

ORIGINAL RESEARCH ARTICLE

Automated assessment of osteopathic manipulative treatment techniques through quantitative video motion analysis: A feasibility study

Ian Nevers, Lea Dalco, Milan Toma*, and Sheldon Yao

Department of Osteopathic Manipulative Medicine, College of Osteopathic Medicine, New York Institute of Technology, Old Westbury, New York, United States of America

Abstract

Osteopathic manipulative treatment represents a cornerstone of osteopathic medical education, yet the assessment of student competency in performing these techniques remains largely dependent on subjective instructor evaluation. This limitation introduces variability in grading standards and restricts the provision of actionable, quantitative feedback to learners. The present study introduces a proof-of-concept automated video analysis system designed to objectively evaluate osteopathic manipulative treatment technique execution through quantitative motion parameter analysis. A computational framework was developed incorporating optical flow algorithms, edge detection methods, and landmark tracking to quantify cervical spine motion during counterstrain technique performance. The system analyzes paired demonstration videos representing correct and incorrect technique execution, extracting angular displacement measurements for flexion, sidebending, and rotation movements. Validation testing using anterior cervical counterstrain techniques demonstrated that the automated system successfully distinguished between correct and incorrect performances, with the correct technique achieving all three therapeutic motion parameters (flexion of 18.1 degrees, right sidebending of 19.5 degrees, and right rotation of 68.6 degrees) while the incorrect technique exhibited reversed sidebending and rotation directions. The system generates comprehensive output reports containing both quantitative angular measurements and qualitative performance assessments. These findings establish the technical feasibility of this proof-of-concept automated motion analysis approach rather than a validated diagnostic tool, offering potential future applications in skills laboratory settings, simulation environments, and remote learning contexts where instructor availability may be limited.

***Corresponding author:**
Milan Toma
(tomamil@tomamil.com)

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1. Introduction

Osteopathic manipulative treatment constitutes a fundamental component of osteopathic medical education and clinical practice, representing the distinctive therapeutic approach

that differentiates osteopathic physicians from their allopathic counterparts.¹⁻⁶ The educational framework for training osteopathic medical students in these manual techniques has traditionally relied upon direct instructor observation and subjective assessment methodologies. While experienced faculty members possess the clinical expertise necessary to evaluate student performance, the inherent subjectivity of visual observation introduces considerable variability in grading standards and limits the specificity of feedback provided to learners. This educational challenge has become increasingly significant as osteopathic medical schools expand enrollment and face growing demands on faculty teaching resources.

The assessment of manual therapy techniques presents unique challenges that distinguish it from other domains of medical education. Unlike knowledge-based examinations or procedural skills that produce discrete, measurable outcomes, the evaluation of osteopathic manipulative treatment requires simultaneous assessment of multiple biomechanical parameters including the direction, magnitude, and sequencing of applied forces and resulting tissue movements. Instructors must visually track subtle positional changes occurring across multiple anatomical planes while simultaneously evaluating the appropriateness of patient positioning, practitioner hand placement, and treatment duration. The cognitive complexity of this assessment task, combined with the brief duration of most treatment encounters, creates conditions favorable for inter-rater variability and inconsistent feedback delivery.⁷⁻¹¹

Modern medical education has increasingly emphasized competency-based assessment frameworks

that require demonstration of measurable skill acquisition rather than simple completion of prescribed training hours.¹² Accreditation standards promulgated by the Commission on Osteopathic College Accreditation mandate that osteopathic medical programs implement robust assessment mechanisms capable of documenting student achievement of defined competency milestones.^{7,13} The subjective nature of traditional osteopathic manipulative treatment assessment creates tension with these regulatory expectations, as faculty evaluations may lack the reliability and validity characteristics expected of high stakes competency determinations. Furthermore, the absence of quantitative performance metrics limits the ability of educational programs to track student progress longitudinally or to identify specific technical deficiencies requiring remediation. This educational gap between traditional subjective assessment and modern competency expectations motivates the development of automated quantitative approaches (Figure 1).

The technological landscape of medical education has undergone substantial transformation in recent decades, with simulation based training, virtual reality applications, and artificial intelligence (AI)-assisted learning platforms becoming increasingly prevalent across multiple educational domains.¹⁴⁻¹⁹ Surgical training programs have successfully implemented motion tracking systems and performance analytics to provide objective feedback on procedural skills, demonstrating the feasibility and educational value of quantitative assessment approaches.²⁰⁻²⁶ Physical therapy and rehabilitation medicine have similarly adopted motion capture technologies to analyze patient movement patterns and treatment outcomes.²⁷ Despite these advances

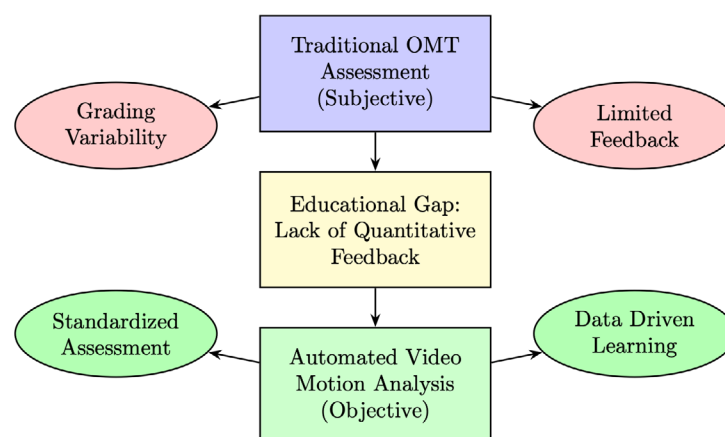


Figure 1. Conceptual framework illustrating the transition from traditional subjective assessment of osteopathic manipulative treatment techniques to automated quantitative video motion analysis. The traditional approach produces grading variability and limited feedback, creating an educational gap that the proposed system addresses through standardized assessment and data-driven learning capabilities.

Abbreviation: OMT: Osteopathic manipulative treatment.

in related fields, osteopathic medical education has been comparatively slow to adopt technology enhanced assessment methodologies, creating an opportunity for innovative solutions that bridge the gap between traditional teaching approaches and contemporary educational expectations.^{28–31}

The counterstrain technique represents a particularly suitable candidate for automated motion analysis due to its well-defined positional parameters and reproducible treatment protocols. Originally developed by Lawrence Jones in the 1960s, counterstrain involves the identification of myofascial tender points and subsequent positioning of the patient to achieve maximum tenderness reduction, typically requiring the practitioner to guide the affected body region through specific combinations of flexion or extension, sidebending, and rotation movements. The anterior cervical counterstrain points, located along the anterior aspect of the cervical vertebrae, require positioning that includes cervical flexion, sidebending away from the tender point, and rotation away from the tender point. These three-dimensional positioning requirements create distinct motion signatures that can be captured and quantified through video analysis methodologies.

The biomechanics of cervical spine motion have been extensively characterized in the scientific literature, providing a robust foundation for automated motion analysis applications. The cervical spine permits movement in three primary planes including sagittal plane flexion and extension, frontal plane lateral bending, and transverse plane axial rotation. These movements occur through the coordinated articulation of seven cervical vertebrae, with the majority of flexion and extension occurring at the atlanto-occipital joint (C0-C1) and upper cervical segments, while rotation is concentrated at the atlantoaxial articulation.^{32,33} The coupled nature of cervical motion, wherein movement in one plane produces obligatory motion in other planes, creates characteristic movement patterns that can serve as targets for automated detection algorithms.

Optical flow analysis represents a computer vision methodology with considerable potential for medical motion analysis applications.³⁴ This computational approach estimates the apparent motion of objects between consecutive video frames by analyzing patterns of brightness variation across the image plane. The Farneback algorithm, a dense optical flow method that computes motion vectors for all pixels in the image field, has demonstrated particular utility for tracking subtle tissue displacements in clinical imaging contexts.^{35–38} By applying optical flow analysis to standardized video recordings of osteopathic manipulative treatment performance, it becomes possible to extract

quantitative motion parameters including displacement magnitude, movement direction, and temporal sequencing of positional changes.

