



# Master Thesis

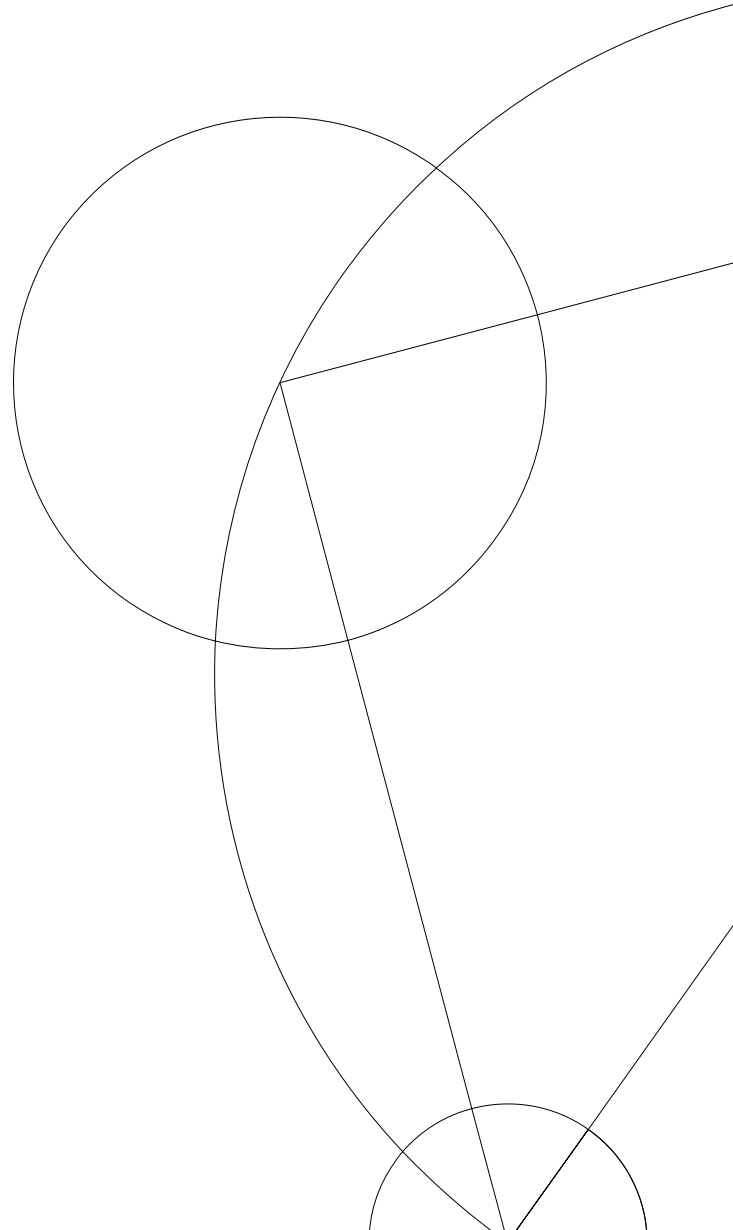
## 2D Tracking in Climbing

### Using Temporal Smoothing

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2023

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## **Abstract**

## Preface

## Acknowledgement

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## Notation

# 1 Introduction

- Imaged-based:
  - Geometry between joints in the target image:
    - \* Poselet conditioned pictorial structures
    - \* Exploring the spatial hierarchy of mixture models for human pose estimation
    - \* Articulated human detection with flexible mixtures of parts
  - Convolutional Pose Machine
  - Stacked Hourglass
  - OpenPose
  - HRNet

## 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 [MANGLER]... . Video-based methods commonly use the correlating information among the frames of the video to perform the pose estimation. Early video-based methods used 3-dimensional convolutions to capture the correlating information between neighboring frames [5, 2]. Other methods use LSTM's [3] to capture the correlating information among the frames [4, 1]. Recently, transformers [6] have started to being used as a way of capturing the correlating information among the frames [7].

## 1.2 Problem Definition

## 1.3 Reading Guide

## **2 Deep Learning Theory**

### **2.1 Feedforward Neural Networks**

### **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**



### **3 Models**

## 4 Dataset

## 5 Experiments

## 6 Discussion

## 7 Conclusion

## 8 References

- [1] Bruno Artacho and Andreas Savakis. *UniPose: Unified Human Pose Estimation in Single Images and Videos*. 2020. DOI: [10.48550/ARXIV.2001.08095](https://arxiv.org/abs/2001.08095). URL: <https://arxiv.org/abs/2001.08095>.
- [2] Rohit Girdhar, Georgia Gkioxari, Lorenzo Torresani, Manohar Paluri, and Du Tran. *Detect-and-Track: Efficient Pose Estimation in Videos*. 2017. DOI: [10.48550/ARXIV.1712.09184](https://arxiv.org/abs/1712.09184). URL: <https://arxiv.org/abs/1712.09184>.
- [3] Sepp Hochreiter and Jürgen Schmidhuber. “Long Short-Term Memory”. In: *Neural Computation* 9.8 (1997), pp. 1735–1780.
- [4] Yue Luo, Jimmy Ren, Zhouxia Wang, Wenxiu Sun, Jinshan Pan, Jianbo Liu, Jiahao Pang, and Liang Lin. *LSTM Pose Machines*. 2017. DOI: [10.48550/ARXIV.1712.06316](https://arxiv.org/abs/1712.06316). URL: <https://arxiv.org/abs/1712.06316>.
- [5] Tomas Pfister, James Charles, and Andrew Zisserman. *Flowing ConvNets for Human Pose Estimation in Videos*. 2015. DOI: [10.48550/ARXIV.1506.02897](https://arxiv.org/abs/1506.02897). URL: <https://arxiv.org/abs/1506.02897>.
- [6] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. *Attention Is All You Need*. 2017. DOI: [10.48550/ARXIV.1706.03762](https://arxiv.org/abs/1706.03762). URL: <https://arxiv.org/abs/1706.03762>.
- [7] Ailing Zeng, Xuan Ju, Lei Yang, Ruiyuan Gao, Xizhou Zhu, Bo Dai, and Qiang Xu. *Deci-Watch: A Simple Baseline for 10x Efficient 2D and 3D Pose Estimation*. 2022. DOI: [10.48550/ARXIV.2203.08713](https://arxiv.org/abs/2203.08713). URL: <https://arxiv.org/abs/2203.08713>.