Temporal Smoothing in 2D Human Pose Estimation for Bouldering

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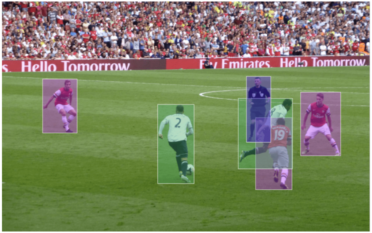
Introduction

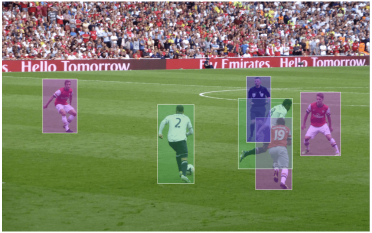
- Increased usage of video analysis in sports.
  - Help referee
  - Improve techniques



https://www.superannotate.com/blog/computer-vision-in-sports

Introduction

- Increased usage of video analysis in sports.
- Often requires the position of the players.
  - Already developed for popular sports.
  - Missing for the less popular sports.



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Introduction

- Increased usage of video analysis in sports.
- Often requires the position of the players.
- Problems with the data
  - Methods require large quantities
  - Unusual poses/movements

https://climbalong.com/lab

Introduction

- Increased usage of video analysis in sports.
- Often requires the position of the players.
- Problems with the data
- ClimbAlong at NorthTech ApS
    - Frame-independent pose-detector for bouldering

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Introduction

- Increased usage of video analysis in sports.
- Often requires the position of the players.
- Problems with the data
- ClimbAlong at NorthTech ApS
  - Frame-independent pose-detector for bouldering
  - Proposition: Incorporate temporal information

https://climbalong.com/lab

Introduction

- Aim: extend the ClimbAlong pose-detector to use temporal information.

The Data

ClimbAlong

- Fully annoated videos of climbers

https://climbalong.com/lab

The Data

ClimbAlong

- Fully annoated videos of climbers
- Problem: very small dataset
  - BRACE
  - Penn Action

https://climbalong.com/lab

The Data

ClimbAlong

- Fully annoated videos of climbers
- Problem: Very small dataset
- Solution: pretrain on related datasets and finetune on ClimbAlong
  - BRACE
  - Penn Action

The Models

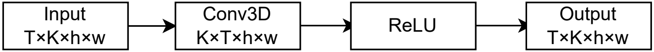
Generally, three approaches

1. Convolutional layer
2. Recurrent neural network
3. Transformer

The Models

3DConv

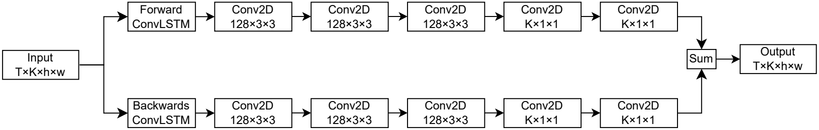
- 3-dimensional conv. layer + ReLU



The Models

bi-ConvLSTM Model S

- Adaptation of Unipose-LSTM by Artacho and Savakis
- Bidirectional convolutional LSTM + conv. layers and ReLU
- Processing directions summed together

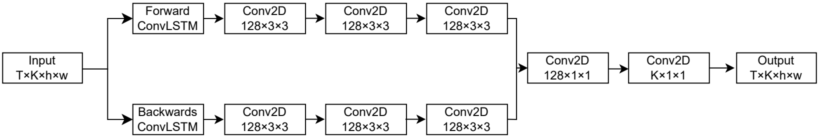


https://openaccess.thecvf.com/content_CVPR_2020/papers/Artacho_UniPose_Unified_Human_Pose_Estimation_in_Single_Images_and_Videos_CVPR_2020_paper.pdf

The Models

bi-ConvLSTM Model C

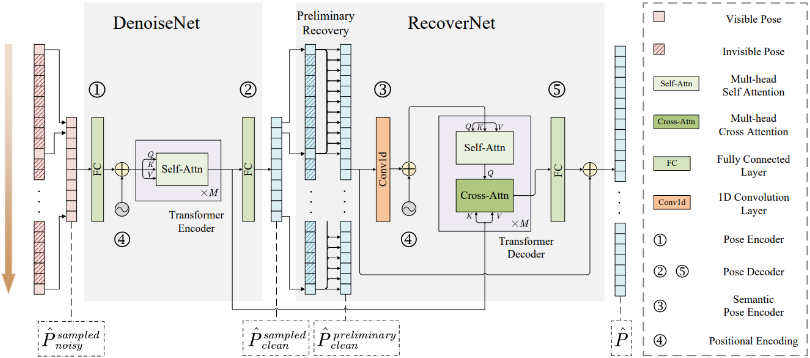
- Problem: Prioritization of processing direction
- Solution: Using convolution



