldsymbol{K_k}$，使得$\boldsymbol{\hat{x}_{k|k}} \to \boldsymbol{x_k}$，也就是估计值的均方误差小

- $e_k = x_k - \hat{x}_{k|k}$，求最小的 $E(\left|x_k - \hat{x}_{k|k}\right|^2)$
- $P_k = cov(\hat{x}_{k|k}) = cov(\hat{x}_{k|k}, \hat{x}_{k|k})$

$$= cov(x_k - \hat{x}_{k|k}, x_k - \hat{x}_{k|k})$$

- 协方差定义：$\boldsymbol{cov(a, b) = E(ab) - (a)E(b)}$
- $P_k = cov(x_k - \hat{x}_{k|k}, x_k - \hat{x}_{k|k}) = E((x_k - \hat{x}_{k|k})(x_k - \hat{x}_{k|k})^T) - E(x_k - \hat{x}_{k|k})E((x_k - \hat{x}_{k|k})^T)$

$$= E((x_k - \hat{x}_{k|k})(x_k - \hat{x}_{k|k})^T)$$

- $E(\left|x_k - \hat{x}_{k|k}\right|^2) = tr(P_k)$

卡尔曼滤波

- **预测状态的协方差**$P_{k|k-1}$
- $cov(\hat{x}_{k|k-1}) = cov(F_k\hat{x}_{k-1|k-1} + B_k u_k + w_k)$

$$= cov(F_k\hat{x}_{k-1|k-1}) + cov(B_k u_k) + cov(w_k)$$

$$= F_k cov(\hat{x}_{k-1|k-1})F_k^T + 0 + Q_k$$

$$= F_k P_{k-1} F_k^T + Q_k$$

- $P_{k|k-1} = F_k P_{k-1} F_k^T + Q_k$

- **测量残差的协方差**S_k
- $cov(y_k) = cov(z_k - H_k\hat{x}_{k|k-1})$

$$= cov(z_k) + cov(H_k\hat{x}_{k|k-1})$$

$$= cov(z_k) + H_k cov(\hat{x}_{k|k-1})H_k^T$$

$$= cov(H_k x_k + v_k) + H_k cov(\hat{x}_{k|k-1})H_k^T = R_k + H_k P_{k|k-1} H_k^T$$

- $S_k = R_k + H_k P_{k|k-1} H_k^T$

卡尔曼滤波

目标：寻找$\boldsymbol{K_k}$，使得$\boldsymbol{\hat{x}_{k|k}} \rightarrow \boldsymbol{x_k}$

- $P_k = cov(x_k - \hat{x}_{k|k}) = cov(x_k - (\hat{x}_{k|k-1} + K_k(z_k - H_k\hat{x}_{k|k-1})))$

$$= cov(x_k - (\hat{x}_{k|k-1} + K_k(H_k x_k + v_k - H_k\hat{x}_{k|k-1})))$$

$$= cov((I - K_k H_k)(x_k - \hat{x}_{k|k-1}) - K_k v_k)$$

$$= (I - K_k H_k)P_{k|k-1}(I - K_k H_k)^T + K_k R_k K_k^T$$

- $P_k = P_{k|k-1} - K_k H P_{k|k-1} - P_{k|k-1} H^T K_k^T + K_k H P_{k|k-1} H^T K_k^T + K_k R K_k^T$

- $tr(P_k) = tr(P_{k|k-1}) - 2tr(K_k H P_{k|k-1}) + tr(K_k H P_{k|k-1} H^T K_k^T) + tr(K_k R K_k^T)$

卡尔曼滤波

- $tr(P_k) = tr\left(P_{k|k-1}\right) - 2tr\left(K_k H P_{k|k-1}\right) + tr\left(K_k H P_{k|k-1} H^T K_k^T\right) + tr(K_k R K_k^T)$

目标：$\frac{tr(P_k)}{tr(K_k)} = 0$

- $\frac{tr(P_k)}{tr(K_k)} = 0 - 2(HP_{k|k-1})^T + 2K_k H P_{k|k-1} H^T + 2K_k R = 0$

