Touch attention Bayesian models for robotic active haptic exploration

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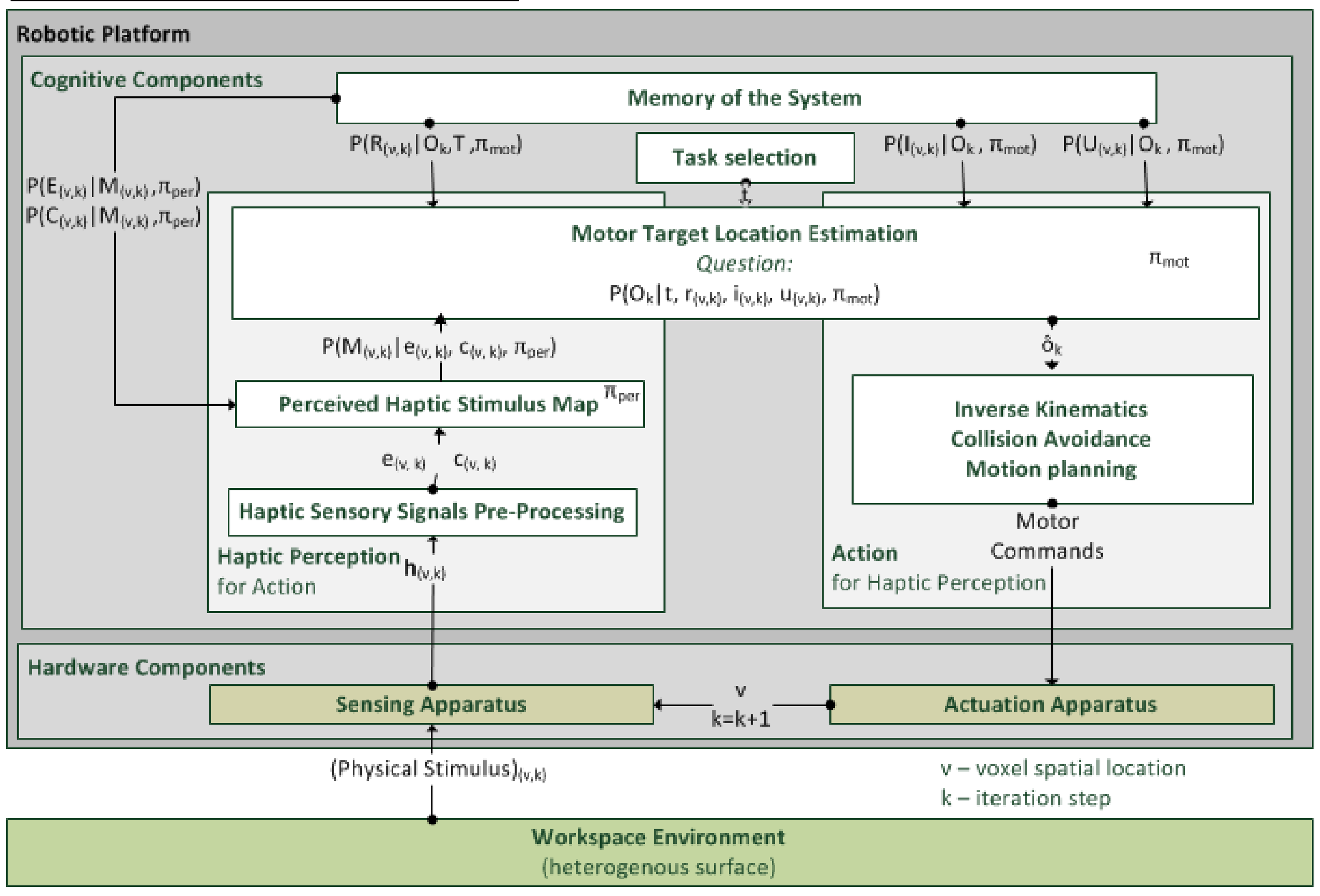
→ Motivation:

•**New generation of robotic platforms:** high diversity of sensory (touch, vision, audition) and actuation apparatus (dexterous robotic hands, arms and legs);
•**Challenging application environments:** unknown and dynamic structure;

