



ROS Wrapper for Real-Time Multi-Person Pose Estimation with a Single Camera

Autor

Miguel Arduengo
Sven Jens Jorgensen

Supervisors

Kimberly Hambuchen
Luis Sentis
Francesc Moreno
Guillem Alenyà

July 2017



Contents

1	Introduction	4
2	Pose Estimation (State-of-the-Art)	6
3	General Architecture of the System	12
3.1	Hardware Architecture	14
3.2	Software Architecture	16
3.2.1	Robot Operating System (ROS)	16
3.2.2	C++ libraries	19
3.2.3	OpenPose	19
3.2.4	Packages: usb_cam, iai_kinect2, tf2, RViz and OpenPose_ROS	20
4	Multi-Person Pose Estimation	21
4.1	OpenPose (Convolutional Pose Machine)	21
4.2	ROS Wrapper for OpenPose	25
4.3	Skeleton-3d Package	30
5	Results	36
5.1	Human pose detection and visualization	36
5.2	Processing speed	41
5.3	Limitations	41
6	User Guide	44
6.1	Installing OpenPose ROS Wrapper	44
6.2	Running the OpenPose ROS Wrapper and the 3d Pose Extractor	45
6.2.1	2d Detection Module	45
6.2.2	3d Detection Module	48
7	Conclusions	55

For robots to be deployable in human occupied environments, the robots must have human-awareness and generate human-aware behaviors and policies. Thus, a human-aware robot must be capable of (1) human detection and tracking, (2) human action or intent recognition and (3) intelligent, human-aware action generation. This work presents a methodology for the first stated capability. Person detection and pose estimation are necessary capabilities for robot engaging in side-by-side collaboration with a human.

Several software packages have been developed for human pose estimation from RGB images or depth images, being the modules that use Convolutional Neural Networks the most promising ones. For the incorporation of these software packages in robotic applications in real time, it is fundamental to use them from ROS.

In general, the modules for $2d$ pose estimation from simple images are the most developed and there even are some quite effective open source packages that have reached a certain popularity. A real-time method to estimate $2d$ multi-person pose efficiently is the so-called OpenPose, developed at Robotics Institute of Carnegie Mellon University. OpenPose is a library for real-time multi-person keypoint detection and multi-threading, written in C++ using OpenCV and Caffe, authored by G. Hidalgo, Z. Cao, T. Simon, S.E. Wei, H. Joo and Y. Sheikh. OpenPose represents a real-time system to jointly detect human body, hand and facial keypoints (130 keypoints in total) on single images. In addition, the system computational performance on body keypoint estimation is invariant to the number of people detected in the image [7, 23]. OpenPose has been converted into popular software and packages for ROS have been very recently developed by CTS Robotics Group of Eindhoven University of Technology, K. Zhang of Carnegie Mellon University and S.J.M. Jorgensen of University of Texas at Austin.

Considering the availability of hardware (webcam and Kinect One) to carry out this work, we have considered the implementation of a ROS package that would allow the estimation of $2d$ pose from simple RGB images, for which we have introduced a ROS wrapper that automatically recovers the pose of several people from a single camera using OpenPose. Additionally, a ROS node to obtain $3d$ pose estimation from the initial $2d$ pose estimation when a depth image is synchronized with the RGB image (RGB-D image, such as with a Kinect camera) has been developed. This aim is attained projecting the $2d$ pose estimation onto the point-cloud of the depth image.

In this way we can have a software package adaptable to different hardware, that will allow us to obtain $2d$ or $3d$ pose estimation depending on the type of available images [2].

The analysis of the processing time shows satisfactory results, since this time is less than the minimum required for a robot to do a task involving human-robot interaction. The most relevant limitation in the use of the implemented software is due to fact that the package for $3d$ detections cannot deal with occlusions. Also, We have made a user guide of the ROS packages implemented, to facilitate their use.

1 Introduction

A human-aware robot must be capable of human detection and tracking. Thus, person detection is a necessary capability for a robot engaging in side-by-side collaboration with a human. The problem of the recognition of postures involves two areas: computer vision and automatic learning (machine learning). A real-time method to estimate multi-person pose efficiently is the so-called OpenPose, developed at Robotics Institute of Carnegie Mellon University.

OpenPose is a library for real-time multi-person keypoint detection and multi-threading written in C++ using OpenCV and Caffe (<https://github.com/CMU-Perceptual-Computing-Lab/openpose>). OpenPose represents a real-time system to jointly detect human body, hand and facial keypoints (130 keypoints in total) on single images. In addition, the system computational performance on body keypoint estimation is invariant to the number of detected people in the image .

OpenPose has been converted into popular software and packages for ROS have been very recently developed.

In this work, we introduce a ROS wrapper that automatically recovers $2d$ multi-person pose from a single camera using OpenPose [2].

Additionally we have developed a ROS node that finds a $3d$ pose estimation from the initial $2d$ pose estimation using a depth image synchronized with the RGB image (for instance, both images can be obtained simultaneously with the Kinect camera) and projecting the $2d$ pose estimation onto the point-cloud of the depth image [2].

Thus, the aim of this work is to implement an open C++ software application working on the Robotic Operating System (ROS) that obtains a pose estimation ($2d$ or $3d$, depending on the cases) from a single camera (a $2d$ image obtained with an RGB camera or a $3d$ image -RGB-D- obtained with a depth camera) [2].

The program will be designed so that it can be used in a larger project. Thus, the data outputs should be easily readable from another ROS program.

The general scheme that describes the objective of this work is shown in Figure 1.

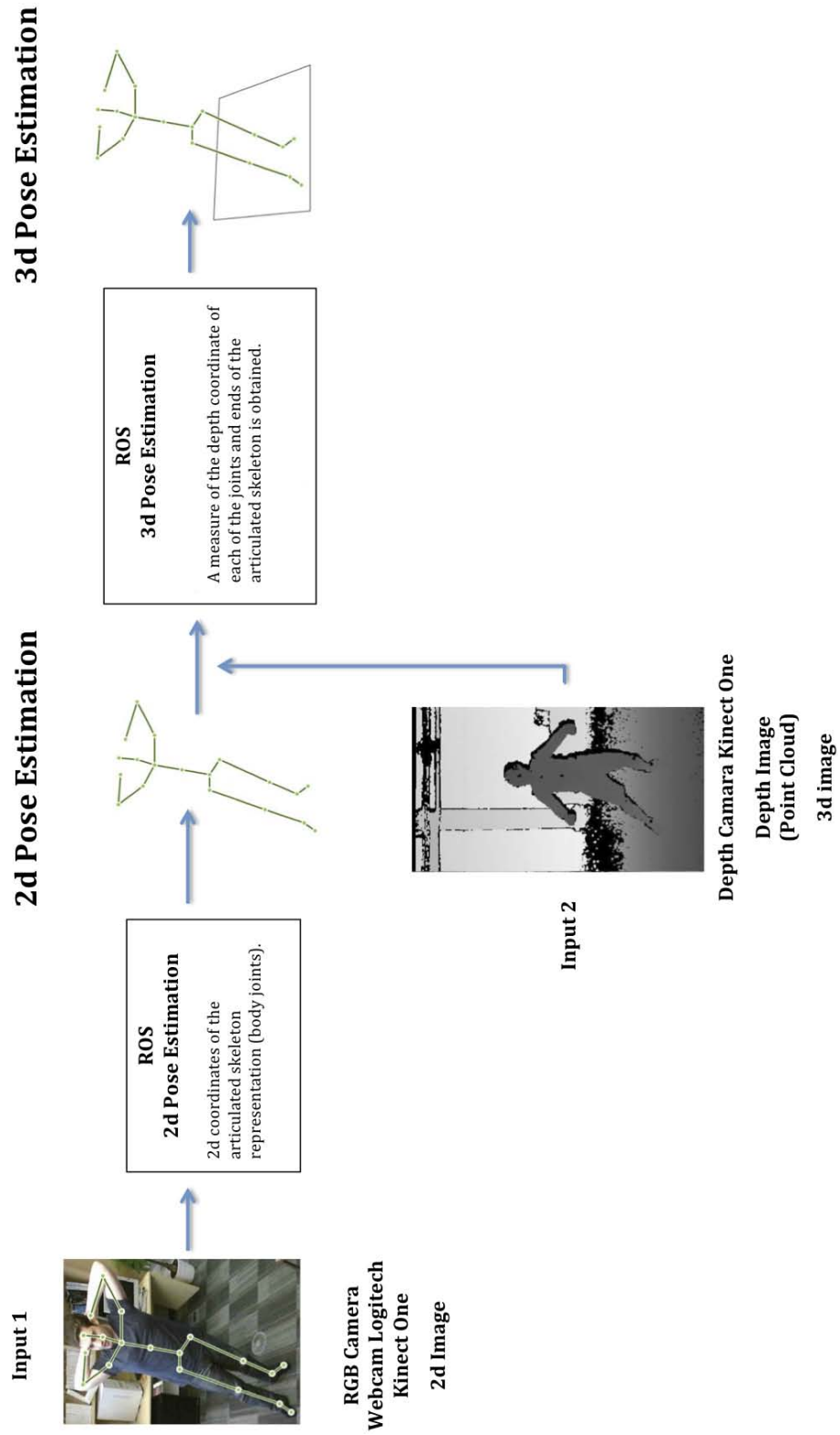


Figure 1: Scheme of this work

2 Pose Estimation (State-of-the-Art)

Human body pose recovery, or pose recovery in short, refers to the process of estimating the configuration of the underlying kinematic structure of a person. Vision-based approaches are often used to provide such a solution, using cameras as sensor inputs. Human pose estimation is one of the key problems in computer vision that has been being studied well over 15 years.

The reason for its importance is the abundance of applications that could benefit from such a technology. For instance, human pose estimation would allow for higher level reasoning in the context of human-robot interaction (HRI) and activity recognition (Figure 2).

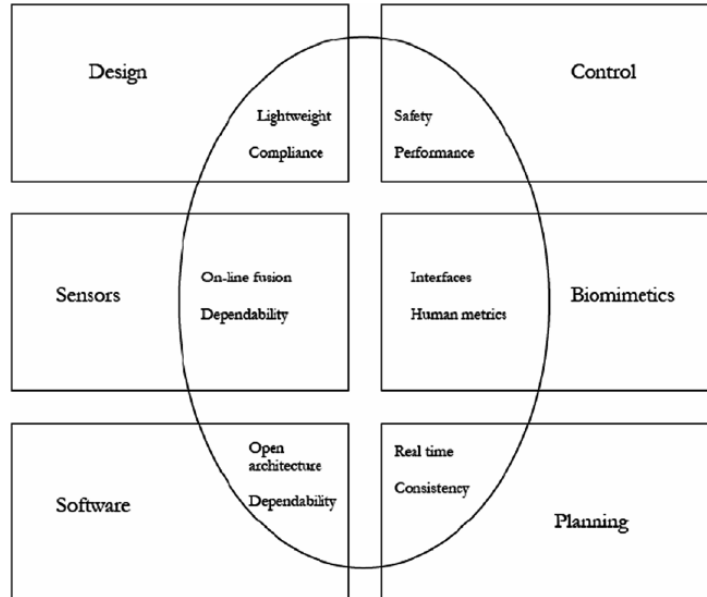


Figure 2: Main issues for Physical Human Robot Interaction (pHRI) [19]

A potential solution for human pose tracking is to require the human to wear specialized markers so that the visual sensors can locate the markers on the human body and infer the human's kinematic pose (i.e. OptiTrack System).

However, using markers has issues as well. The markers may be sensitive to lighting and other environmental conditions (Figure 3). Wearing multiple markers can also be cumbersome to the user. Such systems carry the burden of specially designed equipment or suits, which is inconvenient for many practical applications.

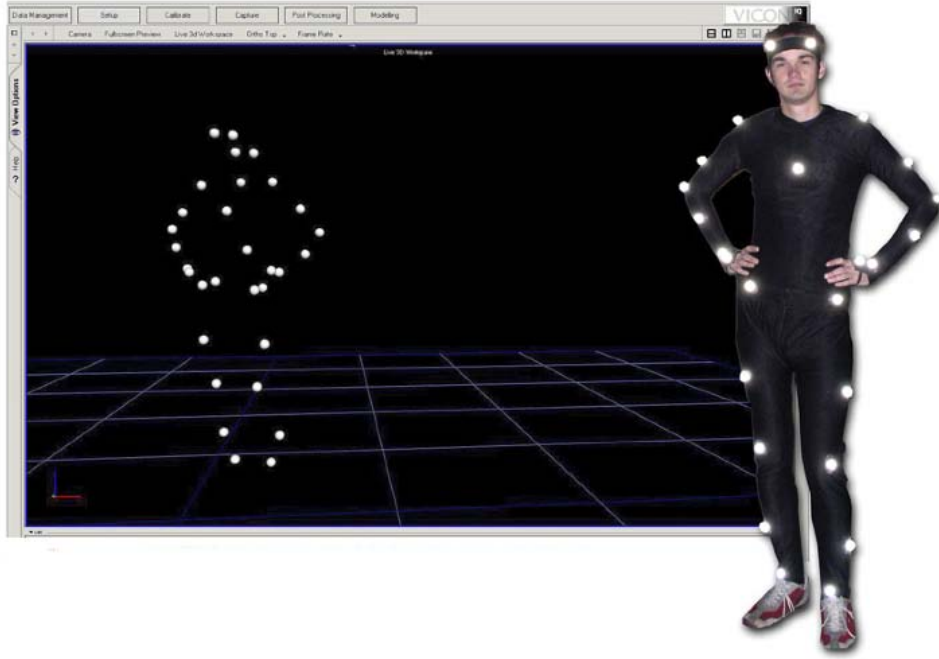


Figure 3: Optical markers that are tracked in real time to pose estimation [6]

Therefore, non-invasive marker-less approaches are the main focus of research in recent years. Most marker-less motion tracking methods in computer vision (Figure 4) fall into three categories [15].

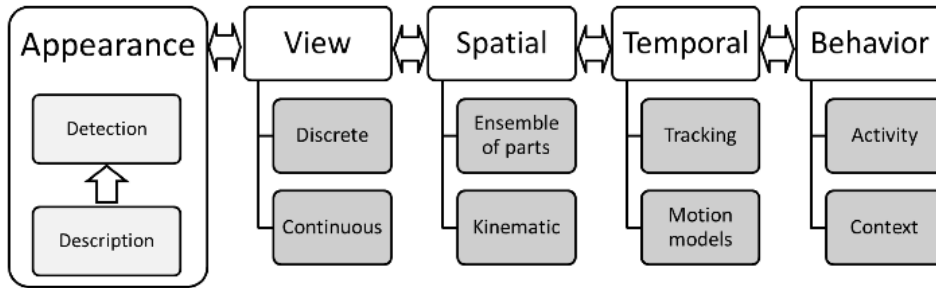


Figure 4: Different classification approaches for human pose recovery [17]

First, learning-based methods which rely on prior probabilities for human poses, and assume therefore limited motions. Second, model-free methods which do not use any a priori knowledge, and recover articulated structures automatically. However, the articulated structure is likely to change in time, when encountering a new articulation for instance, hence making identification or tracking difficult. Third, model-based approaches which fit and track a known model using image information.

In many applications, only one camera is available. In such cases, either only RGB data is considered when still images are available, or it can be combined with temporal information when input images are provided in a video sequence. Most of pose recovery approaches recover the human body pose in the image plane, since, until recently, 2d pose estimation was the main focus of investigation [17].

Despite many years of research, however, pose estimation remains a very difficult and still largely unsolved problem. Among the most significant challenges are [21]:

- variability of human visual appearance in images,
- variability in lighting conditions,
- variability in human physique,
- partial occlusions due to self articulation and layering of objects in the scene,
- complexity of human skeletal structure,
- high dimensionality of the pose,
- the loss of 3d information that results from observing the pose from 2d planar image projections.

Recent works have gone a step further and estimate the human pose in 3d. Without using prior information, monocular 3d human pose estimation is known to be an ill-posed problem [22]. Probably, the most challenging issue in 3d pose estimation is the projection ambiguity of 3d pose from 2d image evidences. This problem is particularly difficult for cluttered and realistic scenes with multiple people, were they appear partially or fully occluded during certain intervals of time [17].

With the advent of a cheap RGB-D sensor (the Microsoft Kinect), the rise of open-source robotics (the Robot Operating System, ROS), and an open-sourced implementation of human pose detection and tracking, researchers have gained access to the necessary off-the-shelf hardware and software implementation to bootstrap their needs for reliably tracking and detecting human poses. However, the Kinect’s implementation for human tracking has limited capability. First, due to hardware limitations, the human must be at a minimum distance from the sensor to prevent point cloud distortion. Second, due to their feature selection, their algorithm requires that the humans unobstructed full-body must face the sensor. These two requirements are too restrictive for a robot engaging in side-by-side collaboration, as humans might be partially occluded when they are on the periphery of the robot’s vision [11].

Some pose estimation methods employ complex appearance models and rely on learning algorithms to estimate model parameters from the training data. The performance of these approaches crucially depends on the availability of the annotated training images that are representative for the appearance of people clothing, strong articulation, partial (self-)occlusions and truncation at image borders [1].

Recent advances in the field of Convolutional Neural Networks (CNNs) are defeating well engineered supervised classification problems (Figure 5). At least in the very near future, CNNs methods are the most promising ones in creating general detection, tracking, and recognition modules for human-aware robots [11].

In the last two years, several researchers have presented algorithms based on CNNs for 2d and 3d human pose estimation from monocular and depth images [4, 5, 7–9, 13, 14, 16, 24, 25].

