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Development of a drone-based evaluation tool for motion analysis in athletics long jump

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Listings

List of acronyms

AI Artificial Intelligence

CPU Central Processing Unit

ESC Electronic Speed Control

FPV First Person View

GPU Graphical Processing Unit

GUI Graphical User Interface

HAT Hardware Attached on Top

PDB Power Delivery board

RPM Revolutions Per Minute

1 Introduction

Long jump is an athletic discipline that is renowned for its technical complexity and the precise movement patterns it demands from athletes. Even apparently small technical inaccuracies can significantly impact an athlete's performance. Moreover, as shown in [1] the forces during the take-off phase can reach up to 10 times the athlete's body weight, increasing the risk of serious injuries due to technical inaccuracies. Therefore, it is crucial to understand and continuously improve these movement patterns in training. However, taken the high approach velocity[1] into account, this can quickly become a difficult task. Especially the take-off phase can be very short and therefore hard to analyze.

Professional athletes often employ expensive high speed camera systems in combination with body pose markers to capture and analyze every single step they make.
Yet, this approach comes with some limitations. Due to their stationary installation, such camera systems are restricted to a fixed location. Moreover, they often combine multiple cameras like Murray et al. [2] used for sprint analysis in order to be able to capture the whole movement from the beginning of the approach until the landing. This leads to complex post-processing software requirements. Additionally, fixed markers need to be attached to an athletes body to be able to track their body position.

While these methods provide exact and reliable results, they are usually not accessible for hobby- and semi-professional athletes.
In recent years however the advances in Artificial Intelligence (AI) and especially within the area of deep neural network paved the way for analyzing methods that require less complex setups. As of 2023 deep neural networks trained for body pose detection are even used in medical applications like gait analysis [3]. Because of the already extremely high and continuously improving accuracy, its application within the area of motion analysis in long jump is treated in the scope of this work.
A semi-autonomous drone based evaluation tool is newly developed. It is supposed to offer a portable alternative to address the lack of existing opportunities in analyzing long jump performances in training. For this purpose, the drone should autonomously fly next

[1] around 10 m/s in male semi-professional long jump

to the athlete throughout the whole jump, capturing their motion and therefore allow for a complete jump analysis. The drone itself is based on First Person View (FPV) drone hardware. It is build from scratch using an onboard single-board computer as flight control unit responsible for capturing the video. Additionally, a ground station software is developed to allow for a convenient jump analysis regarding the overall body pose as well as a fixed set of important parameters, i.e. knee angles, arm angles, hip position. The project's source code is available under `https://github.com/JF631/FLYJUMP`.

2 Methodology

The following chapter provides an overview over the relevant development components that are used within this project. Therefore, the used software packages are introduced before a short outline of the utilized drone hardware is given.

2.1 Software fundamentals

As the main part of this project's software will run on a portable remote computer allowing for not only to control the drone but also for performing the long jump analysis on video inputs, every software component is chosen to demand as little hardware requirements as possible. Especially no Graphical Processing Unit (GPU) is required to run the software. All image processing is performed using the Central Processing Unit (CPU) only. Furthermore, the software is designed to run platform independent.

2.1.1 Programming Language and why Python

Because of its interpreted nature and many cross-platform libraries, Python is one of the most used programming languages in the scientific area. Furthermore, it offers a high level of abstraction allowing for rapid prototyping approaches which is a key factor for this project. Besides fast implementation, Python nevertheless supports complex programming concepts like object-orientation.
Additionally, as stated in subsection 2.1.2 many machine learning and AI projects for detecting body poses have already been successfully implemented using Python.
Third party libraries and frameworks like *OpenCV* for image processing and *PyQt* for Graphical User Interface (GUI) development are widely used and therefore well documented.
This leads to the decision to use Python as programming language within this work.

2.1.2 Mediapipe for detecting body poses

One of the software's main tasks is to perform a human body pose detection on video inputs. Because this part runs on the remote computer only, it can also handle pre-recorded

videos that should be evaluated.
The evaluation itself is performed using the Mediapipe framework. This framework uses a pre-trained convolutional neural network that is able to detect 33 key points in human body poses [4]. The network could theoretically even be fine-tuned to improve its accuracy on specific input types. Even if this so called *transfer-training* method requires significantly less training data than training a neural network from scratch, it is not applied within this project as first test runs already showed reliable results.
Furthermore, the Mediapipe framework does not require any hardware acceleration and is renowned for its precise output. Hii et al. for example showed in [3], [5] that the framework can be applied in medical gait analysis applications to replace marker based approaches.
Moreover, Mediapipe offers three different detection models that differ in terms of speed and accuracy. The fastest detection model offers the lowest accuracy and vice versa.
Additionally, Mediapipe is optimized for multiple input types including videos and live streams, which is ideal for this project.
Figure 2.1 shows an overview of the 33 detectable key points.

