# Demonstrating and Learning Multimodal Socio-communicative Behaviors for HRI: Building Interactive Models from Immersive Teleoperation Data

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## Abstract

The main aim of artificial-intelligence (AI) is to provide machines with intelligence. Machine learning is now widely used to extract such intelligence from data. Collecting and modeling multimodal interactive data is thus a major issue for fostering AI for HRI. We first discuss the egg-and-chicken problem of collecting ground-truth HRI data without actually disposing of robots with mature social skills. Particular issues raised by the current multimodal end-to-end mapping frameworks are also commented. We then analyze the benefits and challenges raised by using immersive teleoperation for endowing humanoid robots with such skills. We finally argue for establishing stronger gateways between HRI and Augmented/Virtual Reality research domains.

## 1 Introduction

Endowing humanoid robots with appropriate multimodal socio-communicative and task-specific behaviors for convincing Human-Robot interaction (HRI) is a challenging issue. The classical approach consists in scaling behaviors collected during Human-Human interaction (HHI). This scheme faces two important issues: (a) the impoverished or augmented sensorimotor abilities of robots that require to map between different scores and reconsider spatio-temporal patterns; (b) the drastic change of observed human behaviors in front of avatars as compared with humans. Adapting HHI models to HRI condition is not straightforward since social rewards are also difficult to objectify.

This paper has four main sections. We first discuss the probemlm of collecting relevant HRI data in section 2. We then sketch in section 3 the benefits and challenges of using immersive teleoperation for teaching multimodal socio-communicative behaviors to humanoid robots. Section 4 introduces the Machine Learning (ML) techniques used to build behavioral models for autonomous HRI using these collected data. We finally discuss challenging issues raised by this data-driven framework.

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## 2 Collecting interactive multimodal data

Several pathways have been explored so far to collect relevant interaction data, as needed by the HRI model-building algorithms.

### 2.1 Interactive human-human data

Most interactive multimodal HRI behavioral models are built from rules picked up in the literature – found in bibles such as Kendon [2004] for gesturing or Kita [2003] for pointing – or multimodal data collected during dyadic HHI [Bilakhia *et al.*, 2015] or group interviews [Oertel *et al.*, 2014].

The collected HHI signals of the source participant are then either directly scaled to perceptuo-motor abilities of the target robot or first converted to stamped perceptuo-motor events (such as "say X to Y at time T", "look at Y at time T", etc; see the SAIBA framework below) which then trigger robot-specific motor primitives/programs (eg. repositories of gestures [Krenn and Pirker, 2004] or gesture controllers [Nguyen *et al.*, 2017b]). If re-targeting of HHI data to virtual agents is mastered, this operation is much more difficult for robots whose kinematics and dynamical behavior are much more constrained.

### 2.2 HRI multimodal data from external views

Numerous datasets have been collected to observe human behaviors when conversing with autonomous virtual agents [McKeown *et al.*, 2012] or robots [Castellano *et al.*, 2010]. If these datasets are very informative about users' expectations and deceptions, they do not actually provide data scientists with signals that can be directly exploited by endogenous sensorimotor capabilities of robots.

### 2.3 Multimodal data from the robot's point of view

Few datasets have been collected from the robot's point of view (POV) since this presupposes that the experiments at least involve a robot that passively experience"s the interaction. As an example, Azagra et al [Azagra *et al.*, 2017] dataset contains recordings of several users teaching different object classes to the robot Baxter. The robot remains still here.

### 2.4 Perception in action

Breaking out the egg-and-chicken problem of collecting ground-truth HRI data without actually disposing of robots with mature social skills is either solved by remotely controlling the robots by human pilots (so called *Wizard-of-Oz*

or *teleoperation*) or by sketchy autonomous behavioral models. So the Vernissage corpus [Jayagopi *et al.*, 2013] comprises multiple auditory, visual, and robotic system information channels from the Nao robot while interacting with two persons as an art guide in a German art museum. The robot behavior (verbal output as well as gaze and nodding) was remotely controlled by a Wizard-of-Oz.

We expect here that the pilot provides the robot with optimal behaviors given the sensory information provided to him/her via the robot's sensors. But scaling human perception – or scene analysis performed by static sensors observing HHI – to active robots is not straightforward neither.

