# TRABALHO 4

Tópicos Especiais em Sistemas Autônomos
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# Agenda

- Modelo Range Beam Finder
- Modelo Learn Intrinsic Parameters
- Modelo Likelihood Field Range
- Modelo Sample Landmark
- Modelo Landmark

# Modelo Range Beam Finder

**Algorithm beam_range_finder_model**($z_t, x_t, m$):

$q = 1$

*for* $k = 1$ *to* $K$ *do*

*compute* $z_t^{k*}$ *for the measurement* $z_t^k$ *using ray casting*

$p = z_{\text{hit}} \cdot p_{\text{hit}}(z_t^k \mid x_t, m) + z_{\text{short}} \cdot p_{\text{short}}(z_t^k \mid x_t, m)$

$\quad + z_{\max} \cdot p_{\max}(z_t^k \mid x_t, m) + z_{\text{rand}} \cdot p_{\text{rand}}(z_t^k \mid x_t, m)$

$q = q \cdot p$

*return* $q$

# Modelo Learn Intrinsic Parameters

**Algorithm learn_intrinsic_parameters($Z, X, m$):**

*repeat until convergence criterion satisfied*

*for all $z_i$ in $Z$ do*

$$\eta = [\, p_{\text{hit}}(z_i \mid x_i, m) + p_{\text{short}}(z_i \mid x_i, m) + p_{\max}(z_i \mid x_i, m) + p_{\text{rand}}(z_i \mid x_i, m) \,]^{-1}$$

*calculate $z_i^*$*

$$e_{i,\text{hit}} = \eta\, p_{\text{hit}}(z_i \mid x_i, m)$$

$$e_{i,\text{short}} = \eta\, p_{\text{short}}(z_i \mid x_i, m)$$

$$e_{i,\max} = \eta\, p_{\max}(z_i \mid x_i, m)$$

$$e_{i,\text{rand}} = \eta\, p_{\text{rand}}(z_i \mid x_i, m)$$

$$z_{\text{hit}} = |Z|^{-1} \sum_i e_{i,\text{hit}}$$

$$z_{\text{short}} = |Z|^{-1} \sum_i e_{i,\text{short}}$$

$$z_{\max} = |Z|^{-1} \sum_i e_{i,\max}$$

$$z_{\text{rand}} = |Z|^{-1} \sum_i e_{i,\text{rand}}$$

$$\sigma_{\text{hit}} = \sqrt{\frac{1}{\sum_i e_{i,\text{hit}}} \sum_i e_{i,\text{hit}} (z_i - z_i^*)^2}$$

$$\lambda_{\text{short}} = \frac{\sum_i e_{i,\text{short}}}{\sum_i e_{i,\text{short}}\, z_i}$$

*return* $\Theta = \{z_{\text{hit}}, z_{\text{short}}, z_{\max}, z_{\text{rand}}, \sigma_{\text{hit}}, \lambda_{\text{short}}\}$

# Modelo Likelihood Field Range

**Algorithm likelihood_field_range_finder_model**($z_t, x_t, m$):

$q = 1$

*for all k do*

*if* $z_t^k \neq z_{\max}$

$$x_{z_t^k} = x + x_{k,\text{sens}} \cos\theta - y_{k,\text{sens}} \sin\theta + z_t^k \cos(\theta + \theta_{k,\text{sens}})$$

$$y_{z_t^k} = y + y_{k,\text{sens}} \cos\theta + x_{k,\text{sens}} \sin\theta + z_t^k \sin(\theta + \theta_{k,\text{sens}})$$

$$dist = \min_{x',y'} \left\{ \sqrt{(x_{z_t^k} - x')^2 + (y_{z_t^k} - y')^2} \,\middle|\, \langle x', y' \rangle \text{ occupied in } m \right\}$$

$$q = q \cdot \left( z_{\text{hit}} \cdot \text{prob}(dist, \sigma_{\text{hit}}) + \frac{z_{\text{random}}}{z_{\max}} \right)$$