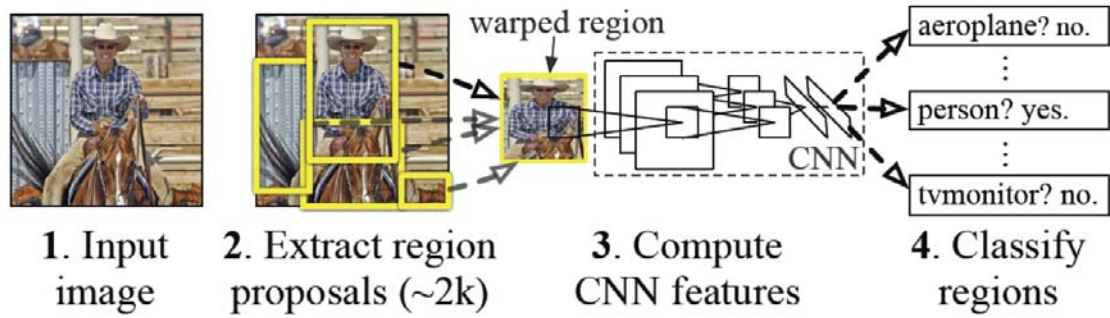


Figure 5: The R-CNN pipeline that uses Caffe for object detection [10]

The configuration of the human body can be represented in a variety of ways. The most direct and common representation is obtained parameterizing the body as a kinematic tree (see Figure 6), where the pose is encoded using the position of the root segment, the orientation of the root segment in the world and a set of relative joint angles (orientations of body parts with respect to their parents along the tree) [21].

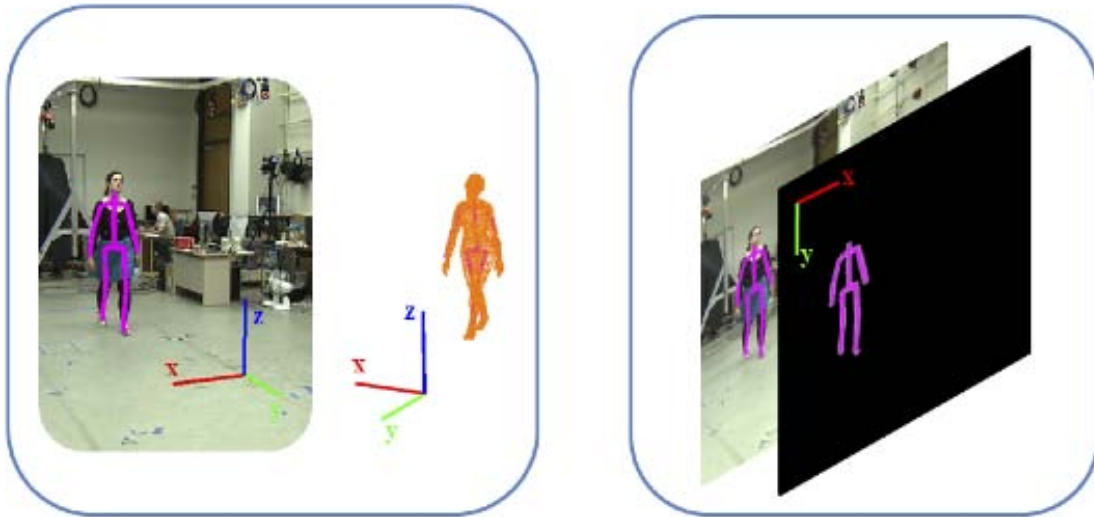


Figure 6: 3d and 2d kinematic tree skeleton representation (left and right, respectively) [21]

There are several databases that provide detailed information for the estimation of the skeleton representation from images:

- Human3.6M is currently the largest publicly available datasets for human 3d pose estimation. The dataset consists of 3.6 million images featuring 7 professional actors performing 15 everyday activities such as walking, eating, sitting, making a phone call and engaging in a discussion. 2d joint locations and 3d ground truth positions are available, as well as projection (camera) parameters and body proportions for all the actors [13].
- MPII is a standard dataset for 2d human pose estimation based on thousands of short youtube videos.

Also, each human pose estimation software uses a specific configuration of the skeleton model, with different number of body joints (the most common configurations have between 14 and 23 joints). The Figure 7 shows some of these configurations.

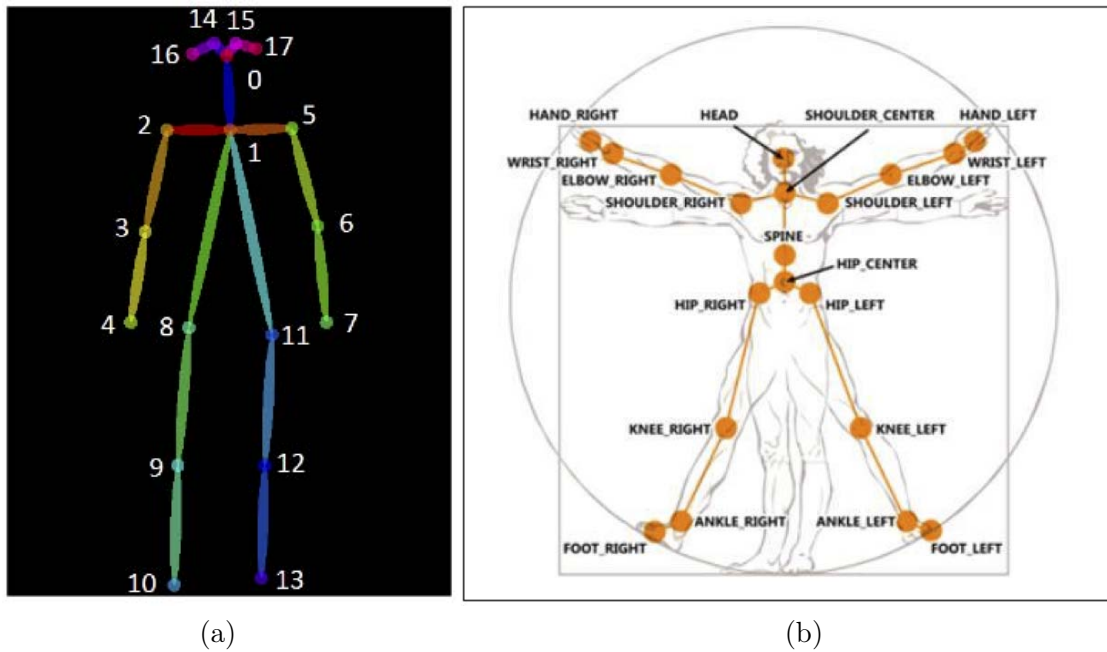


Figure 7: (a) OpenPose output format (COCO) ; (b) Joints tracked by the Kinect sensor

In conclusion, several software packages have been developed for human pose estimation from RGB images or depth images, being the ones based on CNNs the most promising ones.

For the incorporation of these software packages in robotic applications in real time it is fundamental to use them from ROS.

In general, the modules for $2d$ pose estimation from single images are the most developed and there are even some quite effective open source packages that have reached a certain popularity. In particular, OpenPose (based on Convolutional Neural Networks architecture) is an efficient open source software for $2d$ real-time multi-person pose estimation [7].

On the other hand, considering the availability of hardware to carry out this work (we have a Logitech C300 webcam and a Kinect One camera that will be described in the next chapter), we considered the implementation of a package ROS that allows $2d$ pose estimation from simple RGB images [2].

Additionally, a ROS node that can obtain $3d$ pose estimation from the initial $2d$ pose estimation and a depth image synchronized with the RGB image (as in the Kinect camera), by means of projecting pose $2d$ pose estimation onto the point-cloud of the depth image, has been developed [2].

In this way we can have a software package adaptable to the available hardware, that will allow us to obtain $2d$ pose estimation or $3d$ pose estimation depending on the type of available images [2].

3 General Architecture of the System

This chapter provides information about the general structure of the system, the hardware devices and the software implemented.

The functional architecture is designed to accomplish the objectives presented in chapter 1.

Figure 8 shows the general architecture of the Multi-Person Pose Estimation Module and the connectivity between its modules.

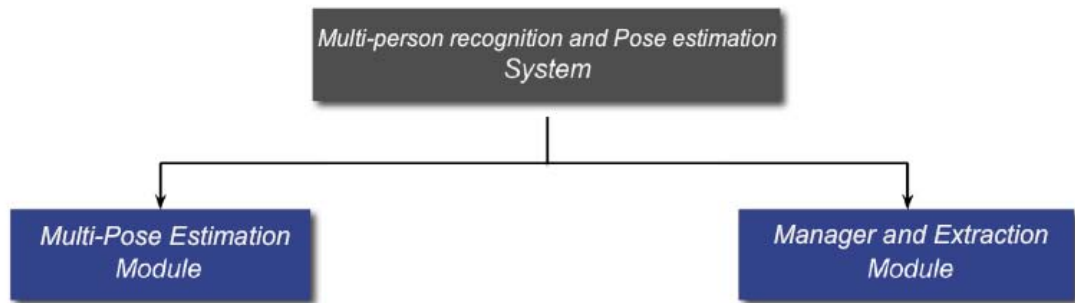


Figure 8: System Architecture

The first module consists of the multi-person human pose estimation process which identifies and recognises the people that appear in the images captured by a single camera. This subsystem estimates the pose for each recognised persons in the coordinate system of the camera that takes the images.

The second module carries out the process of managing the information given by the other module (camera sensor, human pose estimation and coordinate data points) and extracting the data outputs, so that they can be easily read and handled from another ROS program.

Figure 9 shows the architecture of the multi-pose estimation module.

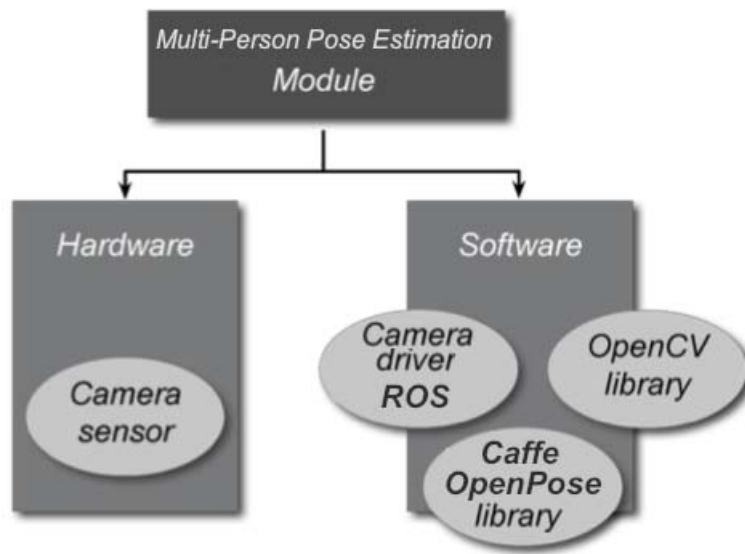


Figure 9: Architecture of Multi-Person Pose Estimation Module

and Figure 10 presents the managing and extraction module.

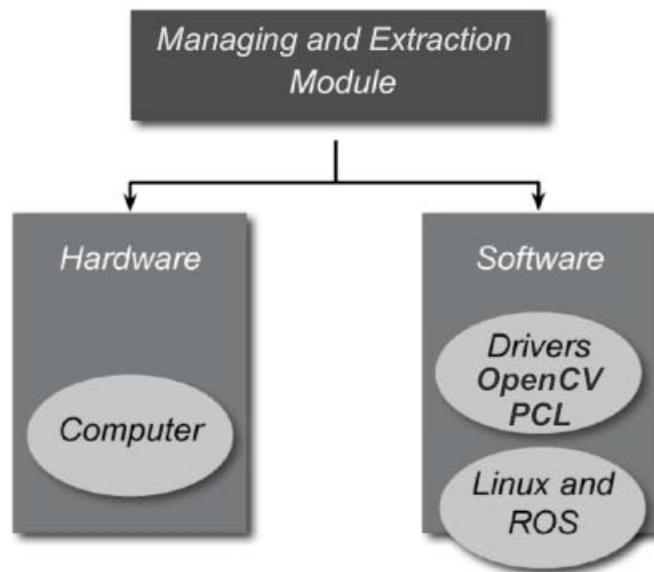


Figure 10: Architecture of Managing and Extraction Module

The difference between the physical (hardware) and non-physical (software) entities is clear and evident in the most engineering projects like the present one. Thus, two schema, one for hardware and other for software will be constructed.

3.1 Hardware Architecture

The hardware architecture refers to the identification and description of the system physical components and their interactions and compatibility with the system architecture. The hardware used in this project consist of camera sensors and a computer that manages the whole system. The graphics card (GPU) that we have used in this is work is a NVIDIA GeForce GTX 1080 (Driver Version: 381.22).

Also, Logitech C300 webcam (Figure 11) and Kinect One camera (Figure 12) have been used in this project. Logitech C300 is a video camara and its 5-megapixel photo capture allows high-resolution 2d snapshots. Its technical specifications are presented in Table 1.



Figure 11: Logitech C300 webcam

 TECHNICAL SPECIFICATIONS	
• True 1.3-megapixel sensor (1280 x 1024 pixels) • Video capture: up to 1280 x 1024 pixels (software enhanced) • Photos: up to 5.0 megapixels (software enhanced) • Up to 30-frames per second video (with recommended systems) • Built-in microphone with Logitech RightSound™ technology • Hi-Speed USB 2.0 certified • Universal clip fits notebooks, LCD or CRT monitors	• Snapshot button for capturing photos • Manual focus Logitech® webcam software: • Logitech® Vid™ • Capture videos and images • E-mail videos and images • YouTube™ upload (registration required) • Logitech® Video Effects™ Fun Filters Works with most instant messaging applications

Table 1: Logitech C300 webcam technical specifications

Depth imaging technology has advanced dramatically over the last few years, and has finally reached a consumer price point. The Kinect One (video game sensor developed by Microsoft) uses a depth camera based on Time-of-Flight (ToF) technology.

In a depth image, pixels indicate the calibrated distance in meters of $3d$ points in the world from the imaging plane, rather than a measure of intensity or color. The RGB-D format of the stream input captured by a Kinect sensor combines visual (RGB colours) and geometric information (depth) in a synchronized format that provides us with the possibility of extracting features from both [20]. This camera is widely used in the robotics community in the field of computer vision due to its low cost. Their technical specifications are present in Table 2.

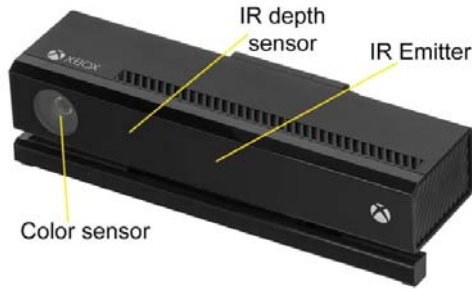


Figure 12: Kinect One components

Kinect One	Specifications
Technology	Time-of-flight
Colour camera	1920 x 1080 @30fps
Depth camera	512 x 424 @30fps
Depth range	0.5m to 4.5m
Field of view (FoV)	60° vertical by 70° horizontal
Tilt motor	No
Frame rate (depth and colour stream)	Up to 30fps
USB standard	3.0
Audio format	Four microphones to capture sound, record audio, as well as find the location of the sound source and the direction of the audio wave.
Dimensions	24.9cm x 6.6cm x 6.7cm. The Kinect cable is 2.9m long
Weight	1.4kg
Accelerometer	No
Price	200 €

Table 2: Kinect One technical specifications

3.2 Software Architecture

The software architecture identifies and describes the system non-physical components and their interaction and compatibility with the system architecture. Computer software interprets the information provided by the physical hardware. Software can be divided into application software and system software.

The first one uses the computer system to perform a specific functionality for the benefit of the user (computer program). The second one includes operating systems, which manage the resources and provide common services for other software working on top of them and device drivers which control the devices connected to the computer [18].

The Multi-Person Pose Estimation System is programmed in C++ language and uses the components shown in Figure 13, that describes the system software and the application software used in this work. Additional information of each one is presented in the following sections.

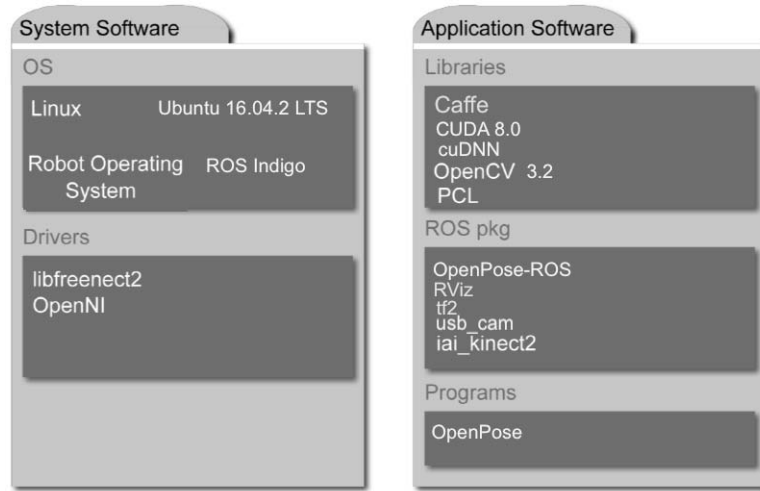


Figure 13: Main software components used in this work

3.2.1 Robot Operating System (ROS)

The Robot Operating System (ROS) is a framework for building robot software. It started at the Stanford University in the mid-2000s by the Stanford AI Robot (STAIR) and the Personal Robots (PR) program. It is an open source software with a large variety of tools, libraries and conventions that simplify the work of creating complex and robust robot applications with a wide variety of robotic platforms. The ROS community exchanges robot software and knowledge through ROS distributions that make easier to install a collection of software. It provides repositories where different institutions can develop and release their own robot software and a ROS wiki where anyone can contribute with his/her own documentation and tutorials.

