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Consistency of vertebral motion and individual characteristics in gait sequences

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A R T I C L E I N F O

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A B S T R A C T

Vertebral motion reveals complex patterns, which are not yet understood in detail. This applies to vertebral kinematics in general but also to specific motion tasks like gait. For gait analysis, most of existing publications focus on averaging characteristics of recorded motion signals. Instead, this paper aims at analyzing intra- and inter-individual variation specifically and elaborating motion parameters, which are consistent during gait cycles of particular persons. For this purpose, a study design was utilized, which collected motion data from 11 asymptomatic test persons walking at different speed levels (2, 3, and 4 km/h). Acquisition of data was performed using surface topography. The motion signals were preprocessed in order to separate average vertebral orientations (neutral profiles) from basic gait cycles. Subsequently, a *k*-means clustering technique was applied to figure out, whether a discrimination of test persons was possible based on the preprocessed motion signals. The paper shows that each test sequence could be assigned to the particular test person without additional prior information. In particular, the neutral profiles appeared to be highly consistent intra-individually (across the gait cycles as well as speed levels), but substantially different between test persons. A full discrimination of test persons was achieved using the neutral profiles with respect to flexion/extension data. Based on this, these signals can be considered as individual characteristics for the particular test persons.

1. Introduction

Analysis of vertebral motion is an important task for obtaining a deeper understanding of the dynamic functionality of the spine. However, the high number of involved articulations and resulting complexity of motion parameters renders the interpretation of data challenging. It is not yet known, which components essentially contribute to a proper functioning of the spine. In particular, this applies to specific motion tasks like gait. Contrary, it has been shown that there is high variation of motion parameters, e.g. regarding general appearance of motion patterns, amplitudes of motion signals, coupling between vertebral levels, or dependency on speed levels. (Christe et al., 2017; Haimerl et al., 2022; Lamoth et al., 2002; Needham et al., 2016) Currently, there is no clear picture, which features are fundamental to characterize individual motion profiles. On the one hand, it is not profoundly understood which

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components are consistent across intra-individual motion tasks. On the other hand, it is not known what discriminates different test persons inter-individually. A characterization, which meets both of these requirements, would be helpful to identify and interpret motion behavior.

The assessment of vertebral kinematics starts with an appropriate acquisition of motion signals. For analyzing static postures, x-ray based radiography is considered to be the gold standard. In particular, this applies to the analysis of spinal pathologies like scoliosis (Applebaum et al., 2020; Knott et al., 2016). For dynamic situations, x-ray based techniques usually are not adequate due to the high radiation exposure. Surface topography (ST), also known as rasterstereography (see (Betsch et al., 2013)), was developed as an alternative. ST does not achieve perfect consistency with x-ray based measurements (e.g. in terms of Cobb angles for static postures) (Applebaum et al., 2020). But, it has high correlation for basic parameters and additionally shows high consistency within repeated ST measurements reflecting the patient's current postural status (Degenhardt et al., 2020; Guidetti et al., 2013; Schroeder et al., 2015; Tabard-Fougère et al., 2017). Even for static postures it is considered as a valuable tool, e.g. for screening purposes and repeated examinations (Applebaum et al., 2020; Ćuković et al., 2019; Degenhardt et al., 2020; Guidetti et al., 2013; Mohokum et al., 2015; Schroeder et al., 2015; Tabard-Fougère et al., 2017).

Further on, ST is suited for collecting motion data in dynamic situations like walking exercises (Betsch et al., 2011; Betsch et al., 2013; Gipsman et al., 2014; Liu et al., 2019; Scheidt et al., 2018). For these applications, the reproducibility of ST based dynamic measurements has been demonstrated, e.g. in (Gipsman et al., 2014) in a limited setup using fixed parameters for repeated gait tests (e.g. same speed and general environment) as well as a limited set of measurements (e.g. maximum range of vertebral rotation, incl. kyphosis and lordosis). Additionally, consistency with other optical measurement techniques like marker-based techniques has been shown in (Betsch et al., 2013). A validation with a dedicated synthetic model was provided in (Betsch et al., 2011). Marker-based technologies are considered as an alternative to ST for acquiring data about spinal motion (see e.g. (Betsch et al., 2013; Needham et al., 2016; Papi et al., 2019; Schmid et al., 2017)). However, these techniques can usually only record a limited number of motion segments. Instead, ST-based techniques allow a more comprehensive analysis and are used as the method-of-choice in this paper.

ST is based on an optical technique where light patterns (e.g. stripes) are projected onto the patient's back. The rotational alignment of the particular vertebrae is indirectly derived from the 3D shape of the body surface. The rotation can be measured in all three coordinate directions, i.e. in frontal, sagittal, and axial plane. More details about the implementation of the measurements can be found in (Drerup, 2014). In the dynamic scenario, this acquisition is performed over a certain time frame, yielding a time series of measured directions. For gait analysis, the test persons walk on a treadmill at a predefined walking speed. (Betsch et al., 2013) In summary, each data set contains three rotations per vertebra over a certain range of vertebrae and over a series of time steps. In standard protocols, 17 vertebrae primarily in the lumbar and thoracic spine are recorded as well as the pelvis. The cervical vertebrae C1 - C6 as well as L5 cannot be recorded accurately, according to the specification of the ST system. Thus, they are not included in standard ST measurements.

For assessing intra- and inter-individual variation, repeated test sequences need to be recorded for each test person. In this paper, this was performed while the test persons are walking at different speed levels (2, 3, and 4 km/h) to also include variation with respect to this parameter. In each test sequence, 10 full gait cycles were recorded instead of only 3 cycles as given in the standard acquisition protocols for the ST system. This enabled a more detailed analysis of the results (e.g. comparison between gait cycles) as well as a broader spectrum of processing steps. In (Haimerl et al., 2022), this setup was used to visualize important motion patterns and also to visually assess intra- and inter-individual variation. It was shown that the average vertebral orientation remains considerably consistent across the different gait cycles as well as in repeated test sequences with varying speed levels. This average vertebral orientation across the spine was named neutral profiles. This term is also used subsequently, in this paper. Additionally, these neutral profiles deviated substantially when comparing different test persons. Thus, they seem to qualify as an individual motion characteristic which enables a discrimination between test persons. (Haimerl et al., 2022)

However, the assessment was only performed qualitatively in (Haimerl et al., 2022). Additionally, no specific processing of data was included, which could elaborate concrete signal features. Instead, this paper provides a more operationalized approach. For this purpose, two basic steps are included for the characterization of individual motion. As a first step, a preprocessing of the recorded motion data was performed that separates the motion signals into two components using a filtering technique. The first component reflects the basic gait cycles, i.e. basic oscillations representing the single cycles. The remaining part is dominated by the average vertebral orientation that remains stable across the gait cycles. Subsequently, this was further reduced to a sort of mean values, which characterize the neutral orientation of the vertebra. The collection of all the mean values across the spine reflects the mentioned neutral profiles. Within the first step, the analysis was based on visual representations.

As a second step, a clustering technique (k-means algorithm) (Tan et al., 2014) was utilized to analyze the relationship between intra- and inter-individual variation in a more rigorous way. The main goal of this method was to figure out, whether a full discrimination of test persons could be achieved using this approach. This means, that the k-means algorithm would have to achieve a clustering where each test sequence is assigned to exactly this cluster where all other sequences from the same test person are included. This separation had to be based on the extracted motion components as distinguishing features. In the case of a successful separation, these features can be considered as individual characteristics of the gait patterns.

2. Materials and methods

2.1. Study design and data collection

The analysis in this paper was based on ST recordings of test persons walking on a treadmill at different speed levels (2, 3, and 4 km/

h). This setup allowed to compare intra-individual (same test person, but different speed and gait cycles) to inter-individual variation (different test persons). The ST measurements were performed using the DIERS 4D motion® Lab system (Diers International GmbH, Schlangenbad, Germany) in combination with the pedogait component. The latter was a 1 m long capacitive pressure plate with 48×112 sensors (size of each sensor was 0.845 cm^2). It measures the foot pressure reaction forces while walking. In particular, the starting and end point of the different gait cycles was determined by means of the pedogait component. This information was directly stored in the measurement data.