The present study introduces an automated video analysis system designed to objectively evaluate osteopathic manipulative treatment technique execution through quantitative motion parameter extraction and comparison against defined therapeutic standards. The system employs a computational pipeline incorporating image preprocessing, anatomical landmark detection, optical flow-based motion tracking, and automated performance classification to generate comprehensive feedback reports for both learners and instructors. Importantly, this study is framed strictly as a feasibility and proof-of-concept investigation rather than a validated clinical or diagnostic tool. This proof-of-concept investigation focuses specifically on the anterior cervical counterstrain technique to demonstrate the technical feasibility and potential educational value of the automated assessment approach. The research addresses the hypothesis that video-based motion analysis can reliably distinguish between correct and incorrect technique performance by detecting physiologically meaningful differences in cervical positioning parameters.

The development of automated assessment tools for osteopathic manipulative treatment education addresses multiple stakeholder needs within osteopathic medical programs. For students, quantitative feedback enables identification of specific technical deficiencies and supports self-directed skill development outside of scheduled laboratory sessions.^{39–44} For faculty members, standardized assessment criteria reduce grading burden while improving evaluation consistency across multiple raters and assessment occasions. For educational administrators, objective performance metrics facilitate competency documentation for accreditation purposes and enable identification of curricular areas requiring enhanced instructional attention.^{45–49} The scalability and accessibility of video-based assessment further supports extension of quality feedback to remote learning contexts where direct instructor observation may not be feasible.

The primary objective of this study was to develop and validate an automated video analysis system capable of objectively evaluating osteopathic manipulative treatment technique execution through quantitative extraction of motion parameters. Specifically, the system was designed to analyze cervical spine positioning during anterior cervical counterstrain technique performance and to compare extracted motion measurements against established therapeutic standards to determine technique correctness.

Secondary objectives of this investigation included:

- (i) To determine whether the automated system could reliably discriminate between correct and incorrect technique demonstrations based on detected differences in flexion, sidebending, and rotation parameters.
- (ii) To generate comprehensive output reports containing both quantitative angular measurements and qualitative performance assessments suitable for educational feedback purposes.
- (iii) To assess the computational feasibility of the analysis pipeline for deployment on standard desktop computing hardware without requiring specialized imaging equipment or high-performance computing infrastructure.
- (iv) To establish a methodological framework extensible to additional osteopathic manipulative treatment modalities beyond the anterior cervical counterstrain technique examined in this proof-of-concept study.

2. Materials and methods

2.1. Osteopathic manipulative treatment technique description

Counterstrain is an indirect osteopathic manipulative treatment technique originally developed by Lawrence Jones in the 1960s and widely employed in clinical practice for the management of somatic dysfunction and associated musculoskeletal pain.^{1,50,51} The technique operates on the principle that myofascial tender points, which are small zones of tense, tender, and edematous tissue located within muscles, tendons, ligaments, or fascia, can be alleviated through passive positioning of the patient into a posture of comfort.^{50,52} The practitioner first identifies a tender point by palpation, noting its precise anatomical location and the degree of tenderness elicited upon digital pressure. The patient is then guided into a position that shortens the tissues surrounding the tender point, typically reducing the palpable tenderness by at least 70%. This position of ease is maintained for approximately 90 seconds, during which time the proprioceptive activity responsible for

maintaining the dysfunctional tissue tension is believed to reset.^{50,51,53} Following the holding period, the patient is slowly returned to neutral positioning while the practitioner monitors for any return of tenderness.

The anterior cervical counterstrain points constitute a series of tender point locations situated along the anterolateral aspect of the cervical vertebrae, typically found on or near the anterior surfaces of the transverse processes (Figure 2). These points are numbered according to their corresponding vertebral level; with anterior cervical point one located at the first cervical vertebra and subsequent points descending to the seventh cervical level. Anterior cervical tender points are commonly associated with cervical somatic dysfunction presenting as neck pain, restricted range of motion, or referred symptoms into the head, shoulder, or upper extremity. The therapeutic positioning for anterior cervical counterstrain involves a combination of three cervical movements executed simultaneously to achieve the position of maximum comfort.

The present study focuses on anterior cervical counterstrain point four, designated AC4, located at the level of the fourth cervical vertebra. For a left sided AC4 tender point, the therapeutic positioning standard requires cervical flexion combined with sidebending away from the tender point and rotation away from the tender point. In anatomical terms, this corresponds to forward bending of the head and neck in the sagittal plane, lateral tilting of the head toward the right shoulder in the frontal plane, and turning of the face toward the right in the transverse plane. These three positioning components must be achieved in appropriate combination and magnitude to effectively shorten the tissues surrounding the tender point and produce the therapeutic reduction in tenderness (Figure 3).

Incorrect technique execution may result from errors in one or more of the three positioning components. Common errors include positioning the patient in extension rather

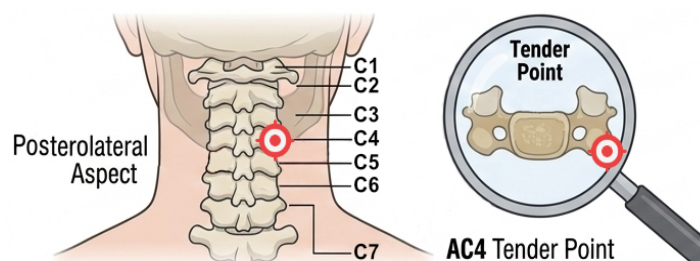


Figure 2. Anatomical location of anterior cervical counterstrain point 4 (AC4). The tender point is situated on the anterolateral aspect of the fourth cervical vertebra, as indicated by the magnified view. The cervical vertebrae are labeled C1 through C7 for reference.

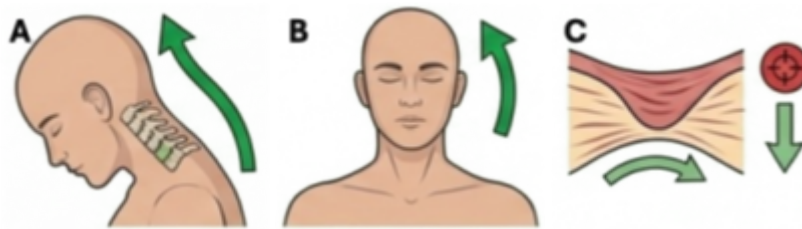


Figure 3. Correct therapeutic positioning for anterior cervical counterstrain point 4 (AC4) treating a left sided tender point. (A) Sagittal view demonstrating cervical flexion. (B) Frontal view demonstrating right sidebending and right rotation, both directed away from the left sided tender point. (C) Therapeutic tissue shortening achieved at the tender point location when the position of ease is maintained for 90 seconds, allowing proprioceptive resetting.

than flexion, sidebending toward rather than away from the tender point, or rotating toward rather than away from the tender point. Such positioning errors prevent adequate shortening of the involved tissues and compromise therapeutic effectiveness. The ability to reliably distinguish correct from incorrect positioning based on objective motion parameters forms the foundation of the automated assessment approach described in subsequent sections.

2.2. System architecture and development environment

The automated osteopathic manipulative treatment assessment system was developed using MATLAB (MathWorks, Natick, Massachusetts) version R2024b, selected for its comprehensive image processing toolbox, computer vision capabilities, and optical flow algorithm implementations. The computational framework was structured as a modular function capable of processing individual video files or batch analyzing multiple recordings within a single execution session. All algorithm development and validation testing were performed on a

standard desktop workstation equipped with an Intel Core i7 processor and 16 gigabytes of random-access memory, demonstrating the feasibility of deployment on commonly available computing hardware without requiring specialized graphics processing units or high-performance computing infrastructure.