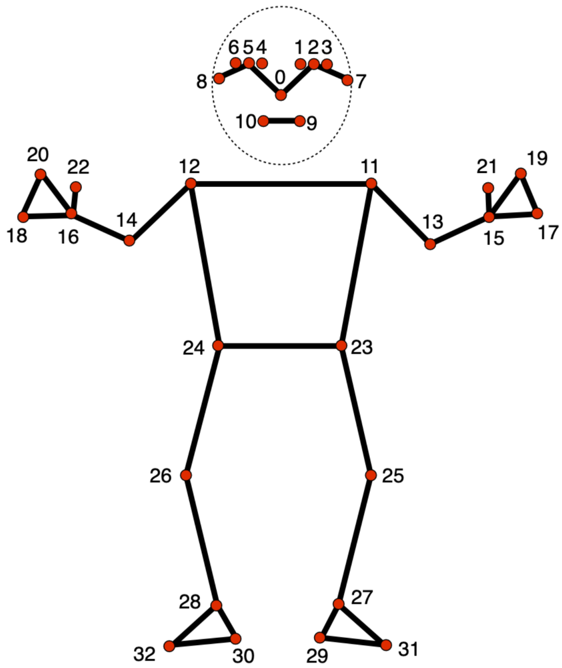


Figure 2.1: Fixed set of detectable body key points offered by the mediapipe framework [6]

Within this work, the key points in the head area (range [0 - 10]) are not of great interest apart from visualization purposes.
The knee, hip and arm key points however will be used for angle calculations and ground contact detection. Thus, a good performance in detecting the according key points within these areas is crucial for the software's overall reliability.

2.1.3 Why Mediapipe?

In recent years many approaches towards accurate body pose detection were developed and implemented. Many of those offer decent accuracies, but often lack reasonable performance, especially when no GPU is available for hardware acceleration. Following two common alternatives to Mediapipe, namely OpenPose and AlphaPose, are shortly presented and differentiated from the chosen Mediapipe framework.
One of the most widely used human pose detection libraries is the open source library *OpenPose*. As shown in [7] it offers a Multi-Person pose estimation that is especially useful when dealing with groups of people. However, as this project is meant to be used for long jump evaluation, only one person needs to be tracked at a time. Even though OpenPose of course can handle one person pose estimation, mediapipe outperforms OpenPose in this area. Back in 2016 Kocabas et al. achieved around 23 FPS using GPU accelerated OpenPose pose detection [8] and Osokin later proposed an improved neural network design, allowing for up to 28 FPS without hardware acceleration [9]. As of 2023 these benchmarks are still reasonable. Mediapipe however achieves speeds of up to 63% higher.
While OpenPose uses a *Bottom-Up* approach due its multi-person application, Mediapipe uses the less computational complex *Top-Down* approach.
Bottom-Up implementations first detect all body key points present in an input image and then move on to grouping the recognized points in clusters. Points in the same cluster are then assigned to one person.
Top-Down approaches however first roughly detect the overall body position within the input image and then define a region of interest[1] around the subject. The following processing therefore only needs to take this defined region of interest into account, leading to significantly less computational complexity.
AlphaPose is another open source library often used for body pose estimation. Just like OpenPose it uses a Bottom-Up approach to reliable offer multi-person body pose detection. Additionally, AlphaPose, like Mediapipe, offers multiple detection models that differ regarding accuracy and speed. Again however, Mediapipe outperforms AlphaPose because of its Top-Down approach and because AlphaPose is designed to work with GPU acceleration, rather than running on CPU only.
Another advantage of Mediapipe is its output. While OpenPose and AlphaPose offer 2D coordinates for each detected key point, Mediapipe additionally offers a depth estimation resulting in a spatial 3D coordinate for each detected key point. Thereby, more comprehensive analysis can be performed.

[1] sometimes also referred to as *Bounding Box*

2.1.4 OpenCV

OpenCV is an open source library commonly used for image processing in the area of computer vision and machine learning. It is written in C++, thus offering high performance in numerical operations, especially matrix operations.
`python-opencv` is the python wrapper for OpenCV which will be used in this project to efficiently read and process video frames. The python wrapper imports the underlying C++ functions as modules to take advantage of C++'s efficiency, resulting in significantly higher performance compared to equivalent Python only implementations. Furthermore, it is fully compatible with the `numpy` library, which allows for seamless conversion between numpy arrays and OpenCV image matrices.

