

Improvement Proposals to Intrinsically Motivational Robotics

Fabien Hervouet, Eric Bourreau

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Introduction: why intrinsically motivated robots?

- ▶ Key challenge is to identify and implement **low-level mechanisms** that allow a **long-term development**.
- ▶ The more low-level these mechanisms are, the more the system can be considered as relevant.
- ▶ Inspect and design **scalable task-independent mechanisms** that may involve the robot in a **self autonomous skill practice**.

Zoom on SAGG-RIAC

SAGG-RIAC

- ▶ Deeply anchored at a sensorimotor level and allows low-level action selection in the **high-dimensional sensorimotor space** for a robot.
- ▶ Explores the **self competence acquisition paradigm**: choose sensory regions where it wants to return to instead of sensorimotor regions where it comes from.
- ▶ Sensory learning guided by a goal which consists in **mixing exploitation phases and local exploration phases**.
- ▶ The purpose of reaching phases is to test the **reliability of the forward motor model** while the purpose of exploration phases is to **improve the inverse model** of the system.
- ▶ Exploration phases are triggered when the **reliability is too low**.

$$\kappa(\sigma_i, \gamma, \sigma_f) = \max\left(-\sum_{i=1}^{i=|S|} \frac{|\sigma_f \cdot S_i - \gamma \cdot S_i|}{|\sigma_i \cdot S_i - \gamma \cdot S_i|}, \kappa_{max}\right)$$

Curious Developmental Living Loop

```

input:  $\xi_r$ : raw experiments;  $\xi_g$ : goal experiments;  $\sigma$ : states;
while True do
  start  $\leftarrow \sigma_t$ 
   $R \leftarrow \text{argmax}(\rho(R_i))$ 
   $\gamma \leftarrow R.\text{randomGoal}()$ 
  actions  $\leftarrow \emptyset$ 
  repeat
    action  $\leftarrow \text{getNextAction}(\sigma_t, \gamma)$ 
    actions  $\leftarrow \text{actions} \cup \text{action}$ 
    execute(action)
     $\xi_r \leftarrow \xi_r \cup \langle \sigma_{t-1}, \text{action}, \sigma_t \rangle$ 
    if  $\kappa_t \leq \kappa_{max}$  then
      for  $i \in \{1..explorationTrials\}$  do
        action  $\leftarrow \text{randomAction}(\sigma_t)$ 
        execute(action)
         $\xi_r \leftarrow \xi_r \cup \langle \sigma_{t-1}, \text{action}, \sigma_t \rangle$ 
      end
    end
  until  $\kappa_t \geq \kappa_{min}$  or timeout exceeded
end
 $\xi_g \leftarrow \xi_r \cup \langle \text{start}, \gamma, \text{actions}, \sigma_t \rangle$ 
   $R.\text{reorganizeMemory}()$ 

```

Improvements proposals to SAGG-RIAC

Although we keep the overall operation of the motivational living algorithm **SAGG-RIAC** we draw some improvements we describe here.

Interest measure

$$\rho(R_i) = LP(R_i) + UCT(R_i)$$

- ▶ **Timestamped derivative** that tends to reduce the interest by flattening the interest curve when experiments are very infrequent.

$$LP(R_i) = \frac{\sum_{j=0}^{|R_i|/2} c_j - \sum_{j=|R_i|/2}^{|R_i|} c_j}{\sum_{j=0}^{|R_i|/2} t_j - \sum_{j=|R_i|/2}^{|R_i|} t_j}$$

- ▶ **UCT based diversification** measure taking into account the number of experiments conducted in the current region relative to the total number of experiments.

$$UCT(R_i) = c \times \sqrt{\frac{\ln n}{n_i}}$$

Next action to reach a goal

- ▶ Using **k-nearest-neighbour** experiments among previously acquired experiments maximizing two criteria.

$$v(\xi_k) = \sum_{j=1}^{j=|S|} |\xi_k \cdot \sigma_i \cdot S_j - \sigma \cdot S_j| + |\xi_k \cdot \sigma_f \cdot S_j - \gamma \cdot S_j|$$

- ▶ Generating a **mean action** with respect to actions performed in these experiments.

$$v(a_i) = \frac{\sum_{j=1}^{j=|\xi|} \xi_j \cdot \text{action}[i]}{|\xi|}$$

Memory restructuring

- ▶ Upgrading **splitting condition** so as to make it dynamic, i.e. correlated with the development of the agent
- ▶ Introducing a mechanism for **merging regions** to allow a subsequent restructuring.
- ▶ Trying to maximize the absolute value of the difference between the learning progress in the two subregions relative to the current learning progress in the mother region.

$$\mu(R_1, R_2, R) = \frac{|LP(R_1) - LP(R_2)|}{LP(R)}$$

Future works

- ▶ Discovering process is underlined by a better **dynamic splitting condition**.
- ▶ Forgetting is only about **parts of the segmentation** of the sensorimotor space that used to make sense with a lack of information but that seems inappropriate with more experience.
- ▶ We are willing to run precise **parametric experiments** to compare our proposals.
- ▶ We are also working at new ways of **defining, evaluating and comparing** performance between different developmental trajectories.

Quick References

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