The system architecture follows a sequential processing pipeline wherein video frames undergo preprocessing transformations, anatomical landmarks are detected and initialized, motion is tracked across the frame sequence using optical flow algorithms, quantitative motion parameters are extracted and compared against therapeutic standards, and automated performance classifications are generated with accompanying qualitative feedback (Figure 4). Each processing stage was implemented as a discrete subroutine to facilitate independent validation and future algorithmic refinement. The modular design additionally supports extension of the system to analyze alternative osteopathic manipulative treatment techniques through modification of the landmark detection and motion

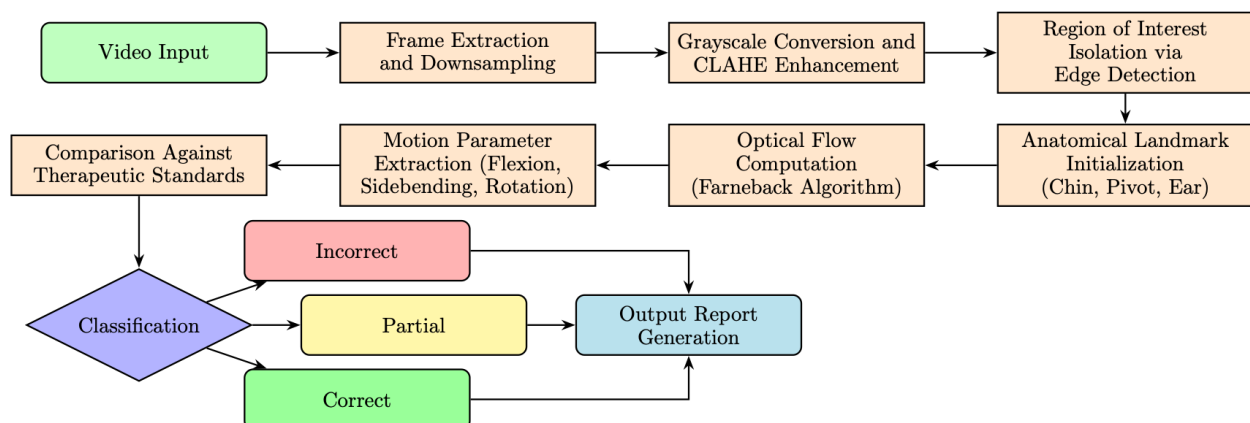


Figure 4. Flowchart representation of the automated analysis pipeline implemented in the assessment system. Video input undergoes sequential processing stages including preprocessing, landmark detection, optical flow computation, and motion parameter extraction before automated classification determines technique correctness and generates the output report.

assessment components while retaining the core optical flow and classification infrastructure.

A detailed summary of the key MATLAB functions, toolboxes, and configurable parameters employed in the automated motion analysis system is provided in Table 1. The implementation requires three MATLAB toolboxes in addition to core MATLAB functionality. The Image Processing Toolbox provides essential functions for image preprocessing and region of interest isolation, including *im2gray* for grayscale conversion, *adapthisteq* for Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance local contrast under variable lighting conditions, *imgaussfilt* for Gaussian smoothing to reduce noise sensitivity, *edge* for Canny edge detection to identify anatomical boundaries, and morphological operations (*imdilate*, *bwmorph*, *strel*) to refine edge connectivity and extract region properties via *regionprops*. The Computer Vision Toolbox supplies the *opticalFlowFarneback* object and *estimateFlow* function that implement the *Farneback* dense optical flow algorithm, enabling computation of frame-to-frame motion vectors for all pixels within the analysis regions. The Statistics and Machine Learning Toolbox contributes the *prctile* function for percentile-based peak detection used in identifying maximum motion excursions. Core MATLAB functions utilized throughout the pipeline include *VideoReader* for video file input, trigonometric functions (*atan*, *asind*, *rad2deg*) for angular computations, *hypot* for Euclidean distance calculations, and *median* for robust central tendency estimation when aggregating optical flow vectors. The algorithm incorporates numerous configurable parameters governing frame downsampling rate, region of interest boundaries, flow magnitude thresholds, landmark detection windows, motion calibration factors, and classification decision thresholds, all of which are enumerated in Table 1 to support reproducibility and future algorithmic refinement.

2.3. Video acquisition and standardization protocol

Demonstration videos were recorded under controlled conditions designed to minimize confounding variables that might compromise motion analysis reliability. The standardized recording protocol specified consistent camera positioning at a fixed distance and angle relative to the treatment table, uniform ambient lighting without harsh shadows or specular reflections, and reproducible patient and practitioner positioning at the start of each recording session. The camera was positioned to capture a lateral view of the cervical region, enabling visualization of flexion and extension movements in the sagittal plane while permitting detection of sidebending and rotation through changes in the apparent width and orientation of anatomical structures.

Table 1. Key MATLAB functions, toolboxes, and configurable parameters employed in the automated motion analysis system

Function/Parameter	Toolbox	Description
<i>opticalFlowFarneback</i> / <i>estimateFlow</i>	Computer Vision	Farneback dense optical flow for frame-to-frame motion vector computation
<i>adapthisteq</i>	Image Processing	Contrast Limited Adaptive Histogram Equalization (CLAHE) for local contrast enhancement
<i>edge</i> (Canny)	Image Processing	Canny edge detection for head boundary and chin landmark identification
<i>regionprops</i>	Image Processing	Extracts bounding box coordinates from edge-detected regions
FLOW THR = 0.12	Parameter	Flow magnitude threshold (pixels) for noise rejection
CALIBRATION = 0.45	Parameter	Flexion angle calibration factor
SB GAIN = 0.68	Parameter	Sidebending angle scaling gain
FLEX MIN DEG = 3.0	Parameter	Minimum flexion threshold for classification (degrees)
SB MIN DEG = 2.0	Parameter	Minimum sidebending for threshold classification (degrees)
ROT MIN DEG = 2.0	Parameter	Minimum rotation for threshold classification (degrees)

Paired demonstration videos were recorded for each technique analyzed, with one recording depicting correct technique execution according to established therapeutic standards and one recording depicting incorrect technique execution characterized by specific positional errors. The pairing methodology enabled direct comparison of motion parameters between correct and incorrect performances, facilitating validation of the system's discriminatory capability. For the anterior cervical counterstrain technique examined in this proof-of-concept study, the correct demonstration positioned the patient in cervical flexion with sidebending toward the right (away from the left sided tender point) and rotation toward the right (Figure 5A), while the incorrect demonstration incorporated cervical flexion with sidebending and rotation in the opposite directions (Figure 5B). The present proof-of-concept study employed a validation dataset consisting of a single trained operator performing one correct and one incorrect demonstration on one volunteer subject ($n = 1$ correct, n

= 1 incorrect), yielding two video recordings representing correct and incorrect technique execution respectively.

Video files were recorded in MP4 format at standard definition resolution, balancing image quality requirements against file size and processing time considerations. The selection of widely available video formats and consumer grade recording equipment reflects the design objective of creating an assessment system deployable in typical educational settings without requiring specialized imaging infrastructure. Frame rates of approximately 30 frames per second provided sufficient temporal resolution for capturing the relatively slow positional changes characteristic of counterstrain technique performance.

2.4. Image preprocessing and region of interest isolation

The preprocessing pipeline applies a series of image transformations designed to enhance motion detection accuracy while reducing computational burden and eliminating irrelevant image content. Input video frames are first subjected to temporal downsampling by a factor of two, reducing the effective frame rate while retaining sufficient temporal resolution for motion tracking purposes. Each retained frame is converted from RGB color space to grayscale representation, eliminating color channel redundancy and standardizing input format for subsequent processing stages.

Contrast enhancement is performed using the Contrast Limited Adaptive Histogram Equalization algorithm, which improves local contrast throughout the image while preventing over amplification of noise in homogeneous regions. This preprocessing step proves particularly valuable for video recordings obtained under variable lighting conditions, as it normalizes brightness distributions and enhances the visibility of anatomical boundaries and tissue interfaces. The enhancement is

applied selectively to the upper portion of each frame corresponding to the head and neck region, as defined by a configurable parameter specifying the fraction of frame height to retain for analysis.

