# Neural Network based Reinforcement Learning for Audio-Visual Gaze Control in Human-Robot Interaction

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## Gaze control for Human-Robot Interaction



- Where to look at?
- What are the good motor commands inorder to obtain a rich environment representation?

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#### Gaze control: related works

- Vast literature on visual servoing [1]: How to align an object (eg. a face) with a target image location (eg. image center)?
  - Not designed for multi-person scenarios
  - It does not use audio information
- Few works on multi-person scenarios [2,3] :
  - Handcrafted rules
  - Without properly combining audio and visual data.

S.Lathuilière et al. (Inria)

Reinforcement Learning for Gaze Control

<sup>[1]:</sup> Cretual and Chaumette, Application of motion-based visual servoing to target tracking, 2001

<sup>[2]:</sup> Bennewitz et al., Towards a humanoid museum guide robot that interacts with multiple persons, 2005

<sup>[3]:</sup> Ban et al., Tracking a Varying Number of People with a Visually-Controlled Robotic Head, 2017

# Gaze control: a difficult problem?



## Gaze control: a difficult problem?



We need to include the body geometry in the decision process.

#### Gaze control: a difficult problem?



The decision depends on:

- Behavior we expect.
- The speech localization accuracy
- Motion properties of the robot.

## Gaze control: a difficult problem?

Handcrafted rules: limitations

• The problem is too complex to handle all possible cases.

We need Learning!

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Handcrafted rules: limitations

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#### We need Learning!

**Problem:** We cannot have a training set containing observations with their associated optimal head commands. A discriminative approach would be difficult.

**Approach:** We evaluate each head movement by counting the number of detected faces after moving the head.

We need Reinforcement Learning (RL)!

#### Gaze control: our contributions

- RL formulation for the Gaze control problem.
- Audio-visual fusion framework.
- Deep RL to model the action-value function (DQN [4]) and propose architectures specifically for our task.
- Simulated environment to train our model.

<sup>[4]:</sup> Mnihn et al. Human-level control through deep reinforcement learning, 2015

## Gaze control in the RL framework

#### Proposed reward:

$$R_t = F_{t+1} + \alpha \Sigma_{t+1},$$

with:

- $F_{t+1} \in \mathbb{N}$ : number of detected faces
- $\Sigma_{t+1} \in \{0,1\}$ :  $\Sigma_{t+1} = 1$  if someone is speaking within the camera field
- $\alpha \geq 0$ : adjustment parameter.

## Gaze control in the RL framework

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#### Set of actions:

$$\mathcal{A} = \{ \varnothing, \leftarrow, \uparrow, \rightarrow, \downarrow \}$$



## Proposed pipeline



#### Zoom on Landmarks Localization:









# Deep Q-Learning[4]:

- Discounted future return: R
  <sub>t</sub> = Σ<sup>T-t</sup><sub>τ=0</sub> γ<sup>τ</sup> R<sub>τ+t</sub>.
  Q-function: Q<sub>π</sub>(s<sub>t</sub>, a<sub>t</sub>) = E[R
  <sub>t</sub> | S<sub>t</sub> = s<sub>t</sub>, A<sub>t</sub> = a<sub>t</sub>].



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#### **Recurrent Neural Network**



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### Gaze control in the RL framework



(a) Early Fusion Net

(b) Late Fusion Net

Figure: Proposed architectures to model the Q-function. Motor position are not displayed

with:

- W: audio maps
- V: visual maps

Simulated Environment

## Simulated Environment for Training



Offline dataset

Human-pose collection

Simulated environment



- Simulated environment
- Nao robot

### Conclusion

#### • We need learning for robot gaze control!

- We propose an RL formulation.
- We show that it outperforms handcrafted strategies.
- Future works:
  - Add other cues such as people pose and gaze, speech recognition...
  - Continuous control