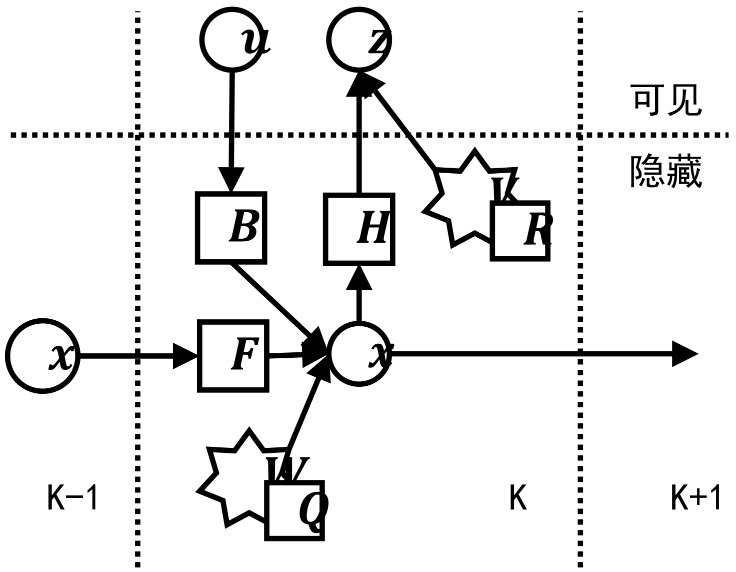
  $\Longrightarrow - P_{k|k-1} H^T + K_k\left(HP_{k|k-1} H^T + R\right) = 0$

- $K_k = P_{k|k-1} H^T S_k^{-1}$
- 代入可得$P_k = (I - K_k H_k) P_{k|k-1}$
- $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k y_k$

卡尔曼滤波

预测

- 预测状态估计（先验）方程：$\boldsymbol{\hat{x}_{k|k-1}} = \boldsymbol{F_k \hat{x}_{k-1|k-1}} + \boldsymbol{B_k u_k}$
- 预测的协方差矩阵估计方程： $P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k$



更新

更新方程需要计算的量：

- 测量残差方程： $\boldsymbol{\tilde{y}}_k = \boldsymbol{z}_k - \boldsymbol{H}_k \boldsymbol{\hat{x}}_{k|k-1}$
- 测量残差协方差矩阵方程： $\boldsymbol{S}_k = \boldsymbol{H}_k \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T + \boldsymbol{R}_k$
- **最优卡尔曼增益：** $\boldsymbol{K_k = P_{k|k-1} H_k^T S_k^{-1}}$

然后用它们来更新滤波器变量x与P：

- 更新的状态估计（后验）方程： $\boldsymbol{\hat{x}}_{k|k} = \boldsymbol{\hat{x}}_{k|k-1} + \boldsymbol{K}_k \boldsymbol{\tilde{y}}_k$
- 更新的协方差矩阵估计方程： $\boldsymbol{P}_{k|k} = (I - \boldsymbol{K}_k \boldsymbol{H}_k) \boldsymbol{P}_{k|k-1}$

使用上述公式计算$\boldsymbol{P}_{k|k}$仅在最优卡尔曼增益的时候有效。

卡尔曼滤波

扩展卡尔曼滤波（Extended Kalman Filter, EKF）

- 现实中控制系统通常会存在不同程度的非线性环节，对于非线性系统：
- $x_k = f(x_{k-1}, u_k, \omega_k)$
- $z_k = h(x_{k-1}, v_k)$

一种直观的想法是利用Taylor级数展开，将非线性系统在滤波结果估计处线性化：

$$f(x_{k-1}) \approx f(\hat{x}_{k-1|k-1}) + F_k(x_{k-1} - \hat{x}_{k-1|k-1})$$

$$\boldsymbol{F}_k = \nabla_{x^T}\boldsymbol{f}(\boldsymbol{x})|_{x=\hat{x}_{k-1|k-1}} \triangleq \left[\frac{\partial \boldsymbol{f}}{\partial x_1} \cdots \frac{\partial \boldsymbol{f}}{\partial x_n}\right] \triangleq \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_n} \\ \vdots & \vdots & \vdots \\ \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_n} \end{bmatrix}$$