Several experiments have shown that multimodal signal processing is impoverished when performed by a moving platform, because of egonoise, constant change of perspective ... Novoa *et al.* [2017] have shown that Word Error Rate (WER) – performed by a PR2 robot that moves its body and head while listening to sentences uttered by a fixed source – raises from $5.4\%$ to $39.5\%$ when displacement velocity is set to $0.6m/s$ and angular head rotation to $0.56rad/s$. For vision, few RGB-D datasets available today simulate robot motion through an environment [Ammirato *et al.*, 2017]. Separating impact of body motion (in particular when supporting sensors) from motions of objects and agents in the scene still remains a challenging problem. The majority of recent research employs motion information (via motor, proprioceptive or exteroceptive) to improve tracking and identification results [Rezazadegan *et al.*, 2017].

Note that current work makes use of passively collected egomotion data [Agrawal *et al.*, 2015]. It remains to be seen if better multimodal representations are learned if the agent can actively decide on how to explore its environment (i.e. active learning [Bajcsy *et al.*, 2018] or interactive perception [Bohg *et al.*, 2017]).

## 3 Immersive teleoperation of robots

Development learning [Lee *et al.*, 2007] and learning by demonstration [Argall *et al.*, 2009] get around this retargeting problem by directly providing the robot with sensorimotor experiences. If these learning frameworks have been intensively explored for tasks involving contacts with the environment – such as walking, grasping, cooking ... – the field of HRI is more recent.

### 3.1 From Wizard-of-Oz experiments to immersive teleoperation

Most Wizard-of-Oz experiments in HRI [Riek, 2012] consist in asking one or several accomplices observing the HRI scene as third parties – often via semi-transparent mirrors – to trigger pre-defined verbal (assisting speech recognition or sentence generation) or non-verbal behaviors (such as performing head nods, pointing or gazing). The task of accomplices is mainly to guide decision and to decide *When* to act. When wizards do actually monitor actuators and sensors directly via their own body motions, they are preferably called *pilots* [Goodrich *et al.*, 2013]. When they perceive the robot's environment via robot's senses, this teleoperation is *immersive*.

One advantage of immersive teleoperation (also termed *beaming* [Normand *et al.*, 2012]) is to provide robots – whose social, emotional, linguistic as well as sensory motor capabilities are impoverished compared to human ones – with a cognitive control that supposedly takes the best use of available robotic features: a human brain *embodied* in a robot. This addresses two main issues already sketched in the introduction, that motivate the increasing interest in the training of social HRI by human demonstrations:

**Scaling** The pilot performs a smart sensory motor mapping rightly scaled to the robot morphology and dynamical abilities.

**Human factors** Human behaviors are monitored in a simulated HRI. Multimodal sensorimotor data collected by the robot during these passive experiences are very close to those that will be experienced during autonomous behaviors if AI is able to reproduce high-level cognitive behaviors.

These issues are mitigated both by technical and human factors: (a) the teleoperation platform should provide the pilot with high-quality sense of self-location, ownership and agency, with minimal cognitive overload – see in particular our effort for enabling faithful gaze control [Cambuzat *et al.*, 2018; Bailly *et al.*, 2018] and our teleoperation plaform in fig. 1; (b) the pilot experience should also be augmented by the "superhuman" capabilities that are conversely expected from robots today – in particular in terms of episodic, autobiographic and encyclopedic memory. The robot may be here considered as a cyberphysical gate between virtual reality, IoT and HRI.

### 3.2 HRI and virtual reality

The area of Virtual, Augmented and Mixed Reality (VAMR) interactions between humans and robots – considering not only robots as a way to augment reality but also ways to perceive and act on cyberphysical spaces through an extended body – opens avenues for research and technology in the field of AI and HRI, by enabling humans and robots to share worlds, bodies and cognitions as well as"gameifying" manufacturing positions. Symptomatic of this trend are the recent workshops organized as satellite of key events of both communities:

**Robotics and VAM** the first International Workshop on Virtual, Augmented, and Mixed Reality for Human-Robot Interactions (VAM-HRI) was organized before HRI 2018 and the "Human in-the-loop robotic manipulation: on the influence of the human role" workshop at IROS 2017 that explored kinesthetic teaching and teleoperation.

