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3D Human Pose Estimation for Assistive Robotics

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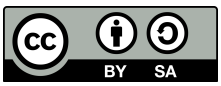

Agradecimientos

Resumen

Summary

Contents

List of Figures

List of Tables

Acronyms

CNN Convolutional Neural Network. 2, 5–8

DL Deep Learning. 2, 3, 5–8

ML Machine Learning. 1

Chapter 1

Introduction

Azul: lista de cosas que faltan por contar; Rojo: a revisar y/o falta;

In recent years, the increase in the computational capacity to collect and store data is producing a revolution in all areas of society (*e.g.* health, sports, education, finance, marketing, security or transport). Robotics is naturally involved in this revolution due to its enormous range of applications, from space to medicine, always with the aim of improving and making our lives more comfortable.

As part of this revolution, Machine Learning (ML) is also undergoing an unprecedented development, enabling many tasks to be performed in real-time, such as fraud detection, speech and face recognition or autonomous driving, just to mention a few ones [33]. In this sense, even though all areas in robotics are influenced by developments in ML, computer vision is perhaps the field which has experienced the most vertiginous growth. Furthermore, the growing interest in assistive robotics has enabled advances in some particular subfields of computer vision, such as human pose estimation, human detection and gesture recognition [30]. In particular, human pose estimation is a very handy capability for assistive robots, such as personal or home robots, as it can serve as an input for solving higher level tasks, for instance, fall detection. Broadly speaking, a precise identification of human pose provides a better understanding of the scene, which is a major requirement for any human-robot interface.

Motion-Capture systems are a well known solution for human pose estimation [**Vicon**]. They typically provide a very precise 3D estimation but require some markers in the person to be tracked. There are many technologies for human pose estimation developed for Ambient Assisted Living []. They use cameras or other sensors around the scenario to build their estimations. Typically the cameras are close to the ceiling and cover the area

to monitor, having a high point of view [**OpenPose**]. The larger the area to monitor, the greater the number of involved cameras. In order to avoid the high costs of managing several cameras, to avoid the need of any installation and to make the system more portable to many homes it is advisable to endow the home robot with the human pose estimation algorithm using only its sensors or cameras. Here the point of view of the cameras is not so high and there may be temporary occlusions, but the robot itself may move around the scenario for clearer views if needed.

The spectacular development of computer vision has been possible due to the push from Deep Learning (DL) techniques, a field of ML enabling to create complex models trained with huge amounts of examples associated to the task to be solved. Thanks to the inclusion of DL based techniques, specially Convolutional Neural Networks (CNNs), the performance of human pose estimation methods has significantly increased in the last years. This factor, in conjunction with the need for more reliable ways of understanding real scenes in applications such as video surveillance, human activity monitoring and human-computer interaction [51], has favored an increasing interest in research within this field. The great variety of tasks that can be addressed through human pose estimation has led to the development of many different approaches. Some solutions are designed considering 2D or 3D single images [13], while others take video streams into consideration [22, 63]. Regarding the output provided by the design, there are also different possibilities ranging from 2D and 3D joints locations [45] to dense estimations [1].

While the irruption of DL has had an undeniable beneficial impact in the development of the field of human pose estimation, the needed amount of real-world data for designing models achieving a good performance is still an issue, as capture and annotation processes are costly and very time consuming. This is specially true for 3D images, where motion capture systems are usually needed for collecting reliable annotations [25, 53]. As a consequence, there is a strong gap in the number of publicly available large-scale datasets in favor of the two-dimensional ones. While 2D estimations might be enough for solving some particular tasks like action recognition [32], 3D estimations are needed in order to achieve a complete visual understanding of the scene [51]. Fortunately, the emergence of robust RGBD sensors at affordable prices allows the integration of real 3D information into human pose estimation pipelines.

