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"Design, evaluation, and application of a workflow for biomechanically consistent markerless kinematics in sports"

"Conception, évaluation, et application d'une méthode biomécaniquement cohérente de cinématique sans marqueurs en sport"

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"To all of you who care about more important stuff than what follows."

Acknowledgements

Should I start this by declaring that these PhD years have been alternatively depressing and engaging, exhausting and stimulating, infuriating and enthralling? This is trite, and true for everyone, PhD student or not. Covid pandemic or not. Child birth or not. Struggles in close friends' and relatives' lifes or not. But there it is. Now that it is stated, let me go straight to my acknowledgements.

Above anyone else, I want to thank my mother. She not only had to deal with the difficult task of raising me and putting up with my constant flow of questions, but also with welcoming the four smaller sisters that came after me. As a widow. With debts to pay off, and very little money coming in. Moving every two years, until we settled in for a small appartment in a neighborhood that some would call a ghetto, although we prefered calling it home. And yet, there was always food on the table. Even better, we had no idea how poor we were, because she literally sacrificed her life for ours, and her passions for our interests. This is quintescential Christlike love. We all had the incredible opportunity of doing at least one physical, and one artistic activity, on top of pursuing university level studies. We also learned how to live happily with very little, which I'm starting to realize is a sort of superpower. Most importantly, she made children that all love each other. Now that I'm a father too, I can measure how high she set the bar, and I can only hope to be half as good as her. I can't award her the Legion of Honor she deserves, but at least here is a little bit of recognition! Thank you from all of us, maman.

I also have a deep thought for my father, who tragically passed away when I was still a little child. He did have to struggle with some issues that would eventually cause his death, but I believe he fought until the very end. He is actually the one who taught me a nice lesson of persistence, surely without even trying. A friend and I were racing up a hill, while my father timed us. I lost. We raced again, I lost again. I tried more, and sure enough, I lost every single race. I went to my dad and complained: "I'm tired papa, can we stop?" "Are you tired, really? Very good, it means that you're on your way to make progress!" I paused, and let it sink in for a few moments. And without a word, I went back running. That's how I learned that getting better goes with accepting to suffer a little. Later on, I also realized that out of any bad experience, be it death, you can take away something positive, something that will halp you grow. Against all odds, I even made a first professional carrier in sports. I am very grateful for both my parents: I am who I am, with all my quirks and all that's to be loved or to be hated, thanks to them.

So many more people to thank! I'm just getting started, sorry to inflict you this. But let's start with the sisters. Esther comes just after me, she married an awesome guy from Congo, and is currently raising two wonderful little girls. She is the closest to what my mom was with us (and still is), making anyone feel home at any time, always on the move, taking care of her family during the day and working at nights, juggling countless tasks and thinking it is all just natural. Then comes Déborah, although she didn't come alone since Joëlla followed 10 minutes later. But believe it or not, she is slightly more than a twin. She has a high sense of justice and a desire to be helpful, which made her switch from the arts history field to the health one, so as to be more true to herself. Joëlla also is incredible. She fights every day her health issues, could not finish high school but still managed to get a bachelor degree, and she now is a professionnal violinist, whose empathy perspires through all her plays. I'm on a roll now, and I don't think you'll be suprised if I tell you that my last sister, Noémie, is decent enough. She also became a professionnal violinist, she runs every day, and she is currently studying psychology. She also spends a lot of energy mediating arguments between people she loves. A family I'm proud of, not only because of their obvisous skills, but because of their virtues.

I want to thank my grand-parents, whose house was the ground base for all of my aunts, uncles, and cousins, who met there during each and every vacation. They made us discover the delightful joy of being cold, wet and exhausted during rainy hikes, to finally end up above a splendid sea of cloud from which protruded just a few sharp peaks, over which Alpine choughs maneuvered with their vigorous flight. They are the true pillars of our extended family. The cycle of life being what it is, they became older and can't hike anymore. I am now very happy to see the whole family striving to take care of them, as much as they have been taken care of. I can sadly not name every single other member of my family, humans or animals, but they are all a crucial part of myself.

I do need to spend some time for the love of my life, Mikaela. We met in Lebanon, she is American, she cares about France as little as I care about the USA, and yet she accepted to come here for me, in the armpit of the old and stinky world. She had the courage to take over my mother's difficult job to bear with my incessant questions. She actually has a lot of answers, since the extend of her knowledge is so wide and well-rounded. She is also an awesome writer, and a qualified editer who plays a large role in making my productions publishable. She is much more than she believes of herself: exceedingly faithful, remarkably generous, paradoxically very introverted but willing to home all the persons in need we come across, and unfortunately suffering of how little her power is to make the world a better place. She also comes with a very nice family in law, and of course, she is the mother of my child Cédric! A stunning baby who spends an excessive amount of energy smiling at every one, all day long (aside from sometimes, when he screams his head off.) He might give me a hard time whenever I get started writing my thesis, but he does it in a very cute way. And he always embodies a very good way for us to get away with our shared legendary absent-mindedness. I'm looking forward to the time I'll be old enough for him to change my diapers.

Life wouldn't be life without friends, old and new ones, whether I see them several times a week or once every two or three blue moons. Friends of the family, friends from church, friends from parkour, friends from the performing world, friends I have no idea how I got to know them. Not to brag, but they are too numerous to name them all.

Finally, let's remember that this is a PhD thesis that I'm writing, and that there is no thesis without a lab, without supervisors, without fellow PhD students, post-docs, interns, researchers, administrative workers, cleaning operatives, and all who are involved in making work enjoyable (sic.) I want to thank them all. Lionel, my director, who saved me from the happy hell of starving performing arts to give me the chance to throw myself in another highly precariously fun situation. Mathieu, my co-supervisor, who was quite present and helpful, always ready to give me quick and valuable feedback, despite he lived in the other end of the country. One expert in computer vision, the other in biomechanics: the perfect fit for the objectives of my doctorate. Thibault, my faithful office colleague, that I often left alone with the sole presence of cold-blooded computer hardware while I worked remotely. Other colleagues from other places such as the INSEP, the LBMC, the Pprime institute, etc. Thank you all!

To sum it up, I owe this work to my family, my friends, my colleagues, and I'm guillible enough to believe I owe it to God above all. I am happy I have overcome it, not only alone but with all of the aforenamed people!

On these words, I suppose I can now start with what I'm here for.

Abstract

Abstract.

Résumé

Résumé.

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State of the art

Motion capture (MoCap) in sports is traditionally performed with marker-based (opto-electronic) systems. However, this presents some drawbacks. As a consequence, alternatives are being investigated, among which thoses offered by Inertial Measurement Units (IMUs) or dept-field (RGB-D) cameras. Markerless analysis from videos sources represents one of the most promising prospects, which has been possible thanks to progress in machine learning. From 2D pose estimation to 3D joint angle determination, this is a new field which opens up new possiblities for motion analysis in a sports context.