Only asymptomatic and pain free volunteers were included in the study, i.e. individuals without self-reported spinal problems. It was required that the test persons were able to walk without problems on the treadmill at each addressed motion speed. The BMI had to be below 30 since this was a limitation of the used ST system. No further demographic data was stored, e.g. mean age or concrete BMI values. Data acquisition took place in Nov 2018. For each test person, the recordings were performed on a single day. All data acquisition and evaluation steps were performed in a fully anonymized way – without any information about the health condition or other personal characteristics. The data was collected within a quality assurance step performed by the manufacturer of the ST system. This means that the analysis for intra- and interindividual variation was not a dedicated endpoint of the assurance tests. Instead, this analysis was performed retrospectively and independently in terms of an exploratory study. The data was provided for this study in the mentioned anonymized way. According to the responsible ethics committee of the medical chamber Rhineland-Palatinate (2021.03.11) there were no objections to statistically evaluate and publish them as anonymous results.

For each test person, three recordings were acquired at a fixed walking speed of 2, 3, and 4 km/h, respectively. The standard equipment of the DIERS 4D motion® Lab/DIERS formetric 4D system (Version 3.10.1, Diers International GmbH, Schlangenbad, Germany) was utilized for the measurements. For instance, markers were attached to anatomical landmarks, including vertebra prominens and both dimples, as defined in the system's manual. Additionally, the measurement steps were performed as specified by the software. A habituation phase was included where the speed was incrementally increased to prevent tripping. The measurement sequences were started directly after the habituation phase. The speed levels were always recorded in the same order, starting with 2 km/h. Each test sequence contained 10 full gait cycles (from right heel strike to right heel strike) in contrast to the 3 cycles in the standard protocol of the ST system. The frequency of the camera recordings was 60 Hz and the frequency of the pedogait system 100 Hz. The acquisition time for each test sequence was approximately 20 s. In total, 12 test persons were recorded including 10 males

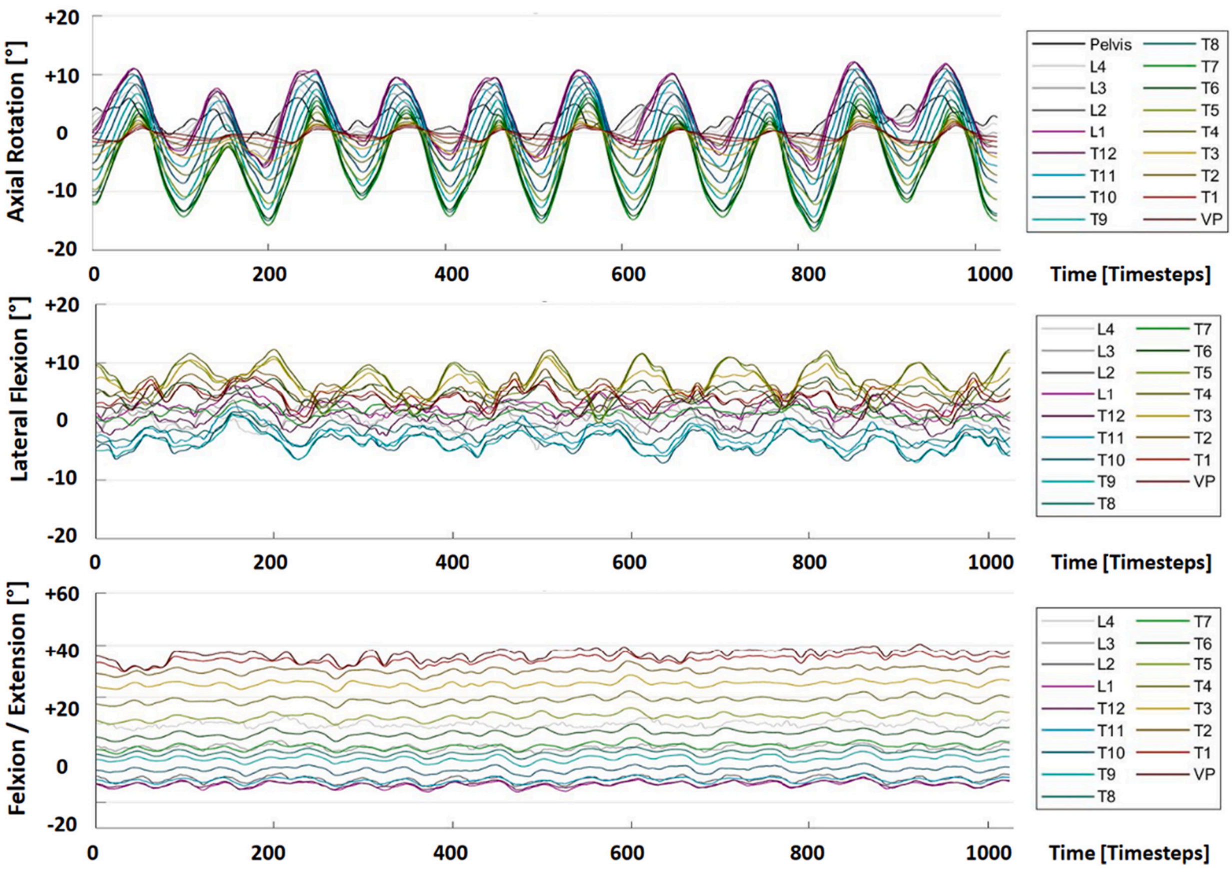

Fig. 1. Recorded ST data of vertebral motion containing ten gait cycles (always beginning with the initial contact of the right foot) for one test case at 3 km/h – top: AxRot, middle: LatFlex, bottom: FlexExt. VP until L4 are shown, for AxRot also pelvis. The y-axis represents rotation in degree, the x-axis the number of the time step (sample in the data set after time renormalization).

and 2 females in the age between 20 and 70. However, the data for one test person had to be excluded from the analysis of this paper. Due to a setup error, not all speed levels were collected for this particular test person.

2.2. Representation of recorded motion signals

Using the ST system, the rotation values were obtained for all vertebrae from the lower end of the cervical spine (C7, vertebra prominens – VP) to the pelvis. L5 was excluded since its rotation cannot be assessed reliably using the ST system. Rotation data was collected for all anatomic directions, including axial rotation (AxRot), lateral flexion (LatFlex), and flexion/extension (FlexExt). All rotation values were measured in a global coordinate system defined by the spatial orientation in the room, i.e. the coordinate system of the test room was calibrated by the system and considered as a global coordinate system. AxRot was determined as a rotation around the up-down axis within the test room, LatFlex as a rotation around the forward gait direction, and FlexExt as a rotation around the left/right direction with respect to the test person. These angular measurements were measured as projection angles in the particular anatomical planes (axial plane for AxRot, coronal plane for LatFlex, and sagittal plane for FlexExt). Regarding the rotational direction, the values were specified according to the following convention.

- AxRot: positive sign reflects counterclockwise rotation of the vertebra / pelvis
- LatFlex: positive sign reflects counterclockwise rotation of the vertebra / pelvis
- FlexExt: positive sign represents flexion, negative sign extension / pelvis

The data sets were rescaled to a common number of 1024 sample points, i.e. time steps, per 10 gait cycles using cubic splines. The restriction to the same signal length was carried out to enable a better comparison between the different test cases. The precise number ($1024 = 2^{10}$ samples) was used to better facilitate the data preprocessing, using a Fourier based filtering technique as described in Section 2.3 below. The particular gait cycles were separated using the information directly stored in the measurement data (acquired with the pedogait component as described in Section 2.1). A rescaling of the particular gait cycles was not performed within this paper. Thus, the gait cycles within each test sequence had a slightly different number of data points. According to the speed level given by the treadmill, there were only minor differences in these numbers. Fig. 1 shows examples of such motion signals for one extracted test case (one particular test person at a speed of 3 km/h) in a standard superimposition approach. The filtering steps described subsequently are applied to these types of signals.