EKF当近似后验均值与真值相差较大时，易造成滤波发散！

$$h(x_k) \approx h(\hat{x}_{k|k-1}) + H_k(x_k - \hat{x}_{k|k-1})$$

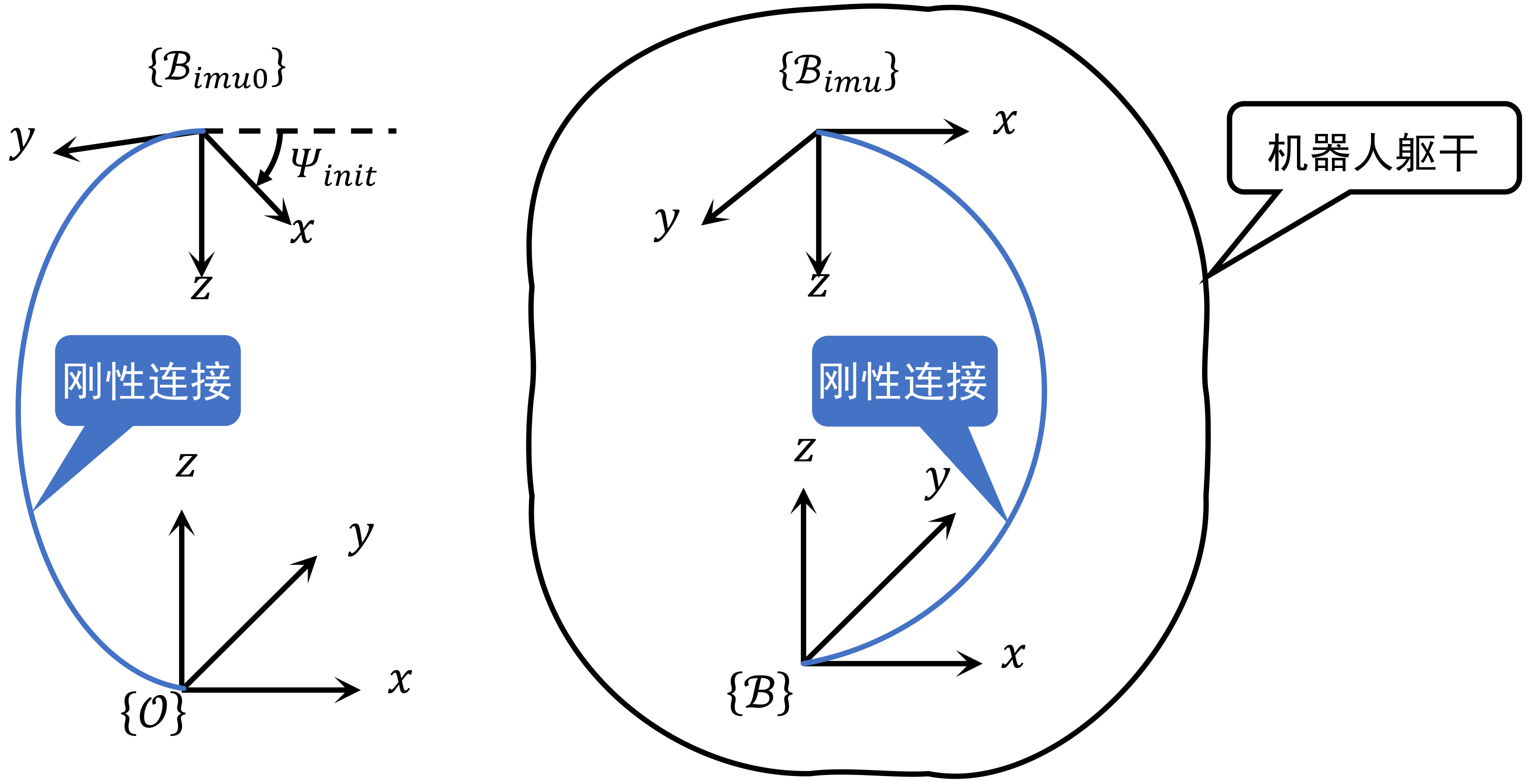
其余操作与线性卡尔曼滤波类似

目录

四足机器人状态方程和观测方程

坐标系与符号说明

四足机器人使用的传感器，包括测量关节角度${}_i\boldsymbol{q}^j$与转速${}_i\dot{\boldsymbol{q}}^j$的电机编码器；以及测量质心加速度${}^{\mathcal{B}}a_{com}$、躯干旋转矩阵${}^{\mathcal{O}}R_{\mathcal{B}}$、躯干角速度${}^{\mathcal{B}}\omega_{\mathcal{O}\mathcal{B}}$的IMU。机器人躯干的转动状态（旋转矩阵与角速度）可以直接从IMU读取，还需要融合多种传感器数据来获取质心在世界系下的位置${}^{\mathcal{O}}p_{com}$与速度${}^{\mathcal{O}}v_{com}$。



