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TOWARD INNOVATIONS

NAZARBAYEV UNIVERSITY

Autonomous Object Recognition System for Shared Autonomy Control of an Assistive Robotic Arm

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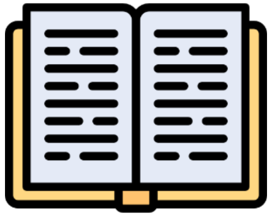
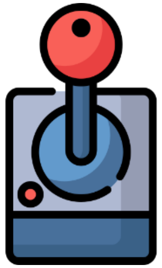
Outline

Introduction,
Problem Statement

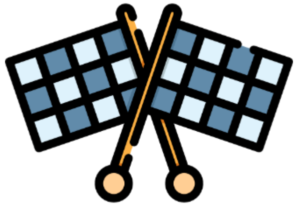


Background research,
Methodology



Manual Control
mode

Object Recognition and
Autonomous grasping



Conclusion and
Future work

1 billion people have special needs (WHO)



<u>300 million</u> people possess severe disabilities

More old people → more people with special needs

Source: World Report on Disability, World Health Organization (2011)
Photo credits: https://www.pexels.com

4.6% of men and 3.4% of women are suffering from disabilities

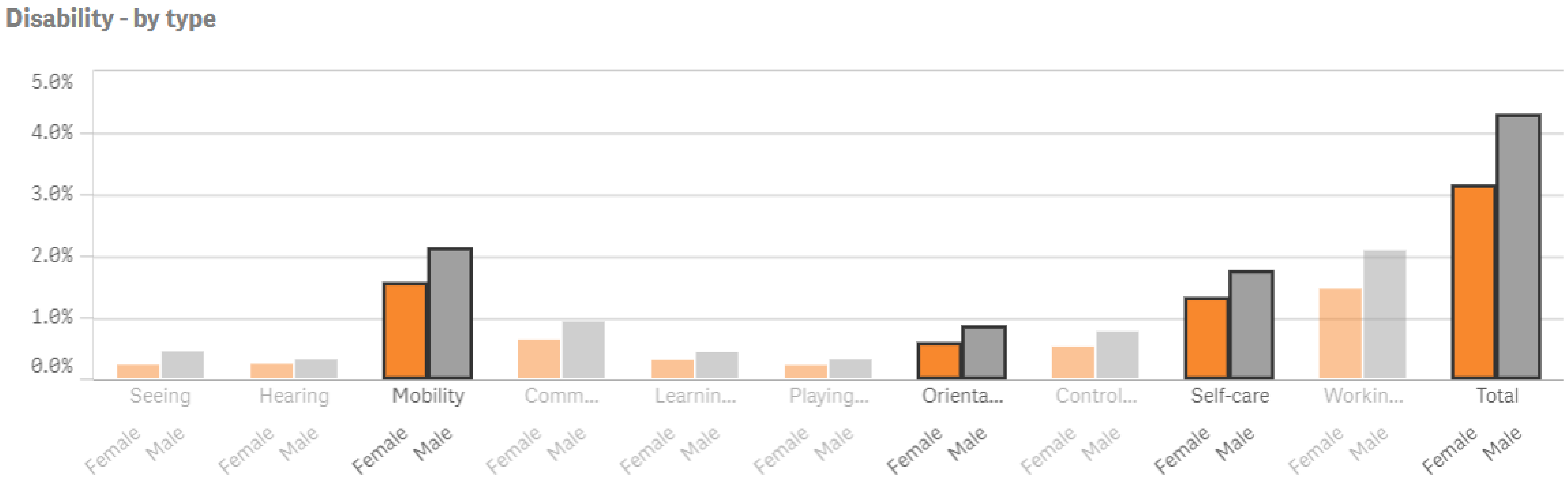


Figure 1. United Nation Disability Statistics (2018) for Kazakhstan

Source: UN Disability statistics

Solution - autonomous assistive robots

Fig 2. Kinova Jaco^2
Assistive Robotic Arm

6 DOF

Weight: 5.2 kg

Payload: 1.6 kg

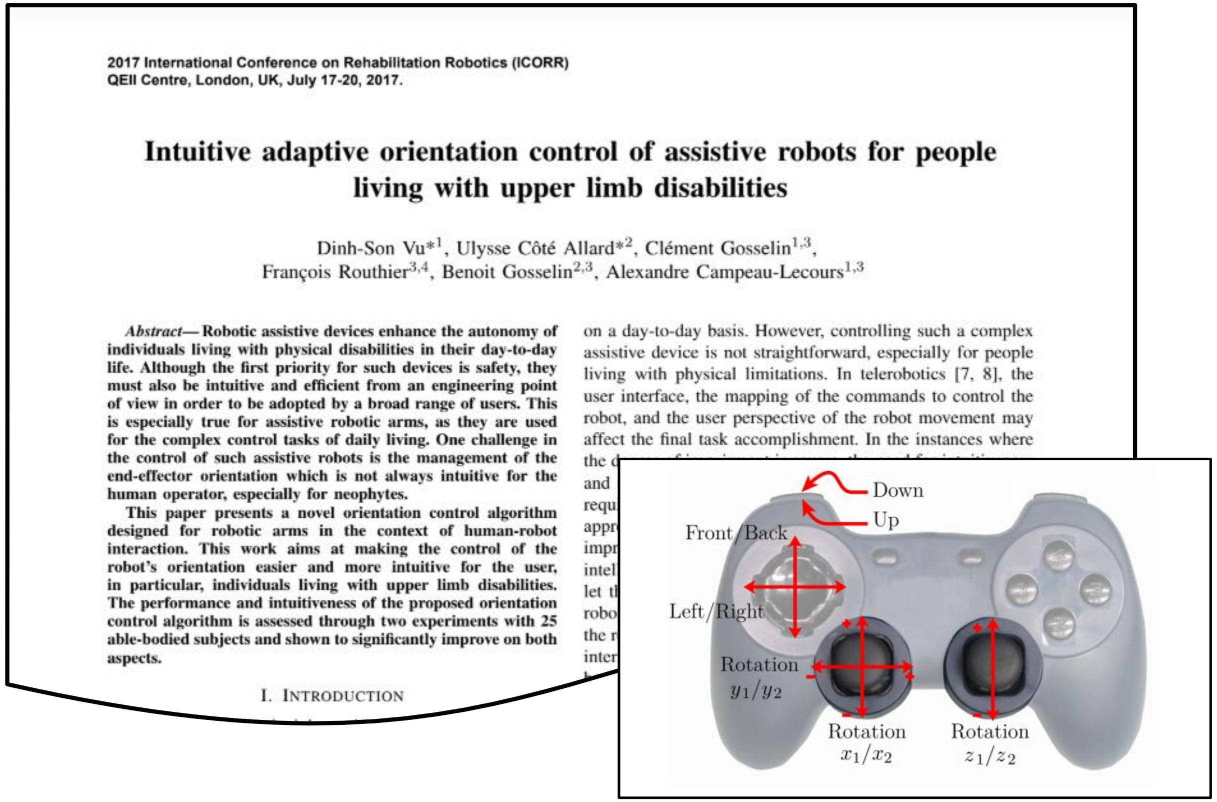
Wrist angle: 60°

Power consumption: 25W

Available at NU facilities

Background Research. Joystick Control

- Intuitive adaptive orientation control proposed by Vu *et al.* *(2017)*
- *"…the default control of the end-effector (hand) orientation has been reported as not intuitive and difficult to understand and thus, poorly suited for human-robot interaction"*
- Proposed control algorithm is not suitable since ordinary gamepad is used



2017 International Conference on Rehabilitation Robotics (ICORR)
QEII Centre, London, UK, July 17-20, 2017.

Intuitive adaptive orientation control of assistive robots for people living with upper limb disabilities

Dinh-Son Vu*[1], Ulysse Côté Allard*[2], Clément Gosselin[1,3], François Routhier[3,4], Benoit Gosselin[2,3], Alexandre Campeau-Lecours[1,3]

Abstract— **Robotic assistive devices enhance the autonomy of individuals living with physical disabilities in their day-to-day life. Although the first priority for such devices is safety, they must also be intuitive and efficient from an engineering point of view in order to be adopted by a broad range of users. This is especially true for assistive robotic arms, as they are used for the complex control tasks of daily living. One challenge in the control of such assistive robots is the management of the end-effector orientation which is not always intuitive for the human operator, especially for neophytes.**

This paper presents a novel orientation control algorithm designed for robotic arms in the context of human-robot interaction. This work aims at making the control of the robot's orientation easier and more intuitive for the user, in particular, individuals living with upper limb disabilities. The performance and intuitiveness of the proposed orientation control algorithm is assessed through two experiments with 25 able-bodied subjects and shown to significantly improve on both aspects.

