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Cross-validation of two independent methods to analyze the sequence of segmental contributions in the cervical spine in extension cineradiographic recordings

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Abstract

Background The sequence of segmental contributions (SSC) offers insight into cervical spine motion, yet accurately analyzing these movements remains challenging. This study compares two tracking methods, developed at two independent centers (AECC and MUMC), to establish their agreement and reliability in measuring SSCs across segments C4 to C7. Understanding spinal biomechanics is crucial for future research into cervical spine pathology and dysfunction.

Methods Twelve asymptomatic participants (ages 18–35 for "young" and 55–70 for "elderly") performed flexion-extension movements. MUMC+utilized self-directed motion, while AECC used a guided protocol. To ensure comparability, 26 frames from the second half of each extension movement were analyzed. Agreement was assessed using ICCs, Spearman's Rho, and Bland-Altman analysis. Although the sample size is small, a post-hoc power analysis indicated sufficient power, supported by a high volume of analyzed data points.

Findings High intraclass correlation coefficients (ICCs) for the cumulative vertebral rotation (0.97), cumulative intervertebral rotation (0.97) and relative intervertebral rotation (0.93) indicated strong agreement between the two methods. Bland-Altman analysis showed minimal median differences (<0.2°) but wider limits of agreement at C6-C7. Normative SSC patterns appeared in 77.8% of younger participants but were absent in elderly participants.

Interpretation This study confirms the reliability of SSC measurement between the two methods, laying the foundation for broader applications. SSC patterns observed in young adults follow a normative pattern, in alignment with previous research. The absence of a fixed pattern in elderly participants could indicate age-related changes or sample variation, warranting cautious interpretation due to the small sample size. Future studies with larger, diverse samples and AI-driven approaches could enhance SSC analysis, enabling better clinical relevance.

Keywords Cervical spine, Biomechanics, Artificial intelligence, Sequence of segmental contributions

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Background

The sequence of segmental contributions (SSC) during flexion and/or extension of the cervical spine has been proposed as a consistent parameter of cervical spine motion [1–3]. The SSC can be seen as a motion pattern based on the rotation of a segment in relation to the total amount of movement. The rotation of a vertebra can be expressed in different ways, most commonly the cumulative vertebral rotation (CVR), the cumulative intervertebral rotation (CIR) or the relative intervertebral rotation (RIR). A fundamental challenge lies in establishing a reliable and generalizable method to analyze rotation of the intervertebral motion segments in continuous recordings to analyze SSCs [4].

Traditional methods of cervical spine motion analysis have focused on measuring global range of motion (ROM), which provides a general assessment of overall spinal movement [1, 5]. While ROM can offer useful insights, it is suboptimal as it represents a static measurement of what is inherently a dynamic process [5–7]. For example, when exploring range of motion (ROM) in static radiographs, it is assumed that maximal rotation occurs at the end of each movement, but in reality, the maximum rotational contribution varies across segments and rarely coincides with maximum extension for any specific segment [1, 3, 8]. Cineradiography enables the capture of real-time dynamic images with minimal radiation exposure, rendering it a more suitable method for the analysis of intervertebral motion [9–11]. For this reason, the definition of a normative SSC offers a more precise and sensitive way of evaluating cervical motion compared to ROM. Previously, a normative SSC was defined as a consistent cranial-to-caudal motion pattern observed during cervical extension. Specifically, it begins with initial peak rotation at C4-C5, followed by C5-C6, and then C6-C7 [3, 12, 13]. Motion patterns have also been studied during flexion; however, since extension demonstrated more consistent results, we chose to focus on extension in the present study.

The absence of standardized methods for analyzing segmental contributions can lead to variation in research approaches, hindering the comparison and generalizability of findings across studies [1].

Relative and cumulative rotations of individual vertebrae and motion segments from subjects obtained at two independent centers will be compared: AECC University College in Bournemouth, United Kingdom, and Maastricht University Medical Center + (MUMC+) in combination with Zuyderland Medical Center (ZL) in the Netherlands. The MUMC + method combines manual annotation with automated algorithms to ensure precision, while the AECC method uses a semi-automated cross-correlation approach that offers efficiency. Slight differences exist in participant motion protocols across centers: AECC participants move from neutral to maximum extension and back, while MUMC + participants move from maximum flexion to extension. MUMC + studies feature free motion, while AECC methods entail guided movement controlling rate and range. Given that the previously defined normative pattern was present during extension in the lower cervical spine, from C4 to C7, this study will focus solely on the analysis of these segments [3, 12, 13].

The comparison of these methods is important because it helps validate the reliability of SSC as a standardized measure in cervical spine biomechanics. Previous studies have used these methods individually, but a cross-validation is necessary to ensure their consistency and robustness in measuring SSC patterns. Investigating an independent dataset with varied motion protocols tests the influence of participant preferences in neck extension. If the normative SSC pattern persists across different protocols, it suggests intrinsic characteristics; however, if it varies, it indicates the influence of participant preferences.