As an alternative representation, the ACIO (all-cycles-in-one) approach introduced in (Haimerl et al., 2022) is used later in this paper. This representation (given in Fig. 2) contains a mixture of superimpositions and juxtapositions, i.e. vertebral levels are shown side-by-side (juxtapositions) from bottom to top, whereas the gait cycles are shown in an overlay mode (superimposition). For each vertebral level, the y-axis additionally reflects the time step within the gait cycle. The scaling of the axis was adjusted in a way that the signals are clearly visible. The scaling was not explicitly shown in the diagrams to keep the representation simple. The x-axis represents the orientation angle during motion.

In (Haimerl et al., 2022), it was demonstrated that the ACIO representation allows a more comprehensive visual analysis, especially regarding a rating of inter- and intra-individual variation. Additionally, it was shown that the signals basically are a combination of an oscillation for each gait cycle and an average rotation, which is largely consistent across the gait cycles. For FlexExt, the frequency of

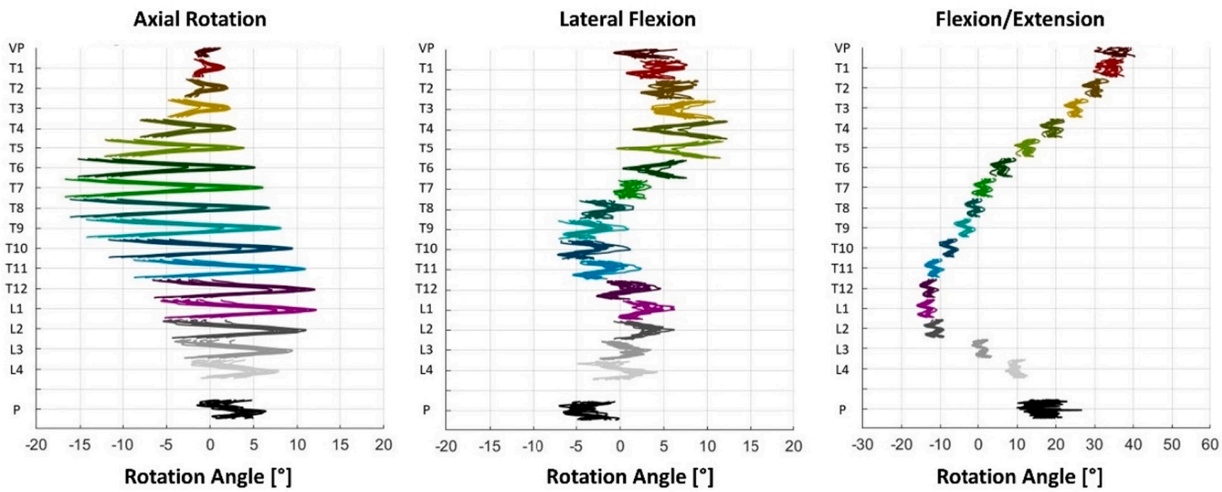

Fig. 2. All-cycles-in-one (ACIO) representation of acquired motion signals (same test case as in Fig. 1) showing the gait cycles in overlay for each vertebra / pelvis – AxRot (left), LatFlex (middle), and FlexExt (right). The vertebrae and the pelvis are shown from bottom to top in a color coding as given in the legend in Fig. 1, additionally they are plotted on the y-axis. In each segment, the y-axis also represents the course of time. For simplicity reasons, the scaling with respect to time was omitted in the diagrams. The x-axis shows vertebral rotation values in degree.

the oscillation is doubled, e.g. there are two oscillations within one gait cycle, due to the left-right symmetry with respect to this rotational direction. This means, that the base frequency for the entire motion signals (containing all 10 gait cycles) is 10.0 for AxRot and LatFlex, but 20.0 for FlexExt. This had to be considered for the further processing steps.

2.3. Separation of main components in motion signals

Based on this observation, the motion signals were separated into their main components using a filtering technique. This was applied to the overall signals as shown in Fig. 1. First, the periodic oscillations reflecting the gait cycles were extracted. In this paper, a Log-Gabor filter $H_{LogGabor}$ was used for this purpose with a frequency distribution given as

$$H_{LogGabor}(\omega) = exp\left(\frac{-log\left(\frac{|\omega|}{\omega_0}\right)^2}{2\ log\left(\frac{\sigma}{\omega_0}\right)^2}\right),$$

where ω is the frequency parameter, ω_0 the base frequency, and σ a scaling parameter. (Bridge, 2017; Kovesi, 2000) In the frequency domain, the filter represents a bandpass characteristic where the filter response strongly decays beside the base frequency ω_0. In the time domain, it represents a wavelet, which consists of one major oscillation mainly representing the base frequency. This behavior can be adjusted using the scaling parameter σ. For AxRot and LatFlex, σ was set to 3.0 to achieve a balance between time and frequency resolution. The frequency parameter ω_0 had to be set to 10.0 according to the number of gait cycles. ω_0 reflects the base frequency required in the present scenario, i.e. 10 gait cycles and thus 10 oscillations in the overall motion signals. For FlexExt, the parameters had to be doubled to $\omega_0 = 20.0$ and $\sigma = 6.0$ according to the observation that the FlexExt signals include a duplication of oscillations according to the basic symmetry between left and right steps in this motion direction. The Log-Gabor filter was directly applied in the Fourier domain after applying a Fast Fourier Transform on the signals.

Next, the Log-Gabor filtered signal (reflecting the basic gait cycles) was subtracted from the original data. The resulting signal is a combination of low frequencies representing the rough course of vertebral orientation as well as high frequencies representing minor details. This signal is subsequently called rough orientational profile. As a first step, intra- and interindividual variation of these profiles was analyzed visually using the ACIO representations. Later on, a more formalized approach using the k-means clustering algorithm as well as a quantitative assessment of clustering quality was applied as described in 2.4.

As a final preprocessing step, the signals were further reduced to the average vertebral rotation using the calculation of robust mean

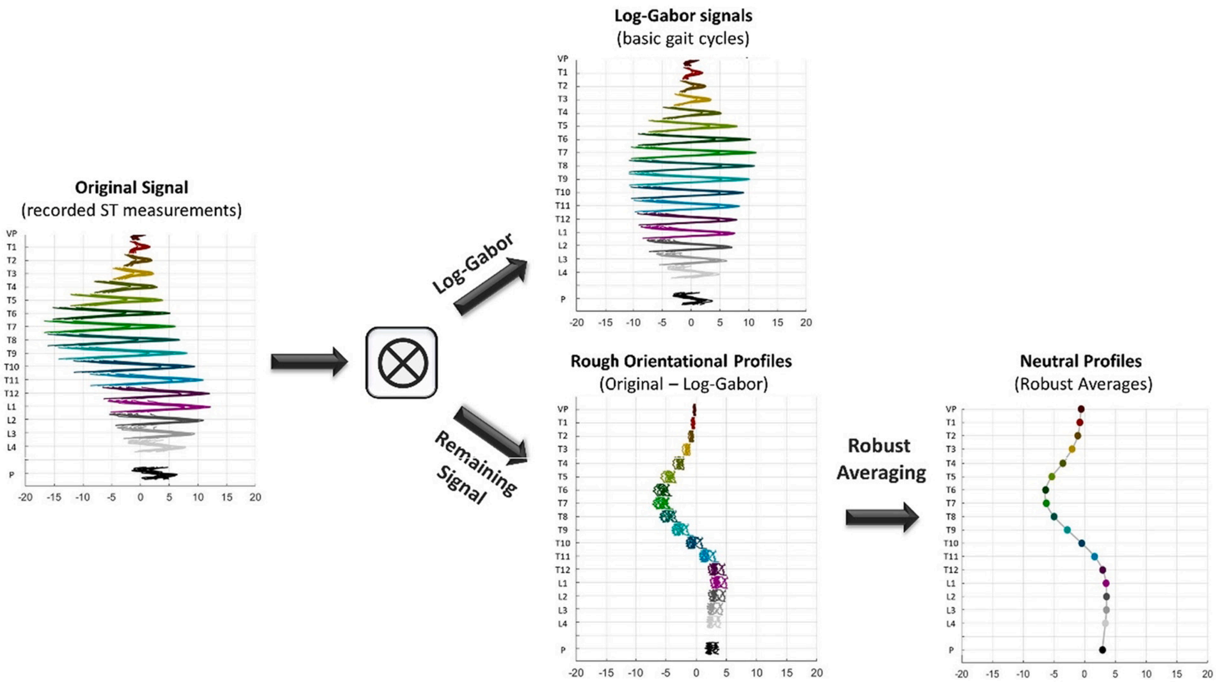

Fig. 3. Separation of motion signals (here AxRot for one test sequence including 10 gait cycles) into Log-Gabor filtered components (basic oscillations) in the top row and rough orientational profiles (bottom row, left diagram) respectively neutral profiles (bottom row, right diagram). The neutral profiles only contain one value per vertebra and test sequence. The same test person as before was used. Parameters for the Log-Gabor filter were set to $\omega_0 = 10.0$ and $\sigma = 3.0$.

