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Computer Vision for Assessing Surgical Movements in Neurosurgery

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Abstract. Objective evaluation of microsurgical technique quality is vital for successful training in neurosurgery. This study aimed to assess the accuracy of automatically detecting a neurosurgeon's proper posture and hand positioning using computer vision. We employed the RTMPose neural network model to identify key anatomical points in the neurosurgeon's projection and calculated various angles formed by connecting these points. By utilizing machine learning on these angles, we were able to classify images of the surgeon's posture and hands into correct positions and various types of errors with an accuracy of at least 0.9. Computer vision enables successful detection and objective assessment of the neurosurgeon's posture and hand positions. The high accuracy of this detection can pave the way for a new training approach in neurosurgery.

Keywords. Neurosurgery, skills, pose estimation, artificial intelligence, computer vision.

1. Introduction

Objective evaluation of microsurgical technique quality is vital for successful training in neurosurgery [1]. Employing specialized simulators for such evaluations may enhance the efficiency and safety of neurosurgical skills formation [2].

Modern neurosurgical manipulation assessment systems such as Northwestern Objective Microanastomosis Assessment Tool (NOMAT) or more general Structured Assessment of Technical Skills (OSATS) emphasize the importance of the surgeon's proper posture and hand positioning to prevent fatigue during surgeries, which is essential for the success of microsurgical procedures [3,4]. This study aimed to evaluate the accuracy of automatically detecting a neurosurgeon's proper posture and hand positioning using artificial intelligence.

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2. Methods

We filmed the body and arm postures of nine neurosurgical residents during their five-year training in a microsurgical laboratory. All participants were right-handed. Each video depicted the participant maintaining the correct posture and hand position, as well as showcasing various incorrect body and hand positions for a minimum of two minutes per task. The selection of incorrect positions was based on established scales used to assess the correctness of a surgeon's posture, as well as on the observations of typical errors made by novice neurosurgeons as noted by experienced supervisors. A comprehensive list of the positions simulated by the participants is provided in Table 1. Each video was labeled according to the corresponding category in Table 1.

Table 1. Various body and arm positions that could potentially be identified using artificial intelligence.

#	Interpretation	Posture	Right hand	Left hand
1	Correct	Correct	Correct	Correct
2	Incorrect	Right shoulder shrug	Elbow to the side	Elbow to the side
3	Incorrect	Left shoulder shrug	Improper tool grip	Improper aspirator grip
4	Incorrect	Tilting forward	Wrist turned inward	Hanging mid-air
5	Incorrect	Leaning back	Wrist turned outward	
6	Incorrect	Mixed errors		

The recording was done with HD videocamera from three perspectives: back, side, and front. Using video recordings with the RTMPose neural network model (integrated into the *mmpose* library) in the Body 2d variant, pre-trained on the COCO+AIC dataset, 17 key anatomical points (mostly joints) on the body and arms were automatically detected in the subjects [5]. We connected key anatomical points with lines and measured angles to describe the position of the body and arms in three-dimensional space:

- *shoulders_angle*: the angle created by the line connecting the shoulders and the horizontal line (from the rear view);
- *axis_angle*: the angle created by the line connecting the shoulder and hip joints and the vertical line (from the side view).

To determine the hand positions, we utilized the RTMPose-I model in the wholebody-2d-133-keypoints variation, which was pre-trained on the COCO-WholeBody dataset and capable of detecting 133 anatomical points [6]. We examined the key points in the hand projection (points 6-11 and 92-133, details on the points can be found via the link [7]). The camera was positioned directly in front, capturing the hands. By connecting these key points for each hand with lines, the following angles were calculated (refer to [7]):

- *wrist_angle*: the angle between the forearm and the hand - lines 9-11 and 11-122;
- *elbow_angle*: the angle at the elbow joint (between the forearm and shoulder - lines 7-9 and 9-11);
- *wrist_thumb_angle*: the angle between the forearm (9-11) and the line 113-115;
- *wrist_index_angle*: the angle between the forearm (9-11) and the line 113-118;
- *wrist_middle_angle*: the angle between the forearm (9-11) and the line 113-122;
- *palm_thumb_angle*: the angle between the line 113-115 and the line 115-127;
- *palm_index_angle*: the angle between the line 113-118 and the line 118-121;
- *palm_middle_angle*: the angle between the line 113-122 and the line 122-125.

Examples of some of the angles we evaluated are displayed in Figure 1.

To evaluate posture suboptimals using the rear-view camera, we determined the optimal cutpoint for the *shoulders_angle* that maximizes the sum of sensitivity and specificity in detecting "*Right shoulder shrug*" and "*Left shoulder shrug*" mistakes. For assessing improper poses using the side camera, we identified the optimal cutpoint for the *axis_angle* that maximized the sum of sensitivity and specificity in detecting "*Tilting forward*" and "*Leaning back*" errors.

Machine learning (ML) was utilized to identify different hand position errors using the eight aforementioned hand angles as predictors. We tackled multiclass classification tasks to differentiate between correct and various types of incorrect positions for the right (5 classes) and left (4 classes) hands (Table 1). These tasks were labeled as *Right_multi* and *Left_multi*, respectively. Additionally, we addressed binary classification tasks to determine the correct hand position against any form of incorrect position (*Right_bi* and *Left_bi*). Furthermore, in a binary classification scenario, we evaluated the potential for detecting more complex errors such as incorrect tool grip with the right hand compared to the correct position (*Right_inst_err*), incorrect use of the aspirator with the left hand compared to the correct position (*Left_asp_err*), and holding the left hand in the air instead of providing support as in the correct position (*Left_hang_err*).