Software in ROS is organized in packages. A package might contain ROS nodes, a ROS-independent library, a dataset, configuration files, a third-party piece of software, or anything else that logically constitutes a useful module. The goal of these packages is to provide useful functionality that is easy-to-consume in a way that the software can be easily reused. A typical structure of ROS package is shown in Figure 14. The structure of the package folders is as follows:

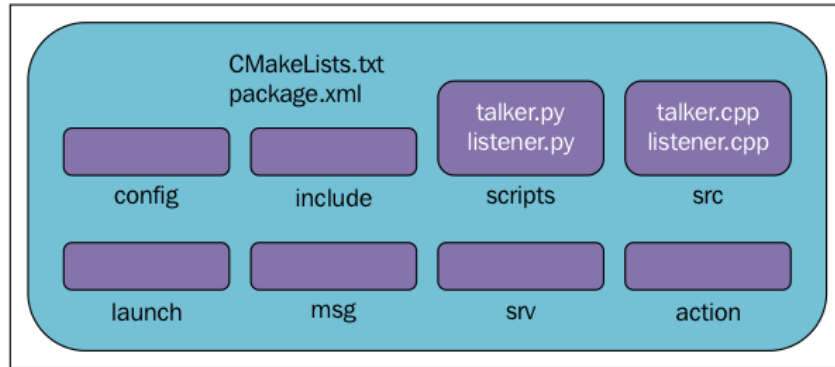


Figure 14: Structure of a typical ROS package [12]

- **config:** All configuration files that are used in this ROS package are kept in this folder. This folder is created by the user and is common practice to name the folder `config` to keep the configuration files in it.
- **include/package_name:** This folder consists of headers and libraries that we need to use inside the package.
- **scripts:** This folder keeps executable Python scripts. In the block diagram, we can see two example scripts.
- **src:** stores the C++ source codes. We can see two examples of the source code in the block diagram.
- **launch:** keeps the launch files that are used to launch one or more ROS nodes.
- **msg:** contains custom message definitions.
- **srv:** contains the service definitions.
- **action:** contains the action definition.
- **package.xml:** This is the package manifest file.
- **CMakeLists.txt:** This is the CMake build file of this package.

Each package directory has to include a CMakeList.txt and package.xml file that describes its contents and how catkin should interact with it. The commands in catkin are the ROS build system that generates executable programs, libraries and interfaces.

The ROS system uses different nodes that communicate with each other, exchanging information and data. However, the whole system needs a running ROS Master in order to notice nodes the existence of other nodes and starting to communicate with each other. The ROS Master enables individual ROS nodes to locate one another in the system and it tracks publishers and subscribers to topics and services. The communications between nodes can be done with client/server or publisher/subscriber methodologies. ROS topics implement a publish/subscribe communication mechanism and ROS services and actions uses a client/server communication method. Figure 15 shows a representation of these three communication ways between nodes.

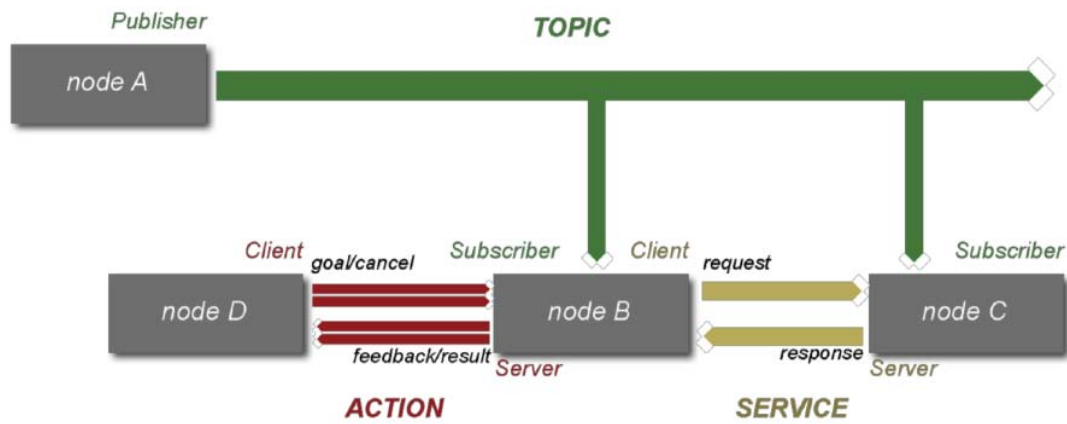


Figure 15: ROS communication mechanisms [18]

One of the most common ways to exchange data in a distributed system is a publish/subscribe communication mechanism implemented by topics. Before node (A) starts to transmit data over topics, it must first advertise the topic name and the type of message that is going to be sent. Node (B) and node (C) have to subscribe to this topic by making a request to ROS Master. Then, both nodes will receive messages from this topic. A topic is one-way communication and it is useful if there are multiple nodes listening.

A service is a synchronous two-way communication that allows one node to call a function that is executed in other node. The server node specifies a function and advertises the service. By making a request, the client node can access this service and then, await a response from the server node.

An action is an asynchronous two-way communication between nodes. It is similar to the request and response of a service. An actions is requested with the aim of obtaining a result. Moreover, the server node can provide feedback for some updates on the progress and the client node can cancel the previous request at any time.

3.2.2 C++ libraries

This section presents different high-level C++ libraries providing useful utilities. Basic colour image processing algorithms are managed using OpenCV library. Point Cloud library (PCL) offers the most important point-cloud processing algorithms. Caffe provides multimedia scientists and practitioners with a clean and modifiable framework for state-of-the-art deep learning algorithms and a collection of reference models.

OpenCV: is an open source library licensed under Berkeley Software Distribution (BSD) that provides real-time computer vision applications. OpenCV was developed to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products. OpenCV is a library designed and optimized for displaying 2d images. OpenCV application areas include: facial detection and recognition, human gesture recognition, object segmentation and recognition, motion tracking, produce 3d point-clouds from stereo cameras, stitch images together to produce a high resolution image, etc. In this work we have installed and used the version OpenCV 3.2.

Point Cloud Library (PCL): is an open source library for 2d and 3d image and point-cloud processing under Berkeley Software Distribution (BSD) license and thus free for commercial and research use. Each element of the array contains the Cartesian (x, y, z) coordinates of that point in space and, if available, the RGB data or other multi-dimensional channels for that point. The PCL library has many algorithms for point-cloud processing such as filtering outliers from noisy data, stitch 3d point-clouds together, feature extraction to recognise objects based on the geometric appearance, surface reconstruction, registration, segment relevant parts of a scene, etc.

Caffe: is an open source C++ library under BSD-licensed with Python and MATLAB bindings for training and deploying general purpose convolutional neural networks (CNNs) and other deep models efficiently on commodity architectures. Caffe fits industry and internet-scale media needs by CUDA GPU computation, processing over 40 million images a day on a single K40 or Titan GPU (≈ 2.5 ms per image). By separating model representation from actual implementation, Caffe allows experimentation and seamless switching among platforms for ease of development and deployment from prototyping machines to cloud environments. Caffe is maintained and developed by the Berkeley Vision and Learning Center (BVLC) with the help of an active community of contributors on GitHub.

3.2.3 OpenPose

OpenPose is a library for real-time multi-person keypoint detection and multi-threading written in C++ using OpenCV and Caffe, authored by G. Hidalgo, Z. Cao, T. Simon, S.E. Wei, H. Joo and Y. Sheikh (Robotics Institute of Carnegie Mellon University). The code has been released for full reproducibility and it is maintained and developed by the authors with the help of an active community of contributors on GitHub (<https://github.com/CMU-Perceptual-Computing-Lab/openpose>).

3.2.4 Packages: `usb_cam`, `iai_kinect2`, `tf2`, `RViz` and `OpenPose_ROS`

The main ROS packages used in this work are the following:

`usb_cam`: This is a collection of tools and libraries for ROS to interface with standard USB cameras (e. g. the Logitech Quickcam). It is developed and maintained by:

- Benjamin Pitzer and Russell Toris:
 - (https://github.com/ros-drivers/usb_cam).

`iai_kinect2`: this is a collection of tools and libraries for ROS to interface to the Kinect One device using `libfreenect2`.

It contains a calibration tool for calibrating the IR sensor to the RGB sensor and depth measurements. It converts raw depth/RGB/IR streams to depth images and registered point-clouds. It is developed and maintained by:

- Thiemo Wiedemeyer from the University of Bremen:
 - (https://github.com/code-iai/iai_kinect2).

`tf2`: `tf2` is the second generation of the transform library, which lets the user keep track of multiple coordinate frames over time. `tf2` maintains the relationship between coordinate frames in a tree structure buffered in time, and lets the user transform points, vectors, etc between any two coordinate frames at any desired point in time. It is developed and maintained by:

- Tully Foote, Eitan Marden-Eppstein and Wim Meeussen:
 - (<https://github.com/ros/geometry2>).

`RViz`: The `RViz` tool is an official 3d visualization tool of ROS. Almost all kinds of data from sensors can be viewed through this tool. `RViz` will be installed along with the ROS desktop full installation. It is developed and maintained by:

- Dave Dershberger, David Gossow, Josh Faust and William Woodall:
 - (<https://github.com/ros-visualization/rviz>).

`OpenPose_ROS`: `OpenPose` has been converted into popular software and packages for ROS have been very recently developed by:

- CTS Robotics Group of Eindhoven University of Technology:
 - (https://github.com/tue-robotics/openpose_ros).
- Kevin Zhang of Carnegie Mellon University:
 - (https://github.com/firephinx/openpose_ros).
- Steven Jens M. Jorgensen of University of Texas at Austin:
 - (https://github.com/stevenjj/openpose_ros).

4 Multi-Person Pose Estimation

Visual interpretation of people plays a central role in the quest for comprehensive image understanding.

A major cornerstone in achieving these goals is the problem of human pose estimation, defined as $2d$ or $3d$ localization of human joints on the arms, legs, and keypoints on torso and face.

4.1 OpenPose (Convolutional Pose Machine)

Convolutional Neural Networks (CNNs) can be incorporated into the pose machine framework for learning image features and image-dependent spatial models for the task of pose estimation. At least in the very near future, CNNs are the most promising in creating general detection, tracking, and recognition modules for human-aware robots.

A sequential architecture composed of convolutional networks directly operate on belief maps from previous stages, producing increasingly refined estimates for part locations, without the need for explicit graphical model-style inference.

Convolutional Pose Machines (CPMs) consist of a sequence of convolutional networks that repeatedly produce $2d$ belief maps for the location of each part (Figure 16). At each stage, image features and belief maps produced by the previous stage are used as input.

The belief maps provide the subsequent stage an expressive non-parametric encoding of the spatial uncertainty of location for each part, allowing the CPM to learn rich image-dependent spatial models of the relationships between parts. The overall proposed multi-stage architecture is fully differentiable and therefore can be trained in an end-to-end fashion using backpropagation [25].

At a particular stage in the CPM, the spatial context of part beliefs provide strong disambiguating cues to a subsequent stage. As a result, each stage of a CPM produces belief maps with increasingly refined estimates for the locations of each part.

In order to capture long-range interactions between parts, the design of the network in each stage of our sequential prediction framework is motivated by the goal of achieving a large receptive field on both the image and the belief maps [25].

Based on CPM architecture, OpenPose is an efficient method for multi-person pose estimation (Figure 19) what uses a nonparametric representation of association scores via Part Affinity Fields (PAFs), a set of $2d$ vectors fields that encode the location and orientation of limbs over the image domain [7, 23].

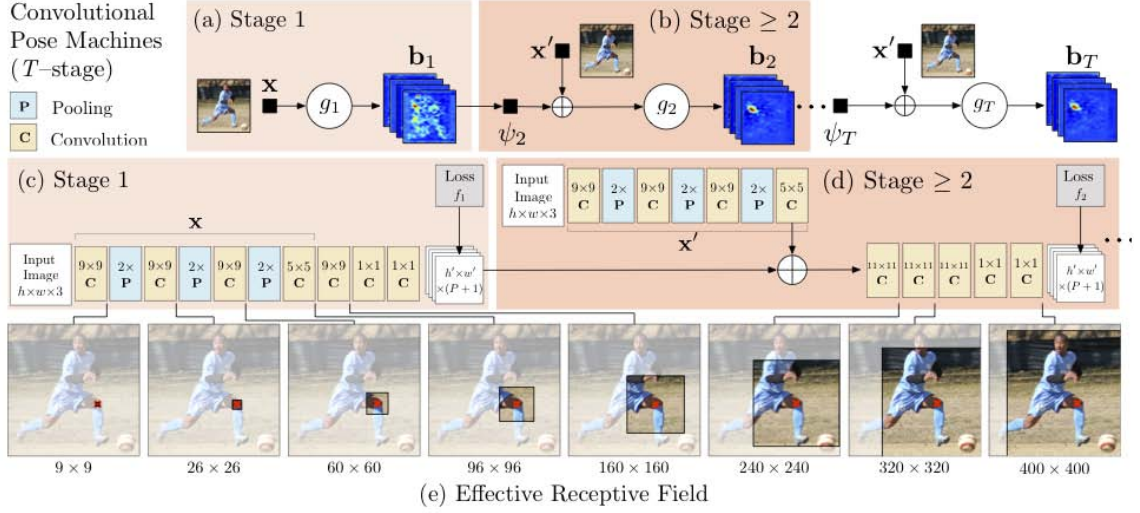


Figure 16: Architecture of Convolutional Pose Machines (CPMs) [25]

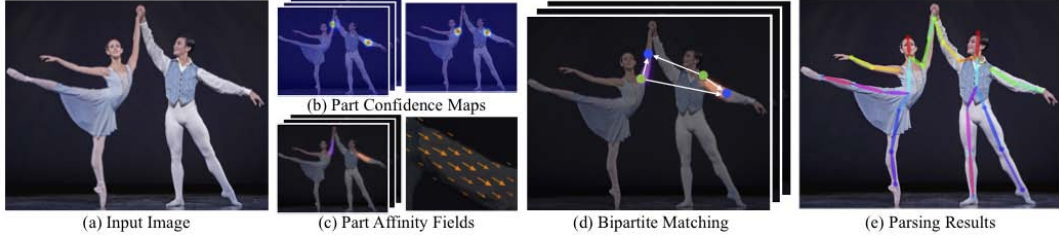


Figure 17: Overall pipeline of OpenPose software [7]

The part affinity is a $2d$ vector field for each limb for each pixel in the area belonging to a particular limb, that encodes the direction that points from one part of the limb to the other. Each type of limb has a corresponding affinity field joining its two associated body parts. A greedy parsing algorithm is sufficient to produce high-quality parses of body poses, that maintains efficiency even as the number of people in the image increase [7].

Figure 17 illustrates the overall pipeline of OpenPose software [7].

- OpenPose takes, as input, a color image of size $w \times h$ (Fig. 17a) and produces, as output, the $2d$ locations of anatomical key-points for each person in the image (Fig. 17e).
- First, a feed-forward network simultaneously predicts a set of $2d$ confidence maps of body part locations (Fig. 17b) and a set of $2d$ vector fields of part affinities, which encode the degree of association between parts (Fig. 17c).
- Finally, the confidence maps and the affinity fields are parsed by greedy inference (Fig. 17d) to output the $2d$ keypoints for all people in the image.

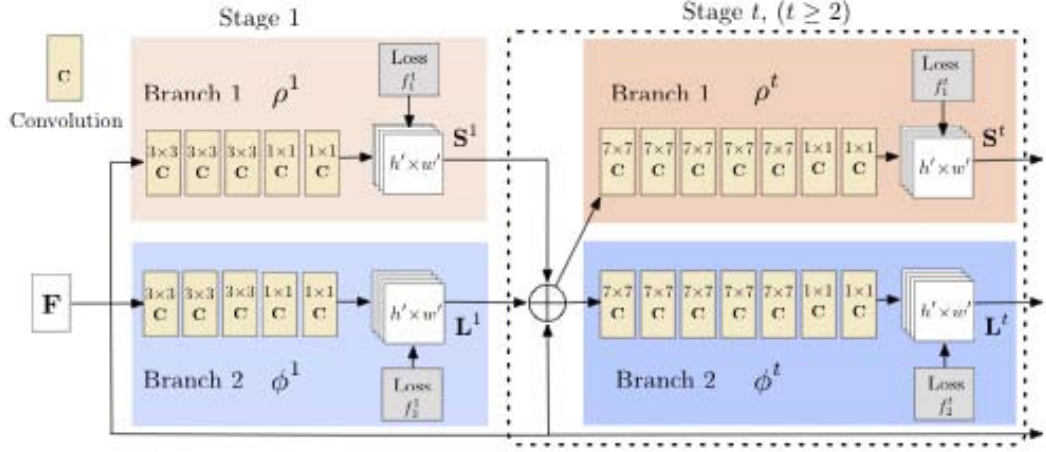


Figure 18: Architecture of the two-branch multi-stage CNN in OpenPose

The architecture of OpenPose, shown in Figure 18, simultaneously predicts detection confidence maps and affinity fields that encode part-to-part association. The network is split into two branches: the top branch, shown in beige, predicts the confidence maps, and the bottom branch, shown in blue, predicts the affinity fields. Each branch is an iterative prediction architecture, following the typical structure of a CMP, which refines the predictions over successive stages, with intermediate supervision at each stage [7].

The runtime analysis, performed on a laptop with one NVIDIA GeForce GTX-1080 GPU, has shown that this software has achieved the speed of 8.8 fps for a video with 19 people, which would allow its use in real-time applications.