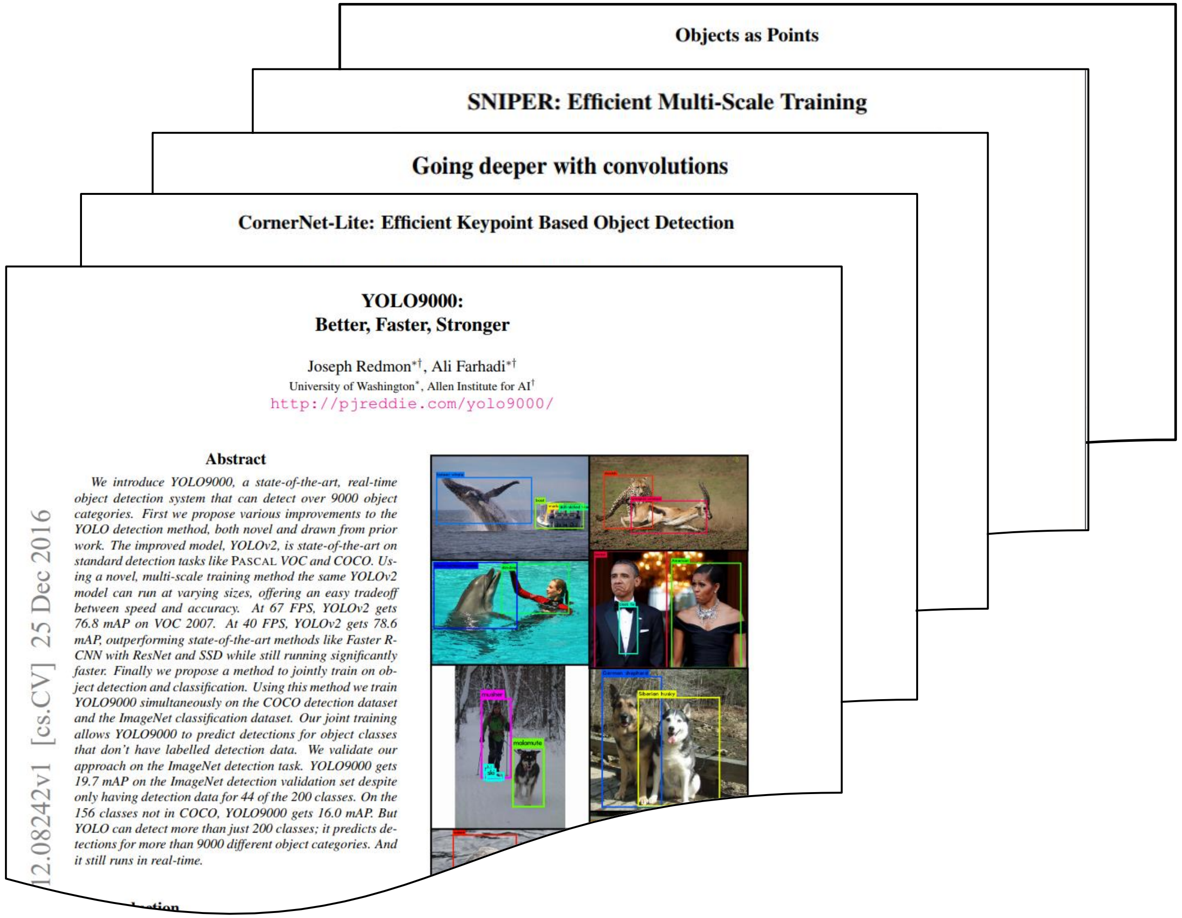
I. Introduction

on a day-to-day basis. However, controlling such a complex assistive device is not straightforward, especially for people living with physical limitations. In telerobotics [7, 8], the user interface, the mapping of the commands to control the robot, and the user perspective of the robot movement may affect the final task accomplishment. In the instances where

