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Effect of Camera Position on the Robustness of a 2D Markerless Motion Capture System for Assessing Shoulder Kinematics

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1. Introduction

Markerless motion capture has emerged as a promising alternative to marker-based systems for assessing shoulder kinematics, offering accessibility and ecological validity. Monocular 2D approaches are particularly attractive because they require only a single camera and minimal experimental setup. However, these models rely on the visual appearance of the shoulder from a single viewpoint; changes in camera orientation or position may therefore influence neural network predictions (Berlinger et al., 2025). Understanding the sensitivity of a 2D markerless system to such variations is essential for reliable implementation in clinical environments, where camera placement may not be standardized.

The objective of this study was therefore to evaluate the robustness of a 2D deep-learning–based markerless system to changes in camera position when estimating humerothoracic (HT), scapulothoracic (ST), and scapulohumeral (SH) angles.

2. Methods

2.1 Participants

Eighty-eight healthy participants (35 women; age: 23.5 ± 3.7 yrs; height: 173.3 ± 7.2 cm; body mass: 68.0 ± 8.5 kg; body fat: 19.1 ± 5.9%) provided written informed consent. The protocol was approved by the local ethics committee (CER-UdL #2022-10-13-002).

2.2. Procedure

Participants held 12 standardized static postures representative of common upper-limb elevations across three movement planes (scaption, flexion, abduction) and the lateral scapular slide test. For each posture, two iPad 10th-generation devices (4032 × 3024 px) captured two successive images: bare back, back with 10 anatomical markers placed after palpation: the seventh cervical vertebra, the eighth thoracic vertebra, and bilaterally the acromial angle, trigonum spinae, inferior angle of the scapula, and lateral humeral epicondyle. A rigid positioning guide was held by the participants to minimize body motion between images. A 300-mm ruler was placed in the thoracic plane enabling pixel-to-millimeter scaling.

The reference iPad was positioned in the frontal plane, 3 m behind the participant, at a height of 1.5 m. The second iPad was systematically displaced to simulate alternative viewpoints. Relatively to the position of the reference iPad, four orientation changes (up/down tilt and left/right pan of ±10°) and four translations (±20 cm in height or lateral position) were applied alone or in combination in random order, resulting in 20 displaced viewpoints.

2.3. Deep neural network training and evaluation

The network (ResNet-50, DeepLabCut) was trained to identify the location of 10 anatomical landmarks for 150,000 iterations on markerless images labeled

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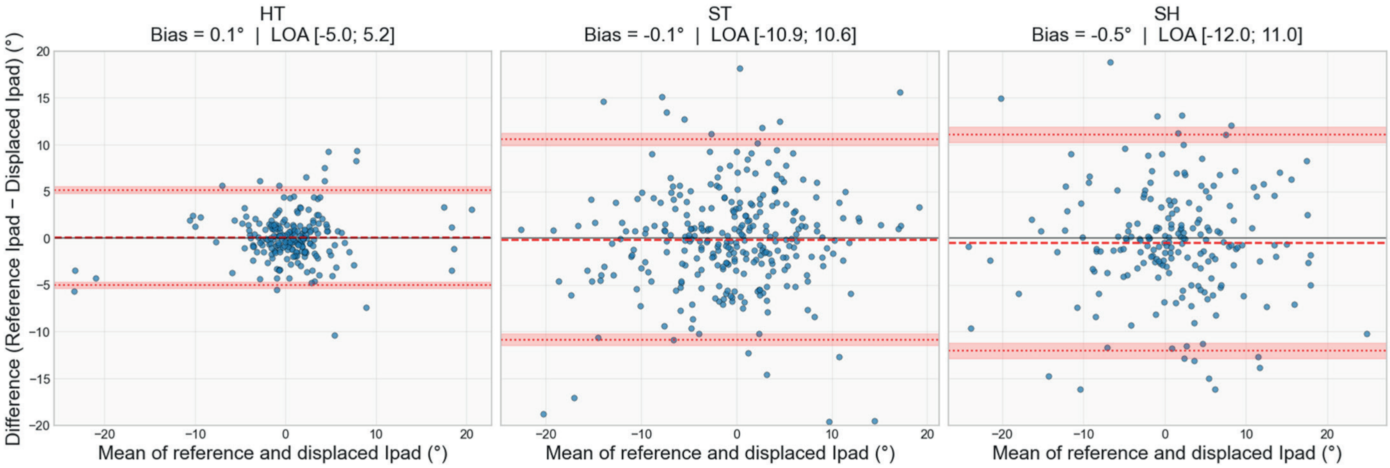