This chapter is an up-to-dat and slightly more detailed version of the introduction of the previously published paper "Pose2Sim: An End-to-End Workflow for 3D Markerless Sports Kinematics—Part 1: Robustness" [Pagnon2021]

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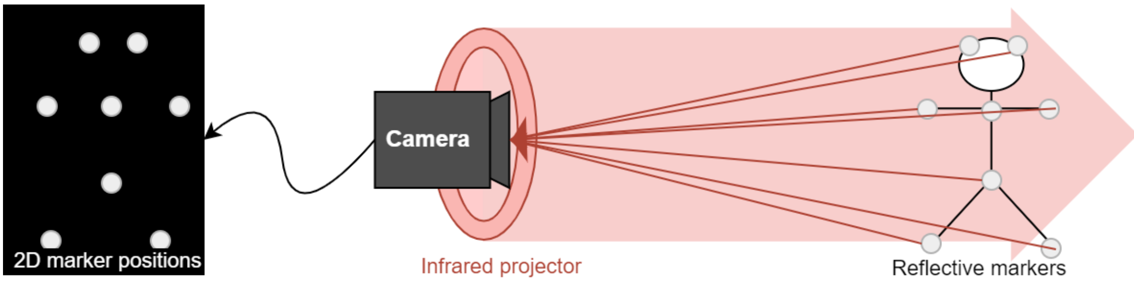
1.1 Overall context of kinematics in sports

1.1.1 General context

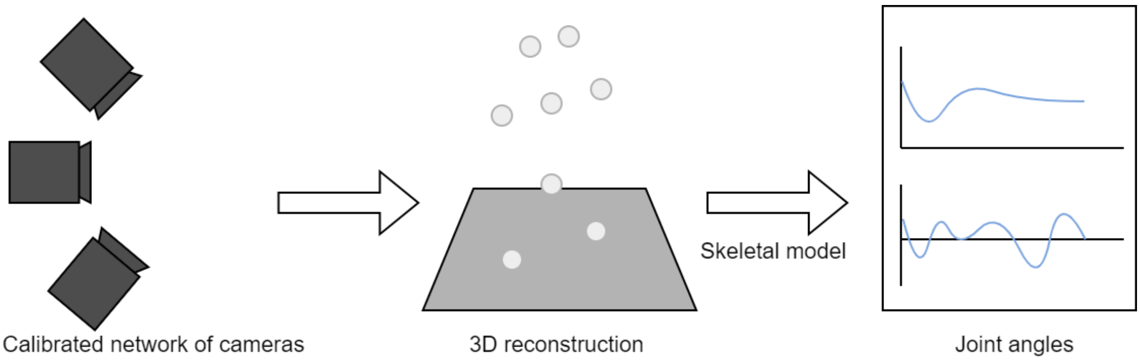
As coaching athletes implies observing and understanding their movements, motion capture (MoCap) is essential in sports. It helps improving movement efficiency, preventing injuries, or predicting performances. For the last few decades, marker-based systems have been considered the best choice for the analysis of human movement, when regarding the trade-off between ease of use and accuracy. However, these methods have proven to be much more challenging in a sports context than in a laboratory setting, and to be generally inappropriate [Mündermann2006, Colyer2018]. As a consequence, other methods have been investigated.

1.1.2 Marker-based systems

Marker-based systems use a network of opto-electronic cameras. Each of these cameras are surrounded by a crown of infrared LEDs, which projects light toward the subject, who is equipped with reflective markers. Ideally, only the light reflected from these markers is captured by the cameras. The camera usually pre-processes the image to make it binary, and only outputs the coordinates of the detected marker (Figure 1.1a).



(a) An opto-electronic camera is traditionnaly surrounded by a crown of infrared LEDs, projecting light toward the subject. The subject wears markers, which reflect light back to the camera. Marker positions are then known in the camera plane.



(b) Once calibrated, a network of these cameras allows for 3D reconstruction of marker positions. Marker coordinates are then used to infer the posture of the subject.

Figure 1.1: Principles of marker-based motion capture. (Figure 1.1a) presents the functionning of an opto-electronic camera. (Figure 1.1b) shows how a network of calibrated motion capture cameras helps obtaining joint angles.

If calibrated, using a network of these cameras allows for triangulating the 2D coordinates. Calibration involves knowing the cameras' intrinsic properties (such as focal length, optical center, distortion) as well as their extrinsic properties (their position and orientation as regards to the global coordinate system.) See Chapter 2.2 on 3D reconstruction for more details. The reconstructed 3D marker positions are then used to optimize the posture of a physically consistent skeleton, scaled to each individual subject. In particular, this allows for obtaining 3D joint angles at each point in time, commonly referred to as inverse kinematics (IK.)

Yet, reflective marker-based camera systems are complex to set up, are time-consuming, and are very expensive. They also require specific lightning conditions, and involve cumbersome cabling. Moreover, markers may fall off the body of the participant due to sharp accelerations or sweat. They can hinder the natural movement of athletes, which is likely to affect their warm-up, focus, and safety. While the accuracy of landmark location is claimed to be sub-millimetric in marker-based methods [Topley2020], marker placement is tedious, intrusive, prone to positioning variability from the operator [Tsushima2003], and subject to skin movement artifacts, especially on soft tissues. Della Croce et al. found out that inter-operator variations in marker placements range from 13 to 25 mm, which can propagate up to 10° in joint angle prediction [Gorton2009, della Croce1999]. For example, tissue artifacts account for up to a 2.5 cm marker displacement at the thigh, which can cause as much as a 3° error in knee joint angles tissues [Benoit2015, Cappozzo1995]. Joint positions must be calculated explicitly in marker-based methods, which introduces more variability: these errors range up to 5 cm, which can contribute up to 3° of error in lower limb joint angles [Leboeuf2019]. Nevertheless, since marker-based methods benefit from decades of research, they are still considered as the reference method for motion capture.

1.1.3 IMU and RGB-D systems

Consequently, other approaches based on alternative technologies have been investigated over the past years. For instance, wearable Inertial Measurement Units (IMUs) can be placed on an athlete's limbs. IMUs are generally made of an accelerometer, a gyroscope, and a magnetometer. The accelerometer measures the linear acceleration, the gyroscope measures the rotational speed, and the magnetometer measures the orientation of the earth magnetic field. Fusing and integrating these signals allows for the determination of their 3D orientations. The orientation of the athlete's limbs can then be used in combination with a skeletal model to infer their posture (Figure 1.2).

IMUs offer the advantages of getting away from all camera-related issues. They are inexpensive, they do not involve any complex setup and calibration, the field of view is larger, they are not sensitive to self- and gear-occlusions, they can be operated outside of a controlled environment, and they can work in real-time [Johnston2019, Chambers2015]. They still have the drawback of being an external equipment to wear, involving high technical skills from the operator, and are sensitive to ferromagnetic disturbances. Above all, they are exposed to drift over time and need to be calibrated every few minutes. Joint angle accuracy is relatively good in the flexion/extension plane, but less so in other rotational planes where errors are greater than 5° for most motions [Zhang2013, Rekant2022]. Moreover, they are not suitable for joint positions assessment, since these are obtained through multiple integrations of the original signal [Ahmad2013].

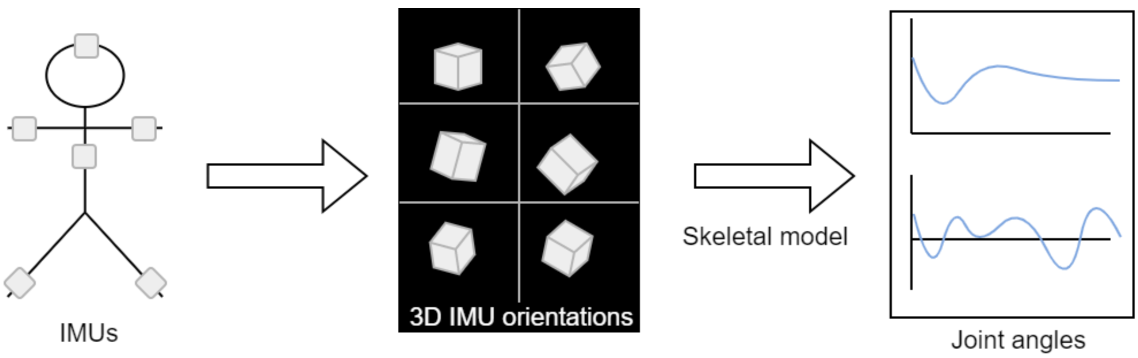


Figure 1.2: IMUs are placed on the subject's limbs. The orientation of the limbs is then used to infer the posture of the subject.