OpenPose takes a $2d$ color image as input and produces the $2d$ locations of anatomical key-points for each person in the image as output (Figures 19 and 20). The (x, y) coordinates of the final pose data array can be normalized to the range: $[0, source_size]$, $[0, output_size]$, $[0, 1]$, $[-1, 1]$, depending on the flag `keypoint_scale`. The values can be assigned to this flag are: 0 to scale it to the original source resolution; 1 to scale it to the net output size (set with `net_resolution`); 2 to scale it to the final output size (set with `resolution`); 3 to scale it in the range $[0, 1]$; and 4 to scale it in the range $[-1, 1]$.

The OpenPose library main functionalities are:

- Multi-person 15 or 18-keypoint body pose estimation and rendering.
- Running time invariant to number of people on the image.
- Image, video and webcam reader.
- Able to save and load the results in various formats (JSON, XML, PNG, JPG, ...).

The code has been publically released by the Robotics Institute of Carnegie Mellon University for full reproducibility, representing the first real-time open source system for multi-person $2d$ pose detection.

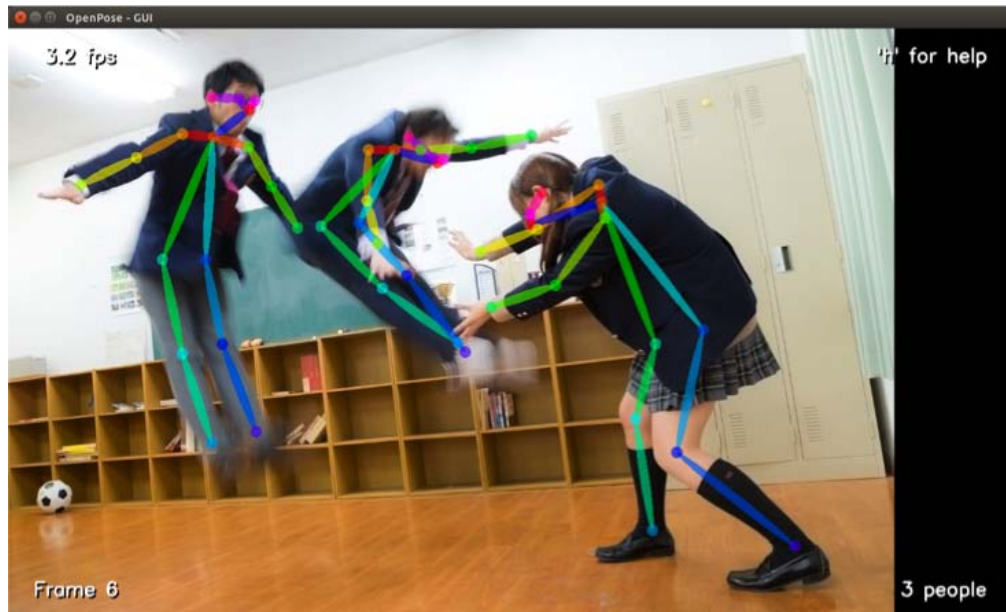


Figure 19: Multi-person pose estimation with OpenPose [7]



Figure 20: Multi-person pose estimation with OpenPose [7]

4.2 ROS Wrapper for OpenPose

OpenPose has been converted into popular software and, taking into account the OpenPose functionalities for $2d$ pose estimation and its open-source condition, several groups have considered incorporating all their functionalities into a simple-to-use ROS wrapper.

The ROS wrapper for OpenPose is an open C++ software application working on ROS that obtains a $2d$ multi-person pose estimation from a simple camera.

From the previous work, and particularly the OpenPose_ROS package published by Steve Jens M. Jorgensen (NSTRF Fellow at NASA and PhD Student at The University of Texas at Austin, to which we especially thank for the help provided), we have implemented a ROS wrapper that automatically recovers the pose of several people from a single camera RGB using OpenPose (Figure 21) [2].

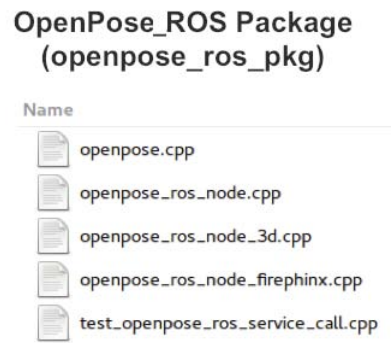


Figure 21: OpenPose-ROS package

A simplified scheme of the operation of the OpenPose_ROS package is shown in the Figure 22, where the topics are mentioned in a rectangle and nodes are represented in ellipses.

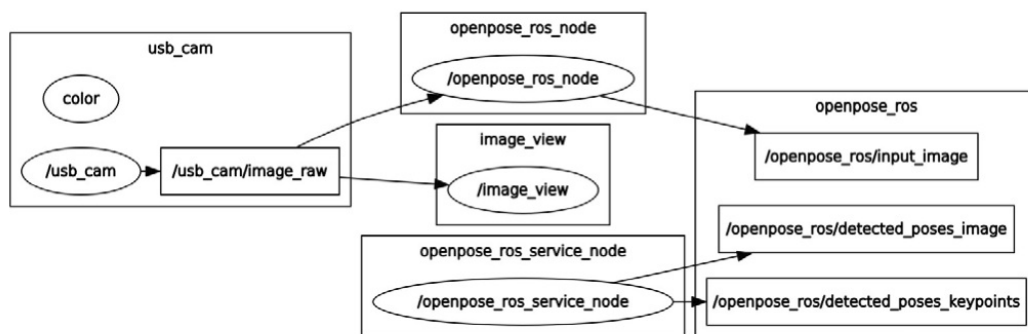


Figure 22: ROS wrapper for OpenPose

On the one hand, we introduce the flow of images, which in our case we do using the `usb_cam` driver.

This image stream (Figure 23) is visualized by `image_view`, which is independent of the `openpose` ROS wrapper.



Figure 23: Image from `/usb_cam`

The topics in the `OpenPose_ROS` package (`openpose_ros_pkg`) are as follows:

- `/openpose_ros/input_image`:
 - Publisher: `openpose_ros_node`.
 - The image that is received from the camera, and is next used to do the segmentation with OpenPose, is published by the node `openpose_ros_node` at the topic `/openpose_ros/input_image` for further comparison with the image with the skeleton drawn in it. The messages published in this topic are of type `sensor_msgs::Image`. There is no subscriber for this topic as this is only for user's visualization.
- `/openpose_ros/detected_poses_image`:
 - Publisher: `openpose_ros_service_node`.
 - The image processed by OpenPose with the skeleton drawn in it, is published in this topic by the `openpose_ros_service_node` implemented inside the node `openpose_ros_node`. The messages published here are of type `sensor_msgs::Image` (Figure 24).

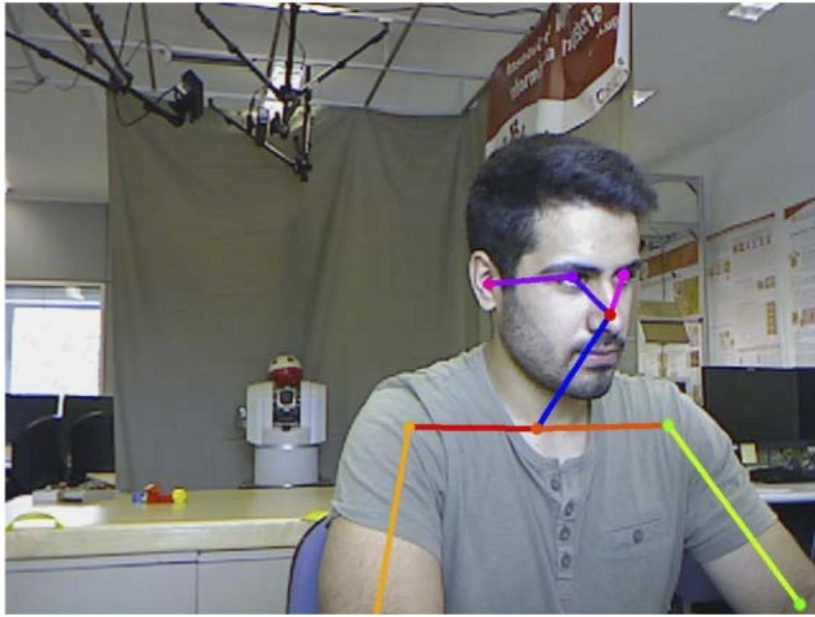


Figure 24: Image processed by OpenPose with the skeleton drawn in it

- `/openpose_ros/detected_poses_keypoints`:
 - Publisher: `openpose_ros_service_node`.
 - The estimated $2d$ positions of the keypoints and the confidence of the estimation are published in the topic `/openpose_ros/detected_poses_keypoints`. They are published by the `openpose_ros_service_node` as a response of the image sent as a request. This topic has no subscribers contained in this package as these data are published for further analysis in other packages.

Figure 25 shows an example of the output. The message has not an standard format so we have defined it.

The message contains a field for the number of people detected, a field for the ID of each detection and a field for each bodypart. Each bodypart contains a field for the x coordinate, for the y coordinate and for the confidence of the estimation (Figure 26). It should be noted that normally we use model COCO and we get 18 bodyparts, since it is the one that uses the program, and it does not seem that the computing capacity is a limit.

In addition, we see how each measure is associated with your time stamp, as in every ROS message.

	A	B	C	D	E	F
1	%time	field_num_people_detected	field_person_ID	field_nose_x	field_nose_y	field_nose_confidence
2	1.49993152815341E+018	4	0	0	0	0
3	1.49993152815341E+018	4	1	0	0	0
4	1.49993152815341E+018	4	2	0	0	0
5	1.49993152815342E+018	4	3	525	335	0.7854701877
6	1.49993152826207E+018	4	0	0	0	0
7	1.49993152826207E+018	4	1	0	0	0
8	1.49993152826208E+018	4	2	0	0	0
9	1.49993152826208E+018	4	3	525	335	0.7854701877
10	1.49993152837404E+018	4	0	0	0	0
11	1.49993152837404E+018	4	1	0	0	0
12	1.49993152837773E+018	4	2	0	0	0
13	1.49993152837774E+018	4	3	525	335	0.7854701877

Figure 25: Outoput of openpose_ros/detected_poses_keypoints

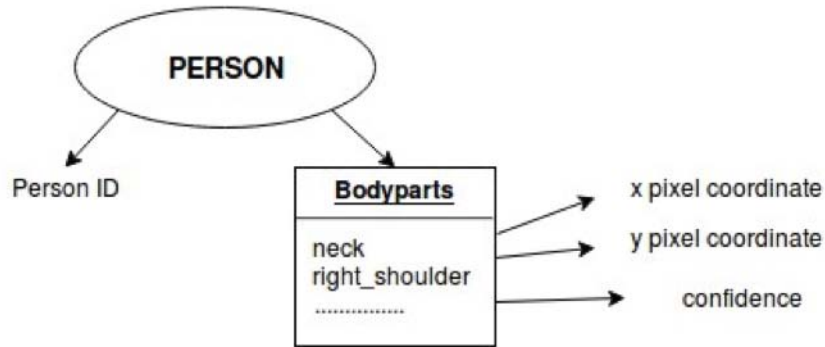


Figure 26: Message published by openpose_ros_service_node

The topics that are involved while running the 2d detection and the flow between them can be seen in the scheme shows in Figure 27. These are all topic while running openpose_ros_node at the same time as openpose_ros_node_firephinx during the publication of images from a camera.

The services in the OpenPose_ROS package (openpose_ros_pkg) are as follows:

- detect_poses:
 - Server: openpose_ros_service_node → Client: openpose_ros_node_firephinx.
 - Request: Input image → Response: Detections.
 - The service involved is the service detect_poses implemented inside openpose_ros_node. The service request field is .image of type sensor_msgs::Image and the service response field is .detections and is associated to a vector where the detections of one image are stored (Figure 28).

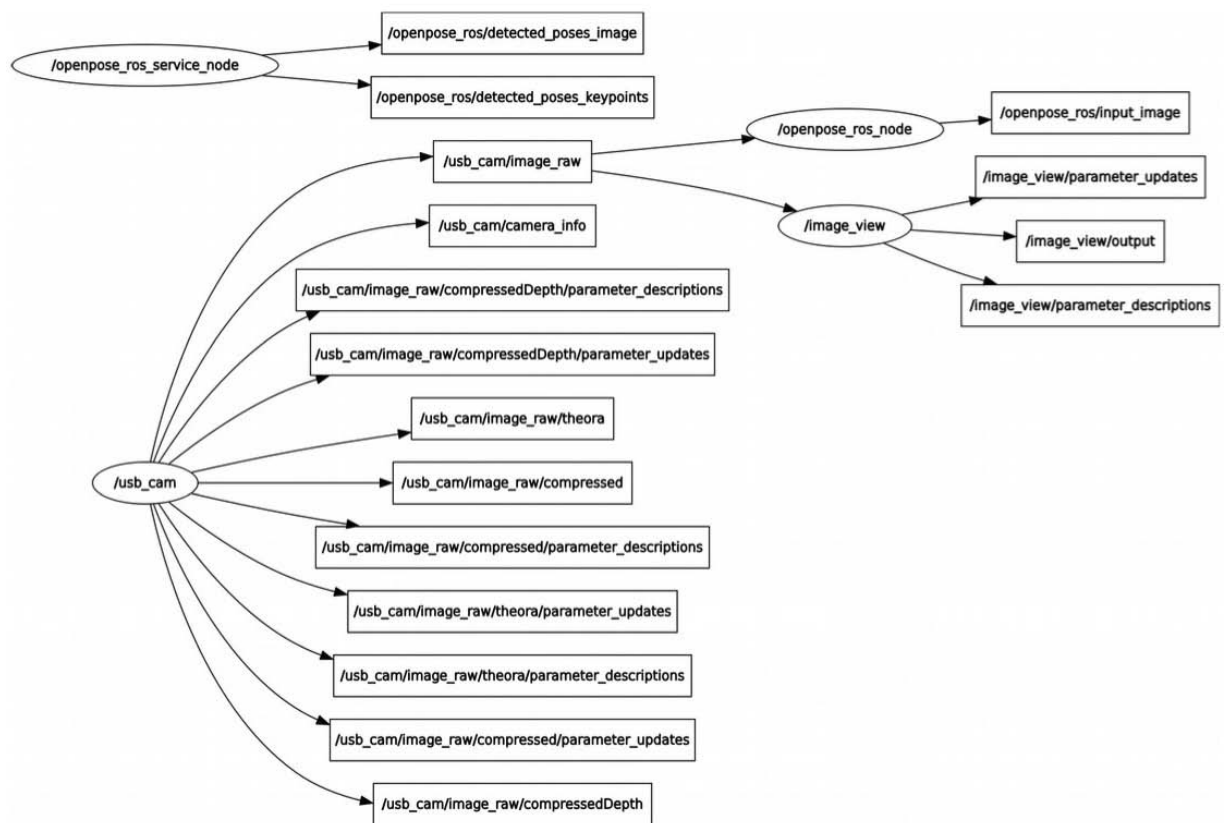


Figure 27: Topics involved with 2d pose detection

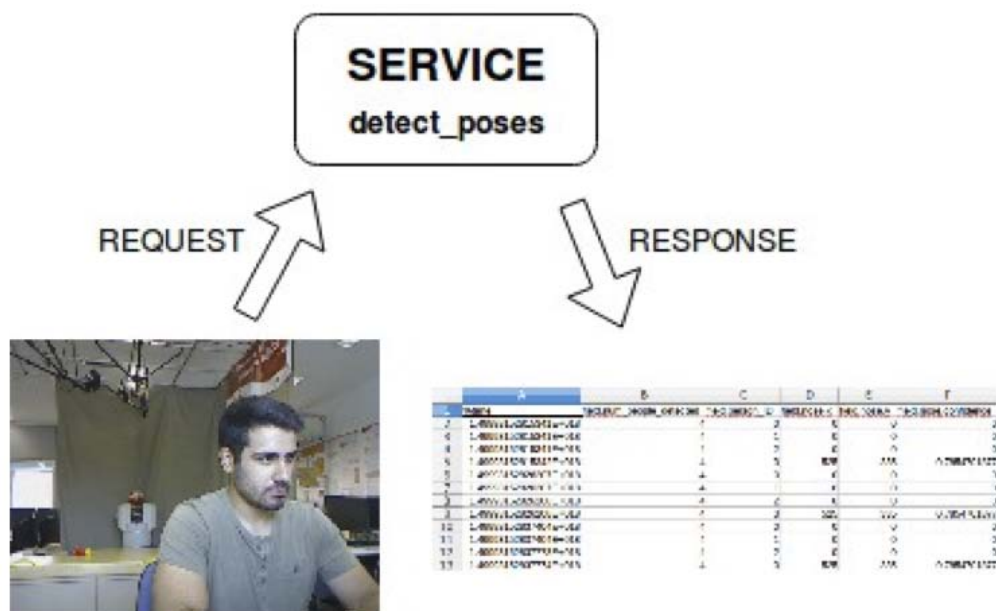


Figure 28: Service detect_poses

A workflow diagram of the OpenPose_ROS package shows in Figure 29.