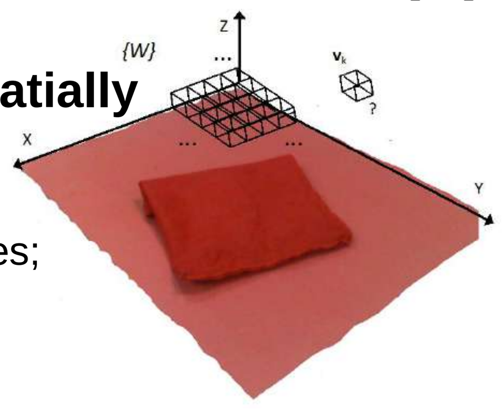
•**Development of touch attention mechanisms:**
-Evaluation of the relevance of the haptic stimulus perceived during the robotic blind exploration of surfaces.
-Determination of the robotic motor reaction to the perceived haptic stimulus.

→ Proposed Approach:



•**The approach integrates information from**:
-**Top-down mechanisms** (information related with the task objective).
-**Bottom-up mechanisms** (relevant characteristics of the stimulus emerging from the environment).

•**The workspace of the robotic system is spatially partitioned in a inference grid:**
-Integration of multimodal data;
-Discrimination of heterogeneous surfaces – discontinuities;
-Planning of motor actions;



v_k -voxel v at time iteration k ; ε - dimension of the cubic voxel

→ Motor Target Location Estimation (Bayesian Model π_{mot})

•Determination of the next workspace region to be explored based on the perceived haptic stimulus map estimated by the Bayesian Model π_{per} .

•**Bayesian Program:**

Program / Description / Specification

Relevant variables:
$O_k, T, R_{(v,k)}, U_{(v,k)}, I_{(v,k)}$
Decomposition:
$$P(O_k, T, R_{(v,k)}, U_{(v,k)}, I_{(v,k)}|\pi_{mot}) = \begin{pmatrix} P(O_k|\pi_{mot}) \\ P(T,\pi_{mot}) \\ P(I_{(v,k)}|O_k,\pi_{mot}) \\ P(U_{(v,k)}|O_k,\pi_{mot}) \\ P(R_{(v,k)}|O_k,T,\pi_{mot}) \end{pmatrix}.$$
Parametric forms:
$P(O_k|\pi_{mot}) \equiv Uniform$
$P(T|\pi_{mot}) \equiv Uniform$
$P(I_{(v,k)}|O_k,\pi_{mot}) \equiv \mathcal{B}(\alpha_I,\beta_I)$
$P(U_{(v,k)}|O_k,\pi_{mot}) \equiv \mathcal{B}(\alpha_U,\beta_U)$
$P(R_{(v,k)}|O_k,T,\pi_{mot}) \equiv \mathcal{B}(\alpha_R,\beta_R)$
Identification:
$\alpha_R, \beta_R -$ *- Empirical values*
$\alpha_I, \beta_I -$ *- Empirical values*
$\alpha_U, \beta_U -$ *- Empirical values*
Question:
$P(O_k|t, r_{(v,k)}, u_{(v,k)}, i_{(v,k)}, \pi_{mot})$
Decision criteria: *MAP - Maximum a posteriori.*
$\hat{o}_k = \arg\max_{o_k} P(O_k|t, r_{(v,k)}, u_{(v,k)}, i_{(v,k)}, \pi_{mot})$

T–“Task objectives”, $T \in \{Task_1, \ldots, Task_\Phi\}$

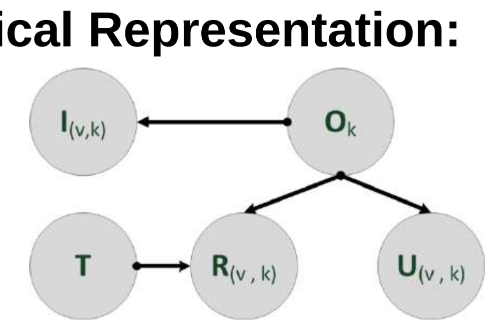
$I_{(v,k)}$ – “Inhition level for cell v”, $I_{(v,k)} \in [0, 1]$
$$I_{(v,k)} = 1 - \Theta d^{\alpha-1}(1|-d)^{1-\beta}, \quad d = \frac{d_k}{d_{max}} \quad \alpha=1{,}01 \quad \beta=9$$