Another approach involves depth-field cameras (RGB-D). Older models projected infrared *structured* light (i.e., a pattern) onto the scene. The relative deformation of the pattern reflected from the scene was then used to estimate depth. Newer models project infrared *modulated* light onto the scene. The time of flight of the light reflected from the scene is then used to estimate depth.

Results are commonly considered to be 2.5D, since only the depth of the front facing plane of view is measured. A network of a few RGB-D cameras can give access to full 3D [Carraro2017, Choppin2013, Colombel2020]. On the other hand, these cameras hardly function in direct sunlight nor at a distance over 5 meters, and they work at lower framerates [Han2013, Pagliari2015].

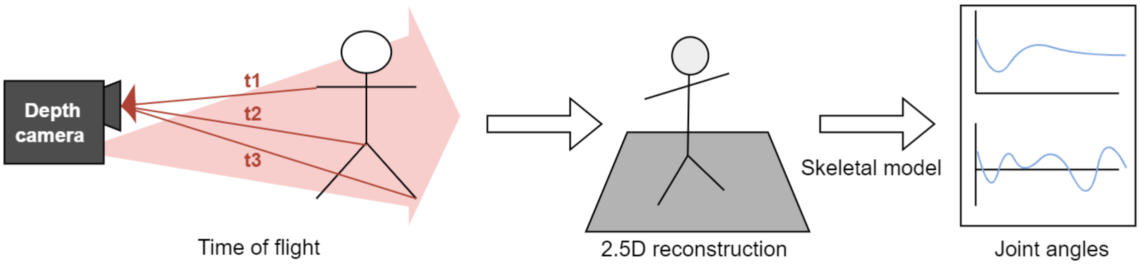


Figure 1.3: A depth-field camera (RGB-D) projects infrared modulated light onto the subject's body. The time it takes for the light to be reflected to the camera sensor (time of flight) depends on distance, and gives access to the depth of the scene. Older RGB-D cameras use structured light rather than time of flight calculations to infer depth.

1.1.4 Markerless systems

A recent breakthrough has come from computer vision, and the advent of 2D pose estimation from image sources, which quickly became more efficient and accurate. The explosion of deep-learning based methods from camera videos, for which the research has skyrocketed around 2016 [Wang2021], is related to the increase in storage capacities and huge improvements in GPU computing. A search on the ScienceDirect database for "deep learning 3D human pose estimation" produced fewer than 100 papers per year until 2015, and the number is now reaching over 1,000, fitting an exponential curve (Figure 1.4).

It has rekindled interest from the biomechanics community towards image-based motion analysis, which is where it all started with the invention of chronophotography in the 19th century by Marey in France, and Muybridge in the USA [Baker2007]. Currently, two approaches coexist in human and animal motion analysis: the first one mostly focuses on joint positions, and is lead by the computer vision and the deep-learning communities; while the second one is interested in joint angles, such as the biomechanics community uses to obtain physically coherent kinematics individualized to each subject. One of the main current challenges is to bridge the gap between these two worlds, and to take advantage of deep-learning technologies for kinematic analysis [Cronin2021, Seethapathi2019].

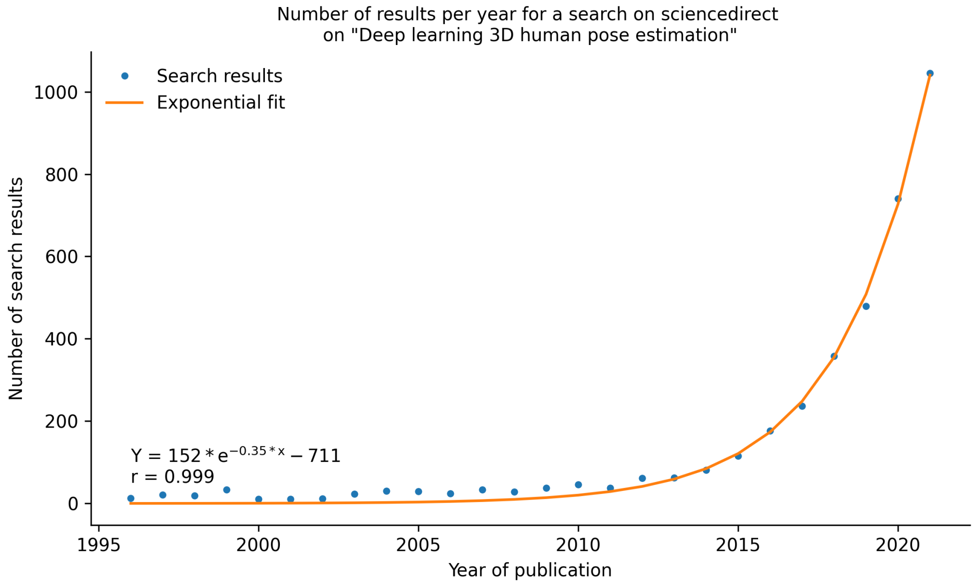


Figure 1.4: The search for "deep learning 3D human pose estimation" (dots) fits an exponential curve (line). The search produced less than 100 results until 2015, and is now well over a 1,000 per year.

1.2 2 dimensional analysis

1.2.1 2D pose estimation

The most well-known off-the-shelf 2D human pose estimation solutions are OpenPose [Cao2019] (Figure 1.5), and to a lesser extent AlphaPose [Fang2017]. While both show similar results, OpenPose has the advantage of being a bottom-up approach, whose computation time does not increase with the number of persons detected [Cao2019]. A bottom-up approach first detects all available joint keypoints, and then associates them to the right persons; while a top-bottom approach first detects bounding boxes around each person, and then finds joint keypoints inside of them. OpenPose has been trained on the CMU Panoptic Dataset [Joo2015], with 511 synchronized videos of multiple people in motion, alone or engaged in social activities.

Other approaches have shown even better results on evaluation datasets (see review [Chen2020]), but they are generally slower and not as widespread. The technology, however, is still maturing and some light-weight systems such as BlazePose [Bazarevsky2020] or UULPN [Wang2022] are being proposed, which can operate in real time on a mobile phone; however, they are still not quite as accurate as required for quantitative motion analysis.

Two other 2D pose estimation toolboxes are DeepLabCut [Mathis2018] and SLEAP [Pereira2022], which were initially intended for markerless animal pose estimation. They have the advantage that they can be custom trained for the detection of any human or not human keypoint with a relatively small dataset. All of the tools presented in this section are open-source.

1.2.2 2D kinematics from 2D pose estimation

Some authors bridge 2D pose estimation to more biomechanically inspired variables, such as in gait kinematics analysis. Kidzinski et al. present a toolbox for quantifying gait pathology that runs in a Google Colab [Kidziński2020]. Stenum et al. evaluate gait kinematics calculated from OpenPose input concurrently with a marker-based method. Mean absolute error of hip, knee and ankle sagittal angles were 4.0°, 5.6° and 7.4° [Stenum2021]. Liao et al. have not released their code, but they use OpenPose outputs to train a model invariant to view [Liao2020]. Viswakumar

Figure 1.5: 2D pose estimation by OpenPose. Image courtesy of [Cao2019].

et al. perform direct calculation of the knee angle from an average phone camera processed by OpenPose [Viswakumar2019]. They show that OpenPose is robust to challenging clothing such as large Indian pants, as well as to extreme lightning conditions. Other sports activities have been investigated, such as lower body kinematics of vertical jump [Drazan2021] or underwater running [Cronin2019]. Both works train their own model with DeepLabCut. Serrancoli et al. fuse OpenPose and force sensors to retrieve joint dynamics in a pedaling task [Serrancolí2020].

