Proceedings on Automation in Medical Engineering
Proc AUTOMED, 2026, Vol. 3, No 1, Article ID 2485, 2 Pages

Infinite Science Publishing

Towards quantitative ergonomic assessment in robotic surgery using depth imaging

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Abstract: Robot-assisted surgery lowers postural load for surgeons, yet desk-like ergonomic challenges persist. We evaluate posture monitoring using the Azure Kinect. Two surgeons performed console training tasks in deliberately "good" and "poor" postures. Using Kinect's body tracking, we estimated the sagittal plane from spinal landmarks and reoriented the skeleton. Three angles were extracted: Lower-Spine (LS), Upper-Spine (US) and Arm-Spine (AS). Surgeon-independent thresholds for LS and US separated favorable from unfavorable postures for the interquartile range, whereas AS was less discriminative. These preliminary results support the feasibility of an automated posture feedback. Validation on a more diverse cohort will refine proposed metrics.

I. Introduction

Recent years have seen an expansion in the number of certified surgical-robotic platforms [1]. In Germany, the number of urological surgeries performed robotically increased exponentially from 2005 to 2021 [2]. Although robot-assisted surgery (RAS) reduces the postural load compared to laparoscopy [3] surgeons still face desk-like ergonomic challenges. Consequently, posture guidelines tailored specifically to the robotic surgical console have been proposed to reduce neck and back fatigue [4]. However, during prolonged procedures, surgeons' focus on the operative field diminishes self-awareness of posture, allowing sub-optimal positions to resurface. Automatic detection of poor ergonomics could provide real-time cues for corrective action and reinforce healthy seating habits, thereby reducing surgeon fatigue and potentially improving operative precision and patient outcomes. Such a system must be non-invasive and easily integrable into existing workflows, features well met by depth cameras. The Azure Kinect combines a depth camera with a Body Tracking SDK that outputs a full 3D skeleton. Crucially, validation against a Vicon gold-standard system shows median joint-position errors below 20 mm for all key joints [5], a precision we consider adequate for coarse ergonomic analysis.

Our contributions are twofold: (i) we record a synchronized, multi-view dataset of two surgeons performing console tasks while deliberately adopting "good" and "poor" postures, and (ii) we propose three spine-centric angular metrics, two of which reliably separate these postural classes irrespective of the surgeon for the interquartile range (IQR).

II. Material and methods

Eighteen depth video sequences were recorded from two experienced surgeons who performed training tasks at a surgical console. Each trial was captured simultaneously from two out of five predefined camera positions, producing paired recordings for evaluating viewpoint effects. Fig. 1 shows an example of two synchronized recordings. In between trials, surgeons alternated between seating positions they personally classified as "good" or "poor". The Azure Kinect was configured to acquire depth data at 1024 × 1024 pixels with 5 fps.

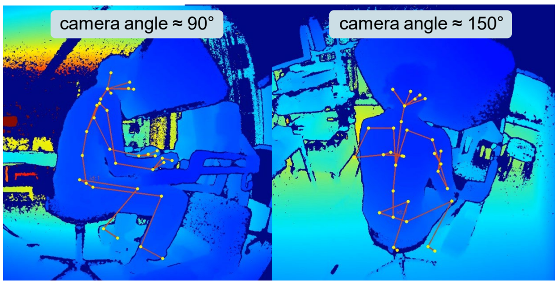

Figure 1: Example depth frame pair from two given concurrent camera angles, both displaying full skeleton overlay.

The Kinect Body Tracking SDK yielded complete 3D skeletal models (Fig. 1) per frame with confidence scores (scale 1-4) for every joint. Joints outside the camera's field of view, such as those on the contralateral body side, were removed, and any joints with a confidence score below 3 were discarded. To normalize body orientation, we fitted a plane to the spine joints (pelvis, spine-navel, spine-chest, neck, head) for each frame. Concretely, given the spine joints $p_i \in \mathbb{R}^3$ ($i = 1 \dots N$), we compute the centroid $c = \frac{1}{N}\sum_i p_i$, form the zero-mean matrix $X = [p_i - c]^\top$, apply singular-value decomposition $X = U\Sigma V^\top$, and take the first two right-singular vectors v_1, v_2 as planar axes with the third v_3 as the normal n. The skeleton was then rotated into this plane to obtain a standardized 90° lateral view (sagittal) as seen in Fig. 2. Motivated by ergonomic guidance on neck/trunk flexion and arm position [4], we defined three angular metrics within the sagittal plane as seen in Fig. 2 left to right:

1. Lower-Spine angle (LS): between pelvis → spine-navel and pelvis → neck.
2. Upper-Spine angle (US): between pelvis → neck and neck → head.
3. Arm-Spine angle (AS): between shoulder → elbow and neck → spine-chest.

