FACULTY OF SCIENCE
UNIVERSITY OF COPENHAGEN

Master Thesis

2D Tracking in Climbing

Using Temporal Smoothing

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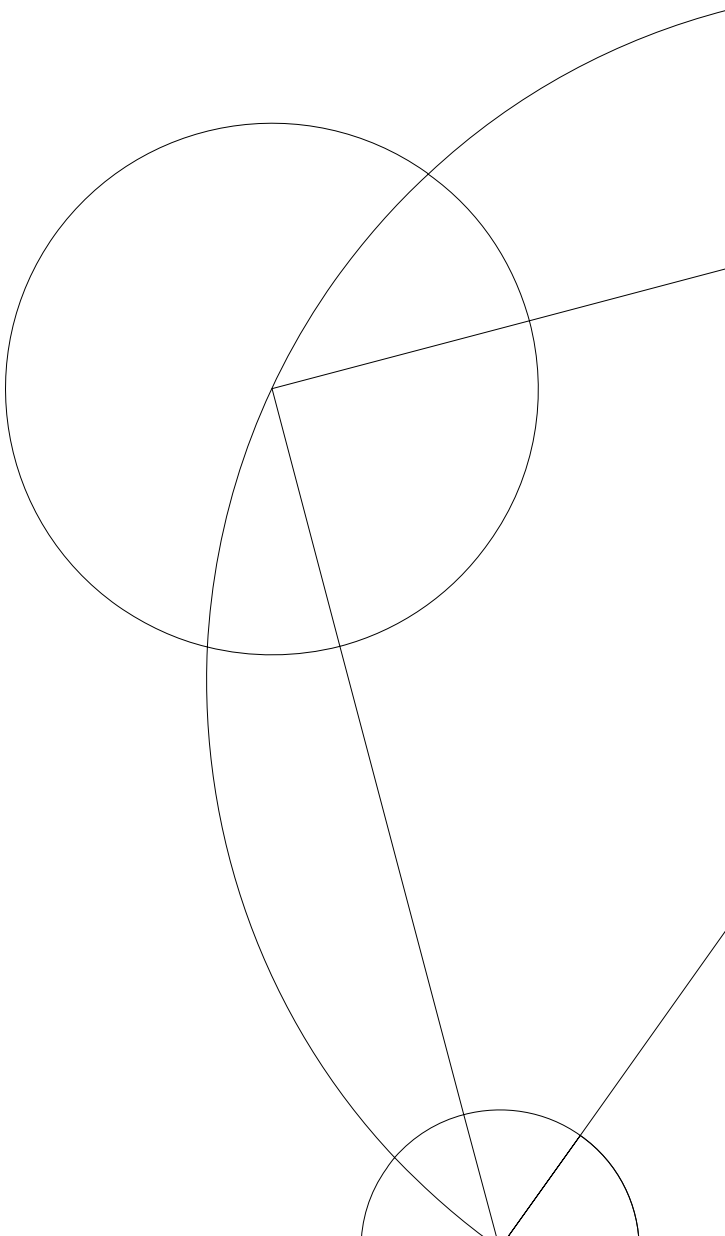

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Abstract

Preface

Acknowledgement

Contents

Notation

1 Introduction

1.1 Related Work

2-dimensional pose estimation can be divided into either being image-based or video-based, where the methods in the latter case use the tempoeral information of the video to perform the pose estimation.

Image-based methods were initially based on the geometry between the joints of the taget image [10, 11, 16]. Following this, were the convolutional-based methods, that used convolutional neural networks [6] to perform the pose estimation [13, 8, 2, 4]. More recent methods use transformers [12] to deliver state-of-the-art results [14, 15].

Early video-based methods used 3-dimensional convolutions to capture the temporal information between neighboring frames [9, 3]. Other methods use LSTM's [5] to capture this temporal information [7, 1]. Like in the case of image-based methods, transformers [12] have recently been introduced to the video-based methods to capture the temporal information and deliver state-of-the-art-results [17].

1.2 Problem Definition

1.3 Reading Guide

2 Deep Learning Theory

The following section covers the most important background theory for the experiments in Section 5. This includes an introduction to various types of neural networks, as well as an introduction to the optimization of such networks.

2.1 Feedforward Neural Networks

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2.2 Convolutional Neural Networks

2.3 Recurrent Neural Networks

2.3.1 Long Short-Term Memory Unit

2.3.2 Gated Recurrent Unit

2.4 Transformer

2.5 Training a Neural Network

3 Models

The following section covers the theory behind the various models that will be introduced in Section 5.

3.1 Mask R-CNN

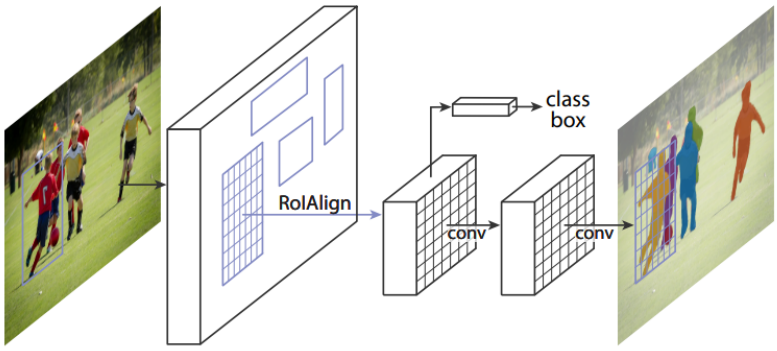

Figure 1: The Mask R-CNN framework for instance segmentation [4].

When we will be performing the pose estimation in Section 5, our developed methods will be a variation of the *Mask R-CNN*, introduced by He *et al.* in 2018 [4]. The following subsection explains the architecture of the Mask R-CNN and is based on an interpretation of He *et al.* [4].

3.2 UniPose-LSTM

3.3 DeciWatch

4 Dataset

5 Experiments

6 Discussion

7 Conclusion

8 References

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