Enhancing Cobot Adaptation to Human Variability through AI Planning

Journées MAFTEC du GDR-RADIA

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Definition (Cobotics)

Cobotics is a neologism formed by the terms "colloborative" and "robotics" proposed first by Peshkin and Colgate to conceptualize the direct interaction between a robot and a human on a dedicated workstation.

- Cobots become more specialized, and engaged in jobs such as selecting, packaging, inspecting and assembling
- No longer confined to cages, more robots will require less physical space and can be more easily interconnected with other robots and employees ⇒ a hybrid human/robot manufacturing paradigm

To characterize a cobotic system, it is necessary to pay attention to :

- 1. The task that must be solved by the cobotics system
 - E.g., transporting, moving or carrying objects, assembling, etc.
- 2. The role of the human
 - E.g., operator, coworker, supervisor, bystander, subject, etc.
- 3. The human system interaction and the interaction frequency
 - E.g., physical, tactile, visual, sound, etc.
- 4. The cobot and its control system
 - E.g., robotic arms, mobile robots, exoskeletons etc.
- 5. The features of the environment
 - E.g., known, partially known, unknown













































• How adapt the cobot behavior to the human variability and not the opposite ?



- How adapt the cobot behavior to the human variability and not the opposite?
- Why is crucial?
 - Cobot behaviors adaptation is important to reduce cognitive load, musculoskeletal disorders, and increase social acceptance



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- Why is crucial?
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- How define human variability?



• What are the approaches to deal with human variability?

How define Human Variability?

Approach 1 : Cobot Programming by Demonstration (PbD)

Approach 2 : Adapting the tasks execution order of the cobot to the human $% \left({{{\rm{D}}_{{\rm{D}}}}_{{\rm{D}}}} \right)$

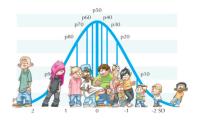
Approach 3 : Anticipating the operator's actions

How define Human Variability?

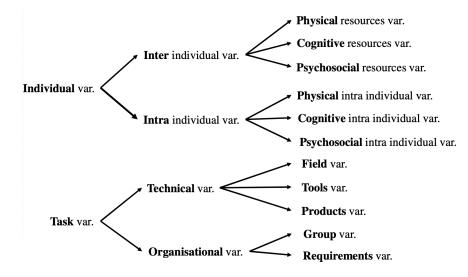
Definition (Human Variability)

Human variability is defined as the variation in average human behavior defined by a norm.

- Human variability is a challenging problem due to its unpredictable nature
- Accommodating Human variability requires answering two cardinal questions :
 - 1. How to detect and quantify human variability?
 - 2. How to adapt to human variability?



Human Variability : Classification



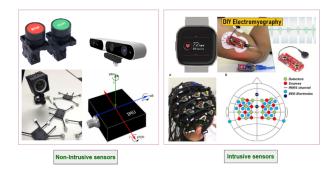
Human Variability Detection Complexity

- Physical Human Variability detection is simple and straight forward by using the proper sensors
- Cognitive Human Variability detection is more arduous, and in many occasions extrapolated indirectly from human behavior, examples are : *emotions* and *mental state*



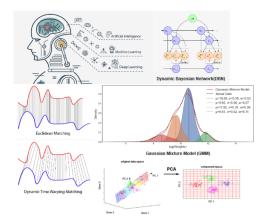
Human Variability Detection

- Two categories of sensors have been used in the literature :
 - 1. Non-Intrusive Sensors : RGB camera, RGBD camera, thermal camera, motion capture, and push buttons.
 - Intrusive sensors : smartwatch, IMU, ECG, EEG, EDA, EMG, and Force sensors.



Human Variability Detection Techniques

• Raw signal, in many cases, has to be processed using various techniques to infer the desired hight level knowledge to characterize human variability based on ML techniques



Human Variability Adaptation Complexity

- The adaptation to the human variability can be :
 - Feasible : the robot adapts its behavior in correspondence to the human
 - Urgent, e.g., dangerous or risky situation detected
 - Non-Urgent, e.g., adjusting the number of part to give to the operator
 - Non-Feasible : variability in the human emotions (sadness/depression)



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• Main issue : How do we know if the adaptation proposed by the cobot is suitable for the operator ?