*return q*

# Modelo Sample Landmark

**Algorithm sample_landmark_model_known_correspondence**($f_t^i, c_t^i, m$):

$j = c_t^i$

$\hat{\gamma} = \text{rand}(0, 2\pi)$

$\hat{r} = r_t^i + \text{sample}(\sigma_r)$

$\hat{\phi} = \phi_t^i + \text{sample}(\sigma_\phi)$

$x = m_{j,x} + \hat{r}\cos\hat{\gamma}$

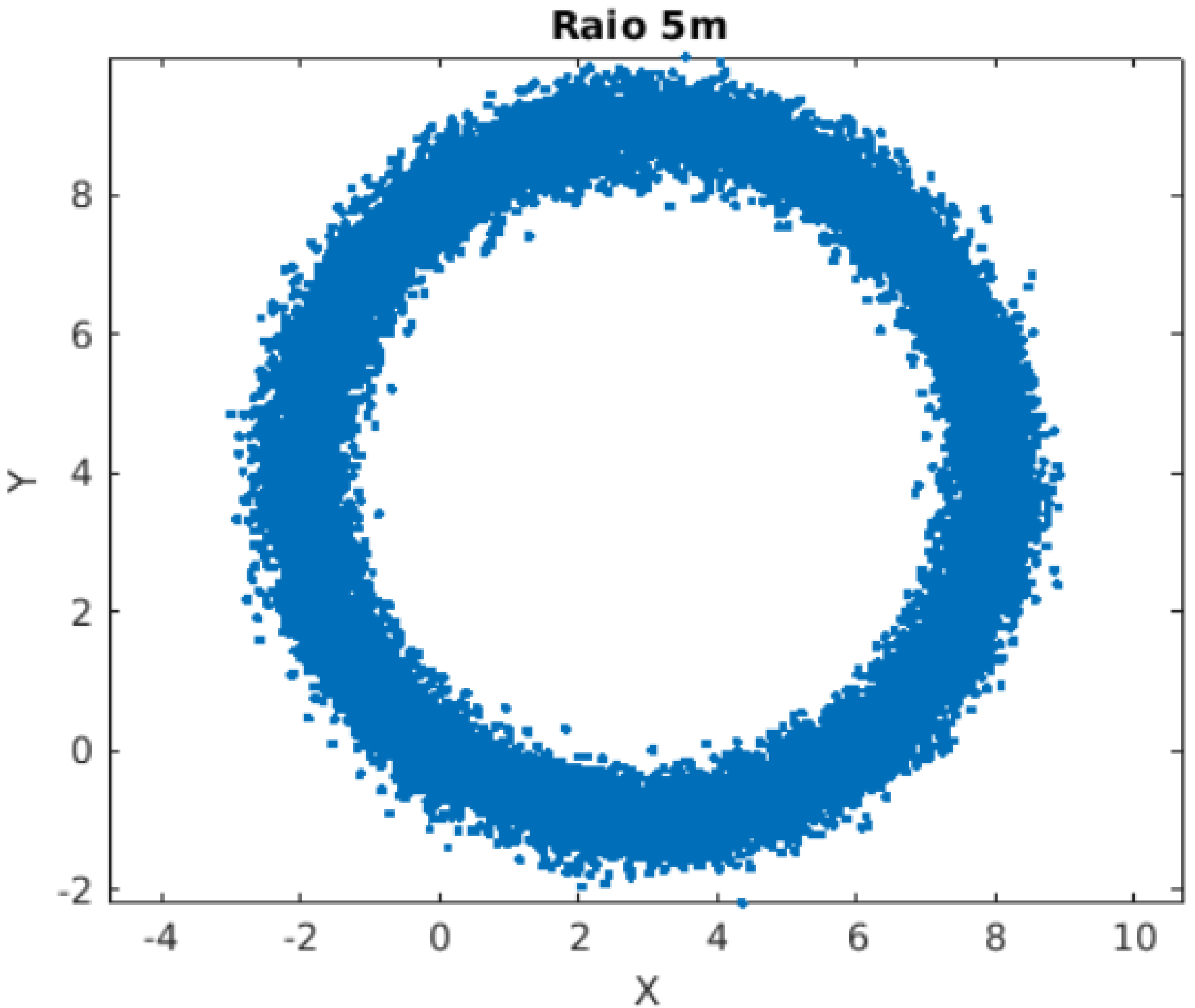
$y = m_{j,y} + \hat{r}\sin\hat{\gamma}$

$\theta = \hat{\gamma} - \pi - \hat{\phi}$

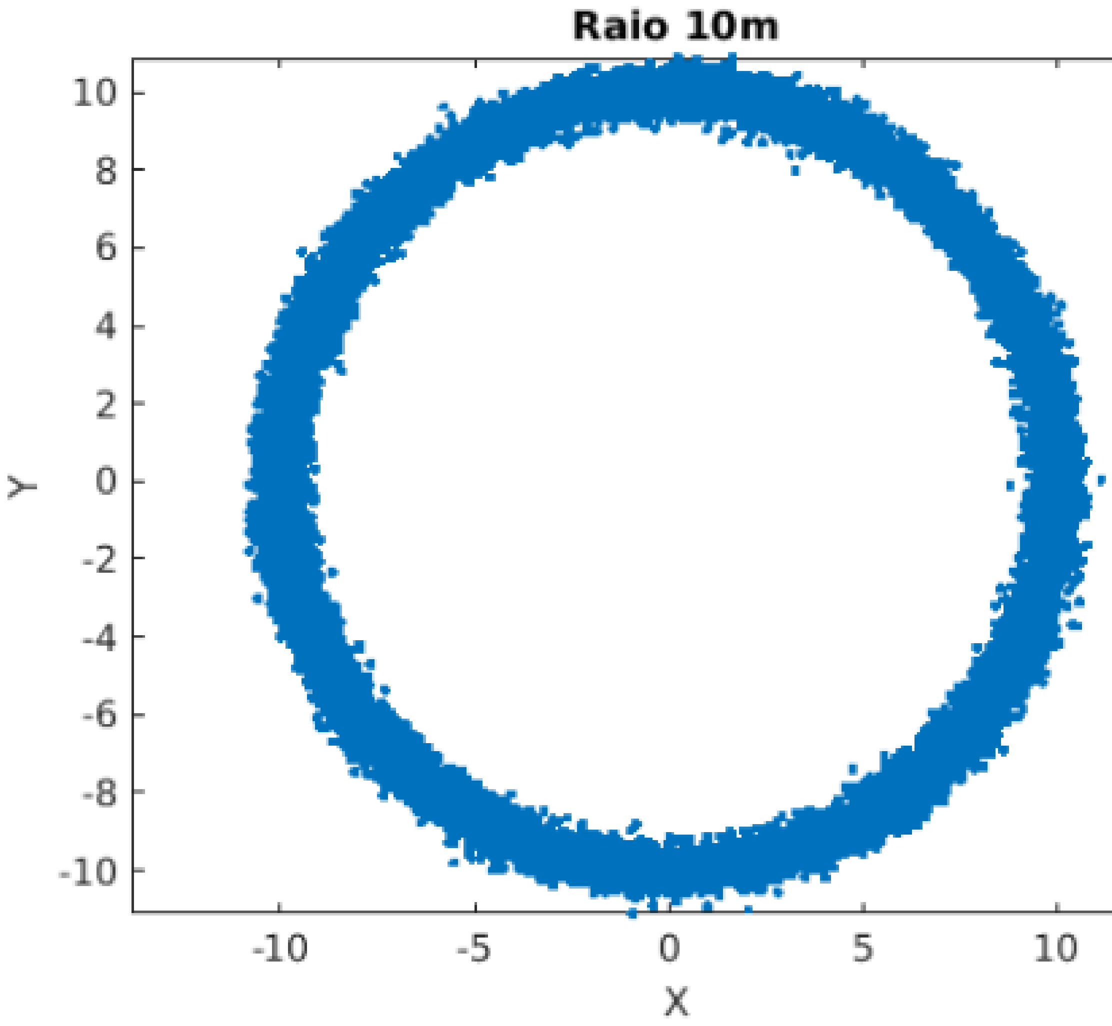
return $(x \;\; y \;\; \theta)^T$

$$f_t^i = (r_t^i \;\; \phi_t^i \;\; s_t^i)$$