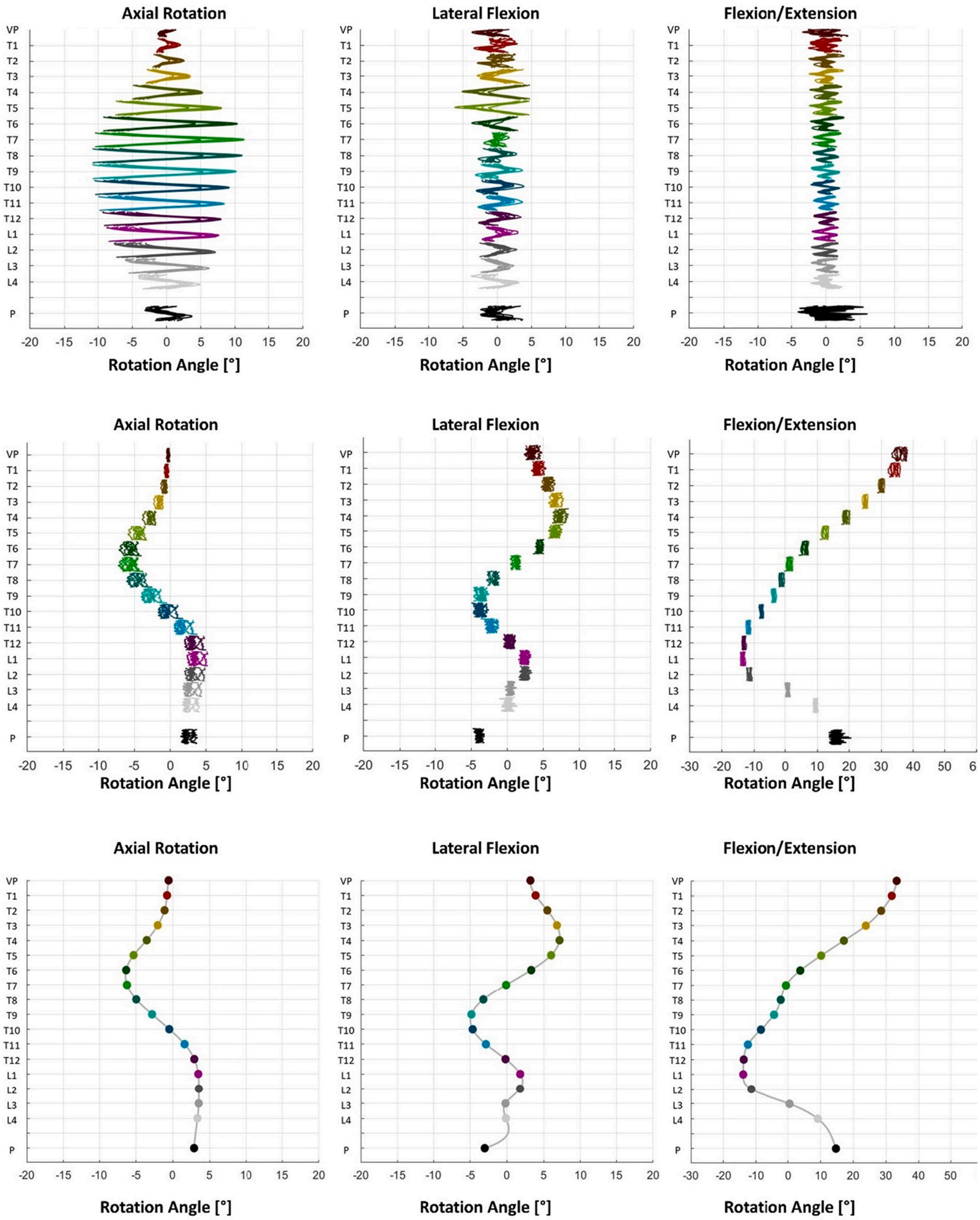

Fig. 4. Visual assessment of main motion components (same test person as before) – top row: Log-Gabor filtered signals (basic gait cycles); middle row: rough orientational profiles (original data minus Log-Gabor filtered data), bottom row: neutral profiles (robust averaging of rough orientational profiles, same as in middle row). Parameters for the Log-Gabor filter were $\omega_0 = 10.0$ and $\sigma = 3.0$ for AxRot as well as LatFlex and $\omega_0 = 20.0$ and $\sigma = 6.0$ for FlexExt.

values for each vertebra across the entire time series. In particular, a trimmed mean (Matlab function trimmean) was used for this purpose. (Huber & Ronchetti, 2011) Such an approach performs an averaging procedure, where outliers are systematically determined and eliminated for the calculation. An empirically determined cut-off value of 0.15 was applied, i.e. the most deviating 15% of the data (7.5% on each side according to the deviation from the mean value) were considered as outliers and discarded for determining the mean value. Only one data point remains per vertebra. The resulting data series reflects the already mentioned neutral profiles and is subsequently called so as the values reflect the basic vertebral orientation across the time series. Fig. 3 shows the overall procedure for the separation of signal components.

For FlexExt, the deviation to a standardized sagittal profile was additionally calculated. This allows a better visual comparison of the cases, since the s-shaped alignment of the spine in the sagittal plane overlays the deviations. Such an approach allows to assess whether the test persons have a walking position which is oriented to a more anterior/flexed or a more posterior/extended position in comparison to the standardized profile. For this purpose, the average orientation across the entire test ensemble was calculated for each vertebra first. The collection of these values along all vertebrae was considered as the average (standardized) profile. Afterwards, the average values were subtracted from the FlexExt values for each test case. For the rotational directions, i.e. AxRot and LatFlex, a zero position was considered as a standard profile, within this study. Thus, no extra processing is required in these cases.

2.4. Discrimination of test persons using a clustering approach

In (Haimerl et al., 2022), it was conjectured that the basic vertebral orientation could be considered as a characteristic motion feature, which is able to discriminate between different test persons. This conjecture can be formalized using clustering techniques. In this paper, a standard k-means algorithm was used for this purpose. The k-means algorithm builds k groups of data, i.e. clusters, for a given set of input data. It finds an assignment where the distances within the groups are minimal in comparison to the distances with members from other groups. Usually, a data set with unknown correspondences is used (unsupervised method in terms of machine learning procedures). In the scenario at hand, the k-means algorithm can be utilized to figure out whether a full and correct discrimination of test persons can be performed, since the assignment between test cases and test persons is known. The discrimination is successful if the test cases (2, 3, and 4 km/h) for each test person are exactly assigned to one single group reflecting this test person. The predefined number k of resulting groups has to be set to the number of test persons, i.e. $k = 11$, in this setup.