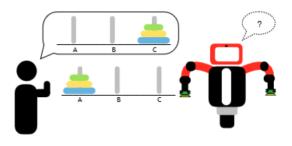
Human Variability Adaptation

- Motion Trajectory
- Motion Speed
- Actions Sequence
- Task Allocation
- Interaction





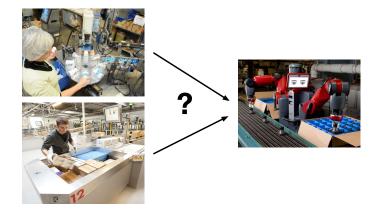
- Variety of techniques are used in the literature to produce the autonomous intelligent behavior :
 - Logic Geometric Programming (LGP)
 - Automated Planning
 - Deep Learning (RL, IRL, Q-Learning, etc.)
 - AND/OR Graph
 - FSM
 - Game Theory



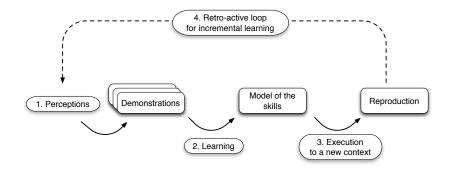
- Detection Metrics
 - Discrete Time Warping (DTW) Distance
 - Accuracy
 - Sensitivity
 - Specificity
- Adaptation Metrics
 - Times (execution, idle, planning, etc.)
 - Accuracy
 - Errors
 - Ergonomic (REBA, RULA, etc.)
 - Cognitive Load
 - Gestures



Approach 1 : Cobot Programming by Demonstration (PbD) How can an operator without programming knowledge program by kinesthetic manipulations and control by objective a cobot to perform tasks in an industrial environment?



PbD Principle Overview



Problem Statement

Create a framework that allows human operators to :

- 1. Teach skill to a cobot in a comprehensive automated planning representation
- 2. Enable a cobot to use the learned actions models to be controlled with a goal oriented approach based on automated planning technique

• Hypothesis :

 \rightarrow User without any programming knowledge should be able to teach actions to fulfill the task

Example (Skill pick-up)

Experimental Context

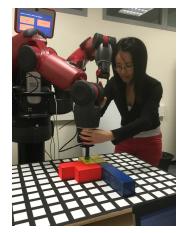
- A classical manipulation task in a manufacturing context
- Skills to teach : pick-up, move, put-down, rotate, etc.





$\Leftarrow \mathsf{vacuum} \ \mathsf{gripper}$

- How a cobot learns a new skill from the user by demonstration
 - **Step 1** : The cobot records the movement and the properties of the world that are modified, e.g. the new location of a block
 - Step 2 : The cobot induces a representation of the skill based on planning representation and validates the skill's semantic with the human operator
 - Step 3 : The cobot replays the skill to check the learning skill induced
 - if Baxter's replay fails it goes back to step 1



- A complex integrated development environment :
 - 1. the cobot is an integral part of the interface
 - 2. A more classical interface with a language (PDDL) and a simulated representation of the cobot
- Collaboration with ergonomists and human-machine interface specialists

Check world conditions	\searrow
Action type	r 🔪 📈
Check world conditions	
Specify landmark properties required for this	
step.	
Main landmark GENERATE	
Obj 6 v	
	\sim
VIEW	
Variance	\sim
Match size 0.0750	
Absolute properties Position Orientation	
v Variance v Variance	
x Variance x Variance 0.73627: 0.0359 0.61782(0.0750)	00100015
0.73627.0.0359	
y Variance y Variance	
0.03510:0.0477 0.40090 0.0750	
z Variance z Variance	
0.77355 0.0750 -89.9343 0.0750	
Relative position	
Reference landmark	
Obj 2 ~	