1.3 3 dimensional analysis

1.3.1 3D pose estimation

There are a lot of different approaches for markerless 3D human pose estimation, and listing them all is beyond our scope (see review [Wang2021]). Some more ancient ones are not based on deep-learning and require specific lightning and background conditions, such as visual-hull reconstruction [Ceseracciu2014]. Some directly lift 3D from a single 2D camera (see review [Liu2022b]), with different purposes: one estimates the positions of a set of keypoints around the joint instead of determining only the joint center keypoint, so that axial rotation along the limb is solved [Fisch2020]; SMPL and its sequels retrieve not only joint positions and orientations, but also body shape parameters [Loper2015]; while XNect primarily focuses on real time [Mehta2020]. A few approaches even strive to estimate 3D dynamics and contact forces from a 2D video input [Li2019, Rempe2021, Louis2022]. Rempe et al. solve occlusions from a 2D input [Rempe2020], but this remains a probabilistic guess that may be unsuccessful in case of unconventional positions of hidden limbs, whereas using more cameras would have given more trustworthy results. Haralabidis et al. fuse OpenPose results from a single monocular video and two IMU outputs, and solve kinematics of the upper body in OpenSim (an open-source biomechanical 3D analysis software [Delp2007, Seth2018]) in order to examine the effects of fatigue on boxing [Haralabidis2020].

Some research attempts to solve 3D pose estimation from a network of uncalibrated cameras, i.e., cameras whose extrinsic parameters (translation and rotation with respect to the coordinate system), intrinsic parameters (focal length, pixel size, etc.), and distortion coefficients are not known (See Chapter 2.2 on 3D reconstruction for more details.) It either uses 2D pose estimations of each view as visual cues to calibrate on [Takahashi2018, Xu2021, Liu2022a], or an adversarial network that predicts views of other cameras, compares them to real views, and adjusts its calibration accordingly [Ershadi-Nasab2021]. Dong et al. recover 3D human motion from unsynchronized and uncalibrated videos of a repeatable movement found on internet videos (such as a tennis serve performed by a celebrity) [Dong2020]. Using uncalibrated videos is still a very experimental trend, that would require more research before being used in biomechanics.

We choose to focus on the methods that estimate 3D pose by triangulating 2D pose estimations from a network of multiple calibrated cameras. The classical evaluation metric is the MPJPE (Mean Per Joint Position Error), which is the average Euclidian distance between the the estimated joint coordinate and its ground truth. Most methods take OpenPose as an input for triangulation, and more specifically the body_25 model. Labuguen et al. evaluate 3D joint positions of a pop dancer with a simple Direct Linear Transform triangulation (DLT [Hartley1997,Miller1980]) from 4 cameras [Labuguen2020]. Apart from the upper body for which error goes up to almost 700 mm, the average joint position error is about 100 mm. Nakano et al. examine three motor tasks (walking, countermovement jumping, and ball throwing), captured with 5 cameras and triangulated with the same methods, with a subsequent Butterworth filter [Nakano2019]. 47% of the errors are under 20 mm, 80% under 30 mm, and 10% are above 40 mm. The largest errors are mostly caused by OpenPose wrongly tracking a joint, for example by swapping the left and the right limb, that causes large errors up to 700 mm. This may be fixed either by using a better 2D pose estimator, or by using more cameras to reduce the impact of an error on a camera, or else by considering the temporal continuity in movement. Needham et al. use 9 cameras and find that ankle MPJPEs are within the margin of error of marker-based technologies (1–15 mm), whereas knee and hip MPJPEs are greater (30–50 mm). These errors are systematic and likely due to “ground-truth” images being mislabeled in the training dataset [Needham2021]. They also run the comparison with AlphaPose and with DeepLabCut. While AlphPose’s results are similar to OpenPose’s; DeepLabCut errors are substantially higher.

Slembrouck at al. go a step further and tackle the issue of limb swapping and of multiple persons detection [Slembrouck2020]. In case of multiple persons detection, one needs to make sure they associate the person detected on one camera to the same person detected on other ones. Slembrouck et al. manage to associate persons across cameras by examining all the available triangulations for the neck and mid-hip joints: the persons are the same when the distance between the triangulated point and the line defined by the detected 2D point and the camera center is below a certain threshold. They only focus on lower limb. Their first trial features a person running while being filmed by seven cameras, whereas their second one involves a person doing stationary movements such as squats while filmed by 3 cameras. After filtering, the average positional error in the first case is about 40 mm, and it is roughly 30 mm in the second case (less than 20 mm for the ankle joint). Other authors deal with the multiperson issue in a slightly different way [Bridgeman2019,Chu2021,Dong2019]. In average, if the detected persons are correctly associated and the limbs don’t swap, the average joint position error for an OpenPose triangulation is mostly below 40 mm.

Some triangulation methods not based on OpenPose reach even better results on benchmarks, although it comes at the cost of either requiring heavy computations, or of being out of reach for non-expert in deep-learning and computer vision. The classic approach reduces the joint detection heatmap to its maximum probability, and then to triangulate these scalar 2D positions. Instead of this, the main state-of-the art methods directly perform a volumetric triangulation of the whole heatmaps, and only then take the maximum probability as a 3D joint center estimate. By working this way, they keep all the information available for as long as possible. They manage to lower their MPJPE to about 20 mm [He2020, Iskakov2019].

1.3.2 3D kinematics from 3D pose estimation

Numerous studies have focused on the accuracy of 3D joint center estimation, but far fewer have examined joint angles [Zheng2022]. Yet, when it comes to the biomechanical analysis of human motion, it is often more useful to obtain joint angles. Joint angles allow for better comparison among trials and individuals, and they represent the first step for other analysis such as inverse dynamics. This issue is starting to be tackled. Zago et al. evaluate gait parameters computed by triangulating 2 videos processed by OpenPose, and notice that straight gait direction, longer distance from subject to camera, and higher resolution make a big difference in accuracy [Zago2020]. D'Antonio at al. perform a simple triangulation of the OpenPose output of two cameras, and compute direct flexion-extension angles for the lower limb [D'Antonio2021]. They compare their results to IMU ones, and point out that errors are higher for running than for walking, and are also rather inconsistent: Range of Motion (ROM) errors can reach up to 14°, although they can get down to 2 to 7° if the two cameras are set laterally rather than in the back of the subject. Wade et al. calculate planar hip and knee angles with OpenPose, AlphaPose, and DeepLabCut with the input of 9 cameras [Wade2021]. They deem the method accurate enough for assessing step length and velocity, but not for joint angle analysis. AniPose, a Python open-source framework, broadens the perspective to the kinematics of any human or animal with a DeepLabCut input, instead of OpenPose. They offer custom temporal filters, as well as spatial constraints on limb lengths [Karashchuk2021]. To our knowledge, it has only been concurrently validated for index finger angles in the sagittal plane, resulting in a root-mean-square error of 7.5° [Geelen2021].