The primary outcome of this study is the agreement and reliability between the measurement of rotation of the vertebrae and motion segments by two independent data capture methods in asymptomatic individuals. The measured CVR, CIR and RIR will be compared between the two individual techniques. The secondary objective is to determine the presence of the previously defined normative pattern in an independent study population.

While the primary focus is on method validation, future studies could explore SSC patterns in larger, more diverse cohorts, including symptomatic populations. This would allow for a deeper understanding of SSC variations across different groups, enhancing the clinical relevance of SSC analysis. By defining normative SSC patterns, clinicians could identify deviations that may indicate or predict cervical spine dysfunction, providing valuable insights into the biomechanics underlying neck pain, cervical spine degeneration, and surgical outcomes.

Additionally, the integration of AI-driven algorithms could enhance the scalability and efficiency of SSC analysis, though careful attention to data quality, patient variability, and ethical considerations, such as transparency and privacy, will be necessary for widespread clinical use.

Methods

Study design

Cineradiographic image sequences of 34 healthy controls performing extension of the cervical spine were acquired from a pre-existing dataset at AECC University College Bournemouth, United Kingdom [14–16]. To match the SCC outcomes with those of previously reported cohorts, two subgroups were established from this database: a healthy younger cohort aged 18–35 and a healthy elderly cohort aged 55–70 [3, 17]. Participants were selected based on the absence of any history of cervical spine injury, surgical interventions, or significant degenerative changes. Specific exclusion criteria included any previous diagnosis of cervical spine pathology, trauma, or chronic neck pain, as well as any imaging-confirmed degenerative changes that might impact cervical motion. To confirm the absence of degenerative changes recent cervical spine imaging was reviewed to ensure no significant degenerative alterations were present.

The study was approved by the medical ethical committees of the involved centers.

Participant instruction and image acquisition

Despite being independently acquired by an unassociated research group, participant instructions and image acquisition methods were similar to those used when acquiring the MUMC + and ZL cohorts. Participants were positioned to ensure consistency in cervical spine alignment across both centers to standardize the SSC measurement conditions. To guide the range and pace of motion, the AECC setup used a cushioned plate and motor arm [15, 16], while MUMC + allowed self-directed movement [3, 17]. In the AECC protocol, participants followed a guided movement from neutral to full extension, while in the MUMC + protocol, participants self-directed their movement from flexion to extension. Cinematographic recordings assessed in this study were all made at the AECC and will be compared to those of the MUMC + cohort.

Image analysis

For all AECC recordings, 26 frames from the second half of extension—spanning from the neutral position to maximum extension—were selected for analysis to match the MUMC + protocol.

This frame selection was chosen to match the range of motion across both methods: while the AECC recordings capture approximately 200 frames moving from extension to neutral and back, the MUMC + recordings move from maximum flexion to maximum extension. Analyzing these 26 frames ensures consistency in the motion phase across both methods, allowing for direct comparability of SSC pattern.

The MUMC + and AECC methods were chosen to evaluate SSCs using two distinct tracking systems. The MUMC + method, which involves manual annotation verified by an automated algorithm, offers high tracking accuracy but is more labor-intensive. In contrast, the AECC method uses a semi-automated cross-correlation technique, which is more efficient for large datasets but may be more sensitive to image quality variations. The MUMC + method employs custom software based on an algorithm developed in Wolfram Mathematica[Wolfram Research, Inc., Mathematica, Version 13.2, Champaign, IL] [13]. Vertebral bodies from C4 to C7 were manually annotated in the median frame of the recording. The contours of the vertebrae were then tracked in every frame using an image recognition algorithm, manually checked, and adjusted if necessary.

The AECC method used algorithms written in the MATLAB environment [18, 19]. Cineradiographic images were enhanced to improve vertebral body identification. Templates for C4 to C7 were manually defined in the first frame, and the vertebrae were tracked in subsequent frames using cross-correlation to match the current image to the reference. The results were visually inspected, and if needed, a new reference image was defined. The average of successful tracings was used to define the rotation and displacement of each vertebra throughout the sequence.

To compare results between systems, the 26 frames selected for MUMC + analysis were identified in the AECC dataset, and the vertebral rotations for these frames were extracted.

Data analysis

For each participant CVR, CIR and RIR were calculated. Differences between methods in CVR, CIR, and RIR were tested for statistical significance using non-parametric analyses, as these variables did not consistently follow a normal distribution. Outliers were identified through Bland-Altman analyses.

Segmental rotation *between* pairs of successive frames of each individual segment within C4 to C7 were plotted against the cumulative rotation in segments C4 to C7 together (block C4-C7). The sequence of segmental contributions during extension is described by the order in which segment peaks ($1^{st,}$ 2^{nd}, or 3^{rd}). The definition of a normative SCC in the second half of extension is an initial peak contribution to rotation of C4-C5, followed by C5-C6 and finally C6-C7 [3, 17]. To determine if the SCC consistently found in younger participants would be present in a protocol where participants were guided in their cervical extension for rate and range of motion, the SCCs were compared [3, 17].