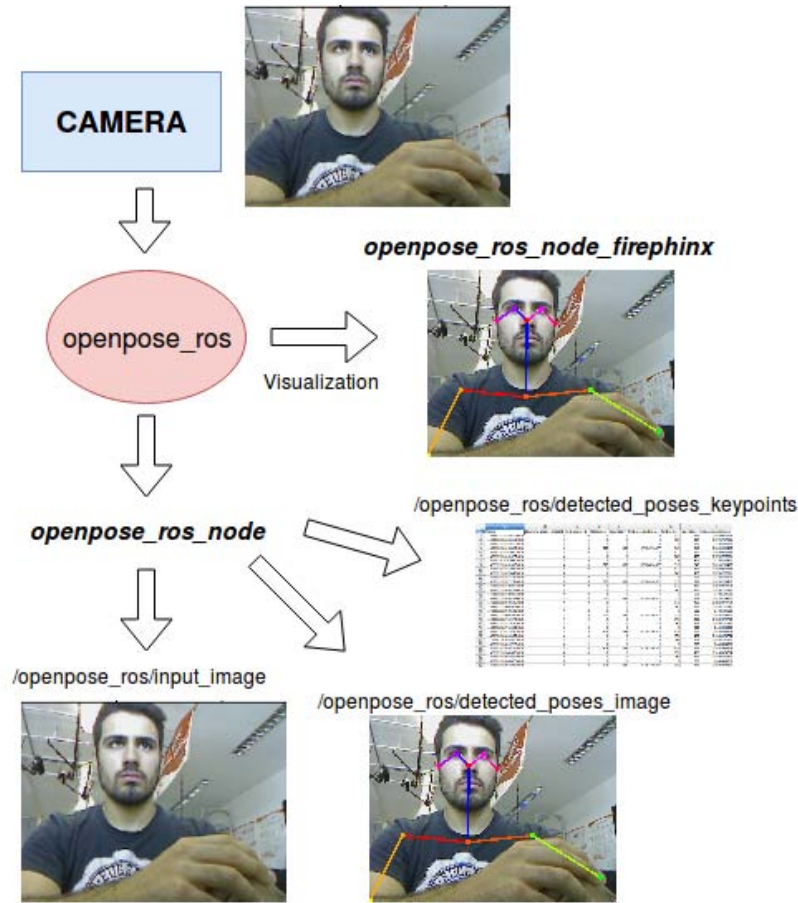


Figure 29: Workflow diagram of the OpenPose_ROS package

4.3 Skeleton-3d Package

Through this node, we can project the 2d pose detections provided by the OpenPose_ROS wrapper in the point-cloud of the depth images, to obtain an 3d multi-person pose estimation in real-time at the camera space coordinate system [2].

For the Kinect camera, the camera space (that is to say, the 3d coordinate system used by the camera) is defined as follows (Figure 30):

- the origin ($x = 0, y = 0, z = 0$) is located at the center of the IR sensor.
- x grows towards the left of the sensor,
- y grows upwards (note that this direction is based on the sensor's tilt),
- z grows out in the direction the sensor is facing, and
- 1 unit = 1m.



Figure 30: The Kinect camera space coordinate system

Depth space is the term used to describe a $2d$ location on the depth image. It can be considered as a row/column location (index value, i) of a pixel, where x is the column and y is the row.

So, for a 960×540 resolution depth image, the point $x = 0, y = 0$ ($i = 1$) corresponds to the top left corner of the image, and the point $x = 960, y = 540$ ($i = 518400$) is the bottom right corner of the image.

In some cases, a z value is needed to map out of depth space. For these cases, simply locate the value associated with the point of the depth image located in the row/column in question, and use that value (which is the depth in millimeters) directly as z .

To know the value of the depth coordinate associated with a pixel of the color image, the operation is relatively easy because the depth and the infrared come from the same sensor in Kinect camera. It is simply necessary to locate the row/column (index value) corresponding to that pixel in the depth image.

The principle of operation is based on associating the pixel corresponding to the coordinates (usually in pixels) provided with the openpose in the $2d$ image of the RGB camera with the corresponding points (or pixels) of the point-cloud of the $3d$ image of the depth camera.

The correspondence between the pixels of RGB image and the points of the point-cloud image, according to the coordinate system used by OpenPose and PointCloud, is shown in Figure 31.

Since a body joint "occupies" on the $2d$ image a "size" larger than a single pixel, and to prevent an incorrect reading of the depth camera at a particular point is very important, projection onto the point-cloud of body joints were performed considering the pixels of a 3×3 square, centered at the point corresponding to the coordinates extracted by OpenPose. The arithmetic mean of the depth readings detected at those 9 points was performed.

In this way we extract the $3d$ "real world" coordinates (in the camera space system) corresponding to the keypoints that we obtain in the $2d$ detections.

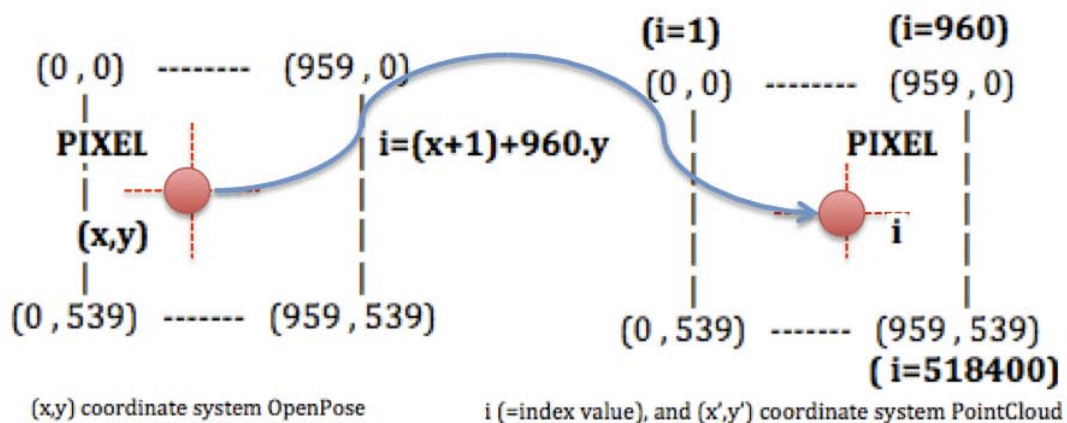


Figure 31: Correspondence between pixels in RGB and point-cloud images

The skeleton-3d package has two main nodes (Figure 32).

Skeleton-3d Package (skeleton_extract_3d)

Name

-  skeleton_extract_3d_node.cpp
-  skeleton_extract_3d_visualization_node.cpp

Figure 32: Skeleton-3d package

The services in this package are as follows:

- detect_poses:
 - Server: openpose_ros_service_node_3d → Client: skeleton_extract_3d_node.
 - Request: Input image → Response: Detections.
 - The service involved is the service detect_poses is implemented inside openpose_ros_node.

The relevant topics in the `skeleton_extract_3d_node` node are the following:

- `/openpose_ros/skeleton_3d/detected_poses_image`:
 - Publisher: `openpose_ros_node_3d_node`.
 - In this topic we are publishing, as we did in $2d$ pose detection, the images with the skeleton drawn. We have selected another name so it will not conflict if we want to run the $2d$ display simultaneously. There is no subscriber.
- `openpose_ros/skeleton_3d/detected_poses_keypoints`:
 - Publisher: `openpose_ros_node_3d_node`.
 - In this topic we are publishing the $2d$ pose detections with the same format. There is no subscriber.
- `/openpose_ros/skeleton_3d/detected_poses_keypoints_3d`:
 - Publisher: `skeleton_extract_3d_node`.
 - This topic displays the $3d$ detections in real world coordinates. The format is shown in Figure 33. This message has the same fields as $2d$ detections with the particularity that the x, y, z coordinates are real numbers and are in "world coordinates" (referred to camera space). There is no subscriber.

	A	B	C	D	E	F	G
1	%time	field_num_people_detected	field_person_ID	field_nose_x	field_nose_y	field_nose_z	field_nose_confidence
2	1.50063613590885E+018	1	0	-0.0154055497	0.283746779	2.793222427	0.9070804119
3	1.50063613639442E+018	1	0	-0.1511128396	0.282182634	2.831222296	0.8941964507
4	1.50063613674613E+018	1	0	-0.3620795608	0.238503262	2.828000069	0.8935434222
5	1.5006361370928E+018	1	0	-0.497540921	0.195191279	2.828666925	0.8885506988
6	1.5006361375121E+018	1	0	-0.5640754104	0.150795802	2.809444427	0.9802207351
7	1.50063613785775E+018	1	0	-0.5086706877	0.206158832	2.830333471	0.9354715943
8	1.50063613840778E+018	1	0	-0.1935517788	0.286243141	2.817777872	0.8981478214
9	1.50063613875576E+018	1	0	0.1060125083	0.349728584	2.896333456	0.9211901426
10	1.50063613918272E+018	1	0 nan	nan	nan	nan	0.9030799866
11	1.50063613956958E+018	1	0	0.0281499829	0.352424055	2.873000145	0.9531800747
12	1.50063613991233E+018	1	0	-0.0426955	0.347103447	2.829666853	0.9489462972
13	1.5006361402873E+018	1	0	-0.1622225791	0.298954248	2.835889101	0.9798388481
14	1.50063614068655E+018	1	0	-0.0319262519	0.288048893	2.835555792	0.992808938
15	1.50063614111584E+018	1	0	0.3764834106	0.223607928	2.845333338	0.9758233428
16	1.50063614155636E+018	1	0	0.5064209104	0.194773033	2.903222322	0.8522841334
17	1.50063614189855E+018	1	0 nan	nan	nan	nan	0.9137311578
18	1.50063614233049E+018	1	0	0.4597145319	0.227052569	2.889111128	0.9590835571
19	1.50063614278862E+018	1	0	0.2294183224	0.28903982	2.8453333576	0.9223447442
20	1.50063614316825E+018	1	0	0.0006340896	0.338341564	2.802000046	0.9007762671
21	1.50063614351344E+018	1	0	-0.0261285957	0.342978179	2.796000004	0.9720357656
22	1.50063614385818E+018	1	0	-0.1542401612	0.354478061	2.889777899	0.9318256974
23	1.50063614427402E+018	1	0	-0.1324286014	0.33568424	2.780000021	0.7785298228
24	1.50063614461974E+018		0	-0.161109075	0.329264045	2.816111326	0.8870015144

Figure 33: Format of the $3d$ detection message

- `/openpose_ros/skeleton_3d/input_pointcloud`:
 - Publisher: `skeleton_extract_3d_node`.
 - In this topic the depth images received are published when a synchronized RGB image has been found.

- `/openpose_ros/skeleton_3d/input_rgb`
 - Publisher: `skeleton_extract_3d_node`.
 - The RGB images received are published in this topic .

The relevant topics in the `skeleton_extract_3d_visualization_node` node are the following:

- `/openpose_ros/skeleton_3d/visualization_markers`: In this topic, the markers corresponding to each joint are published in the form of `sphere_list` (Figure 34). You can adjust various parameters, such as the color, size and shape of markers. These markers can be easily visualized in RViz, which gives us the tool for 3d visualization of the human pose estimation.



Figure 34: Markes for visualization of bodyjoints in RViz

- `/openpose_ros/skeleton_3d/visualization_skeleton`: In this topic we publish the "skeleton" detected. To do this, we simply attach the previously published markers using lines to obtain a human skeleton. We publish this skeleton in the form of a `line_list`. As in the previous case, we can visualize it with RViz (Figure 35a). If we visualize both, the skeleton and the body members, at the same time, the view would be as shown in the Figure 35b.

Summarizing, the operation of the `skeleton_extract_3d_visualization_node` node can be described as follows (Figure 36): we process the message published by the `skeleton_extract_3d_node` node, and publish a message `visualization_msgs::marker` type, in which the position of the points are obtained by assigning the estimated 3d position coordinates for each of the bodyjoints. These messages can be easily viewed with RViz.

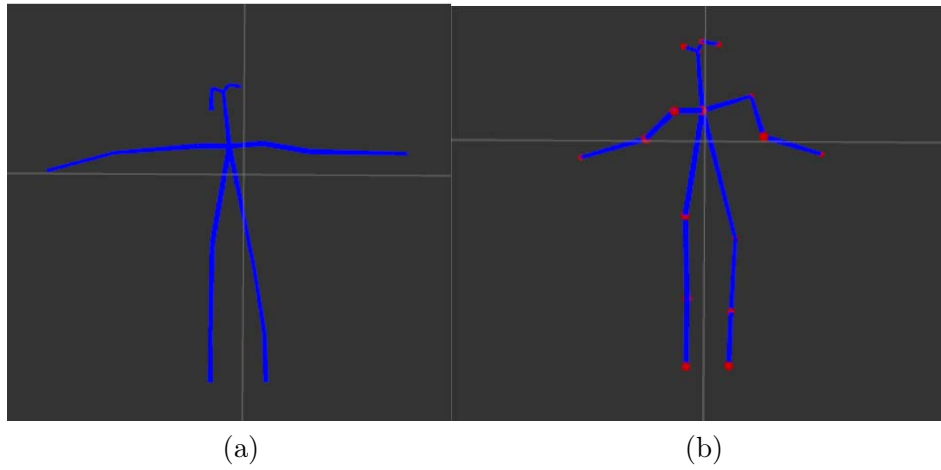


Figure 35: Skeleton in RViz with: (a) line_list and (b) sphere_list+line_list

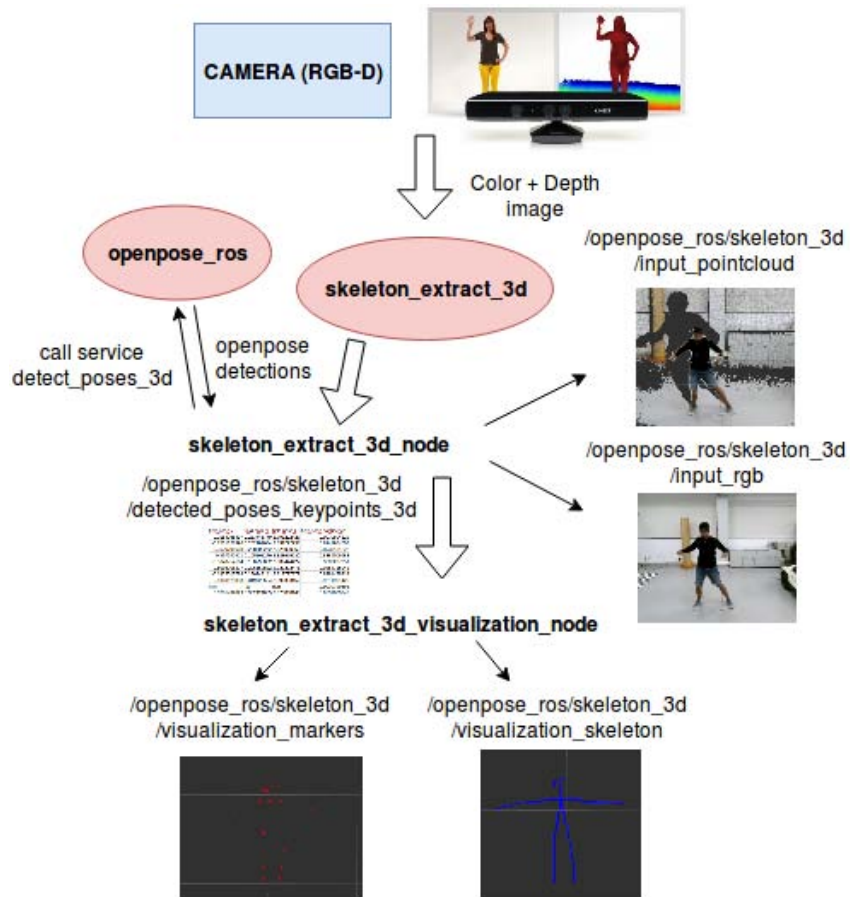


Figure 36: Workflow diagram of the Skeleton-3d package

5 Results

This chapter describes the results obtained in this work, the functionalities and the operation of the ROS packages implemented.

5.1 Human pose detection and visualization

In principle, the mode of operation is streaming and the images captured by the video camera are processed to obtain the multi-person pose estimation in real-time.

The main functionality of this software is $2d$ multi-person pose estimation from the RGB images emitted by a single camera.

The results obtained ($2d$ real-time multi-person pose estimation) with the streaming processing of RGB images captured by a single webcam are shown in the Figure 37.

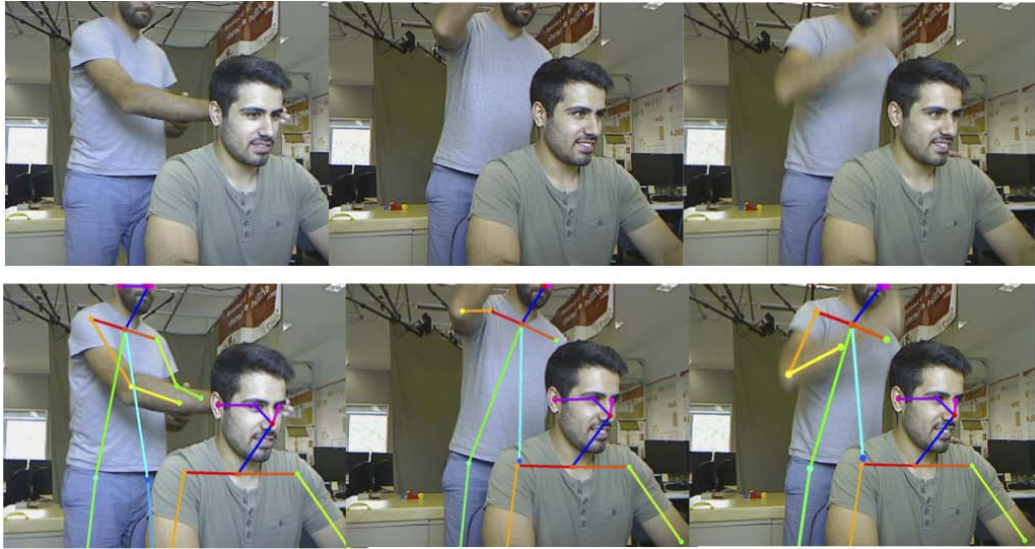


Figure 37: $2d$ real-time multi-person pose estimation from RGB images captured by a webcam

The processing of the RGB images allows us to obtain a confidence value for the estimation of the position of each body joint, as shown in the Figure 38.