Region of interest isolation employs Canny edge detection to identify the boundaries of the head within each frame, followed by morphological dilation to connect fragmented edge segments into continuous contours. Connected component analysis identifies the largest edge bounded region, presumed to correspond to the head silhouette, and extracts the bounding box coordinates for this region. The bounding box is subsequently inset by a configurable fraction to exclude peripheral regions potentially affected by boundary artifacts or background motion. In frames where edge detection fails to identify a suitable region, the algorithm defaults to the bounding box coordinates from the preceding frame or, for the initial frame, applies heuristic estimates based on typical head positioning within the image field.

2.5. Anatomical landmark detection and initialization

The motion analysis framework requires identification of anatomical reference points to establish the baseline geometry of the cervical region and enable tracking of positional changes throughout the treatment sequence. Three primary landmarks are initialized from the first frame of each video: the chin point, representing the inferior margin of the mandible; the pivot point, representing the approximate location of the upper cervical spine articulation; and the ear point, providing an additional reference for head orientation assessment. These landmarks are estimated algorithmically from the edge detected head region rather than requiring manual annotation, supporting fully automated operation of the assessment system.



Figure 5. Paired demonstration photographs for anterior cervical counterstrain point 4 (AC4) technique assessment. (A) Correct technique with patient positioned in cervical flexion, right sidebending, and right rotation directed away from the left sided tender point location, achieving the full therapeutic positioning standard. (B) Incorrect technique showing cervical flexion but with sidebending and rotation directed toward rather than away from the tender point, representing a positioning error that would compromise therapeutic effectiveness.

Chin point detection focuses on the lower portion of the head bounding box, applying edge detection within a subregion extending from approximately 55–100% of the bounding box height and 20–80% of the bounding box width. The algorithm identifies the lowest edge pixel within this subregion, corresponding to the inferior margin of the chin in the lateral view perspective. The pivot point is estimated at a fixed proportional offset from the bounding box origin, positioned at approximately 85% of the bounding box width and 99% of the bounding box height to approximate the location of the atlantoaxial articulation. The ear point is similarly estimated at 78% of the width and 55% of the height, corresponding to the typical location of the external auditory meatus in lateral view.

The geometric relationship between the chin point and pivot point establishes a reference distance used for normalizing subsequent motion measurements. This arc length normalization approach accounts for variations in subject size and camera distance across different recording sessions, enabling comparison of motion parameters on a standardized angular scale. The reference distance is computed as the Euclidean separation between the initial chin and pivot coordinates, with a minimum value enforced to prevent numerical instability in cases of landmark detection failure.

2.6. Optical flow computation and motion tracking

Motion tracking employs the Farneback dense optical flow algorithm to estimate frame to frame displacements throughout the video sequence. The Farneback method approximates local image neighborhoods using polynomial expansion and computes motion vectors by analyzing how these polynomial representations transform between consecutive frames. Unlike sparse feature tracking approaches that estimate motion only at discrete keypoints, dense optical flow provides displacement estimates for all pixels within the analysis region, enabling comprehensive characterization of complex motion patterns.

Optical flow is computed separately for the head region of interest and a chest reference region positioned inferior to the head bounding box. The chest region serves as a motion reference to compensate for global camera motion or patient trunk movement that might otherwise confound analysis of cervical positioning. By subtracting chest region motion from head region motion, the algorithm isolates motion attributable specifically to cervical spine movement rather than whole body displacement.

Flow field computation incorporates Gaussian smoothing of input images to reduce noise sensitivity and applies a magnitude threshold to eliminate spurious motion vectors attributable to sensor noise or quantization artifacts.

Motion vectors with magnitude below the threshold value are set to zero, retaining only those displacements representing physiologically meaningful tissue movement. The threshold value was empirically selected to balance sensitivity for detecting subtle positioning changes against specificity for rejecting measurement noise.

2.7. Flexion and extension quantification

Cervical flexion and extension are quantified through tracking of chin point displacement relative to the initial neutral position. The chin tracking algorithm maintains a patch centered on the current estimated chin location and uses optical flow within this patch to predict chin position in subsequent frames. Specifically, the median horizontal and vertical flow components within the chin patch are extracted and applied as displacement updates to the chin coordinates. In frames where optical flow magnitude is insufficient to support reliable tracking, a refinement step applies local edge detection to identify the lowest edge point within the search region, providing an alternative estimate of chin location.

The flexion angle is computed using an arc length normalization approach that relates chin displacement to the reference distance between chin and pivot points. The Euclidean displacement of the chin from its initial position, with vertical displacement corrected for chest region motion, is divided by the reference distance and converted to angular measure using the inverse sine function. This approach interprets chin movement as rotation about the pivot point, yielding flexion angle estimates in degrees. A calibration factor derived from empirical testing scales the raw angular estimates to match expected physiological ranges for cervical flexion movement.

The sign of the flexion angle, distinguishing flexion from extension, is determined from the predominant direction of optical flow in the lower portion of the head region. Positive (downward) flow in this region indicates forward head movement consistent with cervical flexion, while negative (upward) flow indicates backward movement consistent with extension. A flow sign threshold prevents spurious sign assignments when flow magnitude is insufficient to reliably determine movement direction.

2.8. Sidebending quantification

Lateral sidebending is quantified through analysis of differential vertical motion between the upper and lower portions of the head region of interest. In the lateral view perspective employed for video recording, sidebending toward the camera produces apparent downward displacement of the upper head region relative to the lower region, as the head tilts into the image plane. Conversely,

sidebending away from the camera produces the opposite differential motion pattern. By computing the difference between median vertical flow in the upper band (0%–40% of region height) and lower band (60%–100% of region height) of the head region, corrected for corresponding differential motion in the chest reference region, the algorithm extracts a sidebending displacement estimate.

Cumulative sidebending displacement is accumulated across all analyzed frames, and the peak accumulated value is converted to angular measure using the inverse tangent function with the reference distance as the normalizing factor. A gain parameter scales the raw angular estimate to account for the geometric relationship between true sidebending angle and the apparent differential motion observed in the lateral view. Additionally, a saturation limit prevents unrealistic angle estimates that might result from tracking errors or atypical motion patterns.

The direction of sidebending is determined by the sign of the angular estimate, with positive values indicating rightward sidebending (away from a left sided tender point in the anterior cervical counterstrain context) and negative values indicating leftward sidebending. A minimum angle threshold distinguishes meaningful sidebending from neutral positioning, with estimates below the threshold classified as neutral regardless of sign.

2.9. Rotation quantification

Axial rotation is quantified through analysis of differential motion between the left and right halves of the head region of interest. In the lateral view, rotation toward the camera produces differential motion patterns wherein the near side of the head (visible in the image) moves differently than would occur during pure translation or sidebending. The algorithm computes rotation estimates from both horizontal and vertical flow differentials, selecting the dominant component (that with larger absolute magnitude) as the rotation indicator for each frame.

Specifically, the left half and right half of the core band (10%–45% of region height) are analyzed separately, computing median flow values for each half region. Horizontal rotation differential is computed as the right half median horizontal flow minus the left half median horizontal flow, corrected for corresponding differential in the chest reference region. Vertical rotation differential is computed analogously from vertical flow components. The dominant differential (larger absolute value) is accumulated across frames to yield cumulative rotation displacement.

Conversion to angular rotation estimate employs the inverse tangent function with reference distance normalization, analogous to the sidebending calculation.

Positive rotation angles indicate rightward rotation (away from a left sided tender point), while negative values indicate leftward rotation. The minimum angle threshold similarly distinguishes meaningful rotation from neutral positioning.

2.10. Automated performance classification

The automated classification algorithm compares extracted motion parameters against defined therapeutic standards to determine technique correctness. For the anterior cervical counterstrain technique treating a left sided tender point, the therapeutic standard specifies cervical flexion, sidebending toward the right (away from the tender point), and rotation toward the right (away from the tender point). Each motion parameter is independently evaluated against its corresponding standard, with flexion assessed for presence above the minimum threshold, sidebending assessed for rightward direction above threshold, and rotation assessed for rightward direction above threshold.