In this work, we propose and implement an end-to-end pipeline for augmenting 2D human pose estimations into 3D estimations in real time. This perceptive algorithm

is intended to be run on-board in many assistive or home robots: it works in real time in an off-the-shelf computer, it works with regular RGBD cameras, which are common in robotics, and when those cameras are placed at typical robot height, not close to the ceiling. We have validated it experimentally and performed a wide and detailed comparison with some of the most relevant human pose estimation algorithms, using Berkeley's Multimodal Human Action Database (BMHAD)[42], which is a publicly available and well-known international dataset.

Iterar contribuciones en función de dónde apuntemos??

Our main contributions are summarized as follows:

- We evaluate the performance and accuracy of multiple state-of-the-art methods for 2D human pose estimation;
- We propose and evaluate a straight-forward pipeline for augmenting 2D estimations into 3D estimations in real-time with the inclusion of an RGBD sensor;
- We evaluate and compare our 3D human pose estimation method with a state-of-the-art DL algorithm;
- ~~We build a web-based 3D visualization tool for human activity monitoring;~~
- We demonstrate our proposed pipeline performance with a practical use case for assistive robotics;

The rest of this report is structured as follows. In Section 2, a review of related work and state-of-the-art methods is presented. In Section 3, each step in the proposed pipeline is described in detail. The experiments carried out to evaluate the performance of this pipeline are presented in Section 4. Finally, results are discussed and summarized in Section 5.

Chapter 2

Related Work

From a computer vision perspective, the human body can be considered as a collection of rigid parts connected between them by a number of joints [22]. Following this approach, the goal of human pose estimation methods is to determine the two-dimensional or three-dimensional location of these joints and parts from an image or a sequence of images. Classical approaches usually address the modeling and estimation of these articulated poses building upon the seminal works of [19, 17] in pictorial structures and part-based models. Such is the case of Andriluka *et al.* [3], who combines strong part detectors with pictorial structures, or Yang and Ramanan [61] when proposing a mixture of non-oriented pictorial structures. Other works have further explored these methods [50, 47, 29, 58], even trying to address multi-person scenarios [14] and introducing spatio-temporal cues in video sequences [11, 16, 18, 65].

More holistic approaches started to gain popularity with the inclusion of DL techniques. In [57], Toshev and Szegedy explore the application of CNNs to estimate the body joints locations considering a cascade of Deep Neural Networks refining a coarse initial estimation. In [56], Tompson *et al.* proposed a joint training of a hybrid architecture composed of a CNN (as the part detector) with a part-based spatial model inspired on Markov Random Fields, significantly outperforming previous methods. Since these works, most research in human pose estimation has shifted towards DL-based solutions [15, 6, 31, 8, 12, 10, 60, 4, 28, 39, 24, 59]. Newell *et al.* [39] propose a novel CNN architecture for this particular task forcing *bottom-up* and *top-down* processing with intermediate supervision. In [59], Wei *et al.* inherit the *pose machines* architecture proposed by Ramakrishna *et al.* [49], but introducing CNNs as feature detectors. Their sequential architecture, based on multiple stages which take as input belief maps from the previous stages, enables learning

long-range dependencies among parts. A more general approach for spatial localization tasks is proposed by Gkioxari *et al.* [21]. Because of their intuitiveness and performance, we have chosen [39], [59] and [21] methods as 2D human pose estimators for our work. We will go deeper in these methods in Section 3. One of the most successful works published in the last years is the one proposed by Chen *et al.* [10]. In order to deal with joint occlusions and overlapping of human body parts, they propose the usage of structure-aware CNNs and Generative Adversarial Networks to train a pose generator only yielding plausible poses, implicitly learning priors about the human body structure. This approach is out of the scope of this paper because, to the best of our knowledge, there is no open source code available.