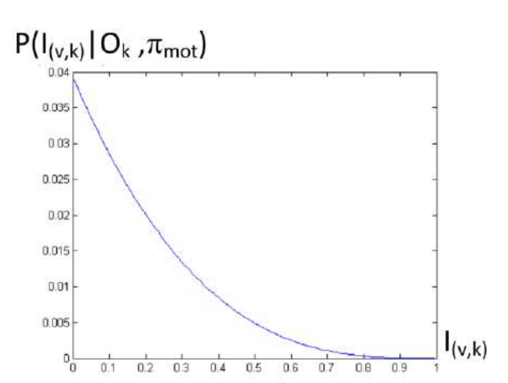
$U_{(v,k)}$ – “Uncertainty level for cell v”, $U_{(v,k)} \in [0, 1]$
$$U_{(v,k)} = \frac{\mathcal{H}(M_{(v,k)})}{max(\mathcal{H}(M_{(v,k)}))}$$

$R_{(v,k)}$ – “Relevance of the haptic stimulus in a 26-th neighborhood region around v”, $R_{(v,k)} \in [0, 1]$
$$r = \frac{\max(|r_x|,|r_y|,|r_z|)}{r_{norm}} \quad r_x = \mathcal{G}_{sobel_x}(\mathbf{d}), s_y = \mathcal{G}_{sobel_y}(\mathbf{d}), \quad r_z = \mathcal{G}_{sobel_z}(\mathbf{d})$$
$$\mathbf{d} = (\Omega_{(v0,k)}, \ldots, \Omega_{(v26,k)})$$
$$\Omega_{(vi,k)} = \frac{1 - \begin{pmatrix} P(M_{(vi,k)} = Material_a | e_{(vi,k)}, c_{(vi,k)}, \pi_{per}) \\ P(M_{(vi,k)} = Material_b | e_{(vi,k)}, c_{(vi,k)}, \pi_{per}) \end{pmatrix} +}{2}$$

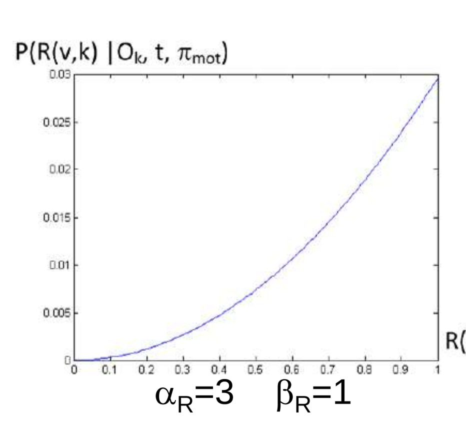
O_k–“Next workspace region to be explored"”,

•**Graphical Representation:**

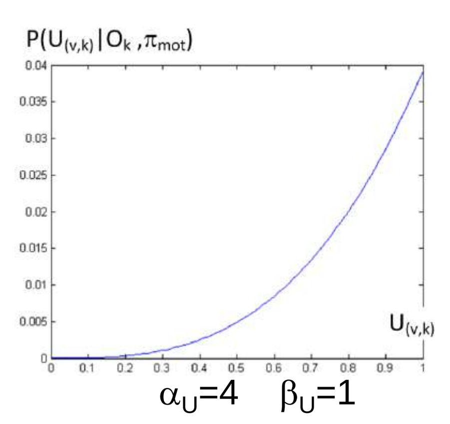




$\alpha_I=1 \quad \beta_I=4$



$\alpha_R=3 \quad \beta_R=1$



$\alpha_U=4 \quad \beta_U=1$

→ Perceived Haptic Stimulus Map (Bayesian Model π_{per})

•Determination of the perceived category of material of the voxel v of the workspace based on the haptic sensory input $\mathbf{h}_{(v,k)}$.