We have also verified that the coordinates of the obtained keypoints correspond effectively with those of the segmented image, as seen in the Figure 39. Note that the coordinates (in pixels) are rotated 180° and located in a specular way to the image that we visualize.

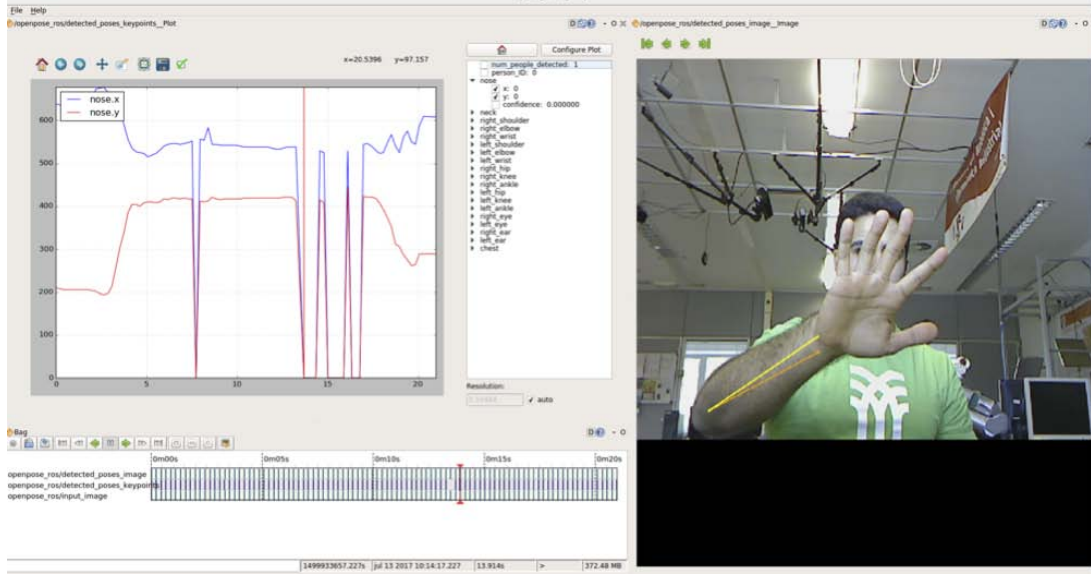


Figure 38: Confidence for some 2d keypoints estimation

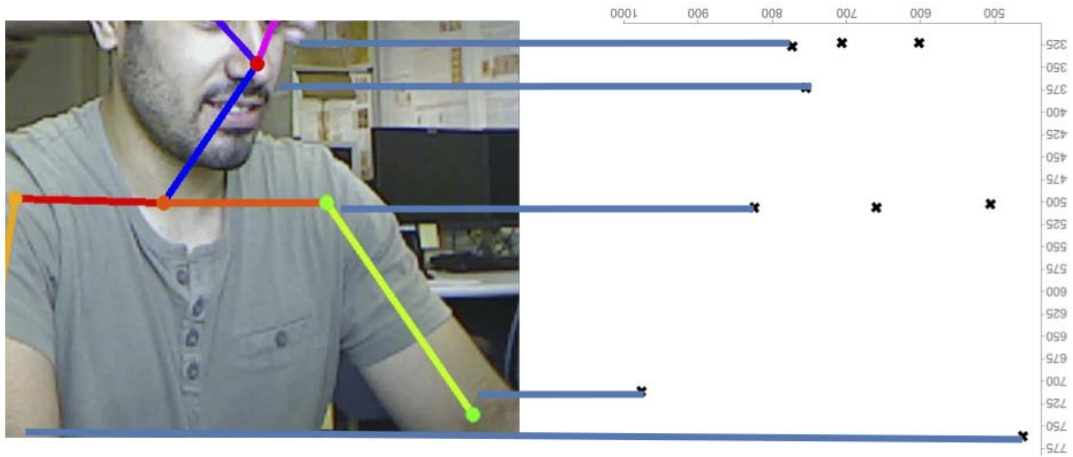


Figure 39: 2d keypoints coordinates and correspondence with segmented image

When the camera captures simultaneously RGB and depth images (RGB-D image), the software projects the body joints of 2d pose estimation, extracted from the RGB image, onto the point-cloud obtained by the depth camera and extracts 3d multi-person pose estimation (Figure 1). This 3d pose estimation can be visualized in RViz.

The results obtained (3d real-time multi-person pose estimation) with the streaming processing of RGB-D images captured by a Kinect One are shown in Figure 40. As we can see, the code matches the 2d detections in the RGB with the pointcloud successfully and extracts the 3d world coordinates.

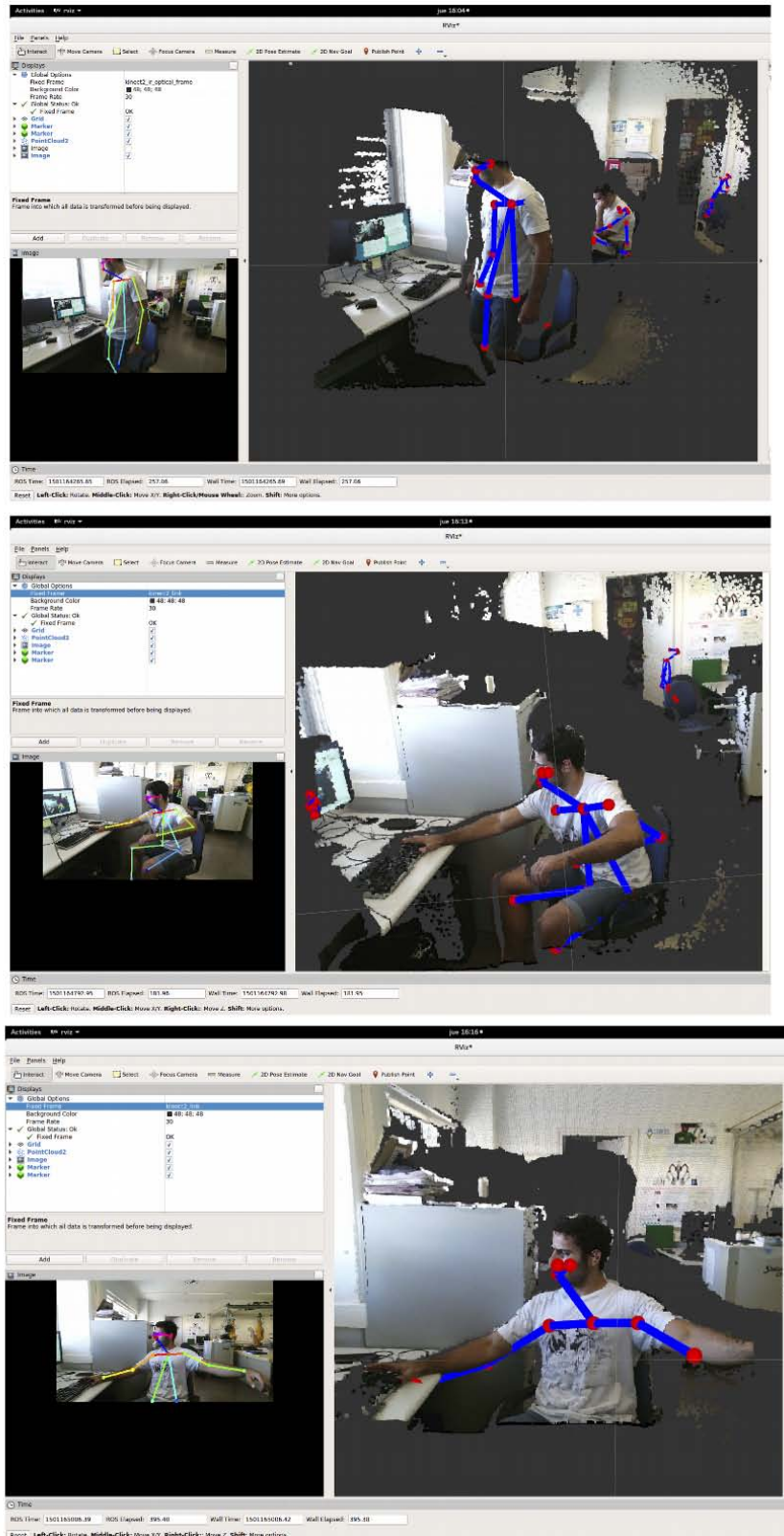


Figure 40: 3d pose estimation from RGB-D images captured by a Kinect One camera

Other mode of operation is the reproduction of images previously stored in a bag. A bag is a file format in ROS for storing ROS message data. Bags (so called because of their .bag extension) have an important role in ROS, and a variety of tools have been written to allow to store, process, analyze, and visualize them. Bags are the primary mechanism in ROS for data logging, which means that they have a variety of offline uses. Researchers can use the bag file toolchain to record datasets, then visualize, label, and store them for future use.

Using bag files within a ROS Computation Graph is generally no different from having ROS nodes sending the same data, though it can run into issues with timestamped data stored inside of message data. For this reason, the rosbag tool includes an option to publish a simulated clock that corresponds to the time the data was recorded in the file.

The bag file format is very efficient for both recording and playing back, as messages are stored in the same representation used in the network transport layer of ROS.

The process of extracting archived images from a bag is shown in Figure 41.

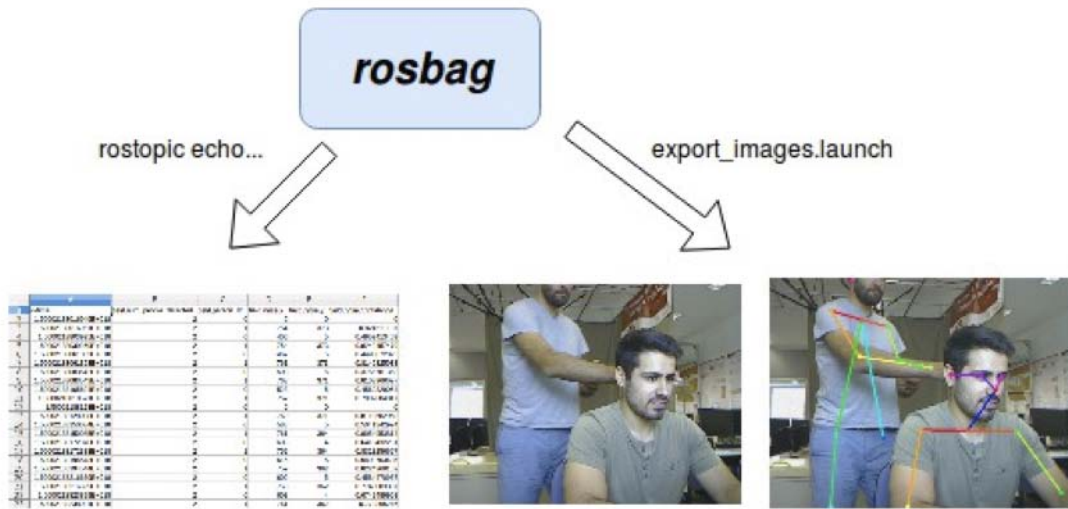


Figure 41: Extraction and processing of images from a bag

We consider that it is interesting to be able to use sequences corresponding to image databases, to contrast and validate the operation of the software that we have implemented. The images obtained from the database will be overturned to a bag, so that they can be processed in this ROS packages.

The bag is prepared for the data to be published in the same topics that have been configured to publish the images coming from the camera.

Using the ROS nodes (`openpose_ros_node` and `openpose_ros_node_firephinx`), the images extracted from the bag are processed as if a camera were connected. The Figure 42 illustrates the processing of images obtained from a bag.

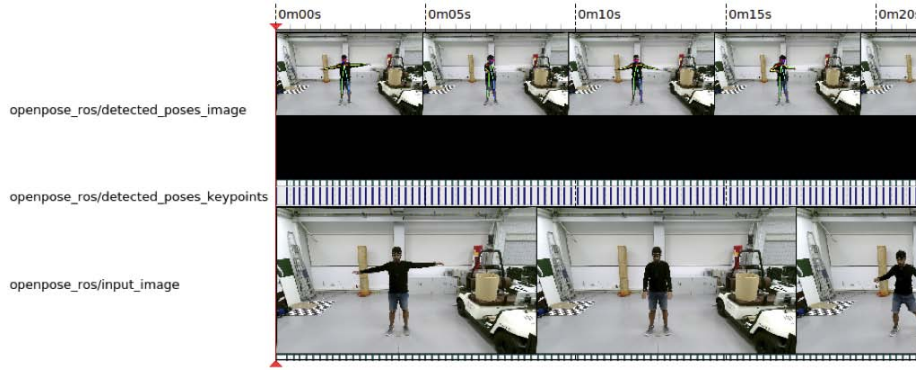


Figure 42: Processing of images obtained from a database

For example, in 2016 the Institut de Robòtica i Informàtica Industrial (IRI) prepared a database with RGB-D human images obtained with Kinect One and simultaneously recorded the position of a series of markers with OptiTrack System [3]. This database allows to know the position of certain bodyjoints of the person whose movements have been registered with OptiTrack and also captured with RGB-D images (Figure 43).

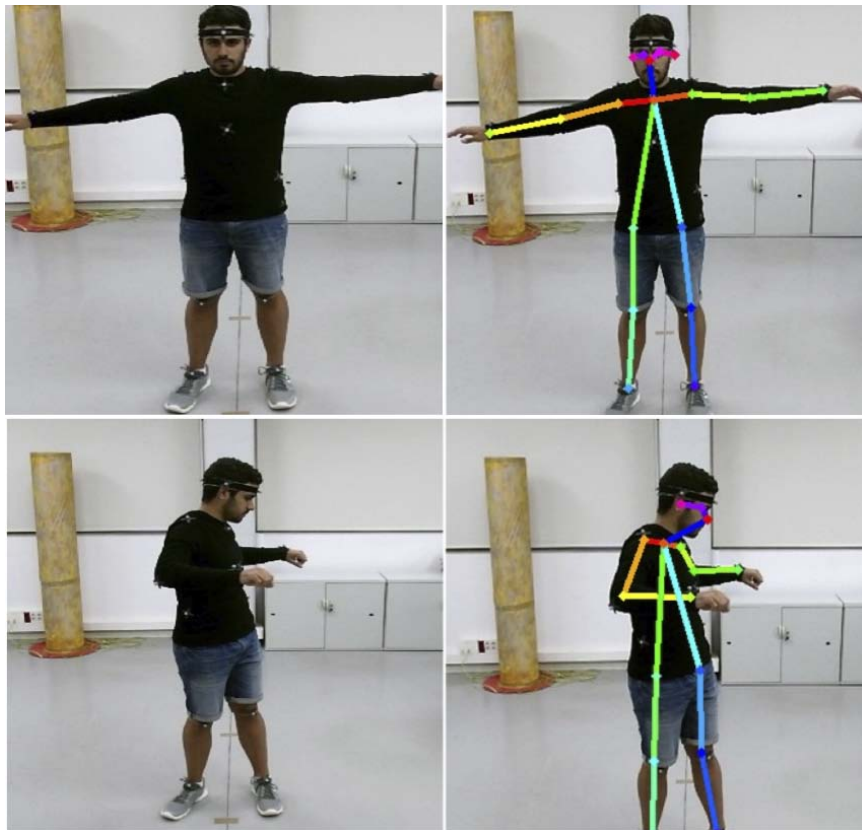


Figure 43: Human pose estimation from images of a database [3]

Therefore, we can compare the estimates of the position coordinates of the keypoints, obtained with this ROS packages for 3d pose detection, with their true coordinates, recorded by Optitrack System, to contrast and validate the results obtained.

5.2 Processing speed

If we record a rosbag and, by running `rqt_bag`, we have a look at the frequency that the 3d detections are sent, we obtain the results shown in the Figure 44.

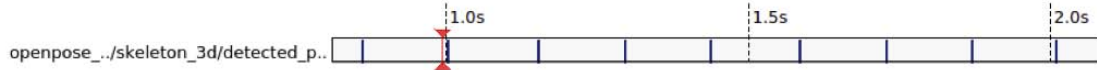


Figure 44: Frequency of the 3d detections

We can see that we get around seven detections per second. This is a satisfactory result that allow the management of the 3d pose estimation practically in real time. Processing time is less than the minimum required for a robot to do a task involving human-robot interaction.

If we record a rosbag with all the topics published by the package, we can see the results shown in the Figure 45.

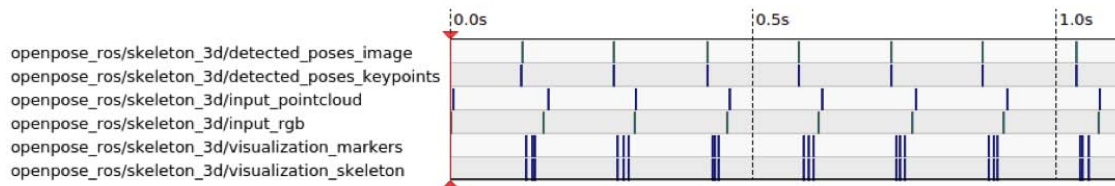


Figure 45: Messages published within the Skeleton-3d package

The first message to arrive, naturally, are the point-cloud and the RGB images. Next, the OpenPose 2d detection, that is the task that clearly takes more time. The following 3d detection and the visualizer messages are published after a very short time interval. This results shows that the implemented code is quite efficient, so it is not necessary to introduce more optimizations, because the processing time is little compared to the processing time of OpenPose package.