Fig 3. Control map proposed by Vu *et al.*

Background Research. Object Detection

- SNIPER – state-of-art 2D object detection system, however, is very slow (Singh *et al. (2018)*)
- DOPE – state-of-art 3D object detection model (Tremblay *et al.* (2018)), small dataset
- YOLOv3 – most popular object detection algorithm proposed by Redmon *et al. (2018)*
- CornerNet – model faster than YOLO, proposed by Law *et al. (April 18, 2019)*
- CenterNet – model, faster and more accurate than YOLO proposed by Zhou et al. (April 25, 2019)



Methodology of Shared Autonomy Control for Robotic Arm

Graduation Project

Megatron Joystick

Intel RealSense D435
RGB-D sensor

Manual Mode

Spherical Coordinates control by joystick

Automatic Mode

Object recognition and autonomous movement towards the object

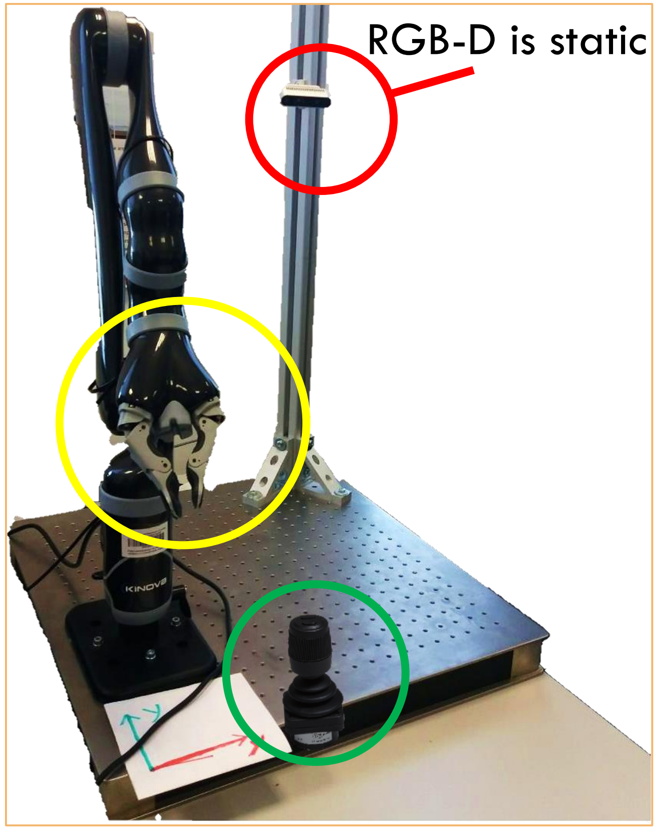
Semi-automatic Mode

Human Intention prediction based on HMM

Object Grasping (Bottle)