**VAM and Robotics** The workshops "BCNAE: Body Consciousness in Natural and Artificial Environments" and "HAPTICS: Wearable and portable haptics for VR and AR" at IEEE VR 2018 explore the use of robotic systems in VAMR applications. ICRA 2018 will also host a workshop on "Robotics in Virtual Reality"

## 4 Modeling interactive multimodal behaviors

Generation of interactive multimodal behaviors of conversational agents often enriches a spoken dialog system that

Figure 1: Beaming the head, eyes, lips and hands of Nina, the GIPSA-Lab iCub robot. Left, we retarget the head, eyes, lips and hand movements of the pilot to directly control the corresponding segments of Nina; The pilot receives audiovisual feedback from Nina's eye-embedded cameras and ear-microphones in the head-mounted display. Right: the remote HRI scene, where Nina instructs subjects to move objects. © Cyril FRESILLON / GIPSA-lab / CNRS Photothèque

first manages verbal content and augments it with multimodal tags. One typical example is the SAIBA framework [Kopp *et al.*, 2006]: the Function Markup Language (FML) describes the agent's communicative functions that are further transformed into utterances tagged with micro-coordinated non-verbal behaviors described using the Behavioral Markup Language (BML). The action-perception loop was then closed by introducing a Perception Markup Language (PML) that converts input multisensory streams into stamped coverbal events [Scherer *et al.*, 2012].

The advent of deep learning models that are capable of mapping multisensory input to semantic content (audiovisual speech, multimodal gesture vs. activity recognition, paralinguistic challenges aiming at estimating affects, physical or mental states of subjects) has changed the horizon. More recently, generative models have also been developed that conversely generate images, sounds and text from semantic content.

But AI *end-to-end* models able to directly map multisensory input streams – that should be aware of output actions and attentive to expected reactions – to motor streams are still scarce. If several works have demonstrated the efficiency of graphical models and deep learning in capturing causal relations between some multimodal signals in rather specific tasks (cf. backchannel opportunities [Ruede *et al.*, 2017], head movements [Ding *et al.*, 2014], gaze [Nguyen *et al.*, 2017b] ...) multimodal machine learning [Baltrušaitis *et al.*, 2018] still faces the problem of learning joint and coordinated representations that can be permeable to the task, the environmental conditions and adapt to the desired or observed *style* of interaction (see recent attempts for speech generation [Henter *et al.*, 2017; Wang *et al.*, 2018]).

## 5 Discussion

The use of AI for learning multimodal behavioral models for HRI still raises unsolved issues.

**Interactive data vs. models** Training an AI model that map multimodal perception to action with ground truth interactive data is a delicate challenge: since the model draw part of its input cues from reactions to actions that have not yet been performed, this odd open-loop training process may lead to unsuccessful expectations or unexpected reactions when used in a veridical close-loop test situation.

**Domain of competence and social relevance** If robots are all equipped with emergency red buttons, social misfunctioning is much harder to detect and process. First of all, it's hard to record adversarial social behaviors: by definition, humans deliver socially acceptable behaviors and non observed behaviors can either be false positive (non observed but acceptable variants) or just negative samples. One possibility for collecting negative samples is to ask perceivers to rate by consensus the model's behavior [De Kok *et al.*, 2010]. Incidentally erroneous social behaviors could be then detected and penalized.

**Evaluation** Well-designed rewards and loss functions do not preclude subjective assessment that should go beyond self-assessments, behavioral measurements, psycho-physiological measures or task performance metrics [Sim and Loo, 2015]. We should be able to provide HRI engineers and designers with diagnostic tools that can identify *What* and *When* social behaviors or co-adaptation went wrong. Localized HRI events – lack of responsiveness, improper social signals ... – can in fact strongly degrade subjective evaluation of behaviors which globally improve. New evaluation methodologies should be proposed, in particular that give access to online processing of HRI by involved subjects or third parties (e.g. see [Nguyen *et al.*, 2017a]).

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