•**Bayesian Program:**

Program / Description / Specification

Relevant variables:
$E_{(v,k)}, C_{(v,k)}, M_{(v,k)}$
Decomposition:
$$P(E_{(v,k)}, C_{(v,k)}, M_{(v,k)}|\pi_{per}) = \begin{pmatrix} P(E_{(v,k)}|M_{(v,k)},\pi_{per}) \\ P(C_{(v,k)}|M_{(v,k)},\pi_{per}) \\ P(M_{(v,k)}|\pi_{per}) \end{pmatrix}.$$
Parametric forms:
$P(E_{(v,k)}|M_{(v,k)},\pi_{per}) \sim \mathcal{N}(\mu_E(M),\sigma_E(M))$
$P(C_{(v,k)}|M_{(v,k)},\pi_{per}) \sim \mathcal{N}(\mu_C(M),\sigma_C(M))$
For $k=0$:
Map initialization.
$P(M_{(v,0)}|\pi_{per}) \sim$ *Uniform*
For $k>0$:
Map update using previous state information.
$P(M_{(v,k)}|\pi_{per}) = P(M_{(v,k-1)}|e_{(v,k-1)}, c_{(v,k-1)}, \pi_{per})$
Identification:
$\mu_E(M), \sigma_E(M), \mu_C(M), \sigma_C(M)$
- Demonstrations in learning stage.
Question:
$P(M_{(v,k}|e_{(v,k)}, c_{(v,k)}, \pi_{per})$
$$P(M_{(v,k)}|e_{(v,k)}, c_{(v,k)}, \pi_{per}) = \frac{\begin{pmatrix} P(e_{(v,k)}|M_{(v,k)},\pi_{per}) \\ P(c_{(v,k)}|M_{(v,k)},\pi_{per}).P(M_{(v,k)},\pi_{per}) \end{pmatrix}.}{\sum_{M_{(v,k)}} \begin{pmatrix} P(e_{(v,k)}|M_{(v,k)},\pi_{per}) \\ P(c_{(v,k)}|M_{(v,k)},\pi_{per}).P(M_{(v,k)},\pi_{per}) \end{pmatrix}.}$$

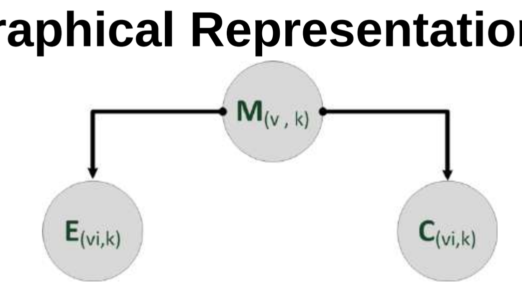
$M_{(v,k)}$ –"Material category of v"
$M_{(v,k)} \in \{Material_1, \ldots, Material_n\}$

$E_{(v,k)}$ – "Texture characterization of v”
$E_{(v,k)} = f(\mathbf{h}_{(v,k)}), \quad E_{(v,k)} \in \mathbb{R}$

$C_{(v,k)}$ – “Compliance characterization of v”
$C_{(v,k)} = g(\mathbf{h}_{(v,k)}), \quad C_{(v,k)} \in \mathbb{R}$

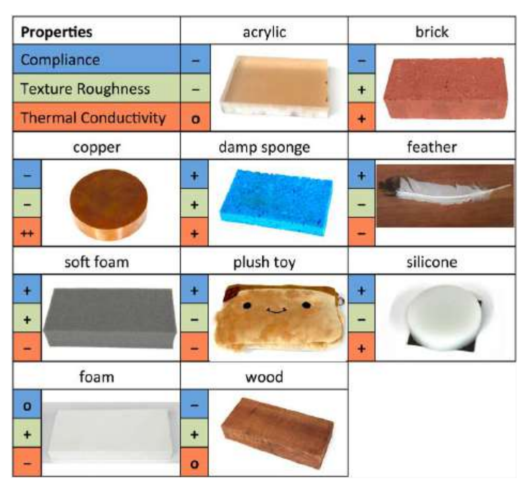
f and *g* described in [Xu et al, 2013]