Statistical analysis

Statistical analysis was conducted with IBM SPSS Statistics 28 and excel. Spearman's rank correlation coefficient and Bland-Altman plots were performed using the Bland-Altman and Correlation Plot developed by Ran Klein and the Statistics and Machine Learning Toolbox in Matlab [18, 19]. Kolmogorov-Smirnov test was used to test that difference between data sets was normally distributed and non-parametric tests were used for non-normally distributed data. Descriptive statistics were employed to assess demographic data.

Table 1 Demographic information of the included population, presented for the younger and elder cohort separately. *M* Male, *F* Female, *SD* Standard deviation

Participant	Sex (M/F)	Age (years)
Young-1	M	34
Young-2	F	27
Young-3	F	23
Young-4	F	21
Young-5	F	25
Young-6	M	29
Young-7	M	33
Young-8	F	33
Young-9	F	22
Average ± SD	37.5% M	27.4 ± 5.0
Elderly-10	M	66
Elderly-11	F	50
Elderly-12	F	54
Average ± SD	33.3% M	56.7 ± 8.3

Agreement between the two methods was evaluated using regression and a non-parametric Bland-Altman analysis, with results presented in plots. In the Bland-Altman analysis, bias was calculated as the mean difference between the two methods, with limits of agreement set at ± 1.96 times the standard deviation of the differences. Additionally, nonparametric limits of agreement (LoA) were calculated to show the interval within which 95% of the differences between the two methods are expected to lie, providing a clear representation of agreement.

Comparability of the two techniques, as measured by the correlation coefficient is expressed by a Spearman's Rho. Two-way mixed, single-score ICCs were computed for both individual vertebrae and motion segments to assess consistency. ICC values above 0.90 are regarded as excellent, higher than 0.75 are considered good, while those between 0.50 and 0.75 are considered as moderate, and below 0.50 are considered poor [20].

To assess whether the study was adequately powered to detect agreement between methods for cumulative vertebral rotation (CVR), cumulative intervertebral rotation (CIR), and relative intervertebral rotation (RIR), a post-hoc power analysis was conducted based on observed intraclass correlation coefficients (ICCs), sample sizes, and a significance level of 0.05. With a sample size of 12 participants and 26 images analyzed per participant, the analysis indicated a medium effect size (Cohen's d = 0.4). The calculated power of the study was 0.80, confirming that the study had sufficient power to detect meaningful differences between the two tracking methods. This supports the reliability of the conclusions drawn, despite the small sample size.

Results

Demographic characteristics

Out of the initial dataset of the AECC ($N = 34$), a total of 12 healthy volunteers, each with two repeated recordings, matched this studies inclusion criteria for comparison to the MUMC + cohort. A total of 22 individuals in the dataset were excluded as they did not match the age cohorts. Nine participants matched the younger cohort, with an average age of 27.4 years old. Three participants matched the elderly cohort, with an average age of 56.7 years old. Baseline characteristics of the included participants are outlined in Table 1.

Level of agreement

The level of agreement, expressed by Rho, bias and Limits of Agreement for CVR, CIR and RIR, were high for all individual levels and motion segments (Table 2). The consistency of the two methods, expressed in ICCs, was 0.97 for CVR, 0.97 for CIR and 0.93 for RIR for grouped data (Table 2). Regression and Bland-Altman plots of the CVR is displayed in Fig. 1, CIR in Fig. 2 and RIR in Fig. 3. The Bland-Altman analysis reveals that there is no significant difference (0° median difference) across all vertebral levels (Fig. 1, bottom), with no consistent bias ($p < 0.05$, $p = 0.047$ (3sf)) between measurement methods. However, the limits of agreement are approximately ± 2°, as indicated by the non-parametric reproducibility coefficient (RPC_{np}) (Fig. 1). For individual levels, the median difference consistently remains < 0.2°, with an RPC_{np} <1.6.

Presence of normative SSCs

As displayed in Table 3, the SCCs observed in the younger cohort align with the previously defined normative SSC for a population under the age of 35 [3, 17]. In the baseline sequences (T1), the same SSC was evident in 7 out of 9 individuals (77.8%) within this study population. However, at the 2 to 4-week follow-up (T2), this SSC was apparent in 6 out of 9 individuals (66.7%). Notably, this SSC was not observed in any of the subjects in the elderly population, neither at T1 nor T2.