The previous studies calculated simple planar angles between 3 joint centers. However, the human skeleton is complex and not only made of pin joints: aside from the flexion/extension rotation axis, the abduction/adduction axis and the internal/external axis are typically also engaged; and some joints also involves some translation, such as the shoulder. In this case, either several markers per joints or a solid skeletal model are needed. So far, little work has been done towards obtaining 3D angles from multiple views [Zheng2022]. Aside from our solution (see Chapter 3 on Pose2Sim), two main others are worth mentioning. Theia3D is a commercial software application for human gait markerless kinematics. It estimates the positions of a set of keypoints around the joint, and then uses a multi-body optimization approach to solve inverse kinematics [Kanko2021a,Kanko2021b]. They notice an offset in hip and ankle angles between their markerless system and the reference marker-based one, likely due to different skeletal models. Once this offset is removed, the root mean square error (RMSE) in lower limb roughly ranges between 2 and 8° for flexion/extension and abduction/adduction angles, and up to 11.6° for internal/external rotation. Although the GUI is user-friendly, it is neither open-source nor customizable. OpenCap [Uhlrich2022] has recently been released, and offers a user-friendly web application working with low-cost hardware. It predicts the coordinates of 43 anatomical markers from 20 triangulated keypoints, imports them in OpenSim, and performs classic inverse kinematics with numerous inferred markers and a skeletal model. However, the source code has not yet been released.

1.4 Statement of need

According to Atha [Atha1984], an ideal motion analysis system involves the collection of accurate information, the elimination of interference with natural movement, and the minimization of capture and analysis times. Yet, even though a marker-based system gives relatively accurate results, it requires placing markers on the body, which can hinder natural movement, it is hard to set up outdoors or in context, and it is strenuous to analyse. As a consequence, in the overwhelming majority of cases, coaches solely use subjective visual observation to assess an athlete's movement patterns and to compare performances. As a matter of fact, despite the advantages of technology, investing in it has its pitfalls: the information gathered can be unhelpful, or inaccurate, or not easily interpretable, or simply not implementable in the context of sports [Windt2020].

The emergence of markerless kinematics opens up new possibilities. Indeed, a network of RGB cameras does not assume any particular environment, and it does not hinder the athlete's movement and focus. However, it still requires delicate calibration, complex setup, large storage space, and high computational capacities. Gathering reliable and usable kinematic data in context is an ambitious challenge, but research has been accelerating in the last few years (Figure 1.4), as have better results.

The objective of this thesis is to participate in building a bridge between the communities of computer vision and biomechanics, by providing a simple and open-source pipeline connecting the two aforementioned state-of-the-art tools: OpenPose and OpenSim. Robustness and accuracy will be assessed, and concrete applications in elite sports context will be discussed.

2

Theoretical framework

Obtaining kinematics from a network of calibrated video cameras means resolving a few theoretical points. First, features must be recognized in images. This is now mostly done with machine learning models. Then, cameras need to be calibrated, so that all of the 2D features detected for each cameras can be reconstructed in the 3D space. Finally, these coordinates must be constrained to a biomechanically consistent model, in order to obtain coherent joint kinematics.

Sommaire

2.1 Pose detection

2.1.1 Feature detection

As a first step, achieving motion analysis from a network of cameras involves detecting features in images. These features can be whole human beings, joint centers, body landmarks, sports gear such as tennis balls, climbing holds, or much more.

Two broad approaches can be implemented: the first one consists in using dedicated algorithms for each task. The gist of it is to understand the task well enough to build an appropriate solution. Among other techniques, corner and contour detection, color thresholding, affine transformation, template matching, watershed segmentation, can be used. For example, if one wants to differentiate two boxers wearing respectively a blue and a red shirt, they can filter them by color. If one needs to identify on which portion of a speed climbing wall an athlete is, they can match the template of each holds on the whole image. OpenCV [Bradski2000] provides convenient tools for this purpose, in C++ and Python languages. This approach is often fast, but also quite complicated to implement, and neither flexible nor robust. If there is other red or blue patches in the boxing scene, if the boxer wears green or if the light is poor, this will not work anymore. Likewise for holds, if the sun casts a large shadow which changes its apparent shape, or if holds are seen from a different perspective.

The second approach takes advantage of machine learning algorithms, which constitute an entirely different paradigm. The idea is to show the machine enough examples for it to "understand" by itself its underlying attributes, so that it manages to detect and label automatically new images. This can be used for both aforementioned tasks, in a much more flexible way: if one wants the system to recognize boxers or holds in challenging condition, they simply have to include such examples while training the machine learning model. The machine learning approach is also suitable for other tasks, such as whole-image classification (i.e., determining whether this a boxing or a climbing scene), background extraction [Bouwmans2019], instance segmentation (i.e., extracting the shape of the climber, as well as each holds, the wall, the background, etc.) [Minaee2021], or keypoint detection (e.g., localization of human joint centers in an image [Chen2020]).

2.1.2 Machine learning timeline and principles

Machine learning is a subset of artificial intelligence (AI.) As such, one can trace its origin back to the discovery of the natural neuron at the end of the 19th century, by Nobel Prize Ramón y Cajal [López-Muñoz2006], followed half a century later by the first model of an artificial neuron [McCulloch1943]. A natural neuron is a simple learning unit, which collects the nervous influx sent by other neurons to its dendrites, and sends an action potential when the total influx weighted and summed in the soma overcomes a threshold value. This potential is then transmitted through the axon to the next neuron as a new influx. Similarly, an artificial neuron receives output vectors from previous neurons, weighs and sums them with a summation function, and transfers the resulting output vector to the next neurons if it reaches a certain threshold determined by an activation function (Figure 2.1).

The perceptron, invented in 1956 [Rosenblatt1958], represents the first practical application of an artificial neuron. It acts as a binary classifier, which automatically adjusts weights by learning from example data (see Algorithm 1). It could be used, for example, to predict whether an athlete is going to be "good" or not, given his force-velocity results on an ergometer test (see step-by-step Example 1 and (Figure 2.2)).