2.1.5 HDF5 file format

To avoid analyzing the same jump, therefore the same video file, multiple times, the jump parameters should be saved after the analysis process alongside with the annotated video file, that visualizes the detected body pose (see Figure 2.1). Because parameters such as knee angles, arm angles, ground contact, etc. need to be stored frame-wise, a structured file format is suitable.
One common open source structured file format is HDF5. It is an acronym for Hierarchical Data Format (Version 5) and is very helpful to store large amounts of data as well as heterogeneous data. As the name already suggests, data is stored in a hierarchical, tree-like way.
A HDF5 tree mainly consists of three pre-defined components that allow to organize data in a file-system like fashion. The tree root, groups and datasets. *Groups* are folder-like structures that can either contain more groups or Datasets. *Datasets* hold the actual data that need to be stored.
Furthermore, each level (tree root, groups and datasets) can hold additional information via metadata. The metadata could for example contain information about metrics, timestamps or any other describing information. Therefore, each HDF5 file itself becomes a self-describing file that does not require any more than the included information to be interpreted correctly.

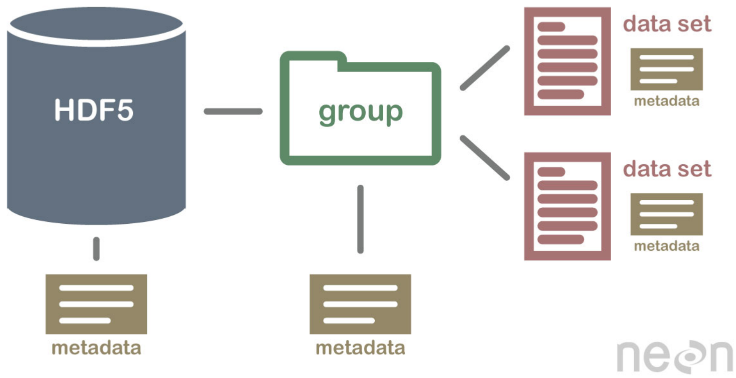


Figure 2.2: Principle HDF5 file structure [2]

Within this work, one HDF5 file will be created per jump analysis. The frames are stored in a group each and the actual calculated parameters are saved group-wise as datasets.

2.2 GUI development

The software that is developed within this work should be useable on-field to allow for a fast analysis process. Besides the video analysis, the drone control should be embedded in the same software to always guarantee control over the drone.
Thus, a simple GUI is developed to offer a convenient drone control and video analysis process.
The GUI is developed using Qt and its Python binding PyQt. Both are presented in this section.

2.2.1 Development framework Qt

Qt is a development framework based on the programming language C++. It includes a GUI toolkit and therefore enables platform-independent application development. All common platforms including Linux, Windows and MacOS are supported by Qt. Additionally, both mobile operating systems, Android and iOS, are supported.
This project however will focus on the development of an application that is able to run under Windows, Linux and MacOS.
The Qt framework is mainly chosen because of its rich and comprehensive documentation[3] and the availability of the well-supported Python binding *PyQt*.
As Qt is based on C++ all Qt source files are translated to C++ code. This step is

[3] `https://doc.qt.io/`

realized by the `Meta Obejet Compiler (MOC)` which is integrated as pre-processor. Thus, all Qt files are translated to so-called *Meta Obejet Code*, which can be seen as C++ source code with some enhancements. The most important enhancement is the signal and slot functionality which allows for an easy communication between different software and design elements (e.g. show a message dialog when a button is clicked).
Another important enhancement for this work is the convenient multi-threading management necessary for offering a responsive GUI even when cpu-bound calculations such as image processing is performed.

The GUI module PyQt

The discrepancy between Qt as C++ based framework and Python as chosen programming language for this project (as explained in **??**) can be overcome using Qt's Python binding PyQt. By using PyQt we can combine Python's machine learning advantages with Qt's platform-independent GUI development. More specifically *PyQt5* [4] is used.
It allows building complex Qt applications using Python only instead of C++. All other described advantages that Qt offer remain valid despite the use of PyQt. Thus, the whole software within this project including the GUI can be developed using Python as programming language.

[4] `https://pypi.org/project/PyQt5/`

3 Implementation

This chapter focuses on the overall project's implementation. It mainly covers the four parts hardware assembly, long jump analysis, drone control and their consolidation into one GUI.

3.1 Hardware

In order to capture high-quality video recordings that cover a complete long jump, from the first step all the way to the landing, a drone is used to fly next to the athlete throughout the whole process. Thus, a drone in form of a quadcopter is built from scratch. Its control will be integrated seamlessly in the projects' GUI.
This section introduces the hardware components that are used for building this drone as well as its flight control unit.
A short outline of the hardware is given in. The assembly is shown in, while ... focuses on the PixHawk flight controller and its setup.