Overall Project Setup

Previous Setup #1



Previous Setup #2

Current Setup

Manual Control - Overview

TRY100 Megatron
3-axis joystick with two buttons

Mode 1: moving the end-effector in the space

Mode 2: keeping the position of the end-effector, rotating it about a point

Mode 3: end-effector's fingers are controlled

Modes are switched through the buttons

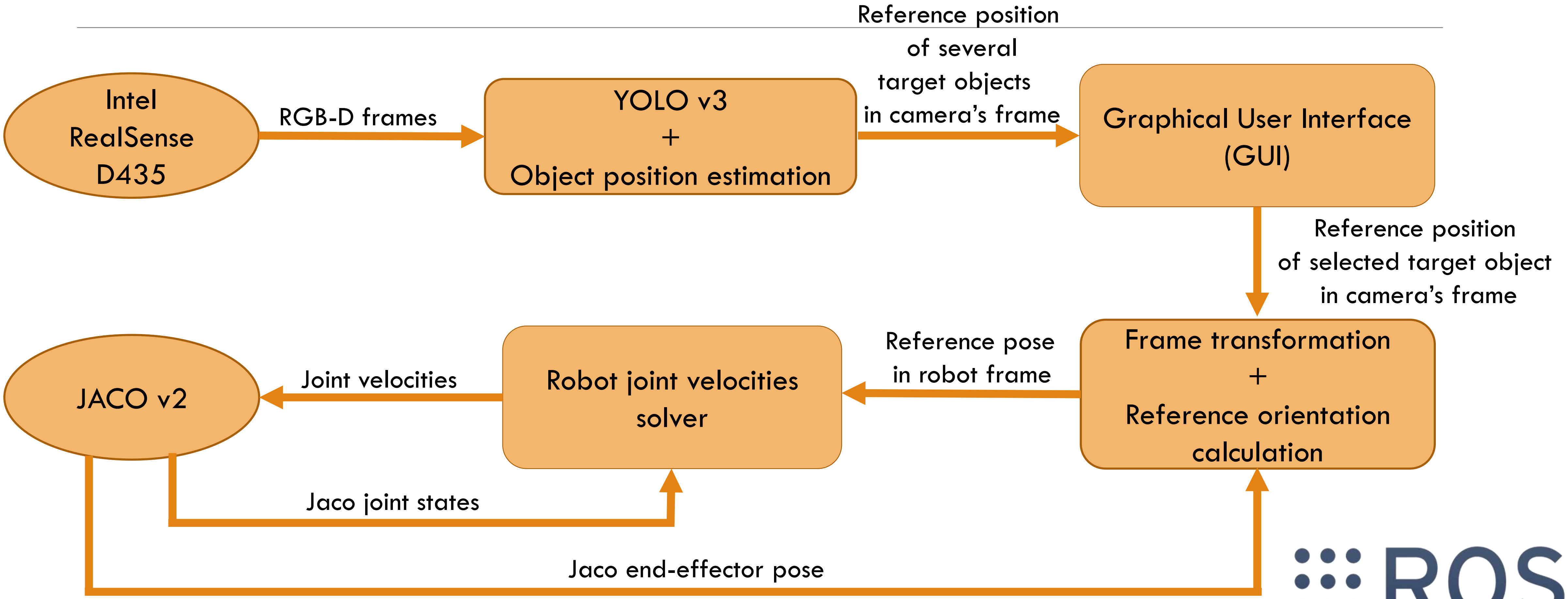
Spatial constraints are set to avoid hitting objects nearby (Computer, walls, etc)

Manual Control – making more intuitive

Control based on Cartesian coordinates (Default)
<u>COUNTER-INTUITIVE</u>

Control based on Spherical Coordinates (Proposed)
<u>INTUITIVE</u>

Control Flowchart of Autonomous Control Mode Implementation



Object recognition – Model Selection

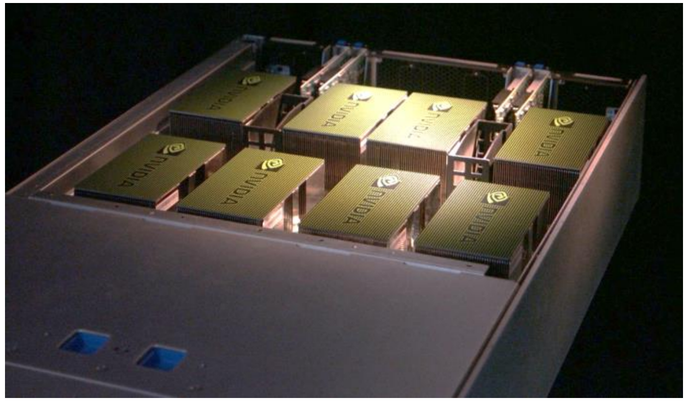
PoseCNN - trained on YCB dataset - over fitted

DOPE – trained on FAT dataset - over fitted

Dense Fusion – trained on YCB - over fitted

YOLOv3 – trained on COCO 2017

CenterNet – trained on COCO 2017



NVIDIA DGX-1 Deep Learning cluster – 8 Tesla V100 GPUs (available at NURIS)