# Modelo Sample Landmark



# Modelo Sample Landmark



# Modelo Landmark

**Algorithm landmark_model_known_correspondence**($f_t^i, c_t^i, x_t, m$):

$j = c_t^i$

$\hat{r} = \sqrt{(m_{j,x} - x)^2 + (m_{j,y} - y)^2}$

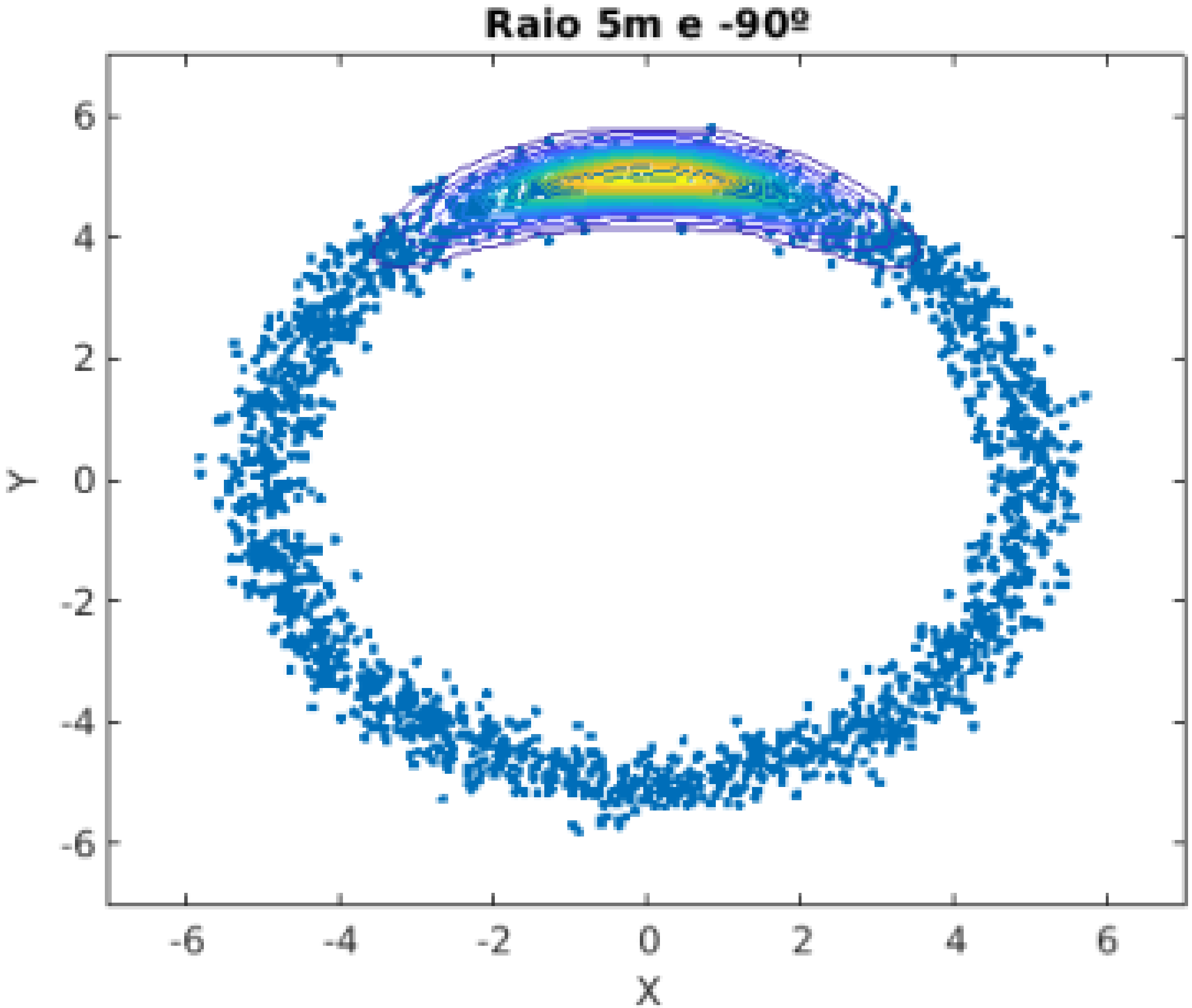
$\hat{\phi} = \mathrm{atan2}(m_{j,y} - y, m_{j,x} - x)$

