Visual assessments of Postural Orientation Errors using ensembles of Deep Neural Networks

Master's Thesis

Filip Kronström

Supervisors: A. Jakobsson[a], J. Älmqvist[b], E. Ageberg[b], M. Creaby[c]

April 13, 2021

Faculty of Engineering, Lund University

[a] Centre for Mathematical Sciences, Mathematical Statistics, Lund University

[b] Department of Health Sciences, Lund University

[c] School of Exercise Science, Australian Catholic University

Agenda

1. Introduction
2. Methods
3. Results
4. Conclusions and Future work

Introduction

Anterior Cruciate Ligament injuries

- Around 8000 yearly Anterior cruciate ligament injuries in Sweden.
- Regular injury mechanism is sudden changes in direction or velocity while knee is bearing weight.
- Rehabilitation typically up to 2 years.
- Increased long and short term risk of, e.g., osteoarthritis, joint instability, and re-injury.

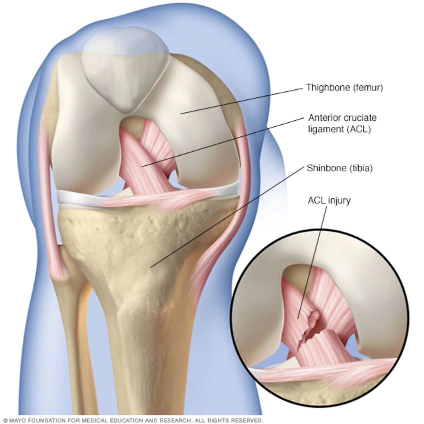


Figure 1: Illustration of ACL in the knee[1].

[1] Mayo Clinic, `https://www.mayoclinic.org/diseases-conditions/acl-injury/symptoms-causes/syc-20350738`

Postural Orientation

Figure 2: Examples of maintained (left) and altered postural orientation (right) during a single leg squat.

- Ability to uphold alignment of body parts.
- Altered PO - seen to increase risk of re-injury.
- No established and feasible method to assess for clinical use.
- When used, found from motion capture systems.

Postural Orientation Errors in this work

- Proposed methods where experts assess motions from videos[2].
- Scoring on ordinal scale, 0 (Good) - 2 (Poor).
- Patient score calculated as median of 4-5 repetition scores.
- Assessments are time consuming, can they be automated?
- Trunk, Pelvis, Femoral valgus, and KMFP POEs evaluated in this work for Single leg squat.

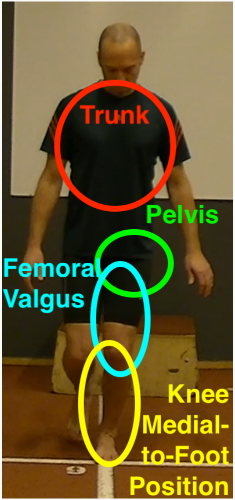


Figure 3: Evaluated POEs.

[2] Nae et al., Extended Version of a Test Battery for Visual Assessment of Postural Orientation Errors: Face Validity, Internal Consistency, and Reliability. 2020

Methods

System overview

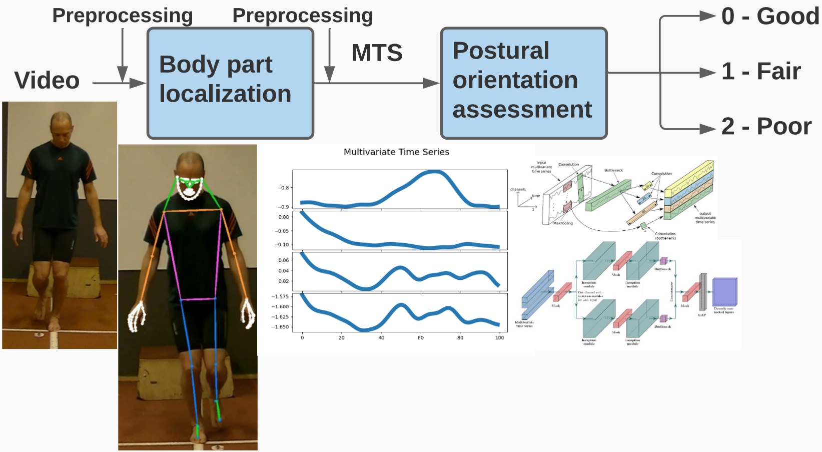


Figure 4: POE assessment system overview.

Body part localization

- Built upon MMPose framework[3].
- HRNet[4] with DARK-pose[5] trained on COCO-wholebody dataset used for pose estimation.
- Outputs 133 keypoint coordinates.