四足机器人状态方程和观测方程

状态方程

加速度与角速度在世界系下的描述：

$$ {}^{\mathcal{O}}\boldsymbol{a}_{com} = {}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}\boldsymbol{a}_{com} $$

$$ {}^{\mathcal{O}}\boldsymbol{\omega}_{\mathcal{OB}} = {}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{OB}} $$

构建卡尔曼滤波器连续状态方程：

$$ \begin{cases} {}^{\mathcal{O}}\dot{p}_{com} = {}^{\mathcal{O}}v_{com} \\ {}^{\mathcal{O}}\dot{v}_{com} = {}^{\mathcal{O}}a_{com} + {}^{\mathcal{O}}g \\ {}^{\mathcal{O}}_{i}\dot{p} = 0 \;\; \forall i \epsilon \{1,2,3,4\} \end{cases} \qquad {}^{\mathcal{O}}g = [0 \quad 0 \quad -9.8m/s^2\,]^T $$

$$ \Downarrow $$

$$ \underbrace{\begin{bmatrix} {}^{\mathcal{O}}\boldsymbol{p}_{com} \\ {}^{\mathcal{O}}\boldsymbol{v}_{com} \\ {}^{\mathcal{O}}\boldsymbol{p}_{foot} \end{bmatrix}_{k+1}}_{x_{i+1}} = \underbrace{\begin{bmatrix} \mathbb{I}_3 & \Delta t \cdot \mathbb{I}_3 & \mathbf{0}_{3\times12} \\ \mathbf{0}_{3\times3} & \mathbb{I}_3 & \mathbf{0}_{3\times12} \\ \mathbf{0}_{12\times3} & \mathbf{0}_{12\times3} & \mathbb{I}_{12} \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} {}^{\mathcal{O}}\boldsymbol{p}_{com} \\ {}^{\mathcal{O}}\boldsymbol{v}_{com} \\ {}^{\mathcal{O}}\boldsymbol{p}_{foot} \end{bmatrix}_{k}}_{x_k} + \underbrace{\begin{bmatrix} \mathbf{0}_{3\times3} \\ \Delta t \cdot \mathbb{I}_3 \\ \mathbf{0}_{12\times3} \end{bmatrix} {}^{\mathcal{O}}\boldsymbol{g}}_{\boldsymbol{u}_k} $$

$$ \Downarrow $$

卡尔曼滤波器的离散状态方程：

$$ x_{k+1} = Ax_k + Bu_k $$

四足机器人状态方程和观测方程

观测方程

利用空间几何关系可以求得本体系下足底位置：

$$
{}^{\mathcal{B}}_{i}\boldsymbol{p} = \begin{bmatrix} {}^{\mathcal{B}}_{i}p^{x} \\ {}^{\mathcal{B}}_{i}p^{y} \\ {}^{\mathcal{B}}_{i}p^{z} \end{bmatrix} = FK(q)
$$

本体系下足底速度与关节速度的关系：

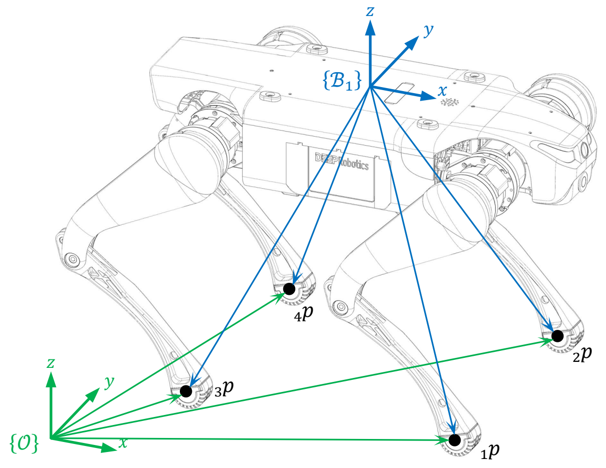
$$
{}^{\mathcal{B}}_{i}\dot{p} = J(q)\dot{q}
$$