PyTorch

TensorFlow

Object Recognition – Position Estimation

- Position is calculated by **new method** of overlaying of the depth image and RGB image
- Center point and boundary box are estimated
- Distance from the camera to the object center box is calculated then is transformed to the robot's frame

Distance estimation and object recognition

RGB and Depth Image Mapping. Experiment

- Two RGB systems were tested on proposed mapping approach
- Both systems have showed stable object detection and consequent motion

Model	Backbone	Input size	Processing time	Reported AP
YOLO v3	Darknet-53	416x416	40 ms	31.0
CenterNet	DLA-34	511x511	60 ms	37.4

Table I. Comparison table for YOLOv3 and CenterNet

Autonomous Grasping. Relative Transformation

- Three reference frames:

{C} – camera's frame
{R} – robot's frame
{G} – gripper's frame (not shown)

- Four point calibration is performed

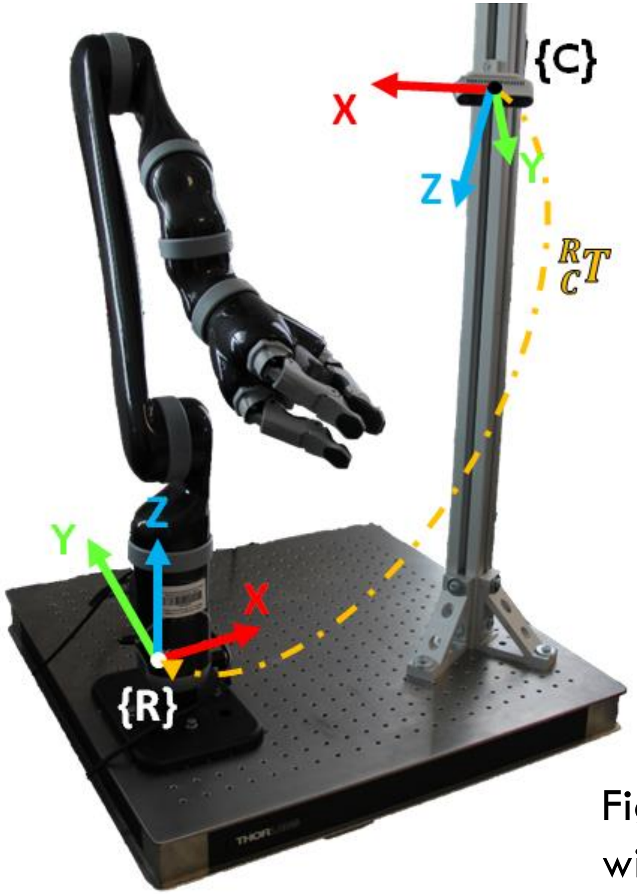
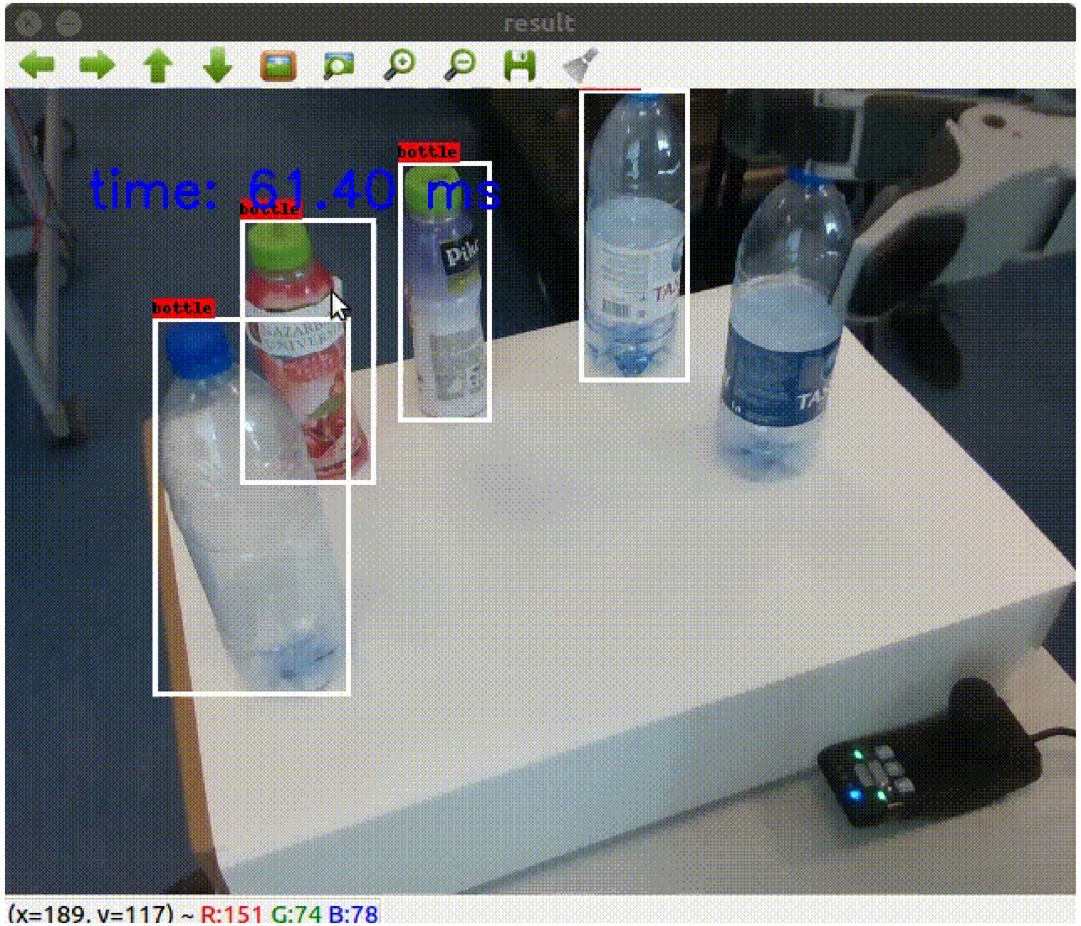