[3] MMPose - OpenMMLab, `https://github.com/open-mmlab/mmpose`

[4] Sun et al., Deep high-resolution representation learning for human pose estimation. 2019

[5] Zhang et al., Distribution-Aware Coordinate Representation for Human Pose Estimation. 2020

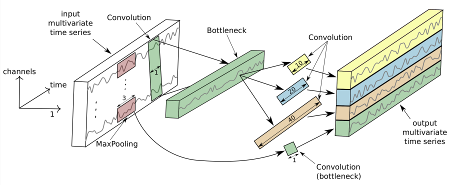


Figure 5: InceptionTime module[6].

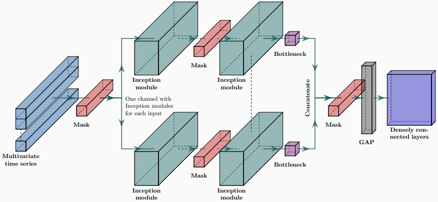


Figure 6: X-InceptionTime.

IncetionTime[6]

Modules with convolutions of different lengths, global average pooling, and densely connected layers for classification.

X-IncetionTime

Like InceptionTime, but input channels are kept separate.

[6] Fawaz et al., InceptionTime: Finding AlexNet for time series classification. 2020

Inputs to classification

Table 1: Input variables for the different POEs. Videos have been mirrored such that action is performed with right leg, if applicable.

Trunk	Pelvis	Femoral Valgus	KMFP
Left shoulder - x	Right shoulder - x	Right shoulder - x	Left shoulder - y
Right shoulder - x	Right shoulder - y	Right hip - x	Right hip - y
Right shoulder - y	Right hip - x	Right knee - y	Angle: right ankle and toes
Left hip - x	Right hip - y	Angle: right knee and ankle	Difference: right hip and knee - x
Left hip - y	Left hip - y		Difference: right knee and ankle - x
Right hip - x	Difference: right hip and knee - x		
Difference: right hip and knee - x	Difference: right knee and toes - x		

Time series classification - Ensembles

- Each classification is obtained from ensembles of 5 classifier models.
- 2 models perform well over all classes - CORAL[7] ordinal classifiers.
- Remaining models optimized for low false positive rates for one class each - class weights or modified cross-entropy loss.

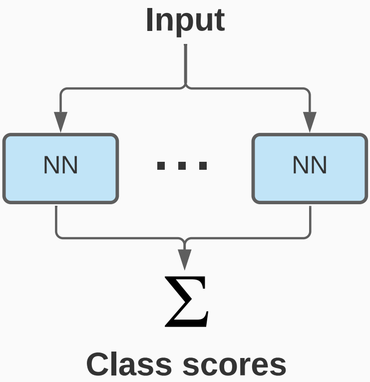


Figure 7: Ensemble struture used for classification.

[7] Cao et al., Rank consistent ordinal regression for neural networks with application to age estimation. 2019

Results

Data

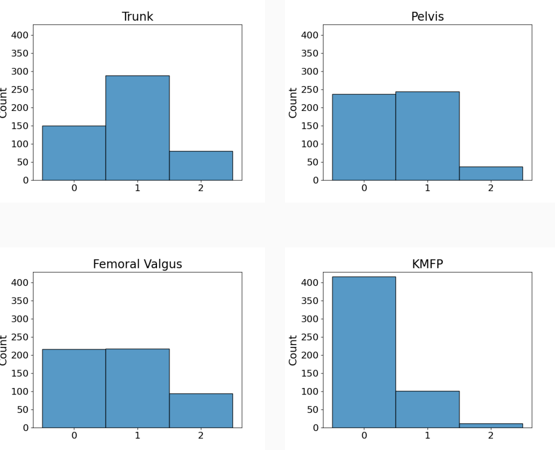


Figure 8: Class distributions for the different POEs.

- Videos with 4-5 repetitions.
- 103 unique subjects.
- Assessments for right and left leg for some subjects/POEs - 105-107 assessed videos, 519-530 repetitions.
- 20% (22 unique subjects, 110 repetitions) test set.
- 10-fold cross-validation used. Results shown are mean (± std) of the 10 resulting models on test set.

Trunk

Accuracy (%): 73.7±4.5 75.0±7.9

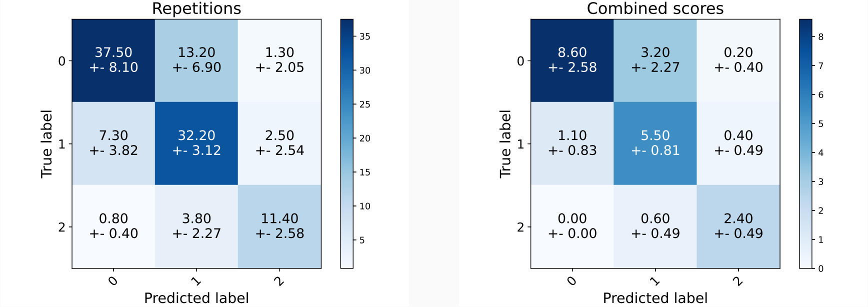


Figure 9: Confusion matrices for the classification of the repetitions (left) and the combined scores (right).