Within this study, the k-means algorithm (see (Tan et al., 2014)) took the profile data as input data, either rough orientational profiles or neutral profiles. For the neutral profiles, each test case consisted of 17 vertebrae for LatFlex and FlexExt and 18 for AxRot. For the rough orientational profiles, the 1024 time steps for each vertebra had to be included additionally resulting in a rather high-dimensional input feature space. Within this paper, the different motion directions (AxRot, LatFlex, FlexExt) were only analyzed separately to figure out their particular influence. A city-block metric $d_{city}(a,b) = \frac{1}{n}\sum_{i=1}^{n}|a_i - b_i|$ (i.e. $L1$-Norm) was used for the calculation of distances between two data points $a = (a_1, a_2, \ldots, a_n)$ and $b = (b_1, b_2, \ldots, b_n)$ in the particular feature space. The k-means algorithm is a procedure which iteratively calculates the groups and associated group centers. It requires an initial configuration, i.e. an arbitrary initial assignment into the $k = 11$ groups. The results for each run of the algorithm depend on this initial configuration. Within this study, 1000 replicates with random initial configurations were applied within each clustering procedure. The end configuration which achieved the minimum distance across all replicates is used as the overall result. For the clustering based assessment, each rotation direction (AxRot, LatFlex, FlexExt) was assessed separately. For each rotation direction, the rough orientational profiles as well as the neutral profiles were analyzed. Overall, this resulted in 6 test scenarios.

2.5. Implementation

All data preparation and analysis steps were implemented in Matlab (Version 2019a, The Mathworks, Natick, Massachusetts, United States). For the k-means algorithm, the standard Matlab implementation was used (function k-means). All other analysis and evaluation steps were performed based on own code.

3. Results

3.1. Visual representation of main motion components

Based on the ACIO representation, a visual inspection of the main components of motion signals, i.e. Log-Gabor signals (basic gait cycles) as well as rough orientational and neutral profiles, was performed first. The results for a single test case are shown in Fig. 4. The Log-Gabor signals (top row) appear to be widely consistent across the gait cycles with some deviations especially for LatFlex as well as in some areas for FlexExt (i.e. pelvis, T1, VP). For FlexExt, the duplication of oscillations gets clearly visible in most of the regions. Between the vertebral levels, the basic gait cycles appear to be significantly different in many aspects. For AxRot, the motion amplitudes are varying substantially across the spine. For LatFlex, the general appearance of the motion signals is quite inconsistent. For FlexExt, the signals look widely similar. In the Log-Gabor signals, it can be recognized that the shifts according to the basic vertebral alignment are mostly eliminated. The signals oscillate around the 0° line, demonstrating a separation of the test cycles from the overall signal.

The middle row in Fig. 4 shows the rough orientational profiles (i.e. original data minus Log-Gabor filtered data). It demonstrates that they consist of the average vertebral orientation plus minor motion details. It can be recognized that the profiles remain in a narrow band around the average vertebral orientation, which dominates the signals. The remaining parts (high frequency parts) appear to be rather inconsistent. But, they play only a minor role. The bottom row shows the neutral profiles, i.e. after applying the robust mean, which more directly pool out the average vertebral orientation. Only single data points remain for each vertebra.

In Fig. 5, a direct comparison of the different speed levels is performed using the neutral profiles. Due to the reduced complexity, this can be achieved in one diagram for each rotation direction. The speed levels are visually coded by different line styles (dotted line: 2 km/h, continuous line: 3 km/h, dashed line: 4 km/h). It can be recognized that the profiles are largely consistent. However, some minor deviations occur for particular test cases and/or areas of the spine. For AxRot, the 2 km/h case deviates a bit from the other two cases across the spine. For LatFlex, there only is a minor discrepancy of the 2 km/h case in the upper thoracic spine. For FlexExt, there is a slight divergence at the most cranial end of the recorded part of the spine, whereas the curves almost perfectly coincide in the lumbar and lower thoracic spine. For FlexExt, the deviation from the standardized sagittal profile is shown in the right-most column. The basic relations are the same as in the third column. But now, it can be seen that the particular test person substantially deviates from the standardized profile in some regions (e.g. more flexed/anterior position in the lumbar and partially also in the upper thoracic region, slightly posterior/extended position in the mid thoracic spine). Additionally, the intra-individual variation can be more easily recognized due to the removed overlay with the standardized profile.

3.2. Visual assessment of motion profiles with respect to intra- and inter-individual variation

In the following, a visual analysis is provided regarding the intra- and inter-individual variation of the extracted motion components. Again, this is performed using the ACIO representation. Fig. 6 shows that the Log-Gabor signals already deviate substantially when comparing the test sequences intra-individually. This means, that test persons have considerably different motion amplitudes when walking at different speed levels. In particular, this can be recognized for the AxRot direction, where the outlines of the Log-Gabor signals have a different shape. For this test person, the gait cycles appear to have a more limited amplitude when walking at 2 km/h. Additionally, the vertebrae with the highest amplitudes in AxRot change from the lower to the mid thoracic region, when changing speed levels from 2 km/h to 4 km/h. For LatFlex, the overall appearance of signals deviates as well. FlexExt seems to be more consistent.

Fig. 7 shows the inter-individual analysis, i.e. variation between different test persons walking at the same speed level. Again, substantial deviation occurs for AxRot and LatFlex. For FlexExt, variation can be visually recognized in some regions, in particular for the upper thoracic region. However, the deviations are more subtle. In general, the analysis shows that the basic gait cycles appear to have substantial variation inter- as well as inter-individually.

In contrast, the rough orientational profiles (i.e. original data minus Log-Gabor filtered data) show high intra-individual consistency on the one hand and high inter-individual variation on the other hand. This can be recognized in Fig. 8 and Fig. 9. In Fig. 8, the profiles look highly consistent for each test case even when the test person is walking at a different speed level. This applies to all three motion directions (AxRot, LatFlex, and FlexExt). Only some minor variations occur in particular regions. This is apparently different, when comparing the motion sequences from different test persons (cf. Fig. 9). In all three motion directions the profiles deviate substantially. For FlexExt, the basic profiles have similarities. However, this is due to the S-shaped sagittal profile of the human spine. If this sagittal profile is subtracted, major deviations get apparent between the test cases. This can be recognized in Fig. 10 and Fig. 11, right column.

In the figures, a full visual comparison regarding intra- and interindividual variation based on the neutral profiles is provided. In each particular diagram, the comparison between the three speed levels (intra-individual variation) can be seen. The inter-individual variation can be assessed by comparing the particular lines reflecting the different test persons. It can be seen, that a high intra-individual consistency is given in most of the cases, whereas the profiles vary substantially between the test persons. Remaining

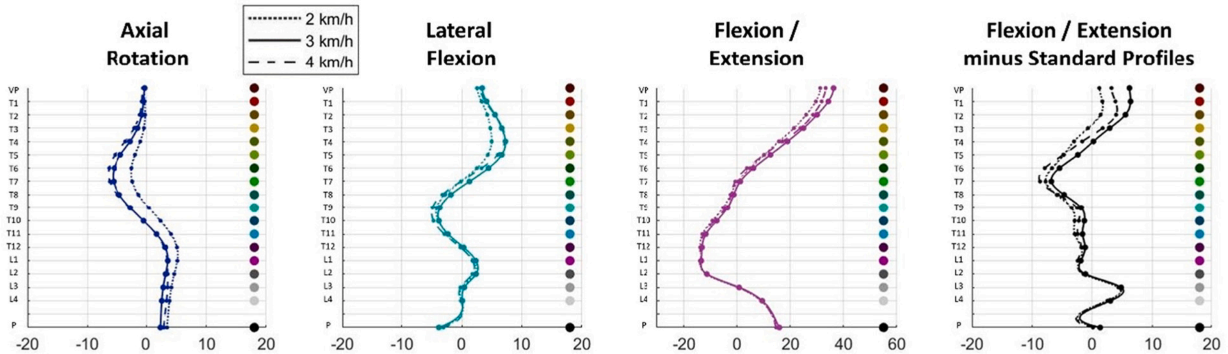

Fig. 5. Intra-individual comparison of neutral profiles of one participant. All three speed levels (coded by different line styles as shown in the uncolored legend at the top) are integrated into single diagrams to allow a more direct comparison. Particular differences can be recognized in some areas of the spine. In the first three columns, the basis rotation directions are shown (AxRot, LatFlex, and FlexExt). In the right-most column, the average sagittal profile across all test persons is subtracted from the FlexExt values. The colored dots illustrate the vertebral levels using the same color schema as used in the previous diagrams.