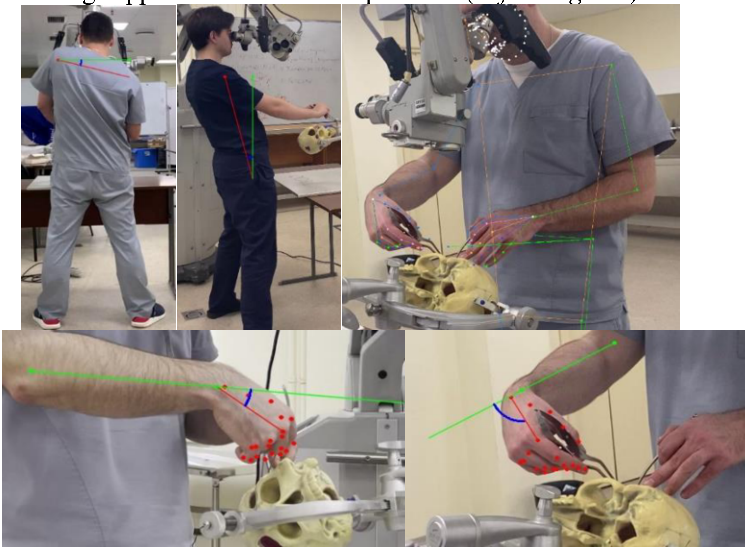

Figure 1. Examples of detecting posture and hand positions. In the top row from left to right: *shoulders_angle* (left shoulder shrug), *axis_angle* (leaning back), general view of pose detection. In the bottom row from left to right: *wrist_angle*, *wrist_thumb_angle*.

To predict the target variable in each dataset, several ML algorithms were tested: k-nearest neighbors (KNN), naïve Bayes (NB), support vector machine (SVM), random forest (RF), logistic regression (LR), catboost (CB), and a baseline featureless model (FM) that predicted with only one predominant class. These algorithms were applied over all tasks, each repeated 100 times with subsampling, with the original dataset split into training and testing subsets for each iteration, comprising 2/3 and 1/3 of the dataset, respectively. The quality metrics (accuracy (ACC), balanced accuracy (BACC), sensitivity (SENS), specificity (SPEC), F1-score, area under the ROC curve (ROC AUC), and area under precision-recall curve (PR AUC)) on testing sets were averaged to obtain more robust performance estimates. The ML procedures were implemented using the *mlr3verse* package ecosystem in R programming language. Optimal cutpoints were calculated using *cutpointr* R package.

3. Results

We obtained 55 videos of 1000 frames each from the rear angle to find the *shoulders_angle* cutpoints in identifying posture variations (first two rows of Table 2). Similarly, 55 videos of 1000 frames each from the side view were utilized to establish the *axis_angle* threshold (last two rows of Table 2). The optimal cutpoint is specified in the OCP column of Table 1.

Table 2. Optimal cutpoints (OCP) for the *shoulders_angle* and *axis_angle* to detect suboptimal neurosurgeon's postures.

Task	OCP	ACC	SEN	SPE	F1	ROC AUC
Right shoulder shrug (shoulders_angle)	≤ -1.61	0.999	0.997	0.999	0.999	0.998
Left shoulder shrug (shoulders_angle)	≥ 6.63	0.998	0.997	0.999	0.998	0.998
Tilting forward (axis_angle)	≥ -7.31	0.987	0.999	0.977	0.984	0.998
Leaning back (axis_angle)	≤ -13.60	0.905	0.820	0.982	0.891	0.966

We utilized 81 videos, each consisting of 1000 frames, to classify 9 hand positions. Nine videos were dedicated to each error type to ensure sample diversity while maintaining balance for ML. The best ML performance for each task with model specifications is outlined in Table 3. In *Right(-Left)_multi* tasks KNN, RF, and SVM ranked in the top 3 best solutions, with a maximum BACC difference of less than 0.009. *Right(-Left)_bi* tasks were better addressed by KNN, RF, and CB, with a maximum BACC delta of less than 0.004 For instrument grip errors, KNN, RF, and CB were the best models, showing a maximum BACC difference of less than 0.0008.

Table 3. The quality metrics for ML models detecting hand position abnormalities.

Task	Model	BACC	ACC	SEN	SPE	F1	ROC AUC	PR AUC
Right_bi	KNN	0.989	0.994	0.982	0.997	0.984	0.998	0.997
Left_bi	KNN	0.991	0.994	0.986	0.997	0.988	0.998	0.997
Right_inst_err	KNN	0.992	0.992	0.992	0.991	0.992	0.999	0.999
Left_asp_err	KNN	0.994	0.994	0.993	0.995	0.994	0.999	0.999
Left_hang_err	CB	0.991	0.991	0.991	0.992	0.991	0.999	0.999
Right_multi	KNN	0.986	0.986	-	-	-	0.998	-
Left_multi	KNN	0.990	0.990	-	-	-	0.998	-

4. Discussion

There are few studies evaluating the efficacy of neurosurgeon movements through videos using artificial intelligence, but this area has started to evolve (8–10). In our study, RTMPose performed well in the task of neurosurgeon's pose detection, as evaluated by both the experts and indirectly by machine learning. The ability to precisely evaluate a neurosurgeon's posture geometry through computer vision offers new possibilities for monitoring the learning process in neurosurgery and delivering automated feedback in suboptimal situations. Moreover, we observed the significant potential of our approach in detecting relatively complex errors like "incorrect tool grip." Our future endeavors will focus on evaluating more subtle neurosurgical movements.

5. Conclusions

Computer vision enables successful detection and objective assessment of the neurosurgeon's posture and hand positions. The high accuracy of this detection can pave the way for a new training approach in neurosurgery. *The study was supported by Russian Science Foundation (grant 22-75-10117).*

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