$q = \mathbf{prob}(r_t^i - \hat{r}, \sigma_r) \cdot \mathbf{prob}(\phi_t^i - \hat{\phi}, \sigma_\phi) \cdot \mathbf{prob}(s_t^i - s_j, \sigma_s)$

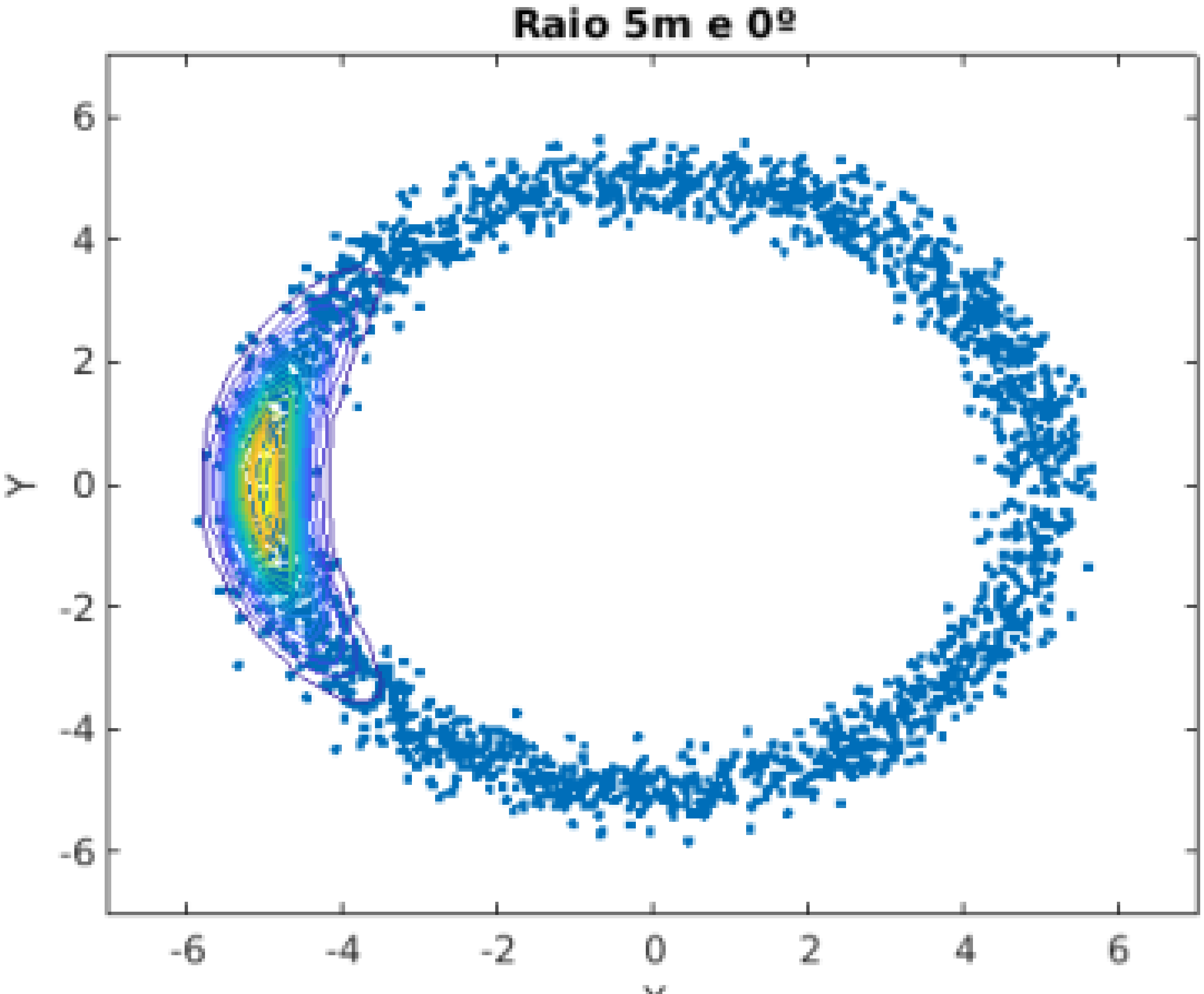
*return* $q$

$$x_t = (x \;\; y \;\; \theta) \qquad\qquad f_t^i = (r_t^i \;\; \phi_t^i \;\; s_t^i)$$