The Models

DeciWatch by Zeng *Et al.*

- Transformer-based
- Samples every *n*th frame
- DenoiseNet + RecoverNet



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https://arxiv.org/pdf/2203.08713.pdf

Pretraining

Procedure

- Not training already-developed pose-detector
    - Different input images

Pretraining

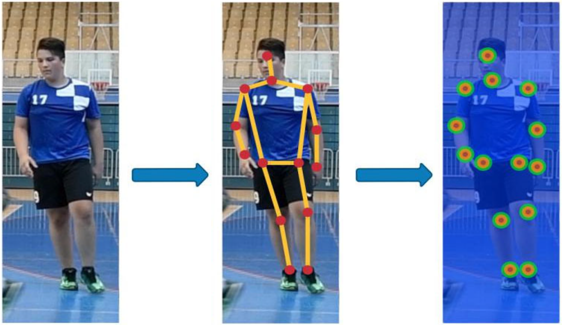
Procedure

- Not training already-developed pose-detector
  - Different input images
- Instead, simulate pose-detector output by shifting keypoints

Pretraining

Finding optimal setting of models

- Three experiments
  1. Various smearing standard deviations

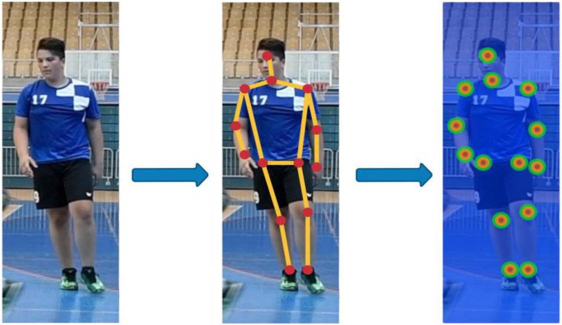


https://www.mdpi.com/2313-433X/8/11/308

Pretraining

Finding optimal setting of models

- Three experiments
  1. Various smearing standard deviations
  2. Fixed smearing standard deviation



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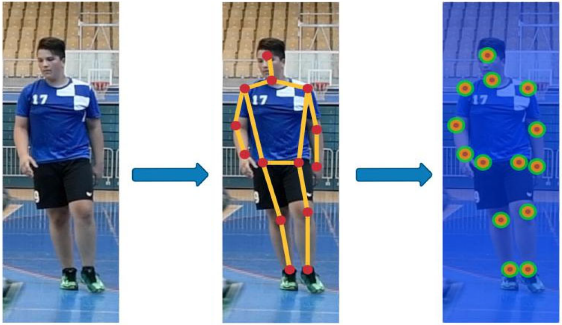
Pretraining

Finding optimal setting of models

- Three experiments
    1. Various smearing standard deviations
    2. Fixed smearing standard deviation
    3. Smearing standard deviations + decreased frame rate



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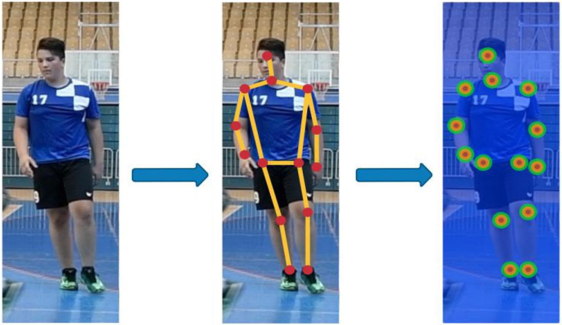
Pretraining

Finding optimal setting of models

- Three experiments
  1. Various smearing standard deviations
  2. Fixed smearing standard deviation
  3. Smearing standard deviations + decreased frame rate
- Two different shifting-scalars



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Finetuning

- Using all of the developed models with pose-detector
- Freezing pose-detector
  1. Quicker fitting
  2. Greater understanding of results

Test results

Only minor difference:

- Shifting-scalar: noise in ClimbAlong data is similar to shifting-scalar $s = 1$
- Translation + scaling vs only translation: standard deviations of peaks in ClimbAlong data not changing as much