Performance classification employs a three-category scheme based on the number of therapeutic standards achieved. Techniques meeting all three standards (flexion present, right sidebending, and right rotation) receive classification as correct. Techniques meeting at least one but fewer than three standards receive classification as incomplete, indicating that some therapeutic motions were achieved while others were absent or in the incorrect direction. Techniques meeting none of the therapeutic standards receive classification as incorrect.

The output report generated by the system includes both quantitative data and qualitative interpretive feedback. Quantitative outputs specify the measured angle in degrees for each motion parameter along with the assigned directional label. Qualitative outputs provide interpretive statements indicating whether each motion achieved the therapeutic target, was absent (neutral), or was in the opposite direction from the therapeutic goal. The final assessment statement summarizes the overall technique classification and identifies specific areas for improvement when relevant.

2.11. Calibration and validation approach

System calibration employed an iterative approach wherein algorithm parameters were adjusted to produce motion angle estimates within physiologically plausible ranges for cervical spine movement. The calibration process utilized known correct technique demonstrations as reference standards, with parameters adjusted until flexion, sidebending, and rotation estimates fell within expected ranges based on published cervical range of motion data. Specific calibration parameters included the

flexion calibration factor scaling raw arc length angles to final flexion estimates, the sidebending gain factor relating differential flow to sidebending angle, and the various threshold values distinguishing meaningful motion from noise.

Validation testing assessed the system's ability to correctly discriminate between correct and incorrect technique performances. The paired video methodology, wherein each technique was recorded in both correct and incorrect versions under otherwise identical conditions, enabled direct comparison of classification outcomes against known ground truth. A successful validation outcome required that correct demonstrations receive correct or partially correct classification while incorrect demonstrations receive partially correct or incorrect classification, with the specific motion parameters responsible for any deficiencies correctly identified.

Given the proof-of-concept nature of this investigation and the small sample size of two recordings total, inferential statistical testing was not performed. Instead, a descriptive comparison of the motion parameters was deemed methodologically appropriate to demonstrate the technical feasibility of the tracking system, as the primary objective was to verify the algorithm's capability to detect directional and magnitude differences rather than to establish population-level statistical generalizability.

3. Results

3.1. Motion parameter extraction outcomes

The automated analysis system successfully processed paired demonstration videos depicting correct and incorrect execution of the anterior cervical counterstrain technique, extracting quantitative motion parameters for flexion, sidebending, and rotation in both conditions. Processing time for each video was approximately 15 seconds on the standard desktop workstation, demonstrating computational feasibility for practical educational deployment without requiring extended processing delays.

For the correct technique demonstration, the system extracted a flexion angle of 18.1 degrees, indicating meaningful cervical flexion above the minimum detection threshold of 3.0 degrees. Sidebending was measured at 19.5 degrees in the rightward direction, consistent with the therapeutic standard of sidebending away from the left sided tender point. Rotation was measured at 68.6 degrees in the rightward direction, again consistent with the therapeutic standard of rotation away from the tender point. All three motion parameters achieved their respective therapeutic targets, resulting in automated

classification of the correct demonstration as correct with the interpretive statement indicating that all therapeutic motions were achieved.

For the incorrect technique demonstration, the system extracted a flexion angle of 11.3 degrees, indicating that cervical flexion was present though at reduced magnitude compared to the correct demonstration. Sidebending was measured at 18.7 degrees in the leftward direction (reported as -18.7 degrees in the raw output), representing movement toward rather than away from the tender point and therefore contrary to the therapeutic standard. Rotation was similarly measured at 51.4 degrees in the leftward direction (-51.4 degrees), again contrary to the therapeutic standard. The presence of flexion combined with incorrect sidebending and rotation directions resulted in automated classification of the incorrect demonstration as incomplete, with the interpretive output specifically identifying the reversed sidebending and rotation as deviations from therapeutic targets.

The quantitative differences in motion parameters between correct and incorrect technique demonstrations are illustrated in [Figure 6](#). The bar chart reveals that while both demonstrations achieved cervical flexion, the correct technique produced greater flexion magnitude (18.1 degrees versus 11.3 degrees). More significantly, the sidebending and rotation parameters exhibit complete directional reversal between conditions. The correct technique achieved rightward sidebending (19.5 degrees) and rightward rotation (68.6 degrees), both directed away from the left-sided tender point as therapeutically required. In contrast, the incorrect technique produced leftward sidebending (-18.7 degrees) and leftward rotation (-51.4 degrees), representing movement toward the tender point contrary to the treatment standard. This directional opposition is clearly evident in the bar chart, where positive values indicate therapeutically appropriate motion and negative values indicate contraindicated positioning.

The chin landmark trajectories throughout each technique execution are shown in [Figure 7](#), providing a complementary visualization of the motion differences captured by the optical flow tracking algorithm. Both trajectories originate from the same neutral starting position, marked with circles, representing the patient's initial head placement before technique execution begins. The blue trajectory corresponding to correct technique demonstrates substantial displacement with an initial brief excursion toward higher Y-values, followed by a dramatic movement toward lower Y-values (reflecting significant upward displacement in the image frame as the practitioner positions the patient), and subsequently a complex return path reflecting the combined positioning through flexion,

sidebending, and rotation. In contrast, the red trajectory corresponding to incorrect technique exhibits markedly limited displacement, remaining confined to a narrow horizontal band with small oscillations that reflect the absence of purposeful therapeutic positioning. The divergence of these trajectories from their common origin visually reinforces the quantitative findings, demonstrating how the automated tracking system captures clinically meaningful differences in technique execution.

The temporal evolution of each motion parameter

throughout the technique execution is illustrated in Figures 8–10. These time-series plots demonstrate how the correct and incorrect techniques diverge progressively as the practitioner positions the patient.

Examination of the flexion time course (Figure 8) reveals that the correct technique establishes cervical flexion rapidly at the onset of positioning, with the head achieving approximately 29 degrees of forward bending within the first few frames before gradually settling to a maintained flexed posture throughout the remainder

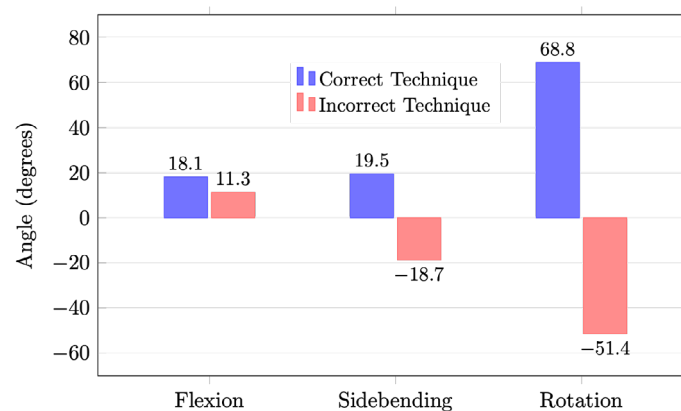


Figure 6. Measured motion parameter differences between correct and incorrect anterior cervical counterstrain point 4 (AC4) technique demonstrations. Positive values indicate motion in the therapeutically correct direction (flexion, right sidebending, right rotation), while negative values indicate motion in the opposite direction. The correct technique achieved all three therapeutic positioning standards, whereas the incorrect technique exhibited reversed sidebending and rotation directions despite achieving flexion.

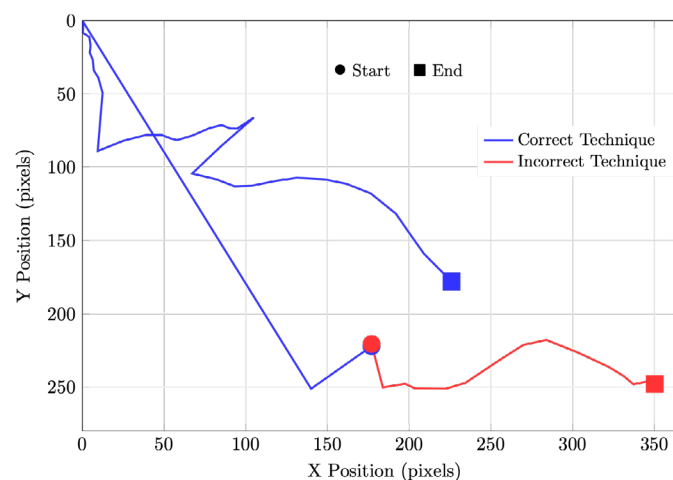


Figure 7. Chin landmark trajectory tracking during correct and incorrect anterior cervical counterstrain technique demonstrations. Both trajectories begin at the same neutral starting position. The blue trajectory shows substantial chin displacement during correct technique execution, with the initial upward movement (toward lower Y values) reflecting cervical flexion as the practitioner positions the patient. The red trajectory shows minimal displacement with small oscillations, consistent with the limited purposeful positioning observed in incorrect technique execution.