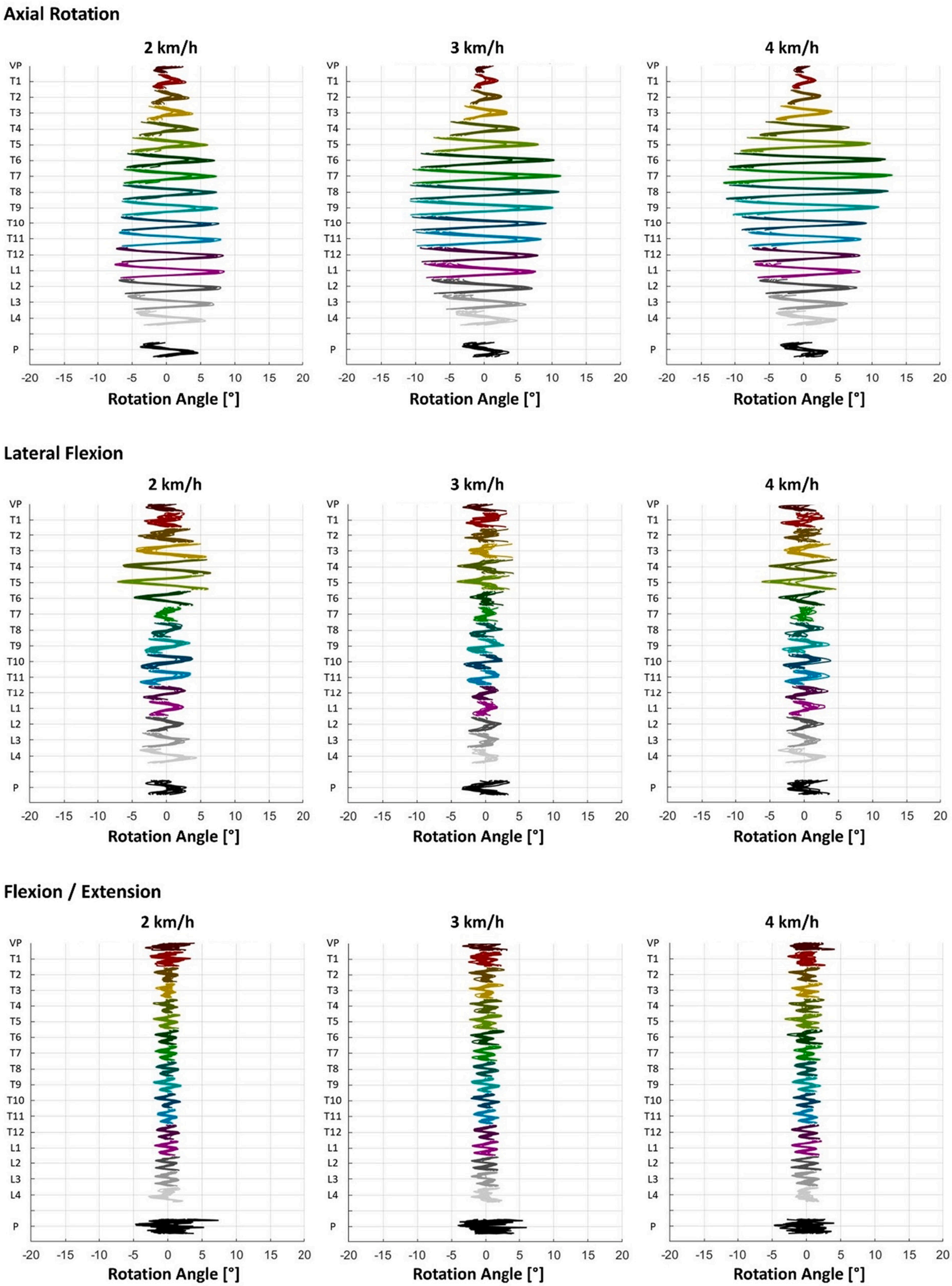

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Fig. 6. Intra-individual variation of Log-Gabor signals (basic gait cycles) – for the same test person as before with a comparison of the different speed levels (2, 3, and 4 km/h). Top row: AxRot; middle row: LatFlex; bottom row: FlexExt. Parameters for the Log-Gabor filter were $\omega_0 = 10.0$ and $\sigma = 3.0$ for AxRot as well as LatFlex and $\omega_0 = 20.0$ and $\sigma = 6.0$ for FlexExt.

intra-individual differences most often occur with respect to the 2 km/h test cases (dotted lines). In other words, a slow walking speed can lead to some deviation in the neutral profiles. In the right-most column, the average sagittal profiles are subtracted from the FlexExt values in order to provide a better illustration with respect to the deviation from a standardized profile. Using this representation, the individual character of this feature can be recognized. The slope with respect to the sagittal alignment appears to be substantially different between the test persons, whereas it is consistent between the speed levels within the particular persons.

In summary, the rough orientational profiles and even more the neutral profiles appear to provide characteristic features for the particular test persons that remain stable across the gait cycles and also when walking at different speed levels. This can be considered as a neutral position of the individual spine. The gait cycles represent an oscillation around these neutral positions with varying motion amplitudes.

3.3. Discrimination of test persons using the k-means algorithm

Up to now, the discriminative power of the proposed features was only shown in a qualitative way using visual representations. The following section demonstrates the operational assessment using the *k*-means algorithm. The analysis consisted of six test scenarios, including all rotation directions as well as two types of signals / features, i.e. rough orientational profiles (ROP) as well as neutral profiles (NP). For these scenarios, the results of the *k*-means clustering are shown in Table 1. This includes the misclassifications which remained in the *k*-means clustering for each test scenario. For AxRot (ROP and NP), there remained some bundles of cases, where a separation between the individuals could not be obtained. For LatFlex, two particular individuals could not be discriminated when using ROP. For LatFlex-ROP as well as FlexExt (ROP and NP), a full separation of the cases could be achieved.

Fig. 12 demonstrates illustrative cases where the discrimination between two test cases failed. The upper row shows the similarity of the neutral profiles for AxRot in the cases #3 and #4. This similarity impedes that the cases can be differentiated in an appropriate way. The bottom row shows a case where LatFlex had issues in separating cases #3 and #10. In both situations, the intra-individual differences, i.e. the distance between the curves in one specific color, is close to the distance to the cases from another individual, i.e. the curves in the other color. It can be seen, that other motion directions may help to separate the cases, e.g. #3 and #4 can be discriminated clearly by FlexExt and also to a certain degree by LatFlex. For cases #3 and #10, this can be well achieved by AxRot. Partially, this focuses on specific regions of the spine, e.g. on the lower thoracic / upper lumbar spine for discrimination between #3 and #4 based on LatFlex.

4. Discussion

Within this paper, it could be demonstrated that neutral profiles, i.e. average vertebral rotation along the spine, shows high intra-individual consistency in gait sequences. Vertebral motion oscillates around these neutral positions according to the roughly periodic motion patterns representing the single gait cycles. This observation was not only obtained for different gait cycles within one test sequence. It also applied to repeated test cases even when the test person was walking at different speed levels. Regarding inter-individual comparisons, these features appeared to have substantial variation. Thus, they reflect a kind of individual characteristic, which can be used to discriminate test persons. This was demonstrated by means of a clustering technique, which was able to separate a set of test cases (ensemble with 11 asymptomatic volunteers walking on a treadmill at 2, 3, and 4 km/h) into the particular groups. This was fully achieved for FlexExt and to a certain degree for LatFlex. For AxRot, the discriminative power was limited. Other motion features like the basic gait cycles, i.e. basic oscillations of the motion signals, showed substantial variation inter- and intra-individually. Thus, they are not consistent within each person and cannot be considered as specific characteristics.