Accuracy metric	PCK@0.05			PCK@0.1			PCK@0.2		
Experiment	1.1	1.2	1.3	1.1	1.2	1.3	1.1	1.2	1.3
Identity function	19.4	19.4	19.4	66.1	66.1	66.1	85.2	85.2	85.2
3DConv	49.7	52.3	53.1	95.7	95.7	95.8	99.2	99.3	99.3
DeciWatch	76.6	76.7	68.1	94.4	94.3	87.3	99.2	99.2	96.1
bi-ConvLSTM - Model S	37.8	34.9	39.0	91.8	92.1	92.2	99.4	99.7	99.2
bi-ConvLSTM - Model C	35.9	39.0	38.5	93.1	93.6	92.6	99.8	99.7	99.7

Accuracy metric	PCK@0.05			PCK@0.1			PCK@0.2		
Experiment	2.1	2.2	2.3	2.1	2.2	2.3	2.1	2.2	2.3
Identity function	19.4	19.4	19.4	66.1	66.1	66.1	85.2	85.2	85.2
3DConv	46.5	51.6	47.3	95.5	95.5	95.8	99.2	99.3	99.2
DeciWatch	76.0	75.9	36.8	94.2	94.2	74.9	99.2	99.2	92.8
bi-ConvLSTM - Model S	38.8	37.4	35.9	92.7	92.1	91.2	99.4	99.5	99.3
bi-ConvLSTM - Model C	39.2	39.5	37.1	92.5	92.9	92.6	99.6	99.3	99.6

Test results

Decreased frame rate:

- 3DConv: benefit
- DeciWatch: drawback
- bi-ConvLSTM: benefit for less noise

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Test results

bi-ConvLSTM: Model S vs Model C:

- Not as a big of a concern

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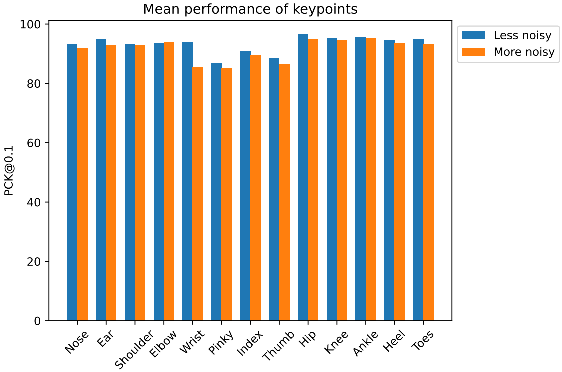
Test results

Worst performing keypoints:

- Pinkies, index fingers and thumbs
- Not included during pretraining (minor effect - heels and toes)
- A lot of movement



Discussion

Which model is the best?

- Greatest testing accuracy: DeciWatch 1.1/1.2

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Discussion

Which model is the best?

- Greatest testing accuracy: DeciWatch 1.1/1.2
- Greatest rough estimation: bi-ConvLSTM Model C 1.1
- Speed and memory: 3DConv

General reflections

Mistakes we have made

- Pretraining
    - Should have estimated parameters of data

General reflections

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  - Should have estimated parameters of data
  - Overlapping video sequences

General reflections

Mistakes we have made

- Pretraining
  - Should have estimated parameters of data
  - Overlapping video sequences
- Finetuning
  - Groundtruth outside of bbox

Discussion

Future work

1. DeciWatch with all frames

Discussion

Future work

1. DeciWatch with all frames
2. DeciWatch with vision transformer

Discussion

Future work

1. DeciWatch with all frames
2. DeciWatch with vision transformer
3. Avoid overfitting

Discussion

Future work

1. DeciWatch with all frames
2. DeciWatch with vision transformer
3. Avoid overfitting
4. Multiple retraining

Conclusion

Succesfully developed and tested the incorporation of temporal smoothing for pose estimation

Extras: Mistakes Were Made!

Misimplemented evaluation-function

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DeciWatch	32.8	33.8	30.9	68.0	68.1	62.7	85.1	84.9	82.8
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1. Generally, same patterns
2. Decreased accuracies

Accuracy metric	PCK@0.05			PCK@0.1			PCK@0.2		
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2. Decreased accuracies
3. Models do not improve the rough estimates

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4. bi-ConvLSTM: Model C is now always better than Model S

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4. bi-ConvLSTM: Model C is now always better than Model S
5. 3DConv is generally the best model

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DeciWatch	21.3	26.4	19.4	51.1	58.7	48.1	77.1	81.0	77.0
bi-ConvLSTM - Model S	30.9	31.6	30.6	71.2	71.6	70.7	86.0	86.1	86.2
bi-ConvLSTM - Model C	31.5	32.2	30.8	71.8	72.0	71.9	86.4	86.4	86.5