Discussion

This study confirms the reliability and agreement of two independent tracking methods for SSC analysis. These results support the application of both methods in future research, including studies aimed at exploring SSC patterns across more diverse populations. The comparison of SSC patterns across age groups was a secondary objective; while some age-related differences were observed, no solid conclusions were drawn due to the small and homogeneous sample. The observed motion patterns in this population also seem to correspond with those identified in prior studies, despite the slightly different study

Table 2 Level of agreement and consistency of measurements between two methods (AECC and MUMC). Spearman's rho = representing level of agreement between the two methods, *ICC* Intraclass correlation coefficient, *LoAnp* Level of agreement non parametric, *AECC* AECC university College, *MUMC* + Maastricht university medical center +

AECC vs. MUMC+	Number of images analyzed (*N*=)	Spearman's rho (*p*-value)	ICC [range]	Bias (median difference)	Bias [LoAnp]
CVR					
Vertebra C4	686	0.99 ($p < 0.001$)	0.99 [0.99-1.00]	0.14	0.14 [1.73–1.45]
Vertebra C5	717	0.97 ($p < 0.001$)	0.98 [0.98–0.99]	0.00	0.00 [1.53–1.53]
Vertebra C6	717	0.95 ($p < 0.001$)	0.99 [0.99–0.99]	-0.13	-0.13 [1.06–1.32]
Vertebra C7	382	0.90 ($p < 0.001$)	0.98 [0.97–0.98]	-0.20	-0.20 [1.27–1.67]
All individual vertebrae	2502	0.97 ($p < 0.001$)	0.99 [0.99–0.99]	0.00	0.00 [1.42–1.42]
CIR					
Segment C4-C5	685	0.96 ($p < 0.001$)	0.96 [0.96–0.97]	0.00	0.00 [2.04–2.03]
Segment C5-C6	716	0.96 ($p < 0.001$)	0.98 [0.97–0.98]	0.06	0.06 [2.11–1.99]
Segment C6-C7	381	0.80 ($p < 0.001$)	0.85 [0.82–0.88]	-0.09	-0.09 [1.81–1.99]
All segments	1784	0.94 ($p < 0.001$)	0.97 [0.96–0.97]	0.00	0.00 [2.03–2.03]
RIR					
Motion segment C4-C5	594	0.89 ($p < 0.001$)	0.92 [0.90–0.93]	-0.01	-0.01 [0.29–0.30]
Motion segment C5-C6	621	0.91 ($p < 0.001$)	0.95 [0.95–0.96]	0.02	0.02 [0.27–0.23]
Motion segment C6-C7	330	0.75 ($p < 0.001$)	0.79 [0.75–0.82]	0.00	0.00 [0.29–0.30]
All motion segments	1547	0.88 ($p < 0.001$)	0.93 [0.92–0.94]	0.01	0.01 [0.28–0.27]

protocol [3, 17]. Several age-related factors may contribute to the absence of SSC in older adults, including degenerative and biomechanical changes in the cervical spine, decreased flexibility, and potential limitations in mobility. These factors may alter cervical spine dynamics and impact SSC patterns. Further research with larger elderly cohorts is needed to explore these influences and determine whether SSC absence is a common feature in aging or specific to certain subgroups.

Despite the limited sample size, a considerable number of measurements were studied, rendering the dataset sufficient for a comprehensive comparison of the two techniques as was shown by the post-hoc power calculation. CVR, CIR and RIR exhibit excellent agreement between the two image tracking methods. It was a deliberate decision to incorporate all outcome measures, including CVR, CIR, and RIR, in the studies despite their interdependence. While acknowledging the interconnected nature of these measures, it was crucial to assess their agreement individually due to their separate utilization in studies examining SSCs, more specifically in those studied in the AECC and MUMC+. The consistency of the measurements across the two methods was above 0.93 for all levels, except for the motion segment C6-C7. The Bland-Altman analysis revealed wider limits of agreement for the C6-C7 segment, with differences occasionally exceeding the expected range. This finding suggests a higher degree of measurement variability for this segment compared to others.

While shoulder over-projection may contribute to variability in the C6-C7 segment, additional biomechanical and methodological factors should be considered. The C6-C7 segment may exhibit increased stiffness or altered biomechanics, for example related to posture, BMI or muscle thickness. Moreover, a potential methodological factor could be the susceptibility of the RIR measurement to a high signal-to-noise ratio.

It is noteworthy that the previously established normative SSC present in younger, asymptomatic participants was evident in 80–90% of individuals. In this study, we observed a 67–78% presence of the normative SSC, aligning closely with previous observations [3]. A variance in findings between T1 and T2 has been documented previously, and is also observed in this study [5]. A possible explanation for the lower presence of this SSC might be the lower overall RoM studied, focusing only on the second half of extension starting from the neutral position. Another explanation might be the guided motion protocol employed in the AECC protocol. It is worth noting that although our study only encompassed three elderly participants, we did not identify the presence of the same SSC in these individuals, consistent with previous research findings [17].