5.3 Limitations

The software works quite well but has, of course, some limitations. The most significant limitation is the occlusions of some part of the body, particularly when trying to obtain 3d human pose estimation. OpenPose solves fairly well the 2d human pose estimation even with occlusions, as we can see in the Figure 46.

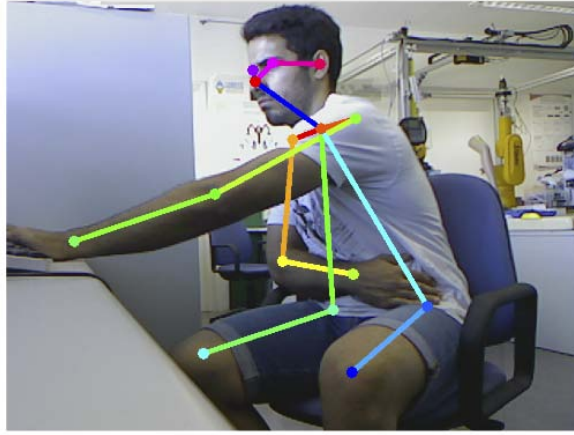


Figure 46: OpenPose with occlusions

But this is not the case with the software we have implemented for $3d$ human pose estimation. We extract the depth coordinate from the point-cloud, given a $2d$ pixel coordinate in the RGB image. But what happens if the camera is at one side, for instance, the left side of a person, as in Figure 47.

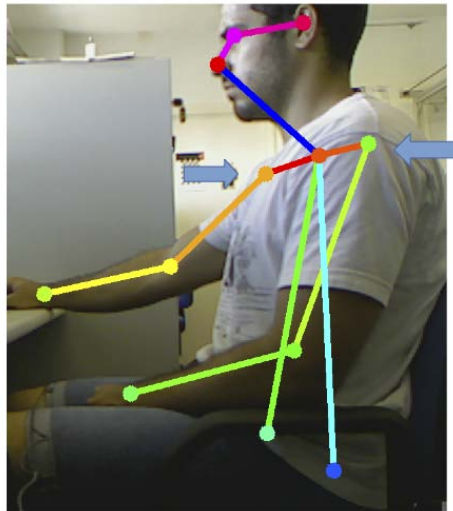


Figure 47: OpenPose with occlusions: camera in the left side

As the camera is in the left side, the detection of the left shoulder will be quite accurate, but what about the right shoulder? As we see, it is behind the chest in the image but OpenPose still detects it. But when we take the depth coordinate of the right shoulder we will use instead the depth coordinate of the chest. That means that our software for $3d$ detections cannot deal with occlusions.

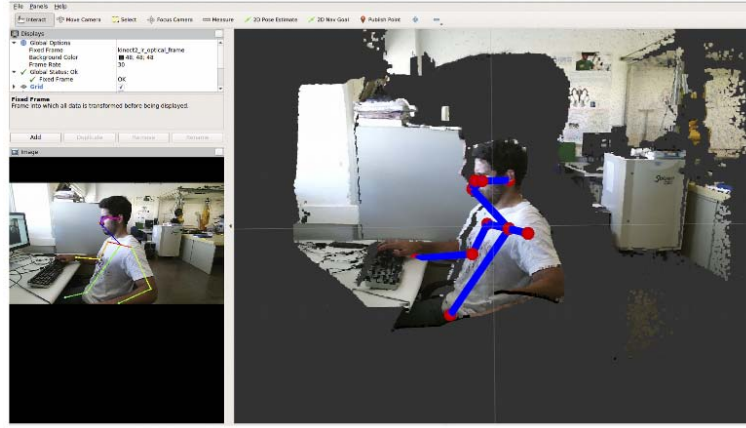


Figure 48: Camera in the left side: 2d and 3d pose estimations

The results when one joint is hidden are described in the Figures 48 and 49. Figure 48 shows the same view in the RGB image and in the depth image. To calculate the depth coordinate, we can move in the cloud of points to check the same with a view from above, as shown in the Figure 49. We can see that the x, y coordinate are taken correctly, but when taking the depth coordinate, z , we have taken the depth of the bodypart that is in front. In our case, we are taking the depth coordinate of the left shoulder instead of the right shoulder.

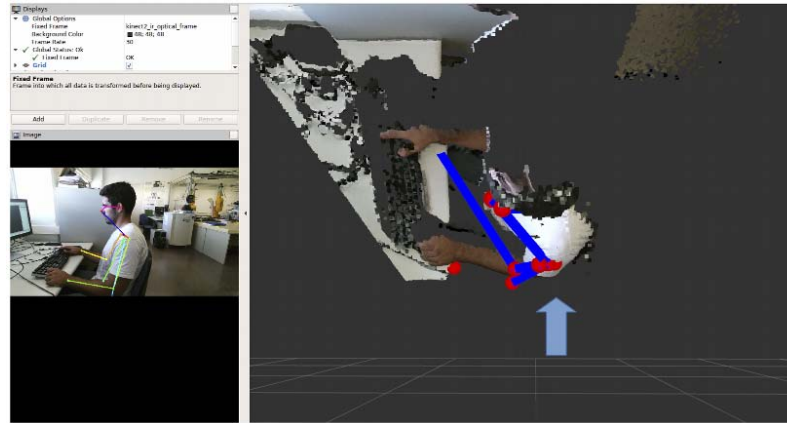


Figure 49: Camera in the left side: 3d pose estimation - View from above

With the method we have used to estimate the 3d pose, it is impossible to estimate the position of the occluded parts as we do not have their depth coordinate. We could try some filtering to obtain the detections of the occluded part.

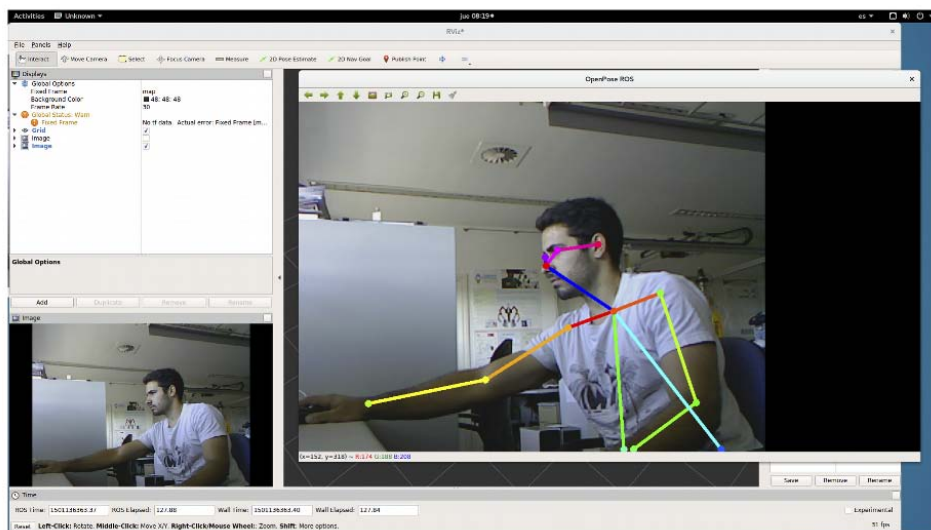
6 User Guide

This chapter describes the ROS implemented packages to facilitate its use.

- ROS wrapper for OpenPose (<https://github.com/CMU-Perceptual-Computing-Lab/openpose> - see commit number a1e0a5f4136e702b5731a268c2993fb75ca4753c) allows the estimation of $2d$ multi-person pose from a single RGB camera.
- When a depth image is synchronized with the RGB image (RGB-D image), a $3d$ extractor node has been implemented to obtain $3d$ pose estimation from the $2d$ pose estimation given by OpenPose through the projection of the $2d$ pose estimation onto the point-cloud of the depth image. Also, a visualization node for the $3d$ results has been implemented.

The package is accessible on the repository GitHub [2]:

https://github.com/MiguelARD/openpose_ros-1.



6.1 Installing OpenPose ROS Wrapper

1. Install openpose and its dependencies (<https://github.com/CMU-Perceptual-Computing-Lab/openpose/blob/master/doc/installation.md>)

NOTE: OpenCV 3.2 recommended, as OpenCV 2.4 might cause some errors.

2. Enable the package running in `openpose_ros` directory:

```
./install_openpose_and_enable_package.sh
```

3. Install PCL (<http://pointclouds.org/downloads/>)
4. If it succeeds, compile:

```
cd ~/catkin_ws/src
```

```
catkin build
```

```
cd ..
```

```
source devel/setup.bash
```

6.2 Running the OpenPose ROS Wrapper and the 3d Pose Extractor

The package can be divided into two modules that work independently. One for *2d* pose detections, with a visualization tool like the one in OpenPose but implemented in ROS. And another for *3d* pose detections, with a visualization node to view the results with RViz. We use the same node to get OpenPose *2d* detections for both modules, but we have duplicated it and the services it provides with different names to avoid trouble while calling it with the *2d* visualization tool and the *3d* extractor node simultaneously.

6.2.1 2d Detection Module

This module is composed of a service node for getting *2d* detections and a node for the output visualization.

First of all, you might want to change some things in the code to adapt it to your necessities:

- Go to `/openpose_ros_pkg/src/openpose_ros_node_firephinx.cpp`, and change `"/usb_cam/image_raw"` for the topic your camera is publishing the `sensor_msgs::Image` messages to:

```
// Camera Topic
DEFINE_string(camera_topic,          "/usb_cam/image_raw",    "Image topic that OpenPose will process.");
```

- You may change the output image resolution. To do so, go to `/openpose_ros_pkg/src/openpose_ros_node_firephinx.cpp` and change:

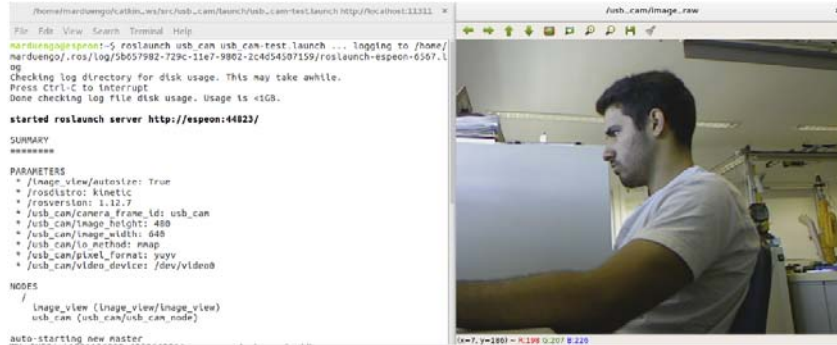
```
#define OUTPUT_RES_X 1280 // Display Resolution Output Width
#define OUTPUT_RES_Y 720  // Display Resolution Output Height
```

Once you have set those parameters repeat step 4 of installation.

Now you can run the code. First connect a RGB camera and run the corresponding ROS drivers to start to publish the images (they must be image_raw). For example you can connect a webcam and use https://github.com/ros-drivers/usb_cam. With this drivers run:

```
roslaunch usb_cam usb_cam-test.launch
```

You should get the something like:



Then, initialize the 2d detection service node:

```
roslaunch openpose_ros_pkg openpose_ros_node
```

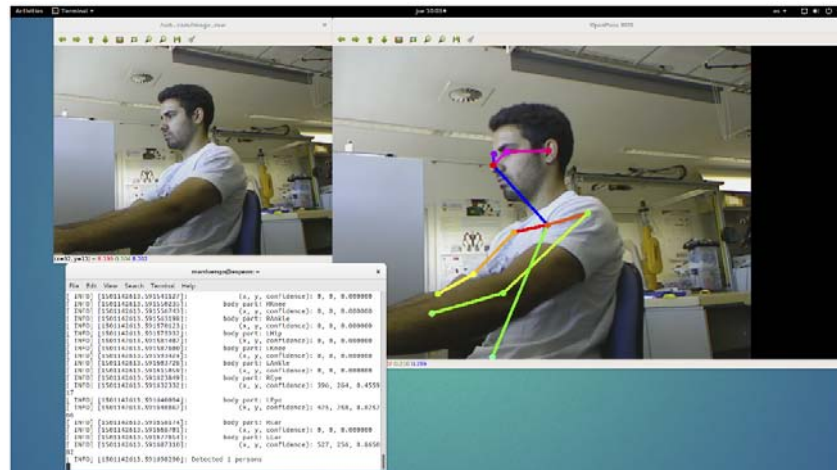
If everything works fine you should see the following output in your shell:

```
[ INFO] [1501140533.950685432]: Initialization Successful!
```

Finally, to get the 2d poses of the images from the camera and visualize the output, run:

```
roslaunch openpose_ros_pkg openpose_ros_node_firephinx
```

You should obtain something similar to:



If everything is running correctly, the package should be publishing in the topics:

`/openpose_ros/input_image`

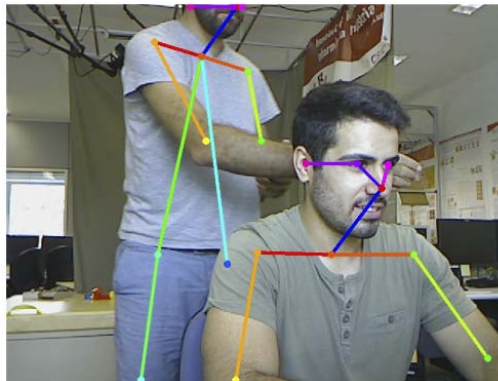
`/openpose_ros/detected_poses_image`

`/openpose_ros/detected_poses_keypoints`

- **`/openpose_ros/input_image`:** The images the 2d detection node is taking to make the segmentation are published here.



- **`/openpose_ros/detected_poses_image`:** Images with the segmentation skeleton drawn in it are published here.



- **`/openpose_ros/detected_poses_keypoints`:** In this topic, the messages with the 2d detections keypoints (openpose bodyjoints) are being published. The messages have the following fields:

- num_people_detected: number of people that are in the image.
- person_ID: ID number assigned to each person.
- bodypart (i.e. Nose): Each bodypart has the following fields:
 - x: x openpose keypoint pixel coordinate.
 - y: y openpose keypoint pixel coordinate.
 - confidence: confidence of the detection.

If you write the data in a csv it should be like this:

	A	B	C	D	E	F
1	%time	field.num_people_detected	field.person_ID	field.nose.x	field.nose.y	field.nose.confidence
2	1.49993152815341E+018	4	0	0	0	0
3	1.49993152815341E+018	4	1	0	0	0
4	1.49993152815341E+018	4	2	0	0	0
5	1.49993152815342E+018	4	3	525	335	0.7854701877
6	1.49993152826207E+018	4	0	0	0	0
7	1.49993152826207E+018	4	1	0	0	0
8	1.49993152826208E+018	4	2	0	0	0
9	1.49993152826208E+018	4	3	525	335	0.7854701877
10	1.49993152837404E+018	4	0	0	0	0
11	1.49993152837404E+018	4	1	0	0	0
12	1.49993152837773E+018	4	2	0	0	0
13	1.49993152837774E+018	4	3	525	335	0.7854701877

6.2.2 3d Detection Module

This module is composed of the same 2d extractor node described in the previous section, a node for getting 3d pose detection and a node for visualization of the output in RViz. We can see the resulting 3d human skeleton and the resulting 3d detections for the joints or both at the same time with the visualization node. An RGB-D camera is needed to run this module.

First of all you might want to change some things in the code to adapt it to your necessities:

- Go to /skeleton_extract_3d/launch/openpose_skeleton_extract.launch. You will see this:

```
<launch>
<!-- Launch openpose service-->
<node name="openpose_ros_node_3d" pkg="openpose_ros_pkg" type="openpose_ros_node_3d" output="screen" />
<!-- Launch the skeleton extractor node -->
<node name="skeleton_extract_3d_node" pkg="skeleton_extract_3d" type="skeleton_extract_3d_node">
  <renap from="~point_cloud" to="/kinect2/qhd/points" />
  <renap from="~image" to="/usb_cam_3d/image_raw" />
  <renap from="~skeleton_2d_detector" to="detect_poses_3d" />
</node>
</launch>
```

- Here you should change “/usb_cam_3d/image_raw/” for the topic your camera will be publishing the sensor_msgs::Image messages (RGB images). You should also change “/kinect2/qhd/points” for the topic your camera will be publishing the sensor_msgs::Pointcloud2 messages (depth images).