The analysis was based on dynamic ST measurements which allowed to record a wide range of vertebral segments during the motion task. Preprocessing was performed to extract the periodic oscillations of the basic gait cycles using a Log-Gabor filter. The resulting signals were subtracted from the original measurements to yield the rough orientational profiles, i.e. average rotations with additional minor details. A robust averaging technique yielded the neutral profiles which allowed a more robust discrimination of the test cases.

The observation that a neutral position of the spine is consistent for particular study subjects was also found in (Zwambag et al., 2019) for bending exercises in healthy subjects. Using a marker-based motion tracking system and a principal component analysis, it was analyzed that 85% of the motion variation for these types of movement is contained in components which basically reflect the neutral position of the spine. This relates to the neutral profiles in this paper. Our study extends the observation in (Zwambag et al., 2019) to gait sequences by demonstrating that the individual neutral position is a fundamental and consistent component of spinal motion. An assessment of intra-individual variation was not performed in (Zwambag et al., 2019) as no repeated tests were included.

For static ST-based analysis of spinal posture, some studies (e.g. (Degenhardt et al., 2020; Guidetti et al., 2013; Schroeder et al., 2015)) systematically assessed intra-individual variation of relevant measurements. High test-retest reliability was found for a substantial part of spinal parameters, even when performed on subsequent days. In (Schroeder et al., 2015), it was determined that the sagittal profile shows the lowest variation. These parameters can be considered as static counterparts of the dynamically assessed neutral profiles, as proposed in our study. In particular, the sagittal parameters are related to flexion/extension as the main rotation

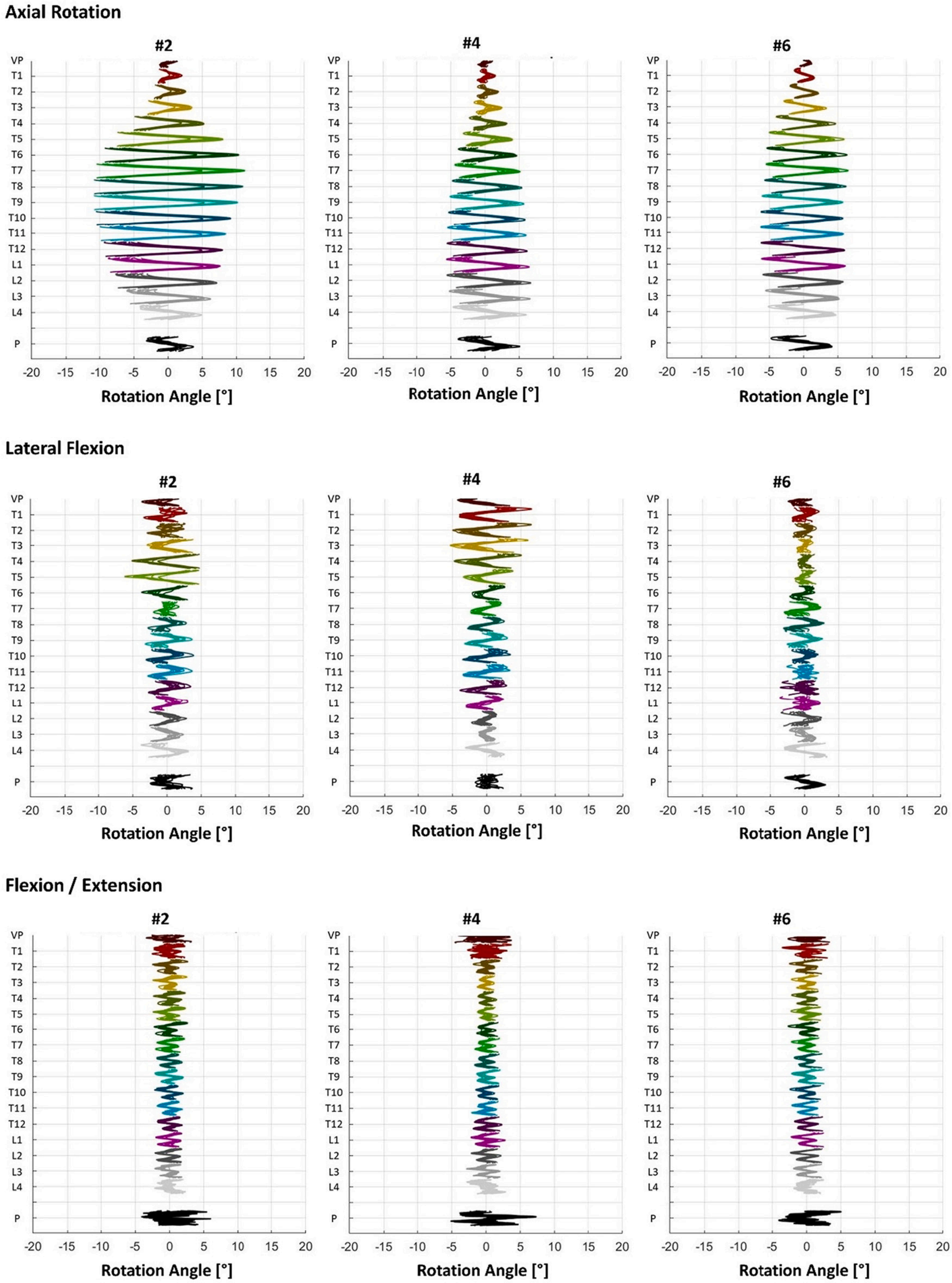

Fig. 7. Inter-individual variation of Log-Gabor signals (basic gait cycles) – for three different test persons walking at the same speed level (3 km/h). Top row: AxRot; middle row: LatFlex; bottom row: FlexExt. Parameters for the Log-Gabor filter were $\omega_0 = 10.0$ and $\sigma = 3.0$ for AxRot as well as LatFlex and $\omega_0 = 20.0$ and $\sigma = 6.0$ for FlexExt.