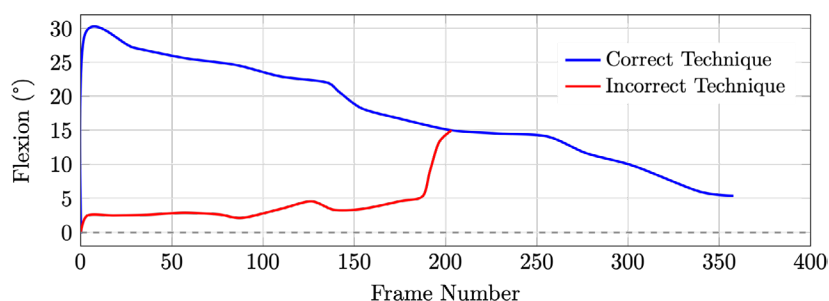


Figure 8. Flexion angle measured over video frames during correct and incorrect anterior cervical counterstrain technique execution. The correct technique (blue) achieves and maintains higher flexion values compared to the incorrect technique (red).

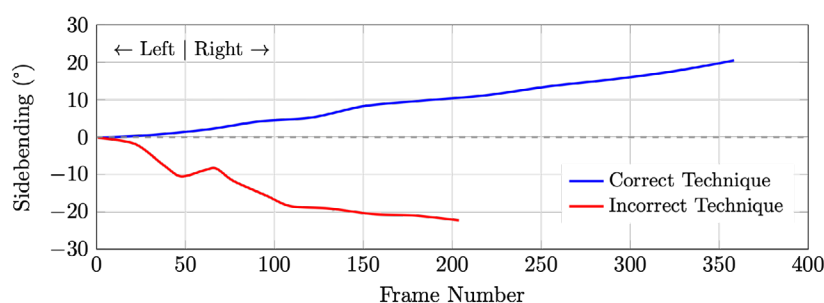


Figure 9. Sidebending angle measured over video frames. Positive values indicate rightward sidebending (away from the left-sided tender point), while negative values indicate leftward sidebending (toward the tender point). The correct technique achieves the therapeutically appropriate right sidebending direction.

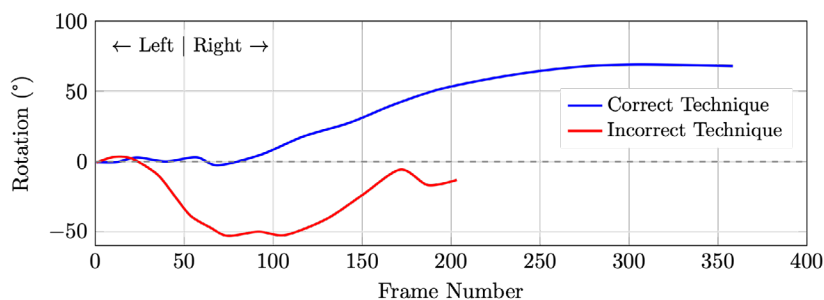


Figure 10. Rotation angle measured over video frames. Positive values indicate rightward rotation (away from the left-sided tender point), while negative values indicate leftward rotation (toward the tender point). The correct technique demonstrates substantial rightward rotation reaching approximately 70 degrees, while the incorrect technique produces leftward rotation of approximately 50 degrees.

of the treatment sequence. In contrast, the incorrect technique maintains minimal flexion during the initial and middle phases, with flexion only developing toward the end of the recording as the practitioner completes positioning. This temporal pattern suggests that correct technique execution prioritizes early establishment of the flexion component before fine-tuning the sidebending and rotation parameters.

The sidebending time course (Figure 9) demonstrates progressive and continuous divergence between the two techniques from a common neutral starting point. During correct technique execution, the practitioner gradually tilts the patient's head toward the right shoulder, with sidebending angle increasing steadily throughout the positioning sequence to reach approximately 20 degrees of rightward lateral tilt. The incorrect technique exhibits a mirror-image pattern, with the head progressively tilting

toward the left shoulder and reaching approximately 22 degrees of leftward sidebending. The smooth, monotonic trajectories in both conditions indicate deliberate, controlled positioning rather than erratic movement.

The rotation time course (Figure 10) reveals the most dramatic differentiation between correct and incorrect technique execution. Following an initial stabilization period of approximately 70 frames during which rotation remains near neutral, the correct technique demonstrates progressive rightward rotation accelerating through the mid-portion of the sequence before plateauing at approximately 70 degrees as the final treatment position is achieved and maintained. The incorrect technique diverges in the opposite direction, with leftward rotation developing rapidly in the early frames and reaching a maximum of approximately 53 degrees before partially returning toward neutral in the later portion of the recording. The magnitude of rotation in both conditions substantially exceeds that of the other motion parameters, consistent with the prominent role of axial rotation in achieving the position of ease for anterior cervical counterstrain points.

The integrated three-dimensional motion trajectory (Figure 11) provides a detailed visualization of how the three positioning parameters evolve simultaneously during technique execution. In this representation, each axis corresponds to one of the therapeutic motion components (*i.e.*, flexion, sidebending, and rotation) allowing the complete positioning sequence to be appreciated as a continuous path through the parameter space. The correct technique trajectory (blue) originates from neutral positioning and progresses into the therapeutically appropriate quadrant characterized by positive flexion, rightward sidebending, and rightward rotation, ultimately terminating at a position representing full achievement of all three therapeutic standards. In contrast, the incorrect technique trajectory (red) diverges early in the sequence, migrating into the opposing quadrant defined by leftward sidebending and leftward rotation despite achieving comparable flexion. The spatial separation between the terminal positions of these trajectories (located in diametrically opposed regions of the parameter space) underscores the clinical significance of directional accuracy in counterstrain positioning and illustrates how the automated system captures the multidimensional nature of technique performance that distinguishes therapeutically effective from ineffective execution.

3.2. Discriminatory performance

The system demonstrated successful discrimination between correct and incorrect technique executions based on the extracted motion parameters. The direction of

sidebending differed by approximately 180 degrees between conditions, with the correct demonstration producing rightward sidebending and the incorrect demonstration producing leftward sidebending of comparable magnitude. This finding confirms that the optical flow-based sidebending detection algorithm is sensitive to the physiologically meaningful directional differences that distinguish correct from incorrect positioning.

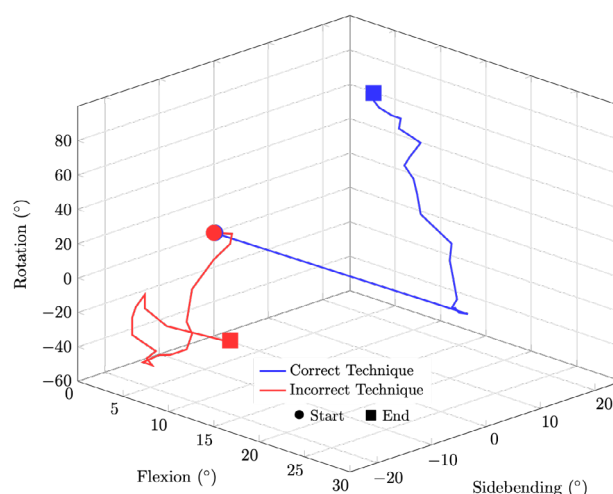


Figure 11. Three-dimensional motion parameter trajectory during correct and incorrect anterior cervical counterstrain technique demonstrations.