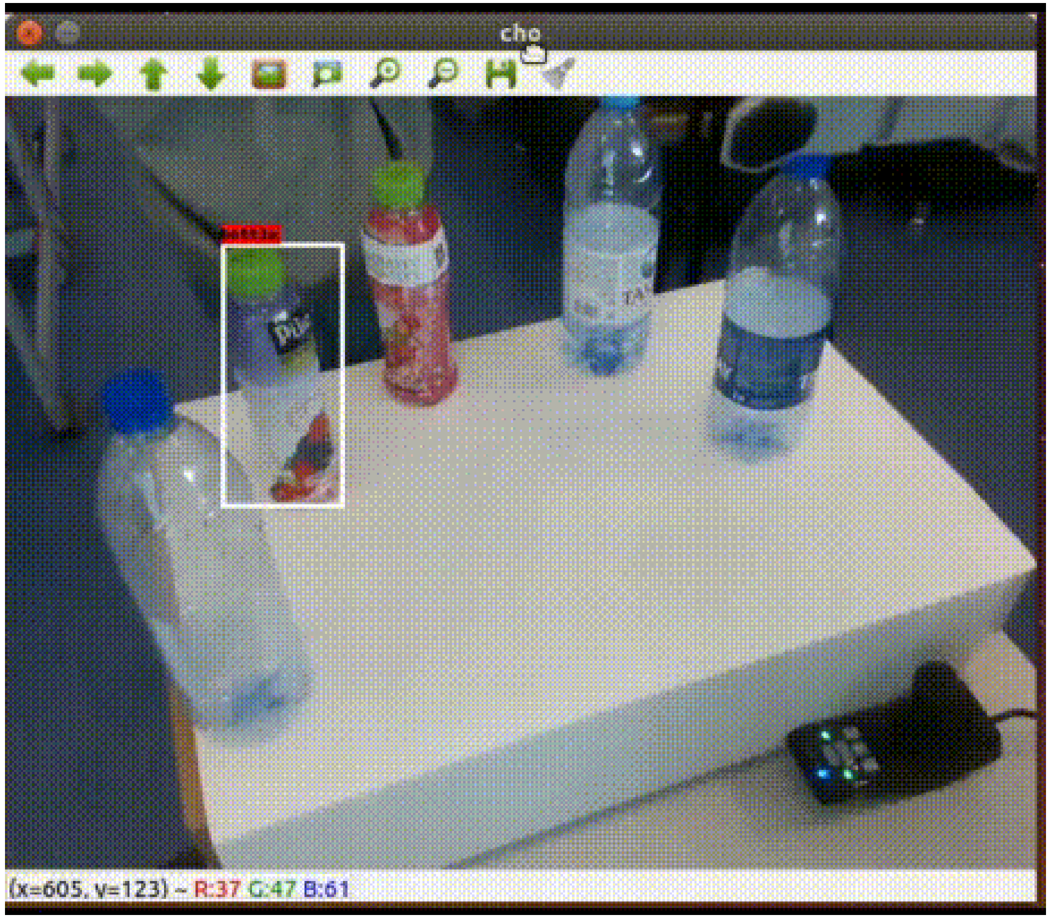
Fig 3. Experimental setup
with defined reference frames