...

a-robot-programming-framework-for-cobotic-environments.mp4

A Robot Programming Framework in Cobotic Environments

Ying Siu Liang, Damien Pellier, Humbert Fiorino, Sylvie Pesty Laboratoire d'Informatique de Grenoble (LIG)

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1. [Liang et al., 2019, Liang et al., 2021]

- Many repetitive tasks consist of stacking and packaging manufactured goods
- How can we simply specify by demonstration to the cobot how to carry out such packaging?
- Given a D demonstration set, how infer :
 - 1. the distance between objects Δ_m and Δ_n
 - 2. the specification of the objective (the size of the grid) $s = m \times n$

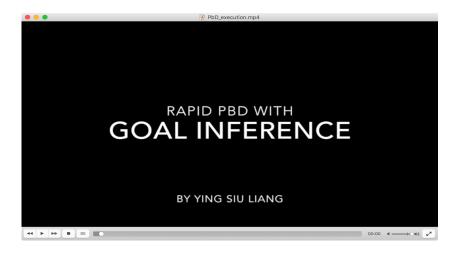




- The inference is based on a probabilistic calculation updated with each new demonstration
- The visualization is carried out via an interface
- The evaluation
 - use of Amazon Mechanical Turk's benchmark
 - 25 different product classes
 - 25 specifications for different purposes
 - The approach covers 90% of indutrial cases







2. [Liang et al.,]

Approach 2 : Adapting the tasks execution order of the cobot to the human

- The objective is to
 - Simulate a collaborative industrial assembly task with Duplo blocks



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 - Simulate a collaborative industrial assembly task with Duplo blocks
- to show that cobot :
 - 1. increases the task performance compared a human human based line
 - 2. reduces the cognitive load of the operator
 - 3. reduces the musculoskeletal disorders, i.e, reduce the number of gestures
 - 4. reduces risk situations for the operator

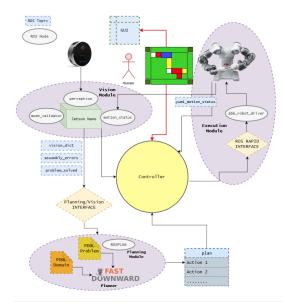


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- The assumptions are :
 - 1. Operators can interact with the cobot through the user interface
 - 2. Operators and robot share the same space and task
 - 3. Operators must not be constrained by an arbitrary order to accomplish the task

A ROS Cobotic Architecture



Vision Module

• The Vision Module utilizes the images from the RGBD/Lidar camera to produce a 3D discrete representation of the environment at 2Hz frequency





Intel Realsense L515

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Discrete Representation

Vision Module

• The Vision Module utilizes the images from the RGBD/Lidar camera to produce a 3D discrete representation of the environment at 2Hz frequency





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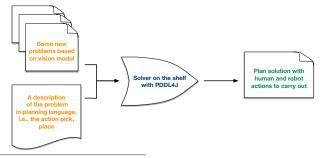
Discrete Representation

• Discrete representation are positions X, Y, Z and color defined in logic representation that can be used the AI Planing decision module

```
Example (Discrete representation)
(on-table yellow_cube1 2 4), (on red_cube1 yellow_cube1 2 4),
(on-table bar_red1 7 2), etc.
```

AI Planning Decision Module

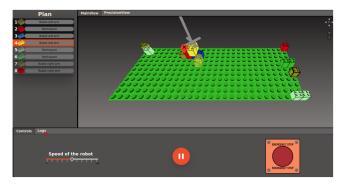
- The Decision-Making Module generates intelligent behavior (task allocation and order) according to information from the vision module
- It takes as input the information from the vision module and the assembly task to carry out and produce a sequence of actions that have to be executed to accomplish the task
- It is based on AI Planning system PDDL4J³



3. http://pddl4j.imag.fr/ - [Pellier and Fiorino, 2018]

Human Robot Interaction

- The user interface improves the 3D visualization of the actions plan by cobot and its perception
- Allows the operator to modify
 - the assignment of tasks between human and cobot
 - the robot speed
 - the operator's dominant arm