Similarly, the rotation parameter exhibited clear directional reversal between correct and incorrect demonstrations, with rightward rotation of 68.6 degrees in the correct condition and leftward rotation of 51.4 degrees in the incorrect condition. The magnitude of rotation was somewhat larger in the correct demonstration, potentially reflecting more confident positioning when the practitioner was executing the intended technique. The directional discrimination for rotation was unambiguous, supporting the validity of the differential flow approach for detecting axial rotation from the lateral view perspective.

Flexion parameters showed less dramatic differences between conditions, with both demonstrations exhibiting forward cervical flexion albeit at different magnitudes. This finding is consistent with the study design, wherein the incorrect demonstration was specifically constructed to include correct flexion positioning but incorrect sidebending and rotation directions. The ability of the system to correctly identify flexion as achieved in both conditions while detecting the directional errors in sidebending and rotation demonstrates appropriate parameter independence in the extraction algorithms.

3.3. Processing reliability observations

The analysis system exhibited consistent performance across multiple processing runs on the same video files, producing identical quantitative outputs and classification results. This deterministic behavior reflects the algorithmic nature of the processing pipeline, wherein each stage applies defined transformations without stochastic elements that might introduce run to run variability. The consistency of results supports the reliability of the assessment approach for educational applications where reproducible feedback is essential.

Region of interest detection successfully identified the head region in all frames of both test videos, with the edge detection and bounding box extraction algorithms adapting appropriately to the gradual positional changes occurring throughout each treatment sequence. The bounding box inset mechanism effectively excluded peripheral image regions where boundary artifacts might have compromised motion estimation accuracy. Landmark initialization produced anatomically plausible chin, pivot, and ear point locations in the first frame of each video, and subsequent chin tracking maintained reasonable position estimates throughout the frame sequences.

Optical flow computation produced well-defined motion fields for both the head and chest reference regions, with the magnitude thresholding effectively suppressing noise while retaining physiologically meaningful motion vectors. The differential analysis approach successfully isolated cervical motion from any global image motion, as evidenced by the appropriate detection of cervical positioning despite minor background movement visible in portions of the video recordings.

4. Discussion

4.1. Interpretation of findings

The results of this proof-of-concept study demonstrate that automated video motion analysis can successfully distinguish between correct and incorrect osteopathic manipulative treatment technique execution by detecting and quantifying physiologically meaningful differences in positioning parameters (Table 2, Figure 6). The system's

ability to identify reversed sidebending and rotation directions in the incorrect technique demonstration, while correctly recognizing the presence of appropriate flexion in both conditions, confirms that the optical flow-based analysis approach captures the specific motion characteristics relevant to technique assessment, as visualized through the divergent chin landmark trajectories (Figure 7). These findings support the feasibility of automated assessment as a complement to traditional instructor evaluation in osteopathic medical education settings.

The magnitude of motion parameters extracted by the system fell within physiologically plausible ranges for cervical spine movement based on published normative data, as illustrated by the temporal evolution of each parameter (Figures 8–10). Total cervical flexion range of motion is typically reported as 45 to 50 degrees, while lateral bending and axial rotation each permit approximately 35 to 45 degrees of movement per side. The flexion measurements of 18.1 and 11.3 degrees represent partial excursion within the available range, consistent with the submaximal positioning typically employed in counterstrain technique. The sidebending measurements of approximately 19 degrees similarly represent moderate lateral positioning. The rotation measurements of 51 to 69 degrees exceed the typically reported single side range, likely reflecting cumulative rotation across multiple cervical segments rather than isolated atlantoaxial movement.

The classification of the incorrect technique as incomplete rather than fully incorrect merits consideration in the context of educational feedback utility. The incomplete designation accurately reflects that one of three therapeutic standards was achieved while two were not, providing more nuanced feedback than a simple correct versus incorrect dichotomy. This graduated classification approach enables identification of specific technique components requiring improvement while acknowledging aspects of performance that were successfully executed. For educational applications, such detailed feedback supports targeted skill development by directing learner attention to specific deficiencies rather than requiring global technique reassessment.

Table 2. Quantitative motion analysis results for correct and incorrect anterior cervical counterstrain technique demonstrations

Video	Flexion	Sidebending	Rotation	Classification
Correct Technique	18.1°	19.5° (Right)	68.6° (Right)	Correct
Incorrect Techniques	11.3°	–18.7° (Left)	–51.4° (Left)	Incomplete

Note: Angular measurements are reported in degrees with directional labels indicating movement relative to the treated tender point location.

4.2. Comparison with related technologies

The automated assessment system developed in this study offers several advantages compared to alternative technology enhanced evaluation approaches that have been explored in medical education contexts. Motion capture systems employing reflective markers or inertial sensors can provide highly accurate kinematic data but require specialized equipment, marker placement protocols, and technical expertise that limit accessibility in typical educational settings. The video-based approach requires only standard camera equipment and can analyze recordings obtained without specialized preparation, substantially lowering barriers to adoption.

Artificial intelligence (AI) approaches employing deep learning for pose estimation have demonstrated impressive capabilities for human motion analysis and could potentially be applied to osteopathic manipulative treatment assessment. However, training deep learning models requires large, annotated datasets that are not currently available for osteopathic techniques, and the computational requirements for neural network inference may exceed those available in resource constrained educational environments. The optical flow-based approach employed in the present study provides interpretable motion estimates without requiring training data or specialized computing hardware, facilitating transparent operation and practical deployment.

Previous research on automated skill assessment in related domains has demonstrated the educational value of quantitative feedback for manual therapy and procedural skills. Studies of surgical skill assessment using motion tracking have shown correlations between kinematic parameters and expert ratings of performance quality, while investigations of physical therapy technique assessment have demonstrated feasibility of video-based evaluation for rehabilitation applications. The present study extends these findings to the osteopathic medical education context, demonstrating that similar approaches can be successfully adapted for evaluating manipulative treatment techniques. Furthermore, this development aligns with a growing interest in enhancing osteopathic manipulative medicine teaching by employing new technologies beyond video motion analysis, such as virtual reality platforms.⁵⁴

4.3. Educational implications

The availability of automated assessment capabilities has potential to transform osteopathic manipulative treatment education by enabling quantitative feedback provision in contexts where instructor availability is limited. Students could record practice sessions outside of scheduled laboratory time and receive immediate objective feedback

on their technique execution, supporting deliberate practice and self-directed skill development. The explicit identification of motion parameters that deviate from therapeutic standards provides actionable information for targeted improvement, in contrast to global assessments that identify deficiency without specifying its nature.

For faculty members, automated assessment tools could reduce the burden of observational evaluation while improving consistency of feedback across multiple students and assessment occasions. The quantitative output format facilitates documentation of student progress over time and identification of persistent technique deficiencies requiring focused remediation. Standardized assessment criteria embodied in the automated classification algorithm support equitable evaluation by applying identical standards to all students regardless of which faculty member conducts the assessment.

The scalability of video-based assessment supports extension of quality feedback to educational settings that might otherwise lack access to expert evaluation. Remote and distributed osteopathic medical education programs could employ automated assessment to provide formative feedback to students practicing at distant locations, while simulation laboratories could integrate automated analysis to supplement debriefing discussions following practice sessions. The low equipment requirements and straightforward operating procedures facilitate broad deployment without requiring substantial infrastructure investment or specialized technical support.

4.4. Limitations and sources of error

Several limitations of the current system merit acknowledgment and suggest directions for future refinement. The video recording standardization requirements impose constraints on the conditions under which reliable analysis can be performed. Variations in camera angle, distance, lighting, or patient positioning from the standardized protocol may compromise motion estimation accuracy by altering the geometric relationships upon which the analysis algorithms depend. Deployment in uncontrolled recording environments would likely require additional algorithmic development to accommodate variable imaging conditions.