Autonomous Grasping – Occurred Problems



- <u>Occlusion</u> – caused by robot arm
- <u>Solved:</u> In 15 cm range ROS “subscriber” does not receive messages

Autonomous Grasping – Occurred Problems



- <u>"Jumping" of bounding box</u> – caused by occlusion and accuracy of the models
- <u>Solved</u>:
  - Accuracy mistake – by applying centroid
  - By sorting objects in each frame

Autonomous Grasping

Autonomous Grasping

Conclusion

- ✓ More intuitive manual control mode was developed
- ✓ New approach in robotics for position estimation was introduced
- ✓ Experiments on RGB models, YOLOv3 and CenterNet, were performed
- ✓ The robot grasps target objects autonomously
- ✓ The worked performed in Git version-control system
- ✓ It is planned to expand the project to include shared autonomy

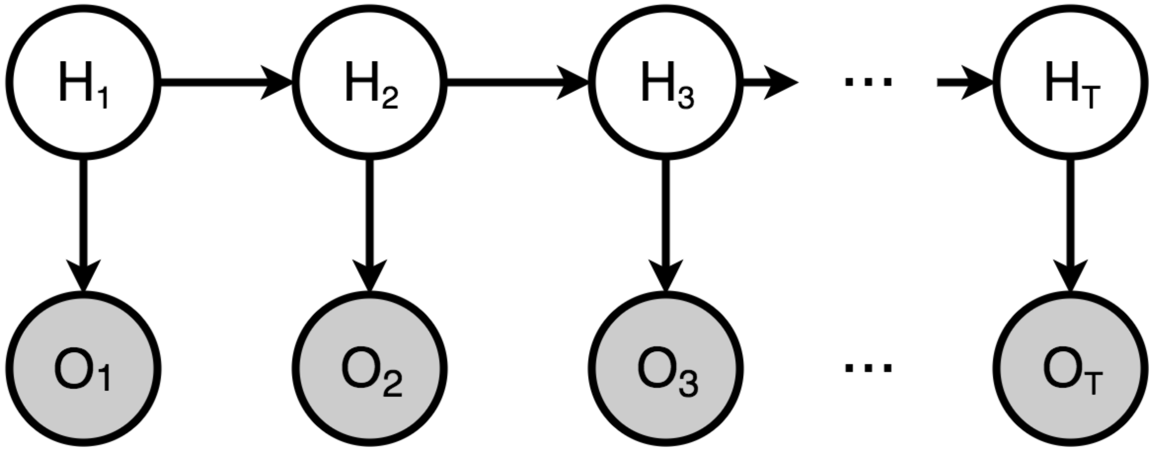
Semi-automatic mode – shared autonomy

Completely autonomous system cannot be very intelligent and may discourage the patients and users

Human intention prediction system should be implemented

There are systems where human intention predicted by Hidden Markov model (Khokar *et al*)

Pomegranate Python package could be used to design HMM



Hidden Markov Model Schematic

Source: Khokar, Karan, Redwan Alqasemi, Sudeep Sarkar, Kyle Reed, and Rajiv Dubey. "A novel telerobotic method for human-in-the-loop assisted grasping based on intentionrecognition." In Robotics and Automation (ICRA), 2014 IEEE International Conference , pp. 4762-4769. IEEE, 2014.