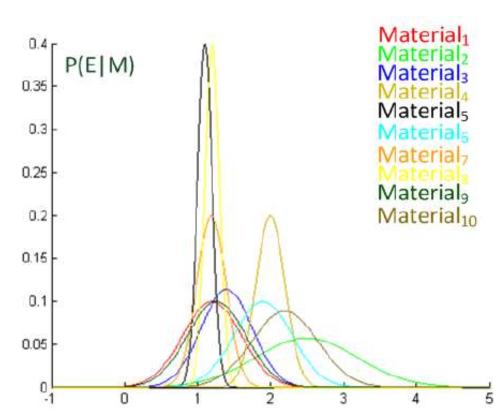
•**Graphical Representation:**

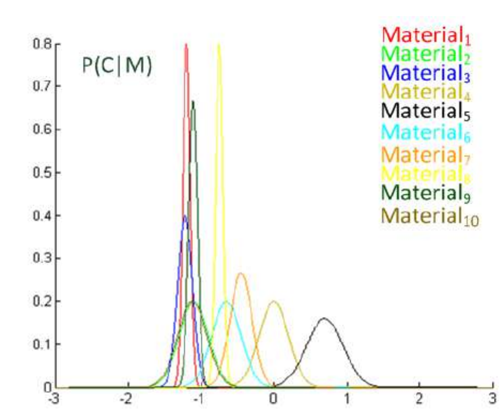


→ Experimental results

•**Learning of $P(E_{(v,k)} | M_{(v,k)}, \pi_{per})$ and $P(C_{(v,k)} | M_{(v,k)}, \pi_{per})$**
-Set of 10 different reference materials explored in 5 training trials.
-$\mu_E(M)$, $\sigma_E(M)$ and $\mu_C(M)$, $\sigma_C(M)$ extracted from the training data. [Xu et al, 2013]



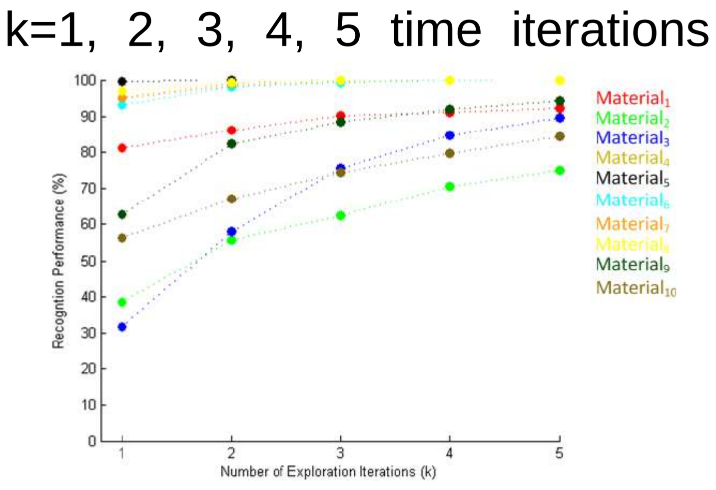




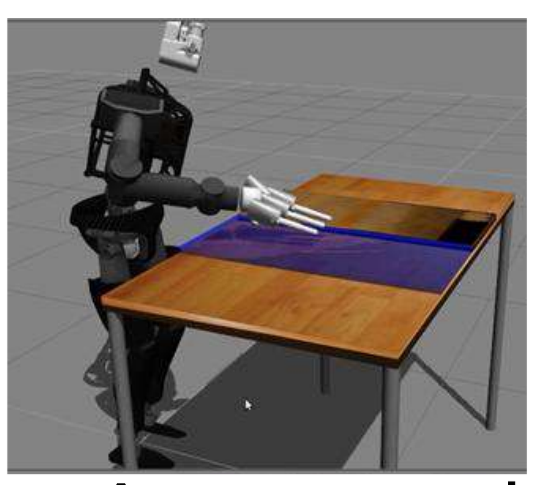
•**Recognition performance of Bayesian model π_{mot} :**
-400 blind exploration trials for each of the 10 reference materials;
-Classification of the material after k=1, 2, 3, 4, 5 time iterations (sensory integration);

$m_{(v,k)} = argmax\ P(M_{(v,k)} | e_{(v,k)}, c_{(v,k)}, \pi_{per})$

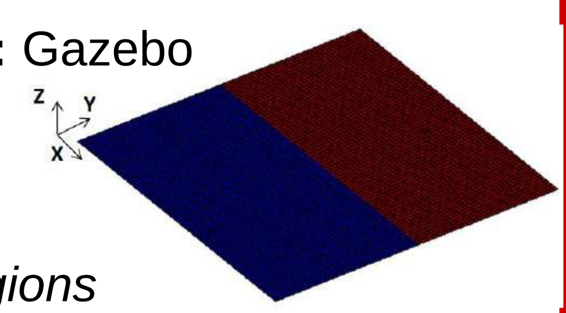
-High recognition performance;
-Recognition performance increases with the sensory integration period.