Specifically, variations in ambient lighting can alter image contrast and edge visibility, potentially compromising the accuracy of Canny edge detection and subsequent landmark identification. The Contrast Limited Adaptive Histogram Equalization preprocessing step partially mitigates lighting inconsistencies by normalizing local contrast, but extreme lighting variations or harsh shadows may still degrade performance. Similarly, changes

in camera distance affect the apparent size of anatomical structures and the pixel displacement magnitude corresponding to a given angular movement. The arc length normalization approach accounts for distance variations to some extent by scaling displacements relative to the reference distance between chin and pivot landmarks, but substantial deviations from the standardized recording distance could introduce systematic errors in angular estimates.

The landmark detection approach employs heuristic estimation based on typical head geometry rather than explicit recognition of anatomical structures. While this approach proved adequate for the standardized demonstration videos evaluated in this study, atypical head shapes, unusual positioning, or occlusion of relevant structures could produce inaccurate landmark estimates that propagate errors to subsequent motion calculations. Integration of more sophisticated computer vision techniques for facial landmark detection could improve robustness to anatomical and positional variation. The system exhibits limited tolerance for incorrect landmark detection, as errors in initial chin or pivot point localization propagate through subsequent motion calculations and affect angular estimates. The algorithm incorporates fallback mechanisms that retain previous frame coordinates when edge detection fails and enforces minimum reference distance values to prevent numerical instability, but these safeguards address complete detection failures rather than subtle localization inaccuracies. Quantitative characterization of the relationship between landmark localization error and angular measurement error was not performed in this proof-of-concept study and represents an important direction for future validation work.

The calibration approach employed in this study optimized algorithm parameters based on a limited sample of demonstration videos, and the generalizability of calibrated parameters to other subjects, practitioners, or recording conditions remains to be established. Formal validation with a larger sample of technique performances rated by expert observers would be necessary to quantify the accuracy and reliability of the automated assessment approach and to establish appropriate calibration procedures for practical deployment.

The current implementation analyzes only the anterior cervical counterstrain technique, and extension to additional osteopathic manipulative treatment modalities would require development of technique specific landmark detection, motion tracking, and classification algorithms. The therapeutic standards for different techniques vary substantially in terms of the relevant anatomical regions,

motion directions, and positioning criteria, necessitating customization of the analysis pipeline for each technique to be assessed. The modular system architecture facilitates such extension, but substantial development effort would be required to achieve comprehensive technique coverage.

Furthermore, robustness testing across subjects with differing anthropometric characteristics was not conducted in this proof-of-concept study. Variations in head size, neck length, facial structure, or body habitus could affect landmark detection accuracy and the geometric relationships underlying motion estimation, meaning that validation across a diverse subject population representing the range of anthropometric variation encountered in clinical and educational settings is a critical prerequisite before the system can be considered suitable for general deployment.

The limited sample size of this proof-of-concept study, comprising a single operator performing one correct and one incorrect demonstration on a single subject, precluded the calculation of classification performance metrics such as accuracy, sensitivity, specificity, precision, and F1-score. Meaningful computation of these diagnostic performance metrics requires a substantially larger dataset with multiple examples of correct and incorrect technique execution to populate a confusion matrix with sufficient observations for statistical validity. Additionally, this extremely small sample size ($n = 2$ recordings total) justifies the absence of inferential statistics, as attempting to compute p-values or confidence intervals on such limited data would be methodologically unsound; hence, only descriptive comparison was utilized to demonstrate technical feasibility.

Another prominent limitation is the absence of verification of the optical-flow-derived angular estimates against an objective reference standard, such as a three-dimensional motion capture system or expert manual measurements. While the system demonstrated physiologically plausible angle estimates and correctly identified directional differences between correct and incorrect demonstrations, a formal quantitative accuracy assessment comparing optical flow angles to simultaneously acquired gold-standard measurements was not conducted, which remains a key requirement prior to clinical or educational deployment.

Finally, the absence of an inter-operator variability assessment represents a major limitation, as only a single trained operator performed the technique demonstrations in this proof-of-concept work. Characterizing inter-operator variability will require video recordings from multiple osteopathic physicians performing the identical technique under standardized conditions, followed by

statistical analysis of measurement variance across operators to ensure the algorithm produces consistent measurements regardless of individual practitioner characteristics like hand size, positioning style, or movement speed.

4.5. Future directions

Continued development of the automated assessment system will focus on several priority areas identified through this investigation. Enhancement of analysis robustness through integration of deep learning-based pose estimation could improve landmark detection accuracy and enable operation under more variable recording conditions.²⁷ Modern pose estimation models can identify anatomical keypoints across diverse subjects and viewpoints, potentially relaxing the standardization requirements that currently constrain system deployment.

Expansion of technique coverage to include additional osteopathic manipulative treatment modalities represents an important direction for increasing educational utility. The counterstrain technique family includes numerous additional tender point locations with distinct therapeutic positioning requirements, while other treatment modalities such as muscle energy technique and high velocity low amplitude thrust techniques present different assessment challenges that could benefit from automated evaluation. Development of a comprehensive assessment platform covering the full scope of osteopathic manipulative treatment techniques would substantially enhance educational value.

Integration with learning management systems and electronic assessment platforms could facilitate seamless incorporation of automated feedback into existing educational workflows. Automated uploading of practice videos, generation of feedback reports, and tracking of student progress over time could be implemented through application programming interfaces connecting the analysis system with institutional educational technology infrastructure. Such integration would reduce friction associated with system use and support routine incorporation of automated assessment into osteopathic medical curricula.

Formal validation studies comparing automated assessment outcomes with expert faculty ratings are needed to establish criterion validity and quantify measurement accuracy. Such studies should employ diverse samples of student performances spanning the skill level spectrum to evaluate whether the system appropriately discriminates among different levels of technique proficiency. Reliability assessment through analysis of repeated performances and comparison of ratings across multiple expert raters would further characterize the measurement properties of the

automated approach.

A prospective, multicenter validation study is eventually planned to compare automated assessment outcomes with both expert faculty ratings and established competency assessment frameworks reported in the osteopathic medical education literature. Such validation will involve multiple institutions, diverse student populations, and standardized comparison protocols to establish the criterion validity and educational utility of the automated approach across varied educational contexts.

Future validation studies will incorporate simultaneous motion capture data acquisition to verify the accuracy of optical-flow-derived angular estimates against gold-standard kinematic measurements. Classification performance metrics, including accuracy, sensitivity, specificity, precision, and F1-score, will be computed from a sufficiently large dataset of labeled technique performances. Furthermore, inter-operator variability will be formally assessed by analyzing recordings from multiple osteopathic physicians performing standardized techniques to characterize measurement consistency across practitioners.

5. Conclusions

This proof-of-concept study demonstrates the technical feasibility of using automated video motion analysis to evaluate osteopathic manipulative treatment technique performance. While not yet a validated diagnostic tool or ready for immediate educational deployment, by providing measurable feedback derived from simple video recordings, the system offers significant educational value to students through support for independent skill development and to faculty through provision of standardized assessment criteria. The technology-enhanced approach represents a meaningful step toward modernizing osteopathic medical education and bridging the gap between subjective evaluation and data driven competency assessment.

The simplicity and scalability of the video-based approach make it well-suited for integration into skills laboratories, simulation settings, and remote learning environments where instructor availability may be limited, once comprehensive validation is completed. While current limitations related to recording standardization and technique coverage constrain immediate deployment, continued development addressing these limitations could yield a comprehensive assessment platform applicable across the full scope of osteopathic manipulative treatment education. The findings of this study provide the technical proof-of-concept foundation and motivation for such continued development efforts.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

Author contributions

Conceptualization: All authors

Data curation: All authors

Formal analysis: All authors

Investigation: All authors

Methodology: All authors

Project administration: All authors

Resources: All authors

Supervision: All authors

Validation: All authors

Visualization: All authors

Writing—original draft: All authors

Writing—review & editing: All authors

All authors have read and agreed to the published version of the manuscript.

Ethics approval and consent to participate

This study did not require ethical approval, as it did not involve external human participants. The only individual featured in the study video was one of the authors, who voluntarily participated in the research.

Consent for publication

The individual depicted in [Figure 5a](#) and [5b](#) is a co-author who provided consent for publication of these images.

Availability of data

Data are available from the corresponding author upon reasonable request.

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