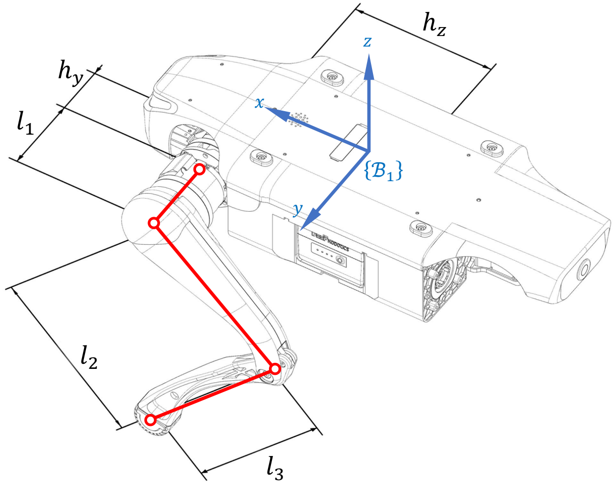
足底坐标从本体系到世界系的映射关系为：

$$
{}^{\mathcal{O}}_{i}p = {}^{\mathcal{O}}p_{com} + {}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{i}p
$$

对上式微分，以求足底速度从本体系到世界系的映射关系：

$$
\begin{aligned}
{}^{\mathcal{O}}_{i}\dot{p} &= {}^{\mathcal{O}}\boldsymbol{v}_{com} + {}^{\mathcal{O}}\dot{R}_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{i}p + {}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{i}\dot{p} \\
&= {}^{\mathcal{O}}\boldsymbol{v}_{com} + {}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{OB}\times} \cdot {}^{\mathcal{B}}_{i}p + {}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{i}\dot{p} \\
&= {}^{\mathcal{O}}\boldsymbol{v}_{com} + {}^{\mathcal{O}}R_{\mathcal{B}} \cdot \left({}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{OB}\times} \cdot {}^{\mathcal{B}}_{i}p + {}^{\mathcal{B}}_{i}\dot{p}\right)
\end{aligned}
$$





四足机器人状态方程和观测方程

观测方程

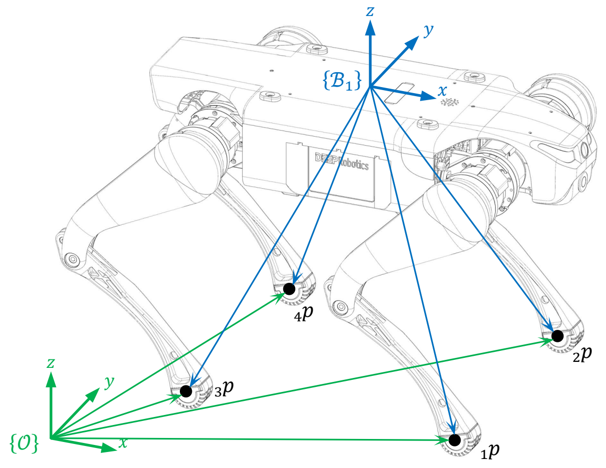
$$
\begin{aligned}
{}^{\mathcal{O}}_{i}\dot{p} &= {}^{\mathcal{O}}\boldsymbol{v}_{com} + {}^{\mathcal{O}}\dot{R}_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{i}p + {}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{i}\dot{p} \\
&= {}^{\mathcal{O}}\boldsymbol{v}_{com} + {}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{O}\mathcal{B}\times} \cdot {}^{\mathcal{B}}_{i}p + {}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{i}\dot{p} \\
&= {}^{\mathcal{O}}\boldsymbol{v}_{com} + {}^{\mathcal{O}}R_{\mathcal{B}} \cdot \left({}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{O}\mathcal{B}\times} \cdot {}^{\mathcal{B}}_{i}p + {}^{\mathcal{B}}_{i}\dot{p}\right)
\end{aligned}
$$