Potential variability from different motion protocols and tracking systems at MUMC + and AECC was considered in our analysis. While the guided protocol at AECC minimized participant variability, the free-motion protocol at MUMC + may have introduced natural variability, which we recognize as a limitation. However, consistent agreement across methods suggests that these differences did not significantly impact the reliability of SSC patterns.

We suspect that the investigation of SSCs is currently limited because of multiple reasons. First of all, technical

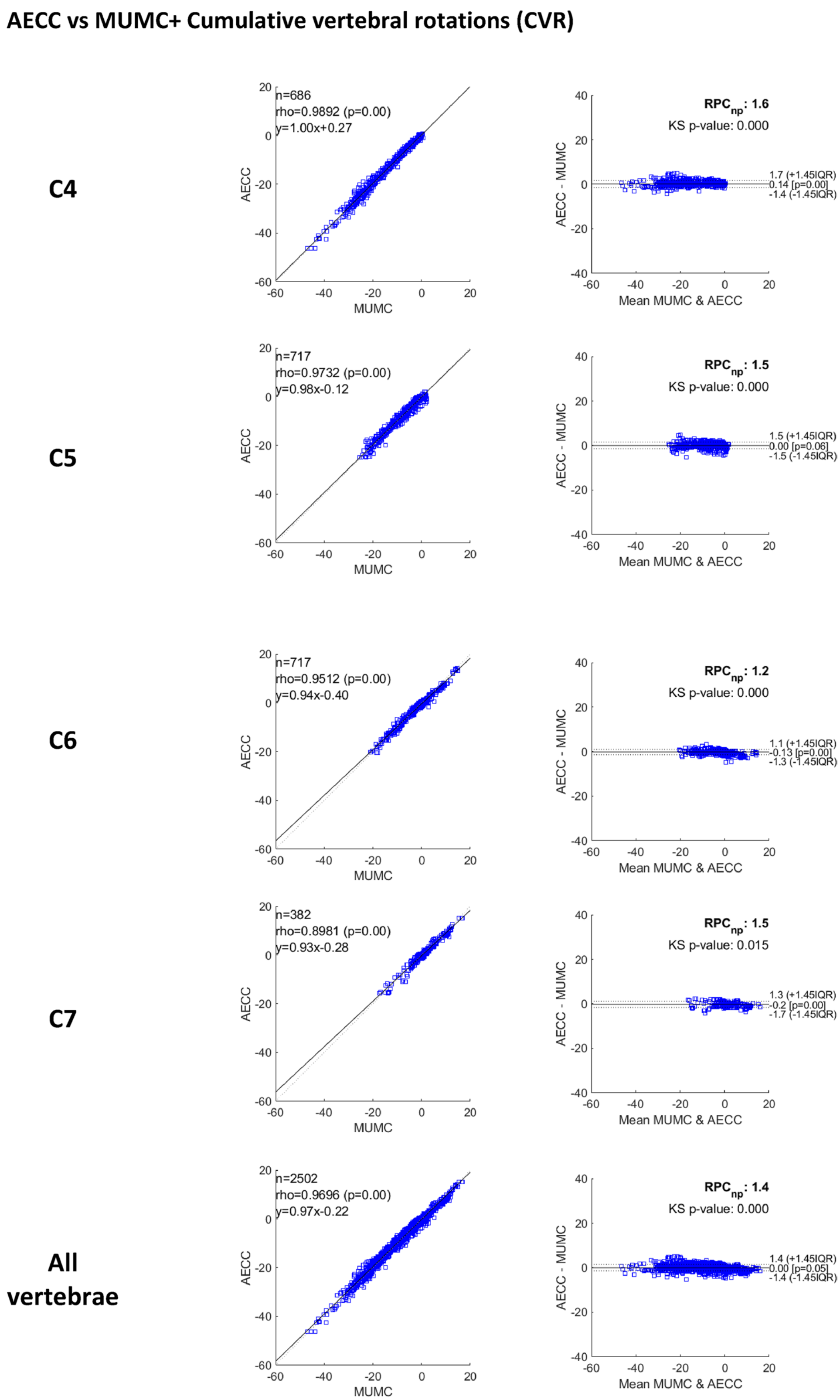

Fig. 1 Comparison of individual vertebrae. Regression (left) and Bland-Altman (right) plots of all individual levels showing level of agreement between AECC and MUMC+. In the Bland-Altman plots, the difference of the two paired measurements is plotted against the mean of the two measurements. *RPC*$_{np}$ Reproducibility coefficient (non-parametric), *n* Number of samples, *Rho* Spearman's Rho (and p value) representing level of agreement between the two methods, *y* Linear regression equation, *KS p value* Kolmogorov-Smirnov test for normality. *AECC* AECC University College, *MUMC+* Maastricht University Medical Center +