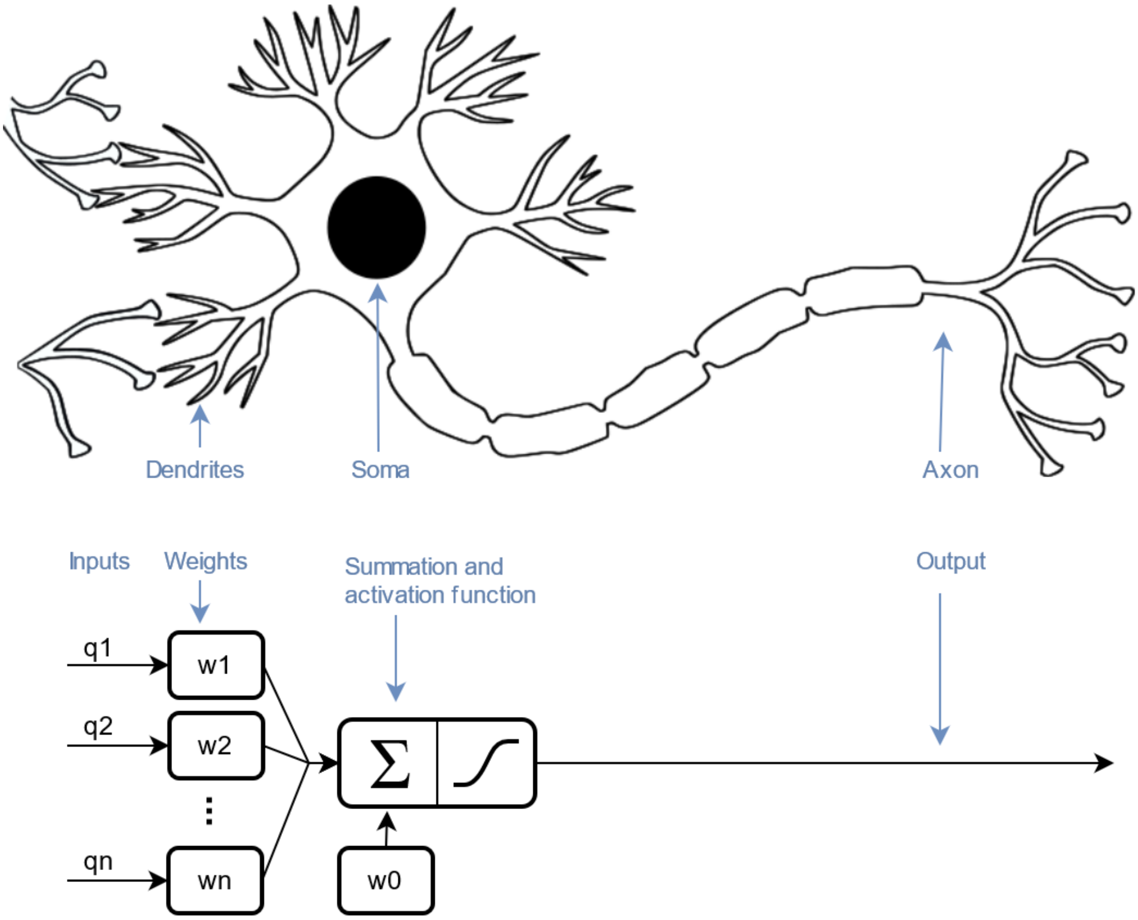


Figure 2.1: The artificial neuron has been modeled after the natural neuron. Inputs and weights act as the total nervous influx firing the dendrites. The collected values are summed, and a signal is activated if a threshold is overcome, as the soma does in a natural neuron. The output signal is conveyed through the axon.

Algorithm 1 Perceptron

Let $\overrightarrow{X^0}$ be the input vector of a first instance of variables $(1, x_1^0, \cdots x_m^0)$, $\overrightarrow{W^0}$ the corresponding weights randomly initialized $(w_0^0, w_1^0, \cdots w_m^0)$ with w_0^0 a bias, and $\sigma^{0,pred}$ the output predicted binary class.

1: The summation function is computed:

$$\overrightarrow{W^0} \cdot \overrightarrow{X^0} = \sum_{k \in [0,m]} w_k^0 x_k^0 \tag{2.1}$$

2: This result is processed by an activation function which determines whether the neuron will be fired or not, i.e., whether one or the other class will be predicted. This is typically a threshold:

$$\sigma^{0,pred} = \begin{cases} 1 & \text{if } \overrightarrow{W^0} \cdot \overrightarrow{X^0} > \theta, \\ 0 & \text{otherwise} \end{cases} \tag{2.2}$$

$\sigma^{0,pred} = 1$ corresponds to one class, and $\sigma^{0,pred} = 0$ to the other.

3: This prediction $\sigma^{0,pred}$ is compared to the actual class $\sigma^{0,actual}$.
If the class is correctly predicted, then weights are retained.
Else, they are updated:

$$\overrightarrow{W^1} = \overrightarrow{W^0} + \eta\ \varepsilon^0\ \overrightarrow{X^0} \tag{2.3}$$

with η the learning rate $\in$ [0,1], and ε the error function. Typically,

$$\varepsilon^0 = \sigma^{0,actual} - \sigma^{0,pred} \tag{2.4}$$

4: The algorithm is repeated with another example $\overrightarrow{X^1}$, and so on until it has gone through the whole batch of the training set. If weights still need to be updated, one can go over it again, for a determined number of epochs or until the average error is under a given value. Then the perceptron is considered trained, and ready to predict a class σ correctly with its final weights.

Example 1 Perceptron

N.B. The code for running this example is available on the thesis repository http://github.com.

Let's consider force-velocity test results as an input
$\overrightarrow{X} = (1, velocity\ (m/s), force\ (hN))$,
and the classification of an athlete as "good" or "bad" as an output $\sigma = 1\ or\ 0$.
A training set of n instances, i.e., example data the perceptron will learn from, could be:
$\{(\overrightarrow{X^i}, \sigma^{i,actual})\}_{i\in[0,4]} = \{((1,1,5),1),((1,2,3),0),((1,7,1),1),((1,4,1),0),((1,5,4),1)\}$.
Let's randomly initialize weights at $\overrightarrow{W^0} = (-9,1,3)$, take a threshold θ=0.1, and a learning rate η = 0.3.

The first instance of the training set gives:
$\overrightarrow{W^0} \cdot \overrightarrow{X^0} = \sum_{k\in[0,2]} w_k^0 x_k^0 = -9\times 1 + 1\times 1 + 3\times 5 = 7$.
Now $\overrightarrow{W^0} \cdot \overrightarrow{X^0} = 7 > \theta = 0.1$, so $\sigma^{0,pred} = 1$.
$\sigma^{0,actual} = 1 = \sigma^{0,pred}$, so the prediction is true and weights don't need to be updated.
As a consequence, $\overrightarrow{W^1} = \overrightarrow{W^0} = (-9,1,3)$.

The second instance gives $\overrightarrow{W^1} \cdot \overrightarrow{X^1} = (-9,1,3)\cdot(1,2,3) = 2 > \theta = 0.1$, so $\sigma^{1,pred} = 1$.
But $\sigma^{1,actual} = 0 \neq \sigma^{1,pred} = 1$, so weights need to be updated.
The error is $\varepsilon^1 = \sigma^{1,actual} - \sigma^{1,pred} = 0 - 1 = -1$.
As a consequence, $\overrightarrow{W^2} = \overrightarrow{W^1} + \eta\ \ \varepsilon^1\ \ \overrightarrow{X^1} = (-9,1,3) + 0.1 \times (-1) \times (1,2,3) = (-9.3,0.4,2.1)$.

Third instance: $\overrightarrow{W^2} \cdot \overrightarrow{X^2} = (-9.3,0.4,2.1)\cdot(1,7,1) = 3-4.4 < 0.1$, so $\sigma^{2,pred} = 0$.
$\sigma^{2,actual} = 1 \neq \sigma^{2,pred} = 0$, so weights need to be updated.
$\varepsilon^2 = \sigma^{2,actual} - \sigma^{2,pred} = 1$.
$\overrightarrow{W^3} = \overrightarrow{W^2} + \eta\ \varepsilon^2\ \overrightarrow{X^2} = (-9.3,0.4,2.1) + 0.1\times 1\times(1,7,1) = (-9,2.5,2.4)$.

Fourth instance: $\overrightarrow{W^3} \cdot \overrightarrow{X^3} = (-9,2.5,2.4)\cdot(1,4,1) = 3.4 > 0.1$, so $\sigma^{3,pred} = 1$.
$\sigma^{3,actual} = 0 \neq \sigma^{3,pred} = 1$, so weights need to be updated.
$\varepsilon^3 = \sigma^{3,actual} - \sigma^{3,pred} = -1$.
$\overrightarrow{W^4} = \overrightarrow{W^3} + \eta\ \varepsilon^3\ \overrightarrow{X^3} = (-9,2.5,2.4) + 0.1\times(-1)\times(1,4,1) = (-9.3,1.3,2.1)$.