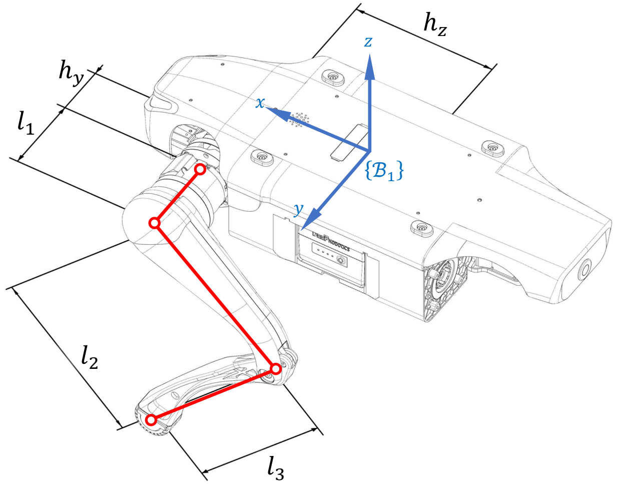
根据支撑足不打滑假设，足底在世界系下静止，即${}^{\mathcal{O}}_{i}\dot{p} = 0$，从而有：

$$
{}^{\mathcal{O}}\boldsymbol{v}_{com} = -\,{}^{\mathcal{O}}R_{\mathcal{B}} \cdot \left({}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{O}\mathcal{B}\times} \cdot {}^{\mathcal{B}}_{i}p + {}^{\mathcal{B}}_{i}\dot{p}\right)
$$

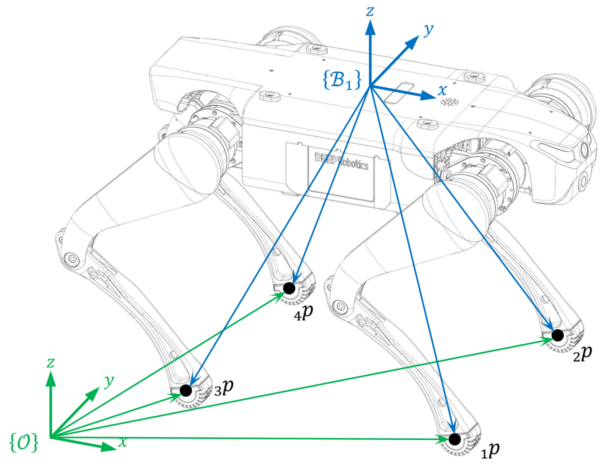
另外，足底高度${}^{\mathcal{O}}_{i}p^{z}$与足底坐标${}^{\mathcal{O}}_{i}p$有如下关系：

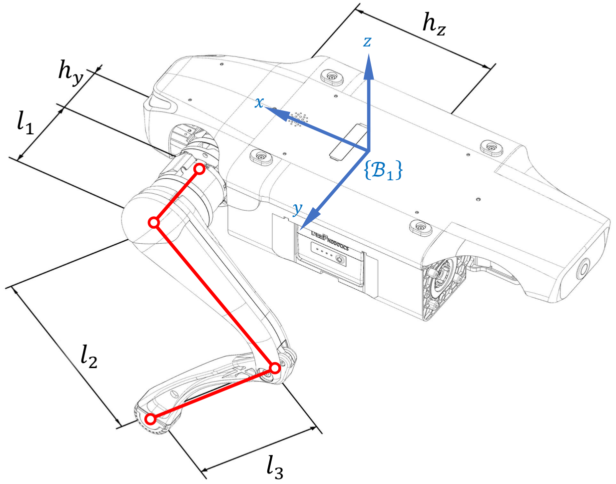
$$
{}^{\mathcal{O}}_{i}p^{z} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \cdot {}^{\mathcal{O}}_{i}p
$$





四足机器人状态方程和观测方程





□ 观测方程

$$
\begin{aligned}
{}^{\mathcal{O}}_{i}p &= {}^{\mathcal{O}}p_{com} + {}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{i}p \\
{}^{\mathcal{O}}\boldsymbol{v}_{com} &= -\,{}^{\mathcal{O}}R_{\mathcal{B}} \cdot \left({}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{O}\mathcal{B}\times} \cdot {}^{\mathcal{B}}_{i}p + {}^{\mathcal{B}}_{i}\dot{p}\right) \\
{}^{\mathcal{O}}_{i}p^{z} &= [0 \quad 0 \quad 1] \cdot {}^{\mathcal{O}}_{i}p
\end{aligned}
\quad \Longrightarrow
$$