A first experience : HHI vs. HRI⁴



Laboratoire d'Informatique de Grenoble





Adapting Cobot behavior to Human Task Variability for Assembly Tasks



Belal HMEDAN, Dorilys KILGUS, Humbert FIORINO, Aurélie LANDRY, Damien PELLIER

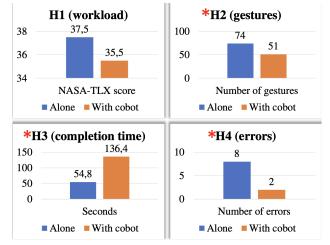
Email: firstName.secondName@univ-grenoble-alpes.fr

Université Grenoble Alpes Bâtiment IMAG - 700 avenue Centrale Domaine Universitaire - 38401 St Martin d'Hères

4. [Hmedan et al., 2022, Fournier et al., 2022]

A first experience : HHI vs. HRI

• Comparison HHI vs. HRI done with 60 participants on the same set of assembly tasks



A second experience : Adding risky actions for human⁵

• Manipulate red blocks is now dangerous and using gloves is mandatory

EFFECTS OF DYNAMIC PLANNING ON ADAPTABILITY OF A COBOTIC SYSTEM TO HUMAN CONSTRAINTS FOR A COOPERATIVE ASSEMBLY TASK

BEATRICE PIRAS

SUPERVISORS: DAMIEN PELLIER, HUMBERT FIORINO

TEAM: MARVIN

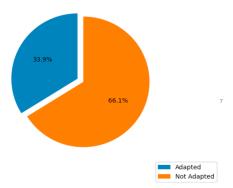
MASTER 2 RESEARCH INTERNSHIP- LIG LABS GRENOBLE

GRENOBLE UGA-INP ENSIMAG

5. Work done in colaboration of Aurélie Landry, Beatrice Piras, Humbert Fiorino and Etienne Fournier

A second experience : Adding risky action for human

• Comparison Cobot with adapated behavior or without on 18 participants

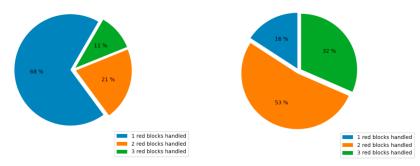


Number of errors made by Adapted

A second experience : Adding risky action for human

% of participants handling # red blocks. Adapted

• Comparison Cobot with adapated behavior or without on 18 participants



% of participants handling # red blocks. Non adapted

- The various dimensions of human variability remain to be explored
- There are two main locks :
 - 1. Perceiving and interpreting human variability
 - 2. Determining the right fit for a particular human beyond ergonomic standards
- Future Work
 - Study the impact of age on the performance of our reference assembly task

Approach 3 : Anticipating the operator's actions

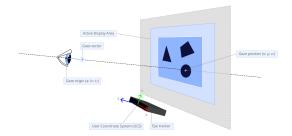
- The objective is to design a cobotic assistance system able to infer human intentions in real time from perceptual-gestural information, in order to better select, synchronize and coordinate tasks distributed between a human and a robot
- How ?
 - 1. By getting perceptual-gestural information using eye tracking techniques
 - 2. By learning a model of the operator from the perceptual-gestural information
 - 3. By integrating this information in the decision module of the cobot

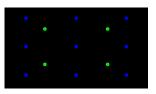
^{6.} Work done in collaboration with Maxence Grand and Francis Jambon (LIG)

Eye Tracking Principle



Eye Tracking Principle





Stationary vs. Mobile Eye Trackers





Stationary

Pros

- Not invasive
- Good Precision

Cons

- Sensitive to head movements
- Not appropriate for physical workspace

Mobile

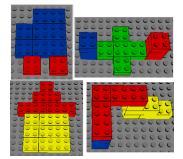
Pros

- Robust to head movement
- Appropriate for physical workspace

Cons

- Dynamic world mapping
- Invasive
- Low Precision

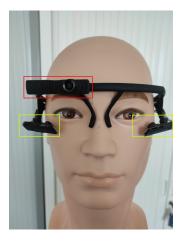
- Study and compare the performance of stationary and mobile eye trackers in a physical workspace
- Eye tracking both on the workplace and the instruction screen