Fifth instance: $\overrightarrow{W^4} \cdot \overrightarrow{X^4} = (-9.3, 1.3, 2.1) \cdot (1, 5, 4) = 17.6 > 8$, so $\sigma^{4,pred} = 1$.
$\sigma^{4,actual} = 1 = \sigma^{4,pred} = 1$, so weights don't need to be updated.
$\overrightarrow{W^5} = \overrightarrow{W^4} = (-9.3, 1.3, 2.1)$(*Figure* 2.2).

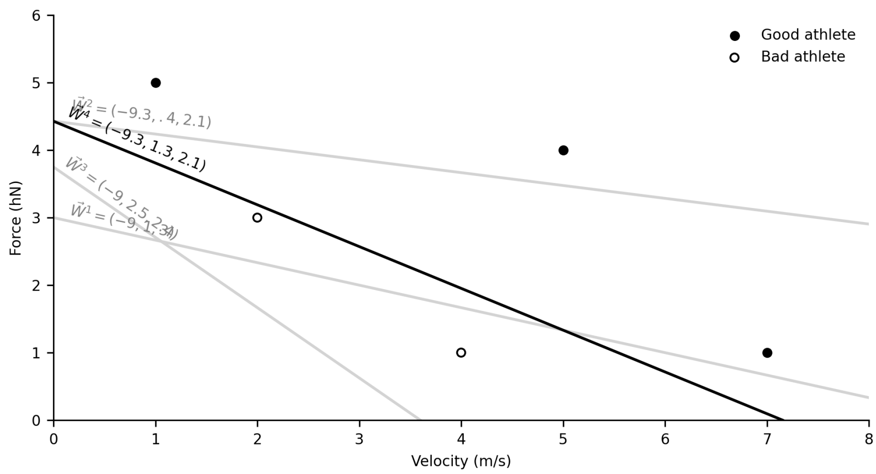


Figure 2.2: Classification of athletes as "good" (black dot) or "bad" (circle) according to their Force-Velocity results. Weights are adjusted (grey lines), until the perceptron classifies athletes correctly (black line.)

Of course, the example below is oversimplified. Being good or not as a sport is multifactorial, and the model would be more exact if more variables were taken into account.

Learning rate, threshold training data size (and quality), number of epochs to run on a batch (i.e., a subset of the training data) activation function, error (gradient descent) only linearly separable multilayer

It would need as a prior some example data

Given a training set, it could learn It could be used, for example, to classify whether an athlete is powerful or not, given his test results on

The perceptron rule is

Let's consider an input $\overrightarrow{X} = \begin{pmatrix} 1 \\ 5 \end{pmatrix}$

$$h = w_0 + \overrightarrow{w} \cdot \overrightarrow{q} \tag{2.5}$$

$$\overrightarrow{w^{t_1}} = \overrightarrow{w^{t_0}} + r\,c\,\overrightarrow{q^{t_0}} \tag{2.6}$$

$$\left\{ (\overrightarrow{q_i}, \overrightarrow{c_i}) \right\}_{i \in [1,n]}$$
$$= \left\{ \left(\begin{pmatrix} 1 \\ 5 \end{pmatrix}, 1 \right), \left(\begin{pmatrix} 2 \\ 3 \end{pmatrix}, -1 \right), \left(\begin{pmatrix} 4 \\ 1 \end{pmatrix}, -1 \right), \left(\begin{pmatrix} 5 \\ 4 \end{pmatrix}, 1 \right), \left(\begin{pmatrix} 8 \\ 1 \end{pmatrix}, 1 \right) \right\} \tag{2.7}$$

in hN and in m/s

$$h(\overrightarrow{q}) = \begin{cases} 1 & \text{if } w_0 + \overrightarrow{w} \cdot \overrightarrow{q} > 0, \\ 0 & \text{otherwise} \end{cases} \tag{2.8}$$

w0 biais

Limitation

Possible de jouer sur le learning rate (adaptive?), sur les poids initiaux, ainsi que sur la fonction d'activation (exemple: sigmoïde) et sur la fonction d'erreur, biais, multilayer?

Pas possible si non linéairement séparable (exemple image)

Define learning step η

Winters 1966 and 1988 (XOR, Turing, power, funding) "the spirit is willing but the flesh is weak." Translated back and forth with Russian, it became "the vodka is good but the meat is rotten." during cold war. Dictionary without context

CNN

Deep learning

-> perceptron mono/multicoucheNeurone: unité d'apprentissage

History natural neuron and formal neuron (dates, names, comparison)

Timeline cahier jaune et wiki

S'inspirer de wikipedia (en, fr, timeline); S'inspirer du mail machine learning starred (exemple du réseau de neurones); S'inspirer du cahier jaune

- deep learning vs CNN (vs SVM, random forest, etc.), AI, machine learning
- classification vs detection vs segmentation

data augmentation, dropout, batch normalization overfitting train / test accuracy loss gradient descent layers, batch size, epochs, activation

transfer learning

2.1.3 Pose detection

Different architectures, different models, different datasets

2.2 3D reconstruction

While some approaches only rely on 2D pose estimation to infer 3D pose with another machine learning model, they are generally not considered to be sufficiently reliable. It is, then, important to use the input from several cameras, and to fuse their informations to obtain 3D coordinates.

2.2.1 Pinhole camera model

Voilà

2.2.2 Calibration

test

2.2.3 Triangulation

suite

2.3 3D joint kinematics

2.3.1 Physically consistent model

autre

2.3.2 Scaling

bref

2.3.3 Inverse kinematics

As opposed to forward kinematics
Compare with 2D angles between 3 points
Different methods (model based vs autres) for angles (cf mail starred)

3

Proposed solution: Pose2Sim Python package

This chapter present our proposed solution, the Pose2Sim python package. This package is meant to consitute a user-friendly bridge between the most common 2D pose detection algorithms, and the OpenSim software so as to provide physically consistent 3D kinematics. Code is available at `https://github.com/perfanalytics/pose2sim`

This chapter is adapted from the article published in the Journal of Open Source Software "Pose2Sim: An Open-source Python Package for multiview markerless kinematics" [?]

Sommaire

3.1 Introduction to the workflow

Pose2Sim provides a framework for 3D markerless kinematics, as an alternative to the more usual marker-based motion capture methods. Pose2Sim stands for "OpenPose to OpenSim", as it connects two of the most widely recognized (and open-source) pieces of software in their respective fields: OpenPose [Cao2019], a 2D human pose estimation neural network; and OpenSim [Delp2007, Seth2018], a 3D biomechanics analysis software. Pose2Sim is accessible at `https://github.com/perfanalytics/pose2sim`.

The repository presents a framework which consists in (Figures 3.1):

1. Preliminary 2D joint coordinate detections from multiple videos, e.g. with OpenPose.
2. Pose2Sim core, including 4 customizable steps:
   (a) Camera calibration.
   (b) 2D tracking of the person of interest.
   (c) 3D keypoint triangulation, and storage in a .trc file.
   (d) 3D coordinate filtering.
3. Scaling to each individual subject, and inverse kinematics via OpenSim, and storage of the full-body 3D joint angles.