•**Autonomous blind exploration of the workspace:**



-**Simulation environment:** Gazebo
-**Robotic platform**: ATLAS
-**Task:** T = t =
"Search and follow of discontinuities between regions with Material8 (blue silicone) and Material10 (wood)"



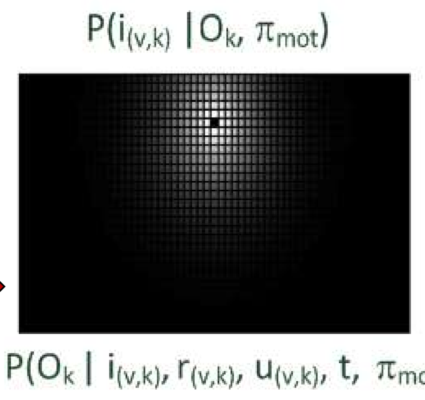
-**Autonomous exploration path – Demo**
Full videos available at *www.isr.uc.pt/~rmartins/reacts2013*

-**Example: Estimation of next region to be explored at k=20**

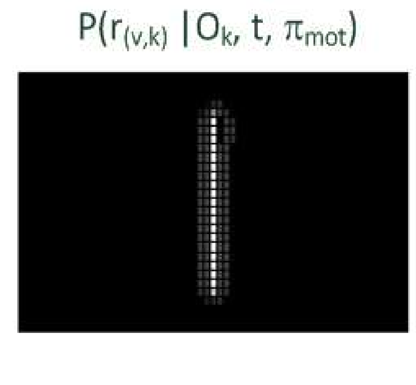
Initialization:
k=0
v=(25,30,1)

k=19
end-effector at v=(7,30,1)

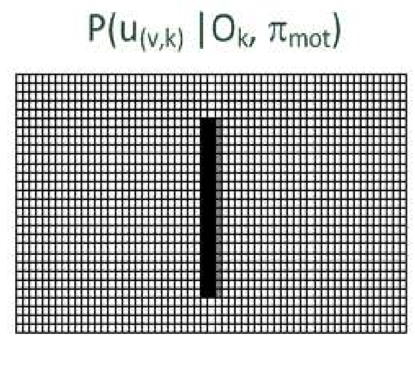
$P(i_{(v,k)} | O_k, \pi_{mot})$



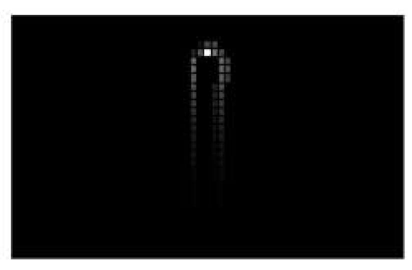
$P(r_{(v,k)} | O_k, t, \pi_{mot})$



$P(u_{(v,k)} | O_k, \pi_{mot})$



$P(O_k | i_{(v,k)}, r_{(v,k)}, u_{(v,k)}, t, \pi_{mot})$



$$\hat{o}_k = \arg\max_{o_k} P(O_k|t, r_{(v,k)}, i_{(v,k)}, u_{(v,k)}, \pi_{mot})$$
$$\hat{o}_k = \arg\max_{o_k} \begin{pmatrix} P(t|\pi_{mot}).P(i_{(v,k)}|O_k,\pi_{mot}) \\ P(r_{(v,k)}|O_k,t,\pi_{mot}).P(u_{(v,k)}|O_k,\pi_{mot}) \end{pmatrix}.$$

Next region to be explored $\hat{o}_{20}$=(6,30,1)

Xu, D., Loeb, G.E., Fishel, J.A.: Tactile identication of objects using bayesian exploration. In: IEEE -ICRA 2013. (2013)

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