Figure 1. Bland–Altman plots comparing joint-angle errors obtained from the reference and displaced iPads for humerothoracic (HT), scapulothoracic (ST), and scapulohumeral (SH) angles. Each plot displays the mean difference (bias: red dotted line) and the limits of agreement (LOA) with a 95% confidence interval (red transparent area).
Credit: Perek.

via palpation, following a previously described labelling procedure (Perek et al., 2026), using images from 59 participants (reference iPad), and tested on all images (reference and displaced iPads) from an independent set of 29 participants. Joint angles (HT, ST and SH) were computed from anatomical landmark 2D coordinates following ISB recommendations (Wu et al., 2005). Then, joint-angle errors were defined, for each pose and iPad, as the differences between neural-network predictions and palpation. Linear mixed models were used to evaluate the effects of PLANE (flexion vs scaption vs abduction) and iPad POSITION (reference vs. displaced) on joint-angle errors, with participants as random intercept. Level of significance was set at $p < 0.05$, Tukey post-hoc tests and effect sizes (η^2 and Cohen's d) were reported when required. Inter-device agreement across configurations was then assessed using Bland–Altman analyses.

3. Results and discussion

Linear mixed models revealed neither significant interaction nor main effects of PLANE and iPad POSITION ($p > 0.05$, $\eta^2 < 0.003$) on joint angles errors, indicating that camera displacements did not systematically bias HT, ST, or SH angle estimates.

Bland–Altman analyses showed small biases in joint angle errors (from −0.5° to 0.1°), with limits of agreement up to ±5° for HT, ±11° for ST and ±12° for SH (Fig. 1).

Although individual predictions varied across configurations, no systematic directional bias was observed, resulting in comparable overall accuracy. In most cases, absolute error magnitudes remained limited; occasional configuration-specific increases or decreases in error were observed, without a consistent trend favoring either the reference or displaced camera positions. Previous monocular 2D markerless studies have reported view-dependent effects across different populations under markedly different camera viewpoints (>20° error) (Baldinger et al., 2025). In contrast, moderate and controlled camera changes have been shown to preserve kinematic accuracy in human gait analysis (Wang et al., 2024). Consistent with these findings, the magnitude of the overall errors (represented by the x-axis of figure 1) observed in the present study (predominantly within −20° to 20°) is comparable to the errors reported in Perek et al. (2026). These findings suggest that our 2D pose estimation system tolerates natural viewpoint changes without systematic bias, while shoulder joint angle estimates remain sensitive to parallax effects.

4. Conclusions

This study demonstrates that changes in camera position do not systematically degrade 2D neural network predictions. These findings suggest that small adjustments in camera positioning, as typically occur in clinical environments, are unlikely to affect neural network accuracy. However, joint angle estimation is likely affected by parallax effects; an optimal camera axis perpendicular to the plane of motion should therefore still be preferred. Future studies should further assess the sensitivity of the neural network to environmental variations (e.g., lighting or background changes).

Conflict of Interest Statement

None.

Contributor Roles

MP: Conceptualization, Methodology, writing original draft; YB: Conceptualization, Methodology, Validation, Supervision, Writing – review & editing draft; FL: software, ressources, review & editing draft; IR: Methodology, Validation, Supervision, review & editing draft; BG: Conceptualization, Methodology, Validation, Supervision Writing – review & editing draft.

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