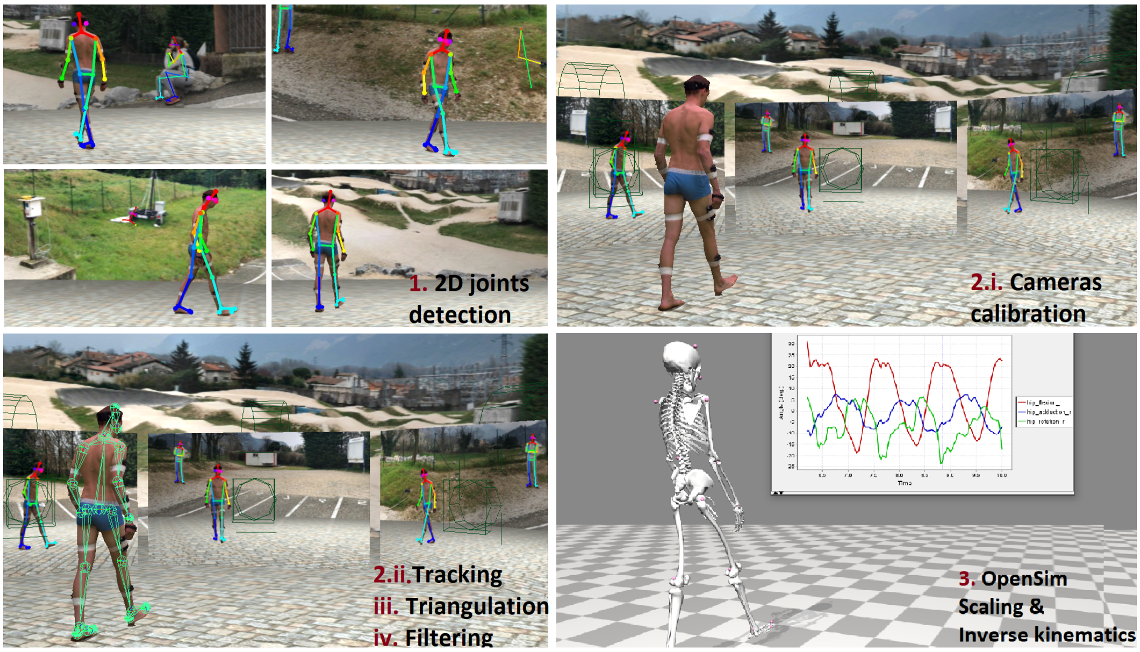


Figure 3.1: Pose2Sim pipeline: (1) 2D joints detection; (2i) camera calibration; (2ii–iv) tracking the person of interest, triangulating their coordinates, and filtering them; (3) scaling the subject, and constraining their 3D coordinates to a physically consistent OpenSim skeletal model

Each task is easily customizable, and requires only moderate Python skills. The whole workflow runs from any video cameras, on any computer, equipped with any operating system (although OpenSim has to be compiled from source on Linux.) Pose2Sim has already been used and tested in a number of situations (walking, running, cycling, dancing, balancing, swimming, boxing), and published in peer-reviewed scientific publications assessing its robustness (see Chapter 4 on Robustness assessment) [Pagnon2021] and its accuracy (see Chapter 5 on Accuracy assessment) [Pagnon2022]. Its results for inverse kinematics were deemed good when compared to marker-based ones, with errors generally below 4.0° across several activities, on both lower and on upper limbs. The combination of its ease of use, customizable parameters, and high robustness and accuracy makes it promising, especially for "in-the-wild" sports movement analysis.

3.2 2D pose detection

3.3 Pose2Sim core

3.3.1 Tracking of the person viewed by the most cameras

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3.3.2 Triangulating by weighted direct linear transform

3.3.3 Filtering

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3.4 Pose2Sim skeletal model

A full-body OpenSim [Delp2007, Seth2018] skeletal model with OpenPose keypoints is provided, as well as scaling and inverse kinematics setup files.

OpenSim is another widespread open-source software which helps compute 3D joint angles, usually from marker coordinates. It lets scientists define a detailed musculoskeletal model, scale it to individual subjects, and perform inverse kinematics with customizable biomechanical constraints. It provides other features such as net calculation of joint moments or resolution of individual muscle forces, although this is beyond the scope of our contribution.

3.5 Limitations and perspectives

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

3.6 Helper functions and vizualisation tools

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3.7 Exemples

3.7.1 Tableaux

Générateur en ligne ici.

Un exemple de tableau générée par cet outil est présenté Table 3.1.

	A	**B**	**C**
α	*fusion*		
β		*1*	*2*
Δ		*3*	*4*

Tableau 3.1: Exemple de tableau

4

Robustness assessment

Résumé du chapitre possible ici.

Sommaire

4.1 Introduction

4.1.1 Robustness definition

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

4.1.2 Assessing robustness

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

4.2 Methods

4.2.1 Experimental setup

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4.2.2 Participant and protocol

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4.2.3 Challenging robustness

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and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

4.2.4 Statistical analysis

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

4.3 Results

4.3.1 Data collection and 2D pose estimation

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4.3.2 Pose2Sim tracking, triangulation, and filtering

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4.3.3 Relevance, repeatability and robustness of angles Results

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

4.4 Discussion

4.4.1 Pose2Sim

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

4.4.2 Relevance, repeatability and robustness

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

4.4.3 Limits and perspectives

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

5

Accuracy assessment

Résumé du chapitre possible ici.

Sommaire

5.1 Introduction

5.1.1 State of the art

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5.1.2 Assessing accuracy

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

5.2 Methods

5.2.1 Data collection

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5.2.2 Markerless analysis

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

5.2.3 Marker-based analysis

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and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

5.2.4 Statistical analysis

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

5.3 Results

5.3.1 Concurrent validation

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

5.3.2 Comparison with other systems

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

5.4 Discussion

5.4.1 Strengths of Pose2Sim and of markerless kinematic

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

5.4.2 Limits and perspectives

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

5.5 Conclusions

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6

Application to boxing, using action cameras

Pose2Sim in suboptimal conditions:

Sommaire

6.1 Objectives

6.1.1 Key Performance Indicators in boxing

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6.1.2 Limits of research-grade systems in competitions

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6.1.3 Objectives

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6.2 Methods

6.2.1 4 conditions

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6.2.2 Pose-calibration on ring dimensions

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet

and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6.2.3 Post-synchronization on 2D movement speeds

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6.2.4 GoPro spatio-temporal base into Qualysis’

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6.2.5 Statistical analysis

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6.3 Results

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

6.4 Discussion

6.4.1 Equipment and protocol vs. pose estimation model

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”?

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6.4.2 Pros and cons of different systems

Auto-calibration with person?
Cloud computing?
Temporal consistency?
Shape information for less cameras?

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

7

Application to BMX racing, capturing jointly pilot and bike

Résumé du chapitre possible ici.

Sommaire

7.1 Introduction

7.1.1 The start in BMX racing

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

7.2 Methods

7.2.1 Material and protocol

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

7.2.2 Pilot inverse kinematics

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

7.2.3 Bike inverse kinematics

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

7.2.4 Joined pilot and bike inverse kinematics

Marche pas avec nos qualités de vidéo : simulations

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet

and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

7.3 Results

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

7.4 Discussion

7.4.1 On these data

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

7.4.2 Limits and perspectives

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

General conclusion

Conclusion here.

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List of Figures

List of Tables

A
Appendix A : Title

Summary here

A.1 Section 1

A.1.1 Sous section 1

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

A.1.2 Sous section 2

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

B
Appendix B : Title

Summary here.

B.1 Section 1

B.1.1 Sous section 1

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

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Appendix C : Title

Summary here.

C.1 Section 1

C.1.1 Sous section 1

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gefburn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

C.1.2 Sous section 2

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"Design, evaluation, and application of a workflow for biomechanically consistent markerless kinematics in sports"

"Conception, évaluation, et application d'une méthode biomécaniquement cohérente de cinématique sans marqueurs en sport"

Résumé

Ici ... résumé en français.

Mots-clés : Mots clés

Abstract

Ici ... résumé en anglais.

Keywords : markerless motion capture; sports performance analysis; kinematics; computer vision; openpose; opensim; python package