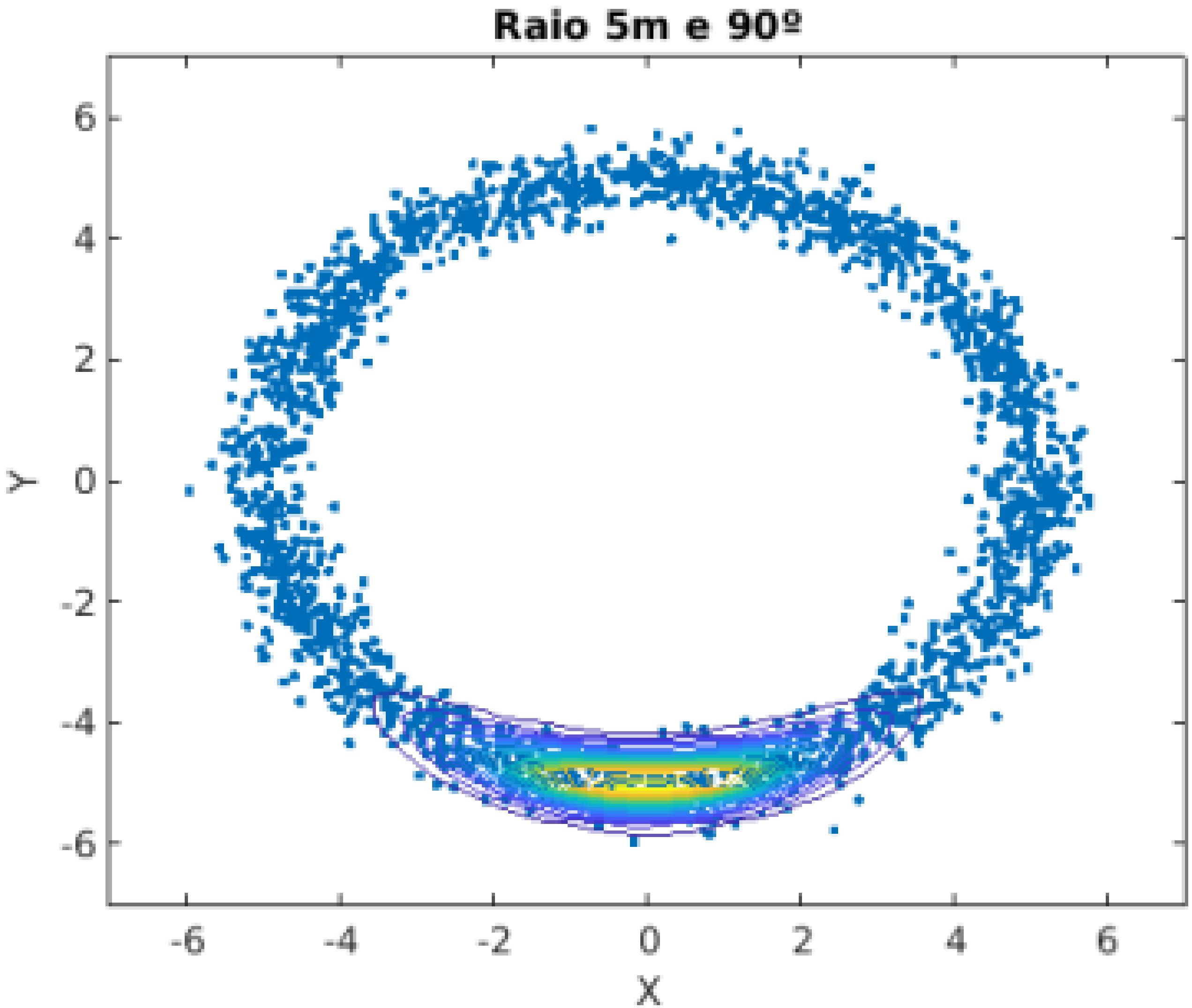
# Modelo Landmark



# Modelo Landmark



# Modelo Landmark



# Modelo Landmark