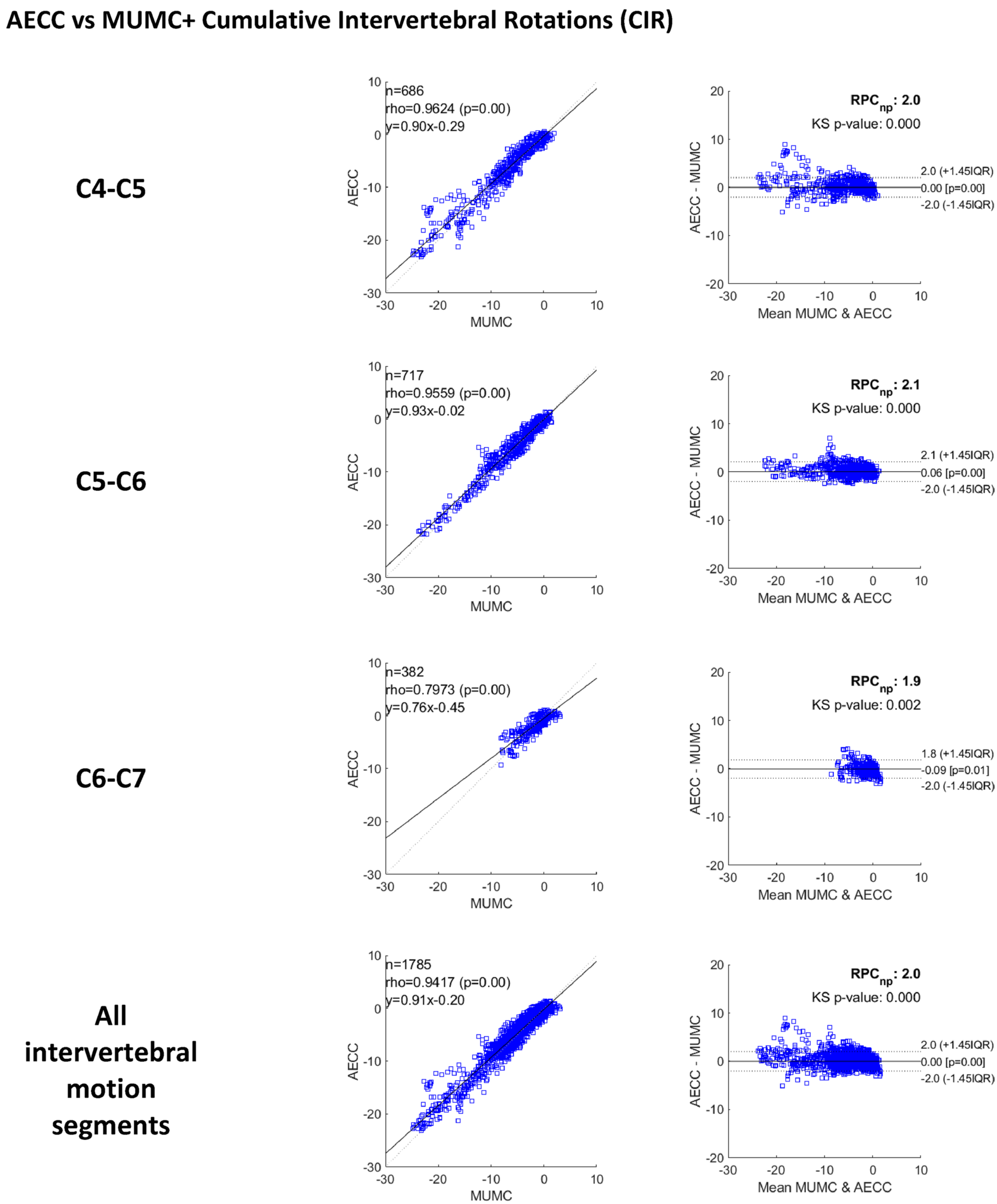

Fig. 2 Comparison of cumulative rotation of the segments. Regression (left) and Bland-Altman (right) plots of all motion segments showing level of agreement between the cumulative rotations of the motion segments C4-C5, C5-C6 and C6-C7 between the methods of AECC and MUMC+. +. In the Bland-Altman plots, the difference of the two paired measurements is plotted against the mean of the two measurements. *RPCnp* Reproducibility coefficient (non-parametric), *n* Number of samples, *Rho* Spearman's Rho(and p value) representing level of agreement between the two methods, *y* Linear regression equation, *KS p value* Kolmogorov-Smirnov test for normality. *AECC* AECC University College, *MUMC+* Maastricht University Medical Center +