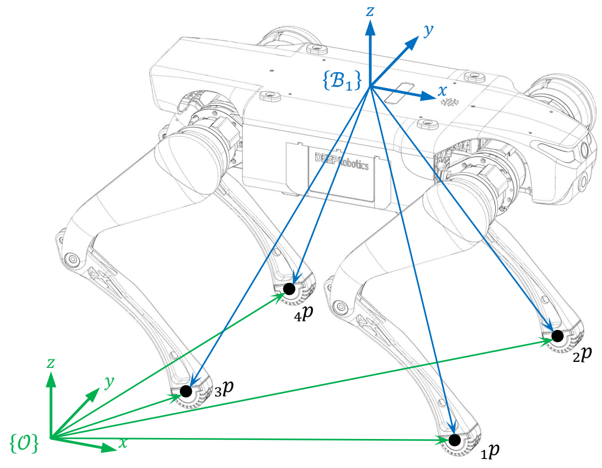
$$
\underbrace{\begin{bmatrix}
-\,{}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{1}p \\
-\,{}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{2}p \\
-\,{}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{3}p \\
-\,{}^{\mathcal{O}}R_{\mathcal{B}} \cdot {}^{\mathcal{B}}_{4}p \\
-\,{}^{\mathcal{O}}R_{\mathcal{B}} \cdot \left({}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{O}\mathcal{B}\times} \cdot {}^{\mathcal{B}}_{1}p + {}^{\mathcal{B}}_{1}\dot{p}\right) \\
-\,{}^{\mathcal{O}}R_{\mathcal{B}} \cdot \left({}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{O}\mathcal{B}\times} \cdot {}^{\mathcal{B}}_{2}p + {}^{\mathcal{B}}_{2}\dot{p}\right) \\
-\,{}^{\mathcal{O}}R_{\mathcal{B}} \cdot \left({}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{O}\mathcal{B}\times} \cdot {}^{\mathcal{B}}_{3}p + {}^{\mathcal{B}}_{3}\dot{p}\right) \\
-\,{}^{\mathcal{O}}R_{\mathcal{B}} \cdot \left({}^{\mathcal{B}}\boldsymbol{\omega}_{\mathcal{O}\mathcal{B}\times} \cdot {}^{\mathcal{B}}_{4}p + {}^{\mathcal{B}}_{4}\dot{p}\right) \\
{}^{\mathcal{O}}_{1}p^{z} \\
{}^{\mathcal{O}}_{2}p^{z} \\
{}^{\mathcal{O}}_{3}p^{z} \\
{}^{\mathcal{O}}_{4}p^{z}
\end{bmatrix}}_{z_k}
=
\underbrace{\begin{bmatrix}
I_3 & 0_{3\times3} & & & \\
I_3 & 0_{3\times3} & & -I_{12} & \\
I_3 & 0_{3\times3} & & & \\
I_3 & 0_{3\times3} & & & \\
0_{3\times3} & I_3 & & & \\
0_{3\times3} & I_3 & & 0_{12\times12} & \\
0_{3\times3} & I_3 & & & \\
0_{3\times3} & I_3 & & & \\
0_{1\times6} & 0 & 0 & 1 & 0_{1\times9} \\
0_{1\times9} & 0 & 0 & 1 & 0_{1\times6} \\
0_{1\times12} & 0 & 0 & 1 & 0_{1\times3} \\
0_{1\times12} & 0 & 0 & 1 & 0_{1\times0}
\end{bmatrix}}_{H}
\underbrace{\begin{bmatrix}
{}^{\mathcal{O}}p_{com} \\
{}^{\mathcal{O}}\boldsymbol{v}_{com} \\
{}^{\mathcal{O}}_{1}p \\
{}^{\mathcal{O}}_{2}p \\
{}^{\mathcal{O}}_{3}p \\
{}^{\mathcal{O}}_{4}p
\end{bmatrix}_k}_{\boldsymbol{x}_k}
\Longleftrightarrow z_k = H \cdot \boldsymbol{x}_k
$$