Mobile Eye Tracker

- Pupil Lab
- Dynamic world mapping needs markers
- Markers detection
 - Size and position of the human operator
 - Lighting
 - Materials
 - Position and orientation



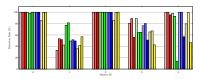


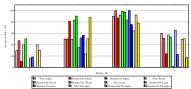
Mobile Eye Tracker - Markers



Compare marker detection levels according to :

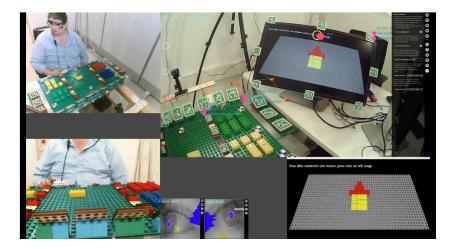
- Material : Paper (Inkjet/Laser), Wood, Plexiglas
- Orientation : Flat, 30°, 45°
- Position



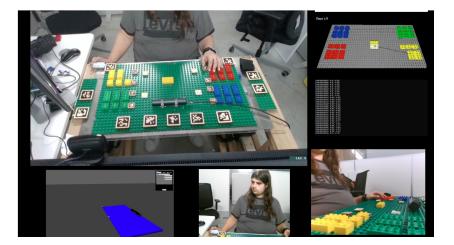


Mobile Eye Tracker – Workplace





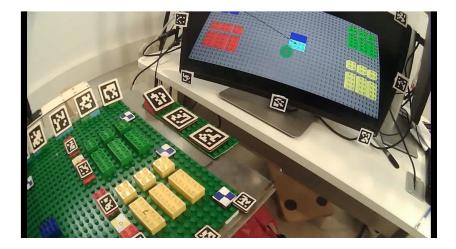
Stationary Eye Tracker



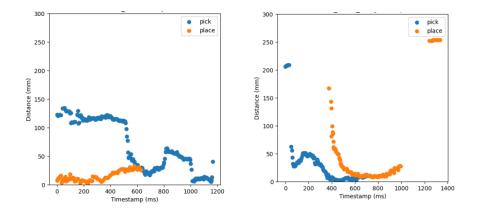
• Experiment are in progress to get the learning corpus

- 90 participants
- 2 training assemblies, 6 assemblies for experimentation
- Assemblies are 2D and 3D
- 4 tested conditions : standing or sitting vs. fixed (Fovio) or mobile (Tobii) eye tracker
- A clear semantic for action pick and place
 - pick : time when the block is touched by the operator
 - place : time when the block is released by the operator
- Experimental protocol validated by the Grenoble Alpes Research Ethics Committee - CERGA

Experiment - Action Semantic



Preliminary results : Picking & Placing Strategies



Eye Tracking Perspectives for Cobot Adapation

- Work in progress with promising preliminary results
 - 1. Work areas can be detected with a high degree of certainty whether the operator is standing or seated
 - 2. Eyes tracking techniques are sufficient to detect objects 2 cm in size, but it's more complicated if object are smaller
 - 3. Ability to detect operator profiles
 - 4. Ability to predict the operator's next action at least 500ms before execution
 - 5. Ability to detect operator errors, e.g., blocking in the wrong place or dropping

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• Future work

- 1. Learning a model with ML techniques
- Integrate the model into the cobot's decision module and experimentally explore the impact of different adaptations on cobot human task performance.

Conclusion



- 1. Collaborative Robotics " cobotics" is coming ... but there are many challenges
- 2. Dealing with the human variabilities is a key lock
- 3. Al Planning can be a great technique to deal with human variabilities
- 4. Lack of reference benchmarks
- 5. Interdisciplinary research that must be carried out over the long term

Questions?

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