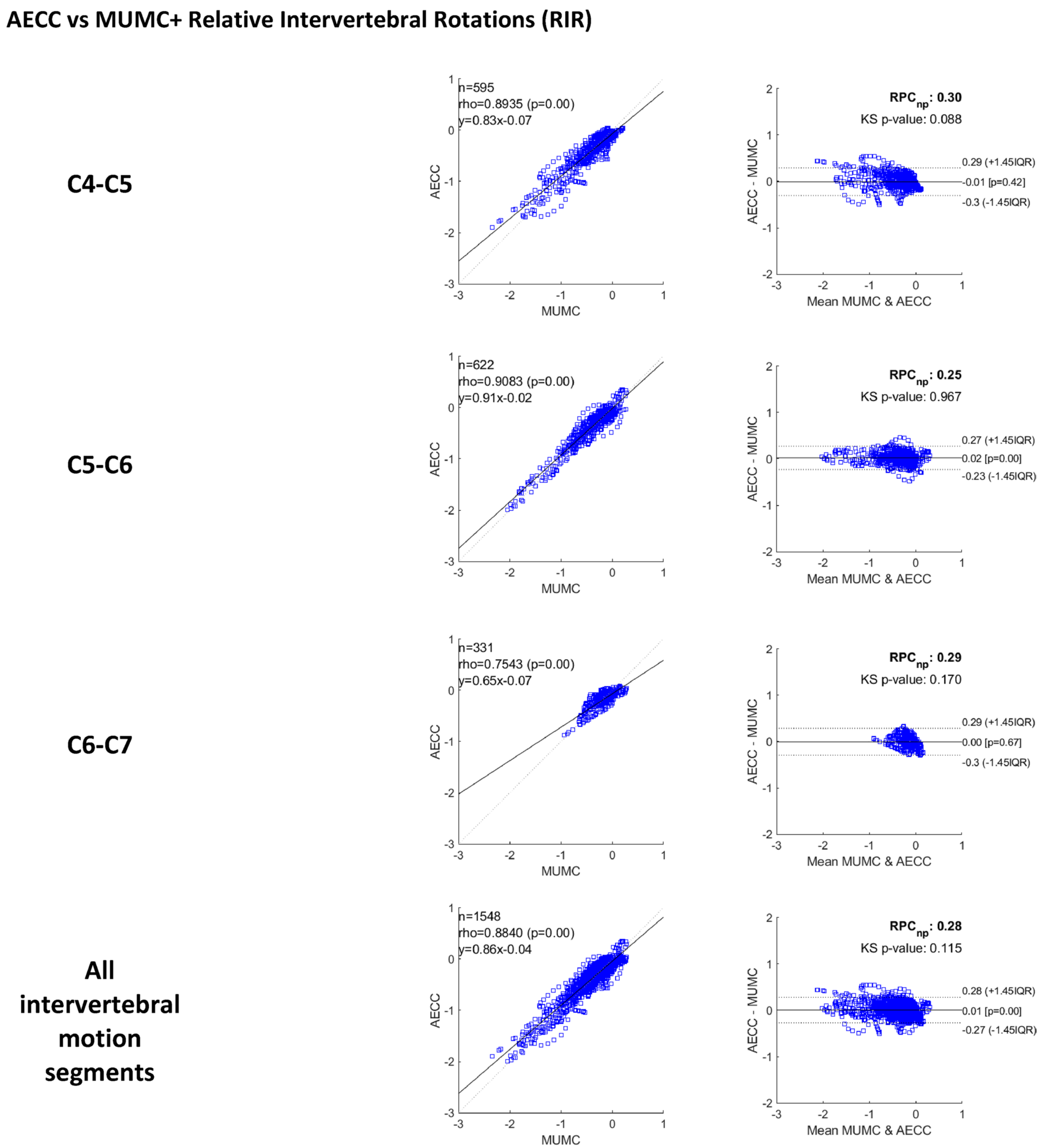

Fig. 3 Comparison of relative rotation of the segments. Regression (left) and Bland-Altman (right) plots of all motion segments showing level of agreement between the relative rotations of the motion segments C4-C5, C5-C6 and C6-C7 between the methods of AECC and MUMC+. In the Bland-Altman plots, the difference of the two paired measurements is plotted against the mean of the two measurements. *RPCnp* Reproducibility coefficient (non-parametric), *n* Number of samples, *Rho* Spearman's Rho (and p value) representing level of agreement between the two methods, *y* Linear regression equation, *KS p value* Kolmogorov-Smirnov test for normality. *AECC* AECC University College, *MUMC+* Maastricht University Medical Center+

challenges. Analysis of SSC requires precise and sophisticated measurement techniques, such as motion capture systems or advanced imaging modalities [21]. Implementing these techniques is complex, time-consuming, and expensive, making it less accessible for researchers and clinicians. Secondly, in clinical settings, the emphasis lies on diagnosing and treating specific spinal pathologies rather than studying normal segmental contributions

Table 3 Presence of normative sequence of segmental contributions in younger and elder individuals, as observed at two different timepoints (T1 and T2)