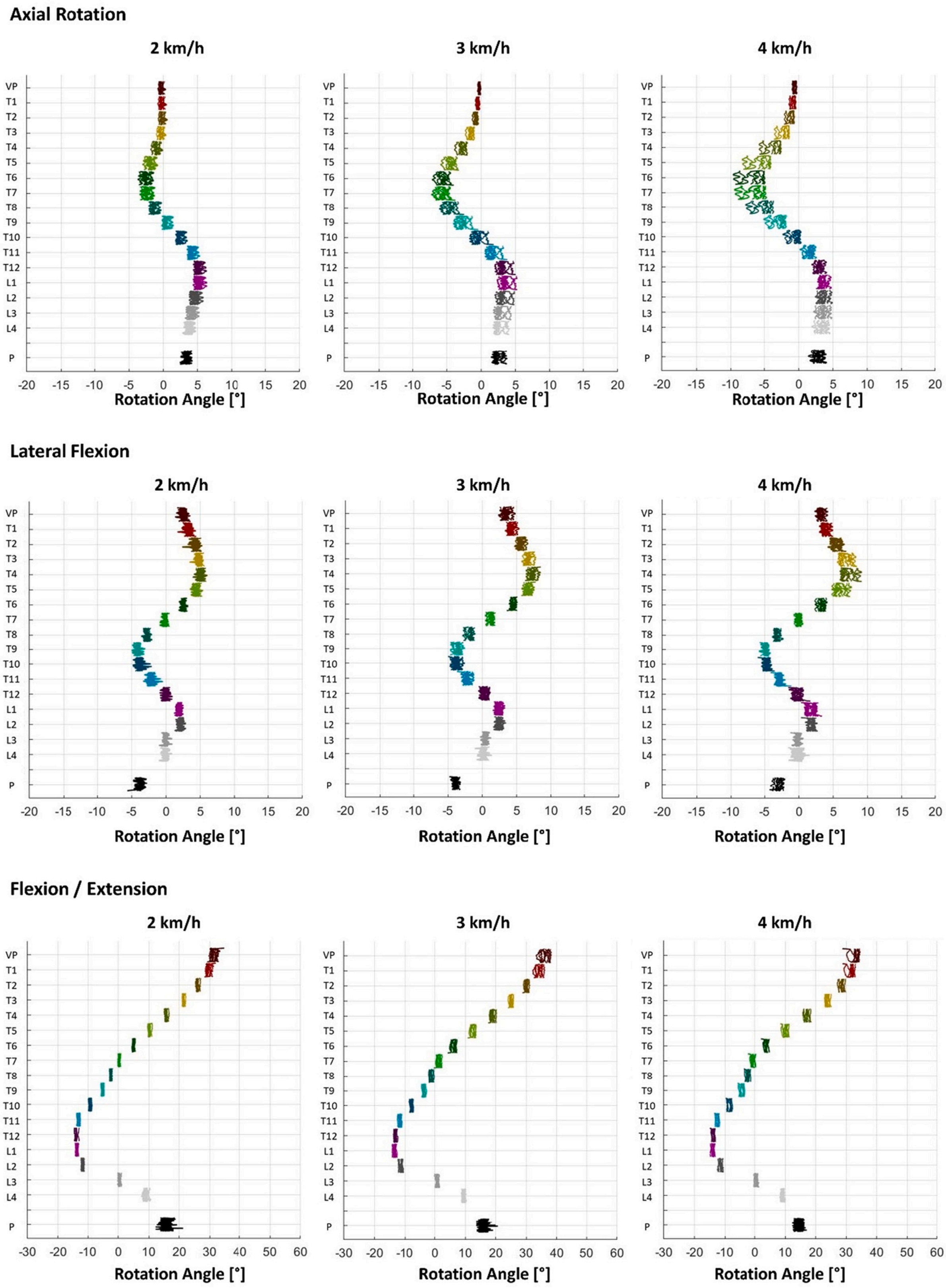

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Fig. 8. Intra-individual variation of rough orientational profiles (i.e. original data minus Log-Gabor filtered data) – for the same test person as before walking at different speed levels (2, 3, and 4 km/h). Top row: AxRot; middle row: LatFlex; bottom row: FlexExt. Parameters for the Log-Gabor filter were $\omega_0 = 10.0$ and $\sigma = 3.0$ for AxRot as well as LatFlex and $\omega_0 = 20.0$ and $\sigma = 6.0$ for FlexExt.

direction. Thus, the results from (Schroeder et al., 2015) are consistent with our findings, that flexion/extension has lowest intra-individual variation. In our study, this was intentionally analyzed in relation to inter-individual variation. Such an assessment was not included in (Degenhardt et al., 2020; Guidetti et al., 2013; Schroeder et al., 2015).

For the visual representations in our study, we used a 0° reference for the AxRot and LatFlex directions. Some studies (Kouwenhoven et al., 2006; Wolf et al., 2021) showed that even for normal subjects there are substantial deviations from this reference. Thus, a completely neutral alignment in terms of 0° is not necessarily given for AxRot and LatFlex. However, this observation does not impact the analysis of intra- and inter-individual variation, including the *k*-means analysis, since only relative deviations and no absolute numbers are relevant here. For FlexExt, there is the known deviation from 0° according to the natural sagittal profile of the spine. For a better visualization of the differences to a normal position in this motion direction, we added one representation where we subtracted the average orientation values across the entire series of test sequences from the neutral profiles.

Dedicated studies about the discriminative power of specific motion features are currently only available in very limited way, to the best of our knowledge. The predecessor paper (Haimerl et al., 2022) provided such an approach. But, (Haimerl et al., 2022) was restricted to a purely qualitative approach using different visual representations. Additionally, it did not separate the motion signals into main components, which could be used to obtain a more formalized and quantitative analysis. In (Dindorf et al., 2021), a machine learning approach was used to elaborate motion features which enable a discrimination between test persons. They found an even higher separation of individuals by combining all information (up to 100%) based on an overall ensemble (training and validation data sets) consisting of up to 226 healthy test persons. Then, their machine leaning approach elaborates features with high discriminative power. The downside is, that such automatically extracted features lack interpretability since they are complex combinations of motion parameters. In (Dindorf et al., 2021), the importance of particular vertebrae and motion directions were assessed as well, focusing on min, max, and range-of-motion (ROM) values. It was found that single values only achieve a limited discriminative power. Thus, a certain combination seems to be required for the separation of the test cases. The min, max and ROM values used in (Dindorf et al., 2021) correspond to the values in our study to a certain degree. The neutral profile values are approximately the average between the min and max values. The importance of particular min or max values may be better reflected by their average values or the neutral profile values, since the ROM of the particular vertebrae, i.e. motion amplitudes, seems to vary substantially, as demonstrated in our study. In general, a balance between accuracy and interpretability of the important features would be appreciated. Thus, the approach presented in (Dindorf et al., 2021) and the methods in our study have different focus points. These approaches may be combined in the future to achieve an even better overall picture of spinal motion.

Other studies (Christe et al., 2017; Mieritz et al., 2014; Needham et al., 2016; Papi et al., 2019; Schinkel-Ivy & Drake, 2015; Schmid et al., 2017; Tsang et al., 2017; Yun et al., 2015) primarily addressed an aggregating analysis of motion parameters based on calculating averages and/or variation ranges of the parameters/recorded data. Variation ranges were usually calculated as confidence intervals or intra-class correlations. A dedicated analysis about the relationship between intra- and interindividual variation was not performed in these studies. The evaluated parameters included specific curvature values (Schmid et al., 2017), mobility parameters and range-of-motion (e.g. (Needham et al., 2016; Papi et al., 2019; Schinkel-Ivy & Drake, 2015; Schmid et al., 2017)), specific gait parameters like cadence or step length ((Needham et al., 2016; Schmid et al., 2017)), or averages of motion waveforms (e.g. (Christe et al., 2017; Needham et al., 2016)). Many of the studies focused on the reliability of the measurements (e.g. (Mieritz et al., 2014; Needham et al., 2016; Papi et al., 2019; Schinkel-Ivy & Drake, 2015; Yun et al., 2015)). Most of the studies utilized marker-based motion capturing systems, which often did not provide signals representing a high number of vertebral motion segments as it was given in this study using ST.

Some of the studies included an analysis of gait (e.g. (Needham et al., 2016; Papi et al., 2019; Schmid et al., 2017)). Others additionally or purely addressed other motion tasks like forward bending, lateral bending, or axial twist (e.g. (Mieritz et al., 2014; Papi et al., 2019; Schinkel-Ivy & Drake, 2015; Tsang et al., 2017; Yun et al., 2015)). One study (Tsang et al., 2017) included an analysis of different speed levels with respect to forward bending. This is similar to our study where differences according to walking speed were a main objective of the analysis. For gait, a comparison of different speed levels was included in other studies (Lamoth et al., 2002; van Emmerik & Wagenaar, 1996; Wessel et al., 2013). It was determined that the relationship between relative phases of vertebral orientation changed depending on the walking speed. This shows the high intra-individual variation of certain parameters of spinal motion, which do not provide individual characteristics. It also shows the complexity of motion patterns in the human spine. In some studies (e.g. (Christe et al., 2017; Mieritz et al., 2014; Papi et al., 2019; Schmid et al., 2017)), a comparison between different groups was included, e.g. healthy vs. pathological conditions. Such an approach also tries to discriminate different test cases. But in this case, this is only performed on a group but not on an individual level. It can be helpful to first figure out, which features are individually consistent before group characteristics are addressed. This was the main focus of our study.

In summary, most of the studies available in the literature do not perform a dedicated analysis of the relationship between intra- and interindividual variation in a formalized way. Only (Dindorf et al., 2021) goes into this direction. Additionally, none of the studies included a separation between the basic oscillations in the gait cycles and the remaining major motion components in gait sequences. These two aspects were the main objectives in this paper. Our study had some limitations. Only a limited number of 11 test persons was included with a non-uniform distribution between males and females. Only asymptomatic and pain free subjects were included. Further on, the inclusion criteria were not formalized (except the BMI limit) and no concrete demographic data was recorded. Thus, an