3.1.1 Hardware selection

Currently, commercial drone hardware on the market is mainly separable into the two large areas of fully remote controlled FPV hardware and hardware for (autonomous) drones that can usually carry more load, e.g. heavy cameras. Even though the quadcopter in this project needs to be remotely controllable from a ground station pc, it is still more likely to be located in the latter one.
Generally the hardware was chosen based on the following criteria:

- price
- compatibility
- size

Flight Hardware

The main hardware that a quadcopter needs to fly will, in the following, be referred to as *flight hardware*. This includes frame, motors, rotors, Electronic Speed Controls (ESCs) and a Power Delivery board (PDB).
The main platform on which all drone hardware is mounted, is referred to as a quadcopter's frame. As this project's drone does not need to carry any heavy load, such as high precision camera systems or other sensors, a rather compact frame would theoretically be sufficient. However, compact frames tend to be less stable compared to larger frame sizes which could lead to a lower video recording quality and thus require more complex post-processing software. Moreover, the assembly process on larger frames is more convenient and replacing parts is easier. Additionally, compact frames are most commonly used in areas that demand quick reaction times for high speed flight maneuvers, e.g. in drone racing. This however is not needed in this project's context.
Taken the mentioned considerations into account the mid-sizes *Holybro S500 V2* frame kit is chosen. Besides the frame, the kit also includes a landing gear and rotors. Moreover, the main platform includes a PDB to split the battery's power equally to all four motors. An overview of all included parts is given in Figure 3.1.

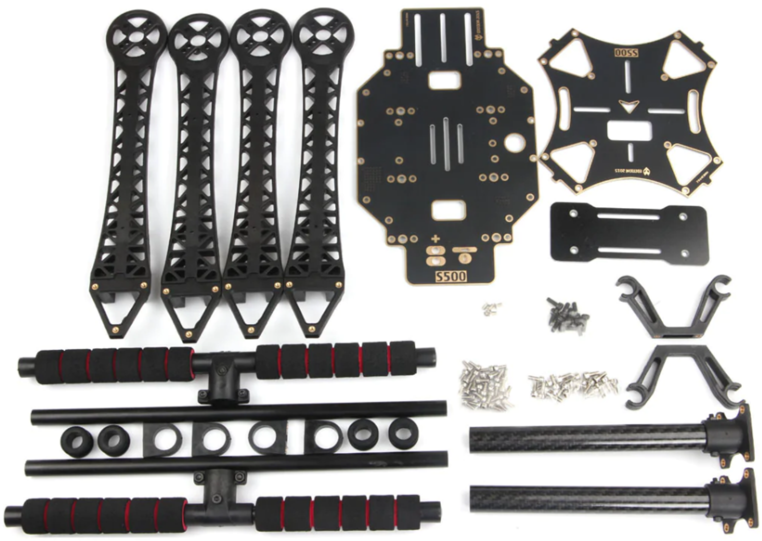
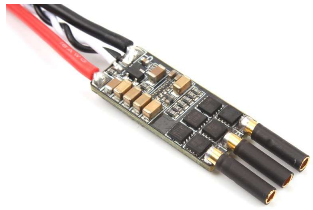


Figure 3.1: Holybro S500 V2 frame kit

Besides the frame, motors and compatible ESCs are crucial flight hardware components. Each motor requires an own ESC that translates signals from a flight control unit to a voltage and thereby control the motors' rotation speed. To guarantee compatibility, both components were chosen from Holybro as well and can be seen in Figure 3.2.

(a) 920KV Motor



(b) Electronic Speed Control

Figure 3.2: Motor (a) and ESC (b)

The drones' motors performance capabilities are defined by the number of Revolutions Per Minute (RPM) they can perform per 1V input. As can be seen in Figure 3.2a, this link between rotation speed and input voltage is expressed in the arbitrary unit KV. The chosen motors are capable of rotate with a speed of 920 RPM per 1V input voltage. Put into context, this is a common rotation speed in commercial and hobby drone applications. Racing drones however, operate at motor speeds of up to 3500 KV.

Control Hardware

In order to control the drone each motor must be controllable individually. This is usually realised using ESCs which connect the motors to a flight control unit. The flight control unit is remotely connected to the ground station and translates directional instructions into motor rotation speeds.
As the this project's quadcopter should not only be manually controllable from a ground station but should also automatically fly next to an athlete, an additional on board companion computer is needed. This companion computer then sends commands to the flight controller itself based on video input without user intervention.
The combination of flight controller and on-board companion computer will in the following be called *control hardware*.
There are many different types of flight controllers commercially available. However, most of them are not meant to be used in combination with a companion computer.
Two of the most commonly used flight controllers in autonomous drone projects are the *PixHawk* and the *Navio2*. The former is a totally independent system which can also operate without a companion computer. Latter is a Hardware Attached on Top (HAT)

specifically designed for a Raspberry Pi as companion computer. Thus, it does not include an own CPU but uses the Raspberry Pis's to perform flight relevant calculations.

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