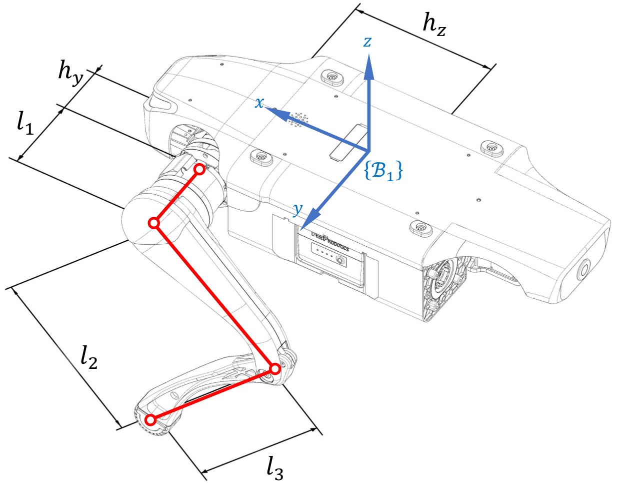
四足机器人状态方程和观测方程

系统估计

假设：${}^{O}_{i}p^{z}=0$

使用标准的卡尔曼滤波递归方程对系统进行估计：





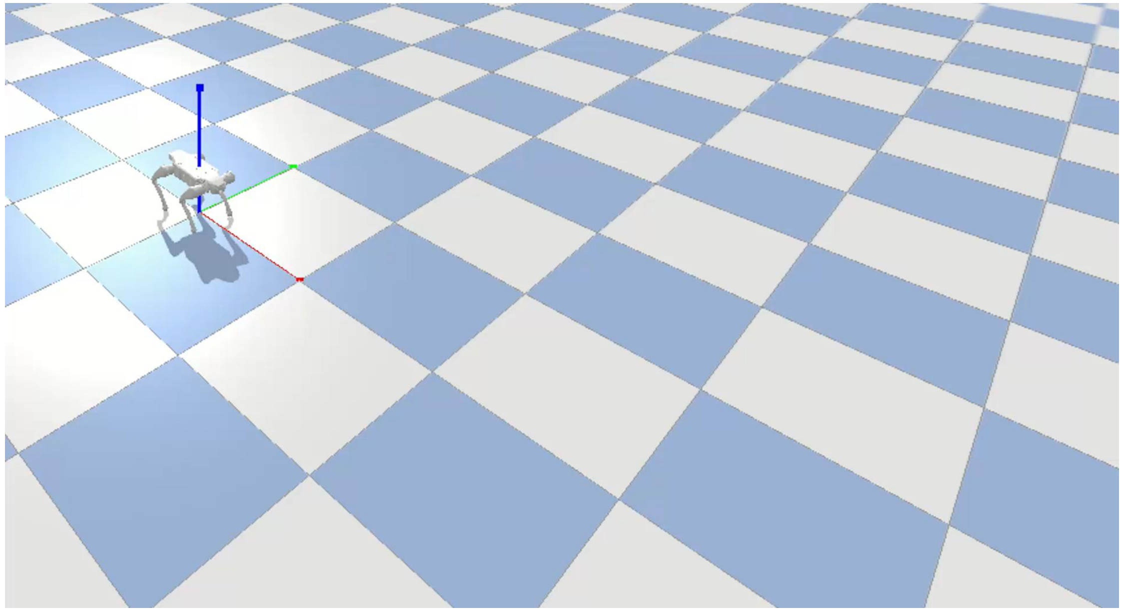
$$
\begin{cases}
\underline{\hat{\boldsymbol{x}}}_k = A\hat{\boldsymbol{x}}_{k-1} + B\boldsymbol{u}_{k-1} \\
\underline{P}_k = AP_{k-1}A^T + Q \\
K_k = \dfrac{\underline{P}_k H^T}{H\underline{P}_k H^T + R} \\
\hat{\boldsymbol{x}}_k = \underline{\hat{\boldsymbol{x}}}_k + K_k\left(\boldsymbol{z}_k - H\underline{\hat{\boldsymbol{x}}}_k\right) \\
P_k = (I - K_k H)\underline{P}_k
\end{cases}
$$

目录

Project

状态估计实践：

- 根据Lite3的离线数据写出预测方程和卡尔曼滤波迭代公式
- 在仿真环境中绘制Lite3的状态估计曲线
- 对比先验数据和后验数据



参考资料

1. DR_CAN. https://space.bilibili.com/230105574/channel/collectiondetail,2021
2. Bloesch M, Hutter M, Hoepflinger M A, et al. State estimation for legged robots: Consistent fusion of leg kinematics and IMU[J]. 2013.
3. 卡尔曼滤波： https://zh.wikipedia.org/wiki/%E5%8D%A1%E5%B0%94%E6%9B%BC%E6%BB%A4%E6%B3%A2

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感谢聆听！

Thanks for Listening