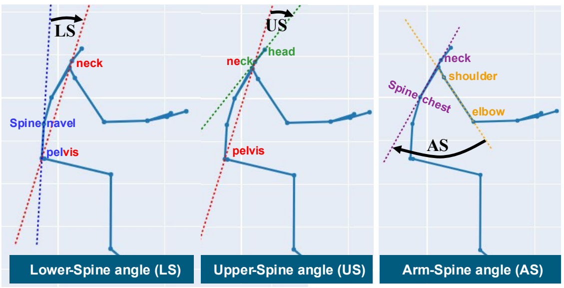

Figure 2: Visualization of the three posture metrics in sagittal plane. Corresponding joints, lines and angles are highlighted.

III. Results and discussion

Synchronous recordings from two different viewpoints did not yield consistent angle measurements after transformation into 90° lateral views; differences were typically around 15°, indicating that oblique views are unsuitable for precise spinal-curvature estimation. Consequently, only the seven sequences obtained at an approximately 90° viewing angle (Fig. 1 left) were retained for further posture analysis.

Fig. 3 summarizes the distributions of the three metrics by surgeon (S1/S2) and posture (good/poor), while Table 1 reports the corresponding median values.

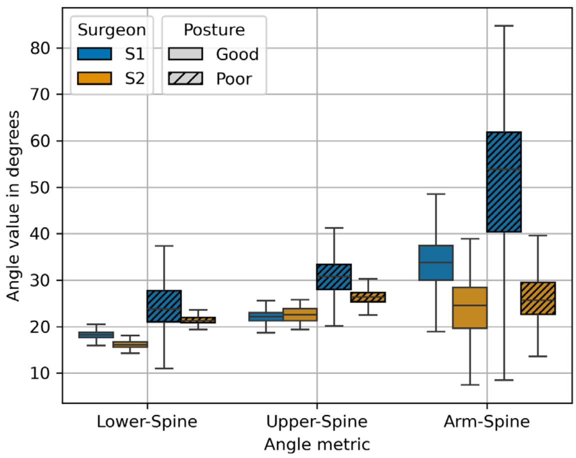

Figure 3: Distribution of three angle metrics separated by surgeon (S1, S2) and posture (good, poor).

Although angle variability appears surgeon-specific, simple thresholds for LS (~20°) and US (~25°) separate "good" from "poor" posture across both surgeons for the IQR. Samples outside the IQR may partially stem from unfiltered, task-irrelevant motions (e.g., turning to speak); their effect will be addressed in future analyses. AS is less discriminative and shows overlap for surgeon S2, likely because each surgeon selected different training tasks requiring different extents of arm movement; future studies will therefore standardize and log task type to minimize such confounding effects. Moreover, further data are required, as the present study involved only two surgeons and focused on deliberately contrasted postures.

Table 1: Median values of three angular metrics separated by surgeon (S1, S2) and posture (good, poor).

Angle	LS	US	AS
S1 | Good	18.25°	22.14°	33.39°
S2 | Good	16.10°	22.56°	24.54°
S1 | Poor	23.75°	30.81°	53.88°
S2 | Poor	21.29°	26.37°	25.68°

IV. Conclusions

Using a single side-view Azure Kinect, we extracted three spine-related angular metrics from two surgeons while they performed training tasks at a surgical console. Two of the three metrics discriminated self-declared "good" from "poor" posture irrespective of the operator for most data-points, demonstrating the feasibility of a camera-based posture-feedback system for robotic surgery. By establishing a more standardized, ergonomically sound posture, such a system may improve procedural precision and, ultimately, patient outcomes. Future work will extend the dataset to a larger, more diverse cohort and will include intermediate postures to refine the proposed thresholds.

Author's Statement

This work was partially funded by the European Regional Development Fund (ERDF), the Federal Government and Land Schleswig Holstein, Project No. 125 24 009. Authors state no conflict of interest. Informed consent has been obtained from all individuals included in this study. Ethical approval was granted by the ethics committee of University Clinic of Kiel (D 448/21).

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