- Go to `/skeleton_extract_3d/src/skeleton_extract_3d_node.cpp` and set the input resolution of the images (the resolution of the depth and the RGB images must be the same):

```
// Set resolution
#define width 960
#define height 540
```

- Go to `/skeleton_extract_3d/src/skeleton_extract_3d_visualization_node.cpp`. You might want to change the color, shape, size etc. of the markers. To see the options you have go to <http://wiki.ros.org/rviz/DisplayTypes/Marker>.
 - To set the options of the bodyjoints:

```
// Set bodyjoints markers
marker.header.frame_id = "/kinect2_ir_optical_frame";
marker.id = person_msg.person_ID;
marker.ns = "joints";
marker.header.stamp = ros::Time();
// Markers will be spheres
marker.type = visualization_msgs::Marker::SPHERE_LIST;
marker.action = visualization_msgs::Marker::ADD;
marker.scale.x = 0.05;
marker.scale.y = 0.05;
marker.scale.z = 0.05;
// Joints are red
marker.color.a = 1.0;
marker.color.r = 1.0;
marker.color.g = 0.0;
marker.color.b = 0.0;
// Set marker duration in 150ms
marker.lifetime = ros::Duration(0.15);
```

- To set the options of the skeleton, go to:

```
skeleton.id = person_msg.person_ID;
skeleton.header.frame_id = "/kinect2_ir_optical_frame";
skeleton.ns = "skeleton";
skeleton.header.stamp = ros::Time();
// Skeleton will be lines
skeleton.type = visualization_msgs::Marker::LINE_LIST;
skeleton.scale.x = 0.03;
skeleton.scale.y = 0.03;
skeleton.scale.z = 0.03;
// Skeleton is blue
skeleton.color.a = 1.0;
skeleton.color.r = 0.0;
skeleton.color.g = 0.0;
skeleton.color.b = 1.0;
// Set skeleton lifetime
skeleton.lifetime = ros::Duration(0.15);
```

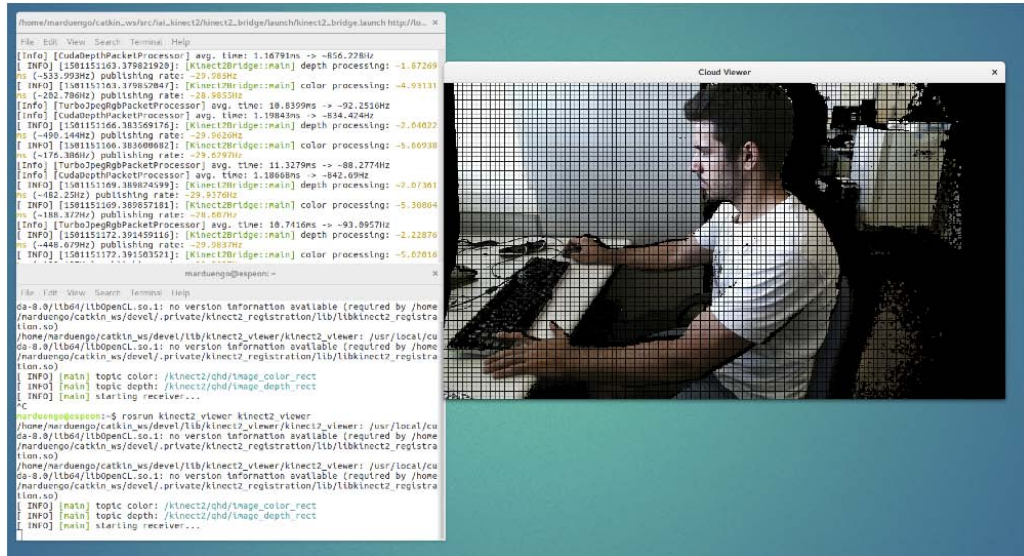
Once you have set the options repeat step 4 of the installation process. Now that you have configured it, you can run the code. First of all, connect your RGB-D and run the corresponding ROS drivers.

For example you can use a KinectOne and https://github.com/code-iai/iai_kinect2 ROS drivers. To initialize the camera with this drivers run:

```
roslaunch kinect2_bridge kinect2_bridge.launch

roslaunch kinect2_viewer kinect2_viewer
```

Then you will see the camera output:



Once your camera is publishing, launch the 2d extractor node and the 3d extractor node by running:

```
roslaunch skeleton_extract_3d openpose_skeleton_extract.launch
```

If everything is working fine you should have something similar to:

```
[ INFO] [1501152408.961898483]: Detected 6 persons
Minimum pointcloud (x,y,z) coordinates:
(-4.53544, -2.76288, 0.839 )
Maximum pointcloud (x,y,z) coordinates:
(3.04243, 2.85475, 9.771 )
Nose pixel coordinates (x,y,z):
( 598, 42, 3.10267)
Nose real world coordinates (x,y,z):
( 0.685628, -1.4638, 3.10267)
Neck pixel coordinates (x,y,z):
( 643, 53, 2.98111)
Neck real world coordinates (x,y,z):
( 0.918424, -1.34303, 2.98111)
Right shoulder pixel coordinates (x,y,z):
( 620, 67, 3.06156)
Right shoulder real world coordinates (x,y,z):
( 0.806914, -1.29637, 3.06156)
Right elbow pixel coordinates (x,y,z):
( 624, 114, 3.189)
Right elbow real world coordinates (x,y,z):
( 0.865194, -1.06046, 3.189)
```

Then you can run the visualization node:

```
roslaunch skeleton_extractor_3d skeleton_extractor_3d_visualization_node
```

Note: To have the fixed frame for visualization you must run:

```
roslaunch kinect2_bridge kinect2_bridge _publish_tf:=true.
```

Now open RViz and select as fixed frame the one you have set for the markers. For example, I have chosen:

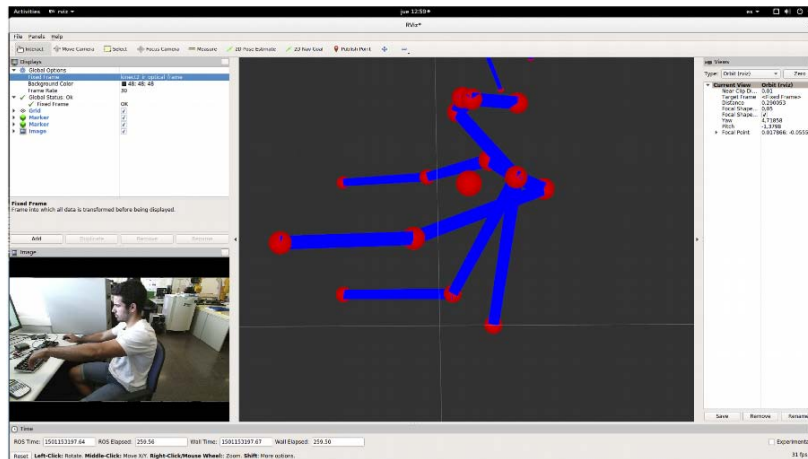
```
kinect2_ir_optical_frame.
```

Select the topics:

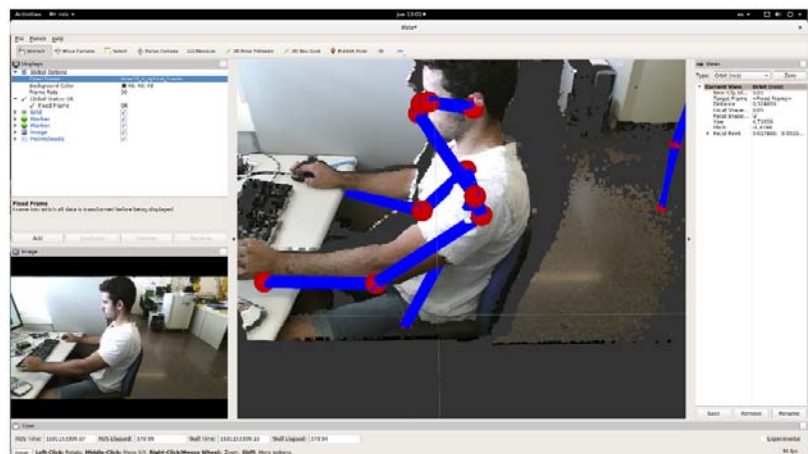
```
/openpose_ros/skeleton_3d/visualization_markers, and
```

```
/openpose_ros/skeleton_3d/visualization_skeleton,
```

and you should have something similar to:



You can also select the pointcloud at the same time:



If everything is running correctly the package should be publishing in the following topics:

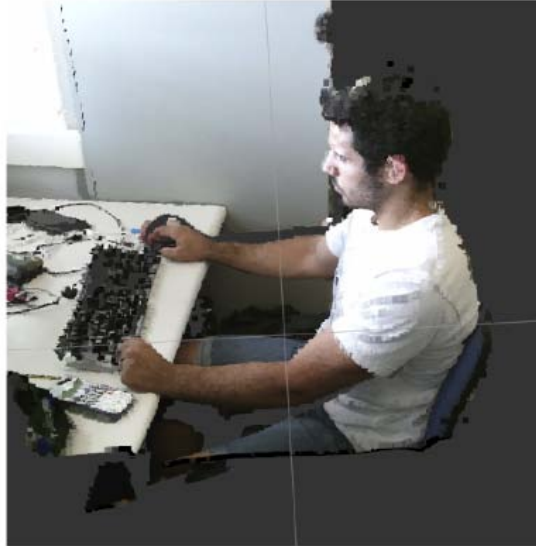
/openpose_ros/skeleton_3d/detected_poses_image
 /openpose_ros/skeleton_3d/detected_poses_keypoints
 /openpose_ros/skeleton_3d/detected_poses_keypoints_3d
 /openpose_ros/skeleton_3d/input_pointcloud
 /openpose_ros/skeleton_3d/input_rgb
 /openpose_ros/skeleton_3d/visualization_markers
 /openpose_ros/skeleton_3d/visualization_skeleton

- **/openpose_ros/skeleton_3d/detected_poses_image:** the same kind of messages are published in this topic as in topic:
/openpose_ros/detected_poses_image in the *2d* module.
- **/openpose_ros/skeleton_3d/detected_poses_keypoints:** the same kind of messages are published in this topic as in topic:
/openpose_ros/detected_poses_keypoints in the *2d* module.
- **/openpose_ros/skeleton_3d/detected_poses_keypoints_3d:** the *3d* detections are published in this topic. The fields are the same as the messages published in:
/openpose_ros/skeleton_3d/detected_poses_keypoints,
but the fields of each bodypart change. Now they are:
 - x: *x* real world coordinate of the joint.
 - y: *y* real world coordinate of the joint.
 - z: depth real world coordinate of the joint.
 - confidence: confidence of the *2d* detections.

If you write the message in a .csv, it should look like this:

	A	B	C	D	E	F	G
1	%time	field.num_people_detected	field.person_ID	field.nose.x	field.nose.y	field.nose.z	field.nose.confidence
2	1.50063613590885E+018	1	0	-0.0154055497	0.283746779	2.793222427	0.9070804119
3	1.50063613639442E+018	1	0	-0.1511128396	0.282182634	2.831222296	0.8941964507
4	1.50063613674613E+018	1	0	-0.3620795608	0.238503262	2.828000069	0.8935434222
5	1.5006361370928E+018	1	0	-0.497540921	0.195191279	2.828666925	0.8885506988
6	1.5006361375121E+018	1	0	-0.5640754104	0.150795802	2.809444427	0.9802207351

- **/openpose_ros/skeleton_3d/input_pointcloud:** Here is published the point-cloud that is synchronized with the RGB image from where we extract the x , y , z real world coordinates of the keypoints.



- **/openpose_ros/skeleton_3d/input_rgb:** the RGB image that we use to make the 2d detections is published in this topic and it is synchronized with the input point-cloud.



- `/openpose_ros/skeleton_3d/visualization_markers`: the markers to visualize in RViz the 3d detections of the joints are published in this topic.



- `/openpose_ros/skeleton_3d/visualization_skeleton`: the skeleton to visualize in RViz the 3d detections is published in this topic.



7 Conclusions

At least in the very near future, Convolutional Neural Networks (CNNs) are the most promising tools to obtain general detection, tracking, and recognition modules for human-aware robots. In general, the modules for $2d$ pose estimation from simple images are the most developed and there are even some quite effective open source packages that have reached a certain popularity. In particular, OpenPose (based on CNNs) is an efficient open source software for $2d$ real-time multi-person pose estimation.

We introduce a ROS wrapper that automatically recovers $2d$ multi-person pose from a single camera using OpenPose. Additionally we have developed a ROS node that obtains $3d$ human pose estimation from the initial $2d$ human pose estimation, when a depth image synchronized with the RGB image is captured, projecting the $2d$ pose estimation onto the point-cloud of the depth image. In this work, we have implemented a software application working on the Robotic Operating System (ROS) that obtains a pose estimation ($2d$ or $3d$, depending on the cases) from a simple image (a $2d$ image obtained with an RGB camera or a $3d$ image -RGB-D- obtained with a depth camera). The mode of operation is streaming and the images captured by the video camera are processed to obtain the multi-person pose estimation in real-time. The main functionality of the OpenPose_ROS package is $2d$ multi-person pose estimation from the RGB images captured by a single camera. When that camera simultaneously captures RGB and depth images (RGB-D images), the Skeleton-3d package projects the keypoints of $2d$ pose estimation (extracted from the RGB image) onto the point-cloud obtained by the depth camera and extracts $3d$ multi-person pose estimation.

Also, we consider that it is interesting to be able to use sequences corresponding to image databases, to contrast and validate the operation of the software that we have implemented. The images obtained from the database will be overturned to a bag. Using the ROS packages, the images extracted from the bag are processed simulating a connected camera. For example, in 2016 the Institut de Robòtica i Informàtica Industrial (IRI) generated a database with RGB-D human images obtained with Kinect One and simultaneously recorded the position of a series of markers with OptiTrack System. This database can be used to contrast and validate the results of the $3d$ pose estimation obtained with this ROS package.

The analysis of the processing time shows satisfactory results, since this time is less than the minimum required for a robot to do a task involving human-robot interaction. The most relevant limitation in the use of the implemented software is due to fact that the package for $3d$ detections cannot deal with occlusions.

Finally, we have made a user guide of the ROS packages implemented, to facilitate their utilization to potential users.

Bibliography

- [1] M. Andriluka, L. Pishchulin, P. Gehler, and B. Schiele. 2d human pose estimation: New benchmark and state of the art analysis. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3686–3693, 2014.
- [2] Miguel Arduengo. ROS Wrapper for Real-Time Multi-Person Pose Estimation with a Single Camera. https://github.com/MiguelARD/openpose_ros-1, 2017.
- [3] Miguel Arduengo, Guillem Alenya, and Frances Moreno-Noguer. Database for 3d human pose estimation from single depth images. Technical report, IRI-TR-16-05, Institut de Robotica i Informatica Industrial, 2016.
- [4] F. Bogo, A. Kanazawa, C. Lassner, P. Geher, J. Romero, and M. J. Black. Keep it smpl: Automatic estimation of 3d human pose and shape from a single image. In *EECV*, 2016.
- [5] E. Brau and H. Jiang. 3d human pose estimation via deep learning from 2d annotations. In *Fourth International Conference on 3D Vision*, 2016.
- [6] Martin Bunker. Evaluation of skeleton trackers and gesture recognition for human-robot interaction. Technical report, Master Thesis, Aalborg University, 2013.
- [7] Z. Cao, T. Simon, S.-E. Wei, and Y. Sheikh. Realtime multi-person 2d pose estimation using part affinity fields. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017.
- [8] A. Haque, B. Peng, Z. Luo, A. Alahi, S. Yeung, and L. Fei-Fei. Towards viewpoint invariant 3d human pose estimation. In *European Conference on Computer Vision (ECCV)*, October 2016.
- [9] J. Huang and D. Altamar. Pose estimation on depth images with convolutional neural network. *Report, Stanford University*, 2016.
- [10] Y.-Q. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell. Caffe: Convolutional architecture for fast feature embedding. In *Proceedings of the 22nd ACM International Conference on Multimedia*, pages 675–678, 2017.
- [11] Steven Jens M. Jorgensen. Human detection, gesture recognition and policy generation for human-aware robots. Technical report, Master Thesis, The University of Texas at Austin, 2016.

- [12] Lentin Joseph. *Mastering ROS for Robotics Programming*. Packt Publishing Ltd. Birmingham, UK, 2015.
- [13] J. Martinez, R. Hossain, J. Romero, and J.J. Little. A simple yet effective baseline for 3d human pose estimation. *arXiv preprint arXiv:1705.03098*, 2017.
- [14] D. Mehta, S. Sridhar, O. Sotnychenko, H. Rhodin, M. Shafiei, H.-P. Seidel, W. Xu, D. Casas, and C. Theobalt. Vnect: Real-time 3d human pose estimation with a single rgb camera. In *ACM TOG (SIGGRAPH)*, 2017.
- [15] C. Menier, E. Boyer, and B. Raffin. 3d skeleton-based pose body recovery. In *Proceedings of 3rd International Symposium 3D Data Processing, Visualization and Transmission*, pages 389–396, 2006.
- [16] A. Newell, K. Yang, and J. Deng. Stacked hourglass networks for human pose estimation. In *European Conference on Computer Vision (ECCV)*, 2016.
- [17] X. Perez-Sala, S. Escalera, C. Angulo, and J. Gonzalez. A survey on model based approaches for 2d and 3d visual human pose recovery. *Sensors*, 14, 2014.
- [18] Aleix Ripoll Ruiz. Object recognition and grasping using bimanual robot. Technical report, Master Thesis, Escola Tecnica Superior d’Enginyeria Industrial Barcelona, Universitat Politecnica de Catalunya, 2016.
- [19] A. De Santis, B. Siciliano, A. De Luca, and A. Bicchi. An atlas of physical human-robot interaction. *Mechanism and Machine Theory*, 43:253–270, 2008.
- [20] J. Shotton, T. Sharp, A. Kipman, A. Fitzgibbon, M. Finocchio, A. Blake, M. Cook, and R. Mooore. Real-time human pose recognition in parts from single depth images. *Mechanism and Machine Theory*, 56:116–124, 2013.
- [21] L. Sigal. Human pose estimation. *Encyclopedia of Computer Vision*, Springer, 2011.
- [22] E. Simo-Serra, A. Quattoni, C. Torras, and F. Moreno-Noguer. A joint model for 2d and 3d pose estimation from a single image. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2013.
- [23] T. Simon, H. Joo, I. Matthews, and Y. Sheikh. Hand keypoint detection in single images using multiview bootstrapping. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017.
- [24] D. Tome, C. Russell, and L. Agapito. Lifting from the deep: Convolutional 3d pose estimation from a single image. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.
- [25] S.-E. Wei, V. Ramakrishna, T. Kanade, and Y. Sheikh. Convolutional pose machines. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014.