Participant	Normative SSC T1	Normative SSC T2
Young-1	Yes	Yes
Young-2	Yes	Yes
Young-3	Yes	Yes
Young-4	Yes	Yes
Young-5	No	No
Young-6	No	No
Young-	Yes	Yes
Young-8	Yes	Yes
Young-9	Yes	No
Average young cohort	77.8% (7/9)	66.7% (6/9)
Elderly-10	No	No
Elderly-11	No	No
Elderly-12	No	No
Average elderly cohort	0%	0%

in asymptomatic individuals [22]. As a result, research in this area might receive less attention. In some cases, research may prioritize macroscopic quantitative motion analysis (e.g., overall range of motion) rather than focusing on the subtle nuances of the sequence of segmental contributions [1, 4, 23–29]. Finally, the more complex interpretation of SSCs in comparison to sRoM. During extension, the cervical spine undergoes multifaceted interactions between the individual segments, involving a sequential and coordinated series of relative rotations. This sequential movement harmonizes the overall spinal function, ensuring optimal load distribution, and safeguarding the integrity of the spinal cord and surrounding neural structures. Interpreting the sequence of segmental contributions requires expertise in spinal biomechanics and affinity with spinal motion patterns. In other words, cervical spine motion is complex, making it challenging to precisely isolate and quantify segmental contributions [5]. The presence of coupled motions further adds to the complexity [5]. This demonstrates why quasi-static radiographs are insufficient to capture all facets of spinal motion and dynamic analyses are required.

Unfortunately, the analysis of dynamic recordings is strongly limited due to its time-consuming nature and the need for trained and experienced individuals [3, 13, 30]. Automated algorithms, such as machine learning models, hold significant potential to streamline cervical spine motion analysis by recognizing segmental patterns and reducing manual input. However, practical implementation would require high-quality, annotated datasets to ensure accurate training and generalization across different anatomical variations. Developing robust AI models for cervical motion analysis will likely involve overcoming challenges related to variability in patient anatomy, imaging quality, and motion capture techniques [31–33]. Ethical considerations are essential when implementing AI in clinical applications, especially for diagnostic support. Ensuring transparency in AI-driven analyses and maintaining data privacy are critical to building trust in these technologies. Additionally, careful consideration must be given to the potential biases introduced by training data, which could affect AI performance across diverse patient populations.

Beyond validating method reliability, this study highlights the potential for SSC analysis to enhance clinical diagnostics and rehabilitation for cervical spine pathology. The accurate assessment of SSC patterns could enable clinicians to detect early signs of dysfunction or predict pathology, and eventually design individualized treatment plans based on segmental motion characteristics.

While this study provides valuable insights, several limitations must be considered. The small sample of elderly participants limits our ability to generalize findings to the wider aging population. Additionally, our focus on cervical levels C4 to C7 does not capture motion patterns in the upper cervical spine, and the analysis was limited to extension without consideration of coupled motions such as lateral bending or axial rotation. These constraints may influence the observed SSC patterns, and future studies should aim to address these aspects to offer a more comprehensive view of cervical spine dynamics.

Participant selection is based on an existing dataset to ensure comparability with previous cohorts. Furthermore, the study's sample size is relatively small. Although an extensive number of levels were analyzed, the inclusion of only a small subset of elderly participants is acknowledged.

Conclusion

This study demonstrates a strong agreement between the two tracking methods, supporting the reliability of SSC analysis for cervical spine motion. Consequently, researchers can confidently share motion data for secondary analysis without the need for repetitive tracking. The observed SSCs should be interpreted with caution due to the small sample size. While the absence of SSC in older participants aligns with some prior research, further studies with larger, more diverse samples are essential to confirm whether this pattern is consistent across broader populations.

Abbreviations

AECC	AECC University College
ICC	Intraclass Correlation Coefficient
MUMC+	Maastricht University Medical Center+
N	Number of measurements
RoM	Range of motion
RPC	Reproducibility coefficient
R^2	R-squared representing level of agreement between the two methods

sRoM	Segmental range of motion
SSC	Sequence of segmental contributions
SSE	Error sum of squares
Y	Regression equation
ZL	Zuyderland Medical Center

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Authors' contributions
1 guarantor of integrity of the entire study: VS, AB, JB, AS, HvS, TB. 2 study concepts and design: VS, AB, AS, HvS, TB. 3 literature research: VS, AS, TB. 4 clinical studies: VS, AB, JB. 5 experimental studies / data analysis: VS, AB, TB. 6 statistical analyses: VS, AB, TB. 7 manuscript preparation: VS, AB. 8 manuscript editing: AB, JB, AS, HvS, TB.

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None to declare.

Data availability
The datasets generated during and/or analyzed during the current study are available in the appendices, with exception of the original recordings. Additional information can be obtained from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The study was conducted according to principles enshrined in the Declaration of Helsinki and in accordance with the Medical Research Involving Human Subjects Act (WMO). The study was approved by the local institutional medical ethical committees (Medical Research Ethics Committee Maastricht UMC+, METC 06-1-098 and UK National Research Ethics Service South West – Cornwall and Plymouth (11/ SW/0072). All participants provided informed consent.

Competing interests
The authors declare no competing interests.

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