Pelvis

Accuracy (%): 63.6 ± 10.7 69.1 ± 10.1

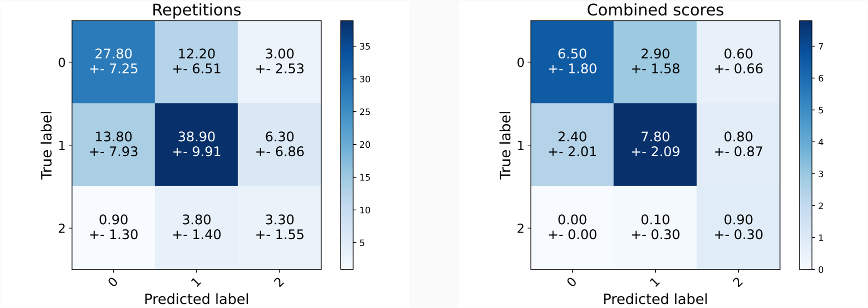


Figure 10: Confusion matrices for the classification of the repetitions (left) and the combined scores (right).

Femoral Valgus

Accuracy (%): 69.6±6.8 79.1±9.3

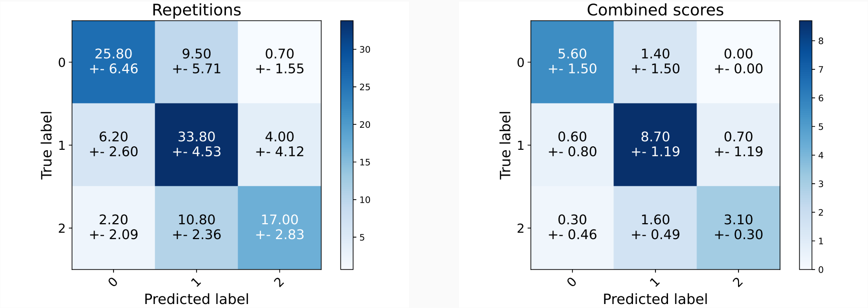
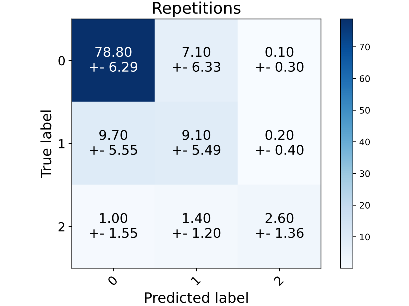


Figure 11: Confusion matrices for the classification of the repetitions (left) and the combined scores (right).

Knee Medial-to-Foot Position

Accuracy (%): 82.3±3.1 89.5±4.5



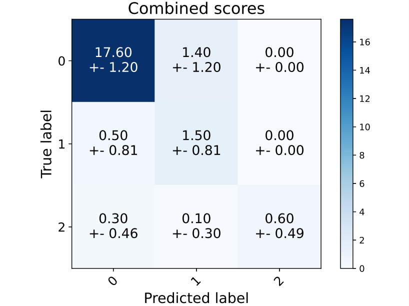


Figure 12: Confusion matrices for the classification of the repetitions (left) and the combined scores (right).

Summary

Table 2: Summary of results, here the combined sccores with thresholds removing samples the models are uncertain about.

	Trunk	Pelvis	Femoral Valgus	KMFP
Accuracy (%)	80.0±7.8	73.3±18.9	82.3±6.0	90.3±4.3
F1 score (%)	79.9±8.9	73.6±22.3	81.0±5.2	74.0±22.3
Recall (%)	81.6±7.2	77.9±14.9	79.5±5.5	81.1±24.7
Precision (%)	83.0±6.8	74.9±23.8	86.5±5.6	71.4±22.6

Conclusions and Future work

Conclusions and Future work

- The results suggests the proposed method could automate assessments.
- Large variance in results suggests more data needed.
- Future work:
    - Multiple experts to assess videos.
    - Assess videos repetition-wise.
    - Evaluate 3D coordinate reconstruction.
    - Non-uniform weighting in ensembles and when combining scores.
    - Assess more POEs and motions.

Thank you

Backup slides

Sometimes, it is useful to add slides at the end of your presentation to refer to during audience questions.

The best way to do this is to include the `appendixnumberbeamer` package in your preamble and call `\appendix` before your backup slides.

METROPOLIS will automatically turn off slide numbering and progress bars for slides in the appendix.