corpusLabe*
– a gamified virtual goniometer prototype–

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[1,2,3,4] **Brighter Eyes Lynxes**

Abstract

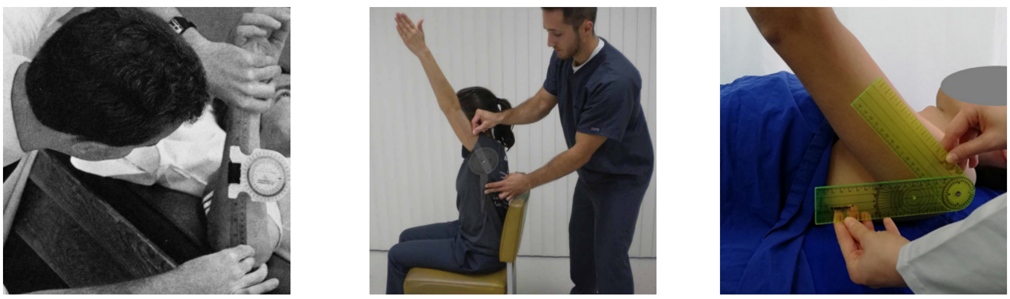
Within the context of the 2021 OpenCV AI Competition, the corpusLabe prototype was developed exploring the use of the OpenCV AI Kit for clinical assessment of posture, as well as, a gamified exercise platform.

Two evaluation strategies were pursued: the first, characterizing the proposed system while poking at the problem of human body pose estimation on an edge device; the second, investigating on the use of computed pose coordinates for measuring shoulder joint angles in comparison to a gold standard goniometer.

The prototype integrating the BlazePose model running on DepthAI hardware was not only able to provide measurements of shoulder angle in an accessible and intuitive way, but also to demonstrate a concept of a gamified goniometer. Despite not being conclusive, the measurement discrepancies between the corpusLabe prototype and the standard instrument for the evaluated shoulder angle were found to be clinically significant in the group of recruited participants.

1 Motivation

As breast cancer survivors (BCS) are living longer, the adverse effects resulting from the cancer treatment are more frequent. Upper body morbidity (UBM) (e.g. decreased range of motion, muscle strength, pain and lymphedema) are among the most prevalent side effects [1]. Arm/shoulder mobility, usually assessed by goniometer-based measurements of flexion or abduction, is an objective measure of UBM that has been used in breast cancer rehabilitation, although its well established use covers much broader application scenarios [2]–[4] (Figure 1).



(Andrews and Bohannon 1989) [2] (Kolber et al. 2011) [3] (Çubukçu et al. 2020) [4]

Figure 1: Illustration of the use of a goniometer for the quantification of shoulder range of motion.

*https://brightereyeslynxes.github.io/

Despite its recognized relevancy [1], [5], [6], and although some methods for monitoring and assessing eventual side effects from breast cancer treatments do exist[7]–[9], an approach able to achieve early detection, promote risk-reduction and self-management, while engaging the user in an appropriate follow-up strategy, seems to be still missing for a myriad of reasons [10]–[12].

2 corpusLabe prototype baseline

Taking the breast cancer treatment follow-up scenario as a study case, and two distinct use case settings (virtual goniometer – Section 3 – and gamified exercise platform – Section 4) the set up schematized in Figure 2 was outlined and developed, considering three main fundamental tasks: 3D pose estimation, analysis and visualization.

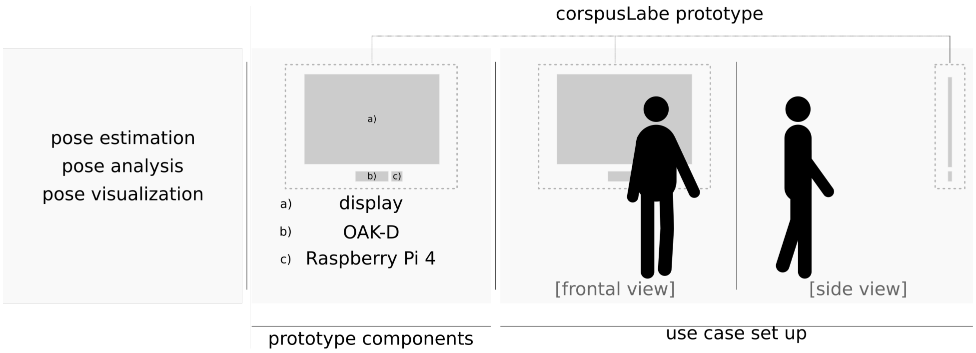


Figure 2: The corpusLabe prototype set up baseline.