The aforementioned works are focused on 2D pose estimation from individuals on single images. However, several authors have also tried to apply DL-based techniques by taking advantage of the temporal information provided by sequences of images [27, 46, 54, 20]. Such is the case of Pfister *et al.* [46], who introduce in their pipeline dense optical flow estimations to warp estimated per-joint heatmaps in consecutive frames. In that way, the trained CNN is forced to learn the temporal relationships between sequences of poses. Another approach to human pose estimation in 2D video is proposed by Girdhar *et al.* [20]. In their work, they propose a 3D extension of the Mask Region-based CNN architecture to couple spatio-temporal information. DL-based methods have also been employed in multi-person scenarios [7, 26, 43, 23] and dense pose estimations, which map image pixels of the human body to its corresponding 3D surface [1].

Regarding the 3D estimation methods, there are different approaches depending on the source of information. Estimating 3D locations from their 2D projections is a highly ill-posed problem, as very different 3D poses can generate very similar 2D projections. However, the *a priori* knowledge about the human body and plausible poses, have allowed researchers to tackle this problem by means of hybrid approaches composed of two-stages: 2D estimation and 3D reconstruction from 2D projections. For instance, Andriluka *et al.* [2] propose a complete framework for multi-person pose detection in videos using tracking-by-detection and 3D exemplars. Regarding the 3D reconstruction from 2D projections, Ramakrishna *et al.* [48] propose an optimization proxy which jointly estimates 3D coordinates from 2D locations of anatomical landmarks and camera parameters while enforcing anthropometric regularity. Most recent methods introduce CNNs for 3D estimation. Chen and Ramanan [9] make use of the Convolutional Pose

Machiness (CPMs) proposed by Wei *et al.* [59] for 2D estimation and then match the resulting pose with a library of 3D exemplars. In [5], Bogo *et al.* estimate 2D poses with the DeepCut model proposed by Pischulin *et al.* [47] and then fit a statistical body shape model to the resulting 2D joints. However, DL-based methods have not only been used for the 2D pose estimations, but they have also proved to be a very straightforward and effective solution for inferring 3D from 2D poses. Thus, Zhou *et al.* [65] propose the inclusion of a *depth regression module* taking the 2D heatmaps generated by a CNN as input, providing a 3D pose estimation as the output. A simple but effective approach is proposed by Martinez *et al.* [36] by training a deep neural network to estimate 3D body joint locations from the corresponding 2D positions. For an adequate performance of the trained model, they consider the inverse transform of the camera to preprocess the 3D ground-truth before training, thus making the 2D to 3D problem similar across different cameras. Tome *et al.* [55] propose a more sophisticated solution which not only predicts 3D poses but also uses them to improve their previous 2D estimation, blurring the separation between the two previously mentioned stages. Several authors [40, 34, 44, 41, 37] have chosen direct inference instead of tackling the problem in these stages. Such is the case of the work proposed by Mehta *et al.* [37]. In their work, not only they infer 3D poses but also add temporal filtering and fit a kinematic skeleton model in order to take advantage of temporal correlation between frames.

The inclusion of depth measurements allows for higher accuracy and better understanding of the scene being analyzed. In [64], Youding *et al.* use video stream from a time-of-flight sensor for detecting and tracking the position of anamotical landmarks using a probabilistic inferencing algorithm. Schwarz *et al.* [52] try to solve the same task using geodesic distances and optical flow. A different approach is presented in [62], where Ye *et al.* estimate body pose by matching and refining pre-captured exemplars. Recently, DL-based solutions have been proposed to address pose estimation from depth maps. Marín-Jimenez *et al.* [35] train a CNN estimating 3D body poses as a linear combination of prototype poses. Moon *et al.* [38] introduce the novelty of designing their model as a 3D CNN, which estimates the likelihood per voxel for each joint in the pose. They test their model performance not only for addressing human pose estimation, but also hand pose. In [66], Zimmermann *et al.* use a 2D keypoint detector to estimate the 2D pose, which is next used together with the depth map as input to train a CNN yielding predictions of real world 3D coordinates. These 3D predictions are used for robotic tasks

learning.

Chapter 3

Proposed method

Chapter 4

Experiments

Chapter 5

Conclusions

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