2.1 3D pose estimation from images

Even though being outside the scope of this report a review of the topic, it can be mentioned that a significant amount of recent work exists appertaining to the long lasting problem of 3D human pose recovery from a single image [13]–[15]. For its convenience and availability within the context of the OpenCV AI Competition, the BlazePose made available by Geax[1] was used as a baseline human pose estimation method for the prototype to which this report refers.

BlazePose [13] is a regression based single person body pose estimation method suitable to run on mobile devices that can compute (x,y,z) coordinates of 33 skeleton keypoints. Its inference pipeline comprises a body pose detector followed by a pose tracker network. Its pose detector approach extends previous work on the stacked hourglass architecture using an encoder-decoder followed by another encoder network to predict joint's heatmaps and regress its coordinates. The aforementioned heatmap step is discarded during inference in order to make it particularly lightweight and thus, contributing to the overall attractiveness of the method to real-time use cases.

2.1.1 Experiments

For exploratory quantitatively evaluation on the 3D joint estimation task, the database Human3.6M [16] was used. The latter database is a standard benchmark captured in a lab environment including millions of 3D human poses from distinct subjects performing 15 actions, such as eating, sitting and walking, acquired from a MoCap system with corresponding images from 4 points of view.

The protocol described in previous works [17]–[19] was transcribed, such that, results for mean per-joint position error (MPJPE) in millimeters (mm) that measures the mean Euclidean distance between the predicted and ground-truth joint positions without any transformation, are reported on data corresponding to subjects S9 and S11 on a 17-joint skeleton.

The aforementioned baseline DepthAI version of the BlazePose model (tested baseline) was compared with reference and state-of-the-art 3D human pose recovery from single-image methods results, found in the literature, as a rough benchmarking of performance. The results are summarized in Table 1.

2.1.2 Discussion

The tested baseline model has high average error although alongside the method that accompanied the original publication of the considered database. Among several points of discussion the comparison suffers from some deviations as the originally proposed protocol implied a given training methodology that is not uniform among the reported results. Moreover, the tested baseline can be recognized as a suboptimal version of the model with

[1] `https://github.com/geaxgx/depthai_blazepose`

Table 1: Quantitative comparisons between the estimated pose and the ground-truth on the Human3.6M dataset.

Method	Publication	Average MPJPE (mm)
PoseAug	Gong et al.[20]	50.2
HMR	Kanazawa et al.[18]	56.8
Ordinal Depth Supervision	Pavlakos et al.[21]	115.1
LinKDE	Ionescu et al.[16]	162.1
tested baseline	-	167.3

several tuning opportunities available that were not explored (namely: competitive landmark models available[2], or number of SHAVES associated with the MyriadX specific architecture[3]).

2.2 Pose analysis and visualization

This work focused on a single pose to explore the use of the outlined prototype: the maximum angle of shoulder abduction, as illustrated in Figure 3.

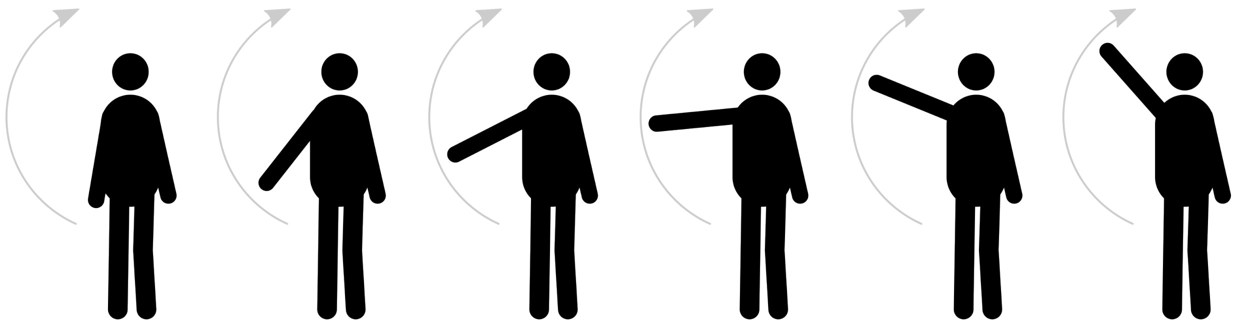
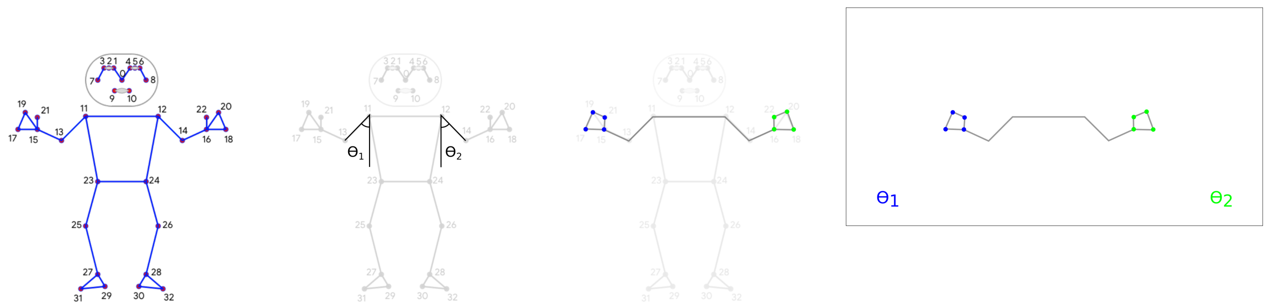


Figure 3: Illustration of the shoulder abduction movement.

Similarly as in [7], and using the skeletal data provided by the BlazePose model (Figure 4 a)), the positions of shoulder and elbow joints relative to the vertical projection of the shoulder were used to measure the angles of shoulder abduction in degrees, as illustrated in Figure 4 b). Considering indications from past work [22] that a more anthropomorphised representation in a virtual world, seems to not be the preferred representation of the self among the breast cancer survivors population, an abstract representation was adopted (Figure 4 c) and d)).



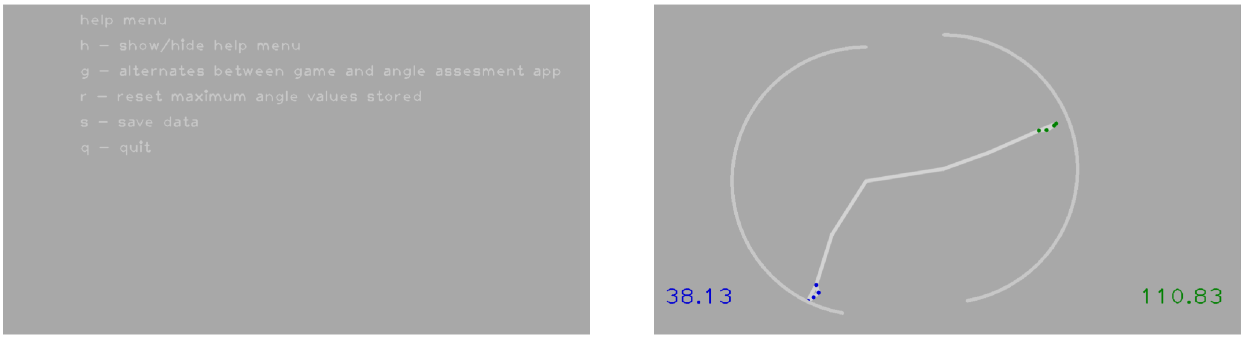
a) b) c) d)

Figure 4: corpusLabe main elements for pose analysis and visualization tasks: a) reference BlazePose topology; b) shoulder joints angle measurement computation from estimated locations of elbow, shoulder, and vertical projection of the latter; c) selected body segments proposed for human abstract representation in the virtual space with colored left and right encoding; d) corpusLabe prototype baseline graphical user interface illustration, including proposed representation of the tracked user and visualization of the considered shoulder joint angles.

[2] https://google.github.io/mediapipe/solutions/pose.html
[3] https://docs.luxonis.com/en/latest/pages/model_conversion/

3 corpusLabe as a virtual goniometer

The hereafter evaluated virtual goniometer was accomplished by modifying the corpusLabe prototype baseline (outlined in Figure 4) to store the maximum registered reference shoulder joint angles and adding the possibility of an operator to reset the registered maximum angles or saving the values to file (Figure 5).



a) b)

Figure 5: corpuLabe prototype main help menu (a)) and virtual goniometer user interface (b)).

3.1 Methods

Shoulder joint angle of maximum attempted abduction for each side was assessed using the CorpusLabe virtual goniometer prototype and a standard goniometer.

3.1.1 Participants

A convenience sample of four adult females participated in the study recruited via personal invitation from surgeon-led follow-up consultations of breast cancer survivors at the the Breast Cancer Care unit at the University Hospital Center of São João. All participants were fluent in Portuguese and did not get paid for their participation.

3.1.2 Data capture and processing

Goniometer

Goniometric measurements of shoulder maximum abduction were performed using standardised methods [3], [7]. The goniometer axis was aligned to the posterior aspect of the shoulder joint by the examiner, who would also read and record the measurement (in degrees), a single time for each side of each recruited participant.

corpusLabe prototype

Respecting the aforementioned reference protocol, the considered pose was performed facing the CorpusLabe prototype (Figure 2). The examiner would be able to save at a press of a button the maximum values of abduction registered during a session.

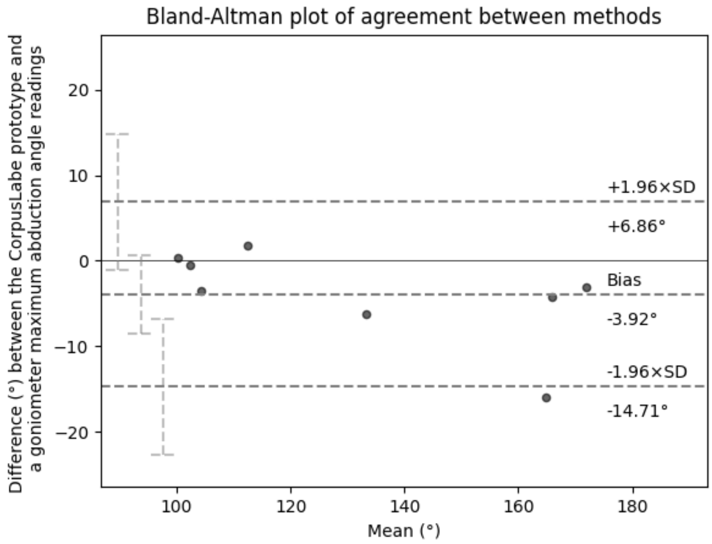
3.1.3 Statistical analysis

The 95% limits of agreement (LOA) between the corpusLabe prototype and the measurement reference goniometer for the shoulder joint angle were computed for the considered pose to approximate a validity study, similarly as in the work by Huber et al. [7]. To obtain the 95% LOA, the mean of the two shoulder angle measurements from each method was calculated. Next, the mean and standard deviation (SD) of differences between the corpusLabe prototype and the goniometer measurements were computed. The 95% LOA were defined as the mean difference ± 1.96 SD of the difference, such that 95% of differences lay within these limits. If the 95% LOA were greater than $\pm 5°$, the discrepancies between measurement systems were considered to be clinically significant.

3.2 Results

The 95% LOA between the corpusLabe prototype and the goniometer are shown in Figure 6.

Abduction to maximum was the only pose in which the corpusLabe prototype measures of shoulder angle were compared with the reference goniometer. However, the 95% LOA for the discrepancy between systems exceeded $\pm 5°$, which was defined as clinically significant.



View	Pose	corpusLabe vs goniomter	
		Mean bias	95% Limits of agreement
Frontal	Abduction to maximum	-3.92°	-14.71 to 6.82°

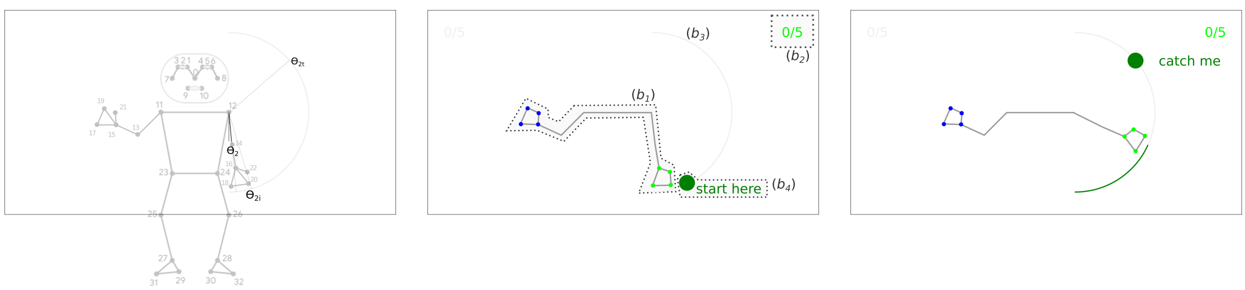
Figure 6: Bland-Altman analysis and limits of agreement, calculated as 1.96 standard deviation of the difference, between measurements of shoulder joint angle obtained using the corpusLabe prototype and a goniometer.

3.2.1 Discussion

Using the skeletal data from the aforementioned version of the BlazePose model for DepthAI hardware and the proposed pose analysis approach, the corpusLabe prototype was found to be able to provide measurements of shoulder angle. However, the measurement discrepancies between the corpusLabe prototype and the measurement standard were clinically significant. Notwithstanding the above, the small recruited sample, the variability of the movement considered, particularly in the studied population, and the width of the confidence intervals in the Bland-Altman analysis, suggests that further experimentation should be explored, including, and not exhaustively, more poses to be evaluated or adding more repetitions for each pose to the protocol of data acquisition.

4 corpusLabe as a gamified exercise platform

Considering the aforementioned approach to pose analysis and visualization (Section 2.2) and inspired by previous work on breast cancer survivors' expressed preferences in a physical activity promotion intervention [22], a gamified goniometer was developed as schematized in Figure 7 and summarily illustrated in Figure 8. Considering the selected movement (Figure 3), a straightforward approach using restrictions to the detected arm pose and average reference angles, enabled an exercise counter and the implementation of a guided execution of alternating arms abduction movement game with predefined target goals for each new user to attempt to reach.



a) b) c)

Figure 7: Gamified goniometer prototype overview: a) reference BlazePose model topology and example reference shoulder joint angles for a given movement of abduction – current, starting and target angles (θ_2, θ_{2i} and θ_{2t}); b) example annotated user interface with abstract representation of the tracked user (b_1), movement counter indicator (b_2), approximate trajectory of the arm extremity movement (b_3), starting angle visual representation and accompanying text (b_4); c) example user interface with target goal for the abduction movement.

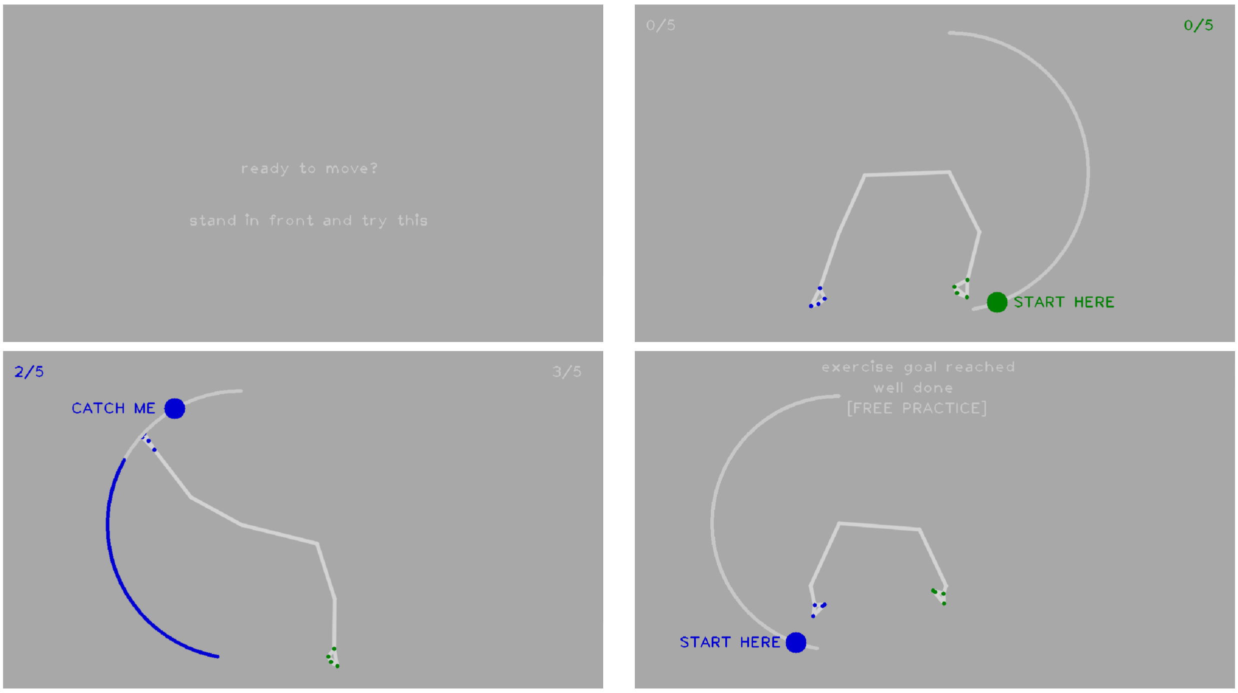


Figure 8: corpuLabe prototype example virtual goniometer based gamified demonstrator user interface.

5 Closing Remarks

A prototype exploring the use of the OpenCV AI Kit for a particular task of clinical assessment of posture and a related approach including gamifying elements aimed at promoting physical activity was developed.

Even though a suboptimal version of the BlazePose model was used to perform inference on the DepthAI hardware, the reported average mean per-joint position error in the Human3.6M database standard testing subset is in line with the results of the article that accompanied the publication of said database. Notwithstanding, and considering, not just the tuning opportunities of the evaluated method that were not investigated in this reported work, but also, the possibility to explore from the vast array of methods and databases related to the task of 3D human pose estimation recently made available, the reported results of relatively high average error in Section 2 can, in the humble opinion of the authors of the report, be regarded as somewhat pessimistic with respect to what the system can achieve, although this can, and should, be further explored in future work.

Somewhat similarly to what is stated above, the very limited sample of recruited users and evaluated poses, as well as, the specificity of the considered pose of maximum shoulder adbuction and its natural variability, doesn't allow the validity study presented in Section 3 to be conclusive, even though, the results reported show clinically significant differences between the angle measurements obtained using the corpusLabe prototype and the gold standard goniometer.

Although a playable version of the proposed gamified goniometer (Section 4) was achieved, this application was not properly evaluated. Its installation is, notwithstanding, planned for two distinct contexts (namely, a waiting room in a breast cancer treatment unit, and a common room in a technological institute). It is intended with this experiment to collect usage data (e.g. number of people detected, and number of exercises completed) as a rough assessment of the possibility of such an implementation to promote some type of autonomously executed physical activity, and to investigate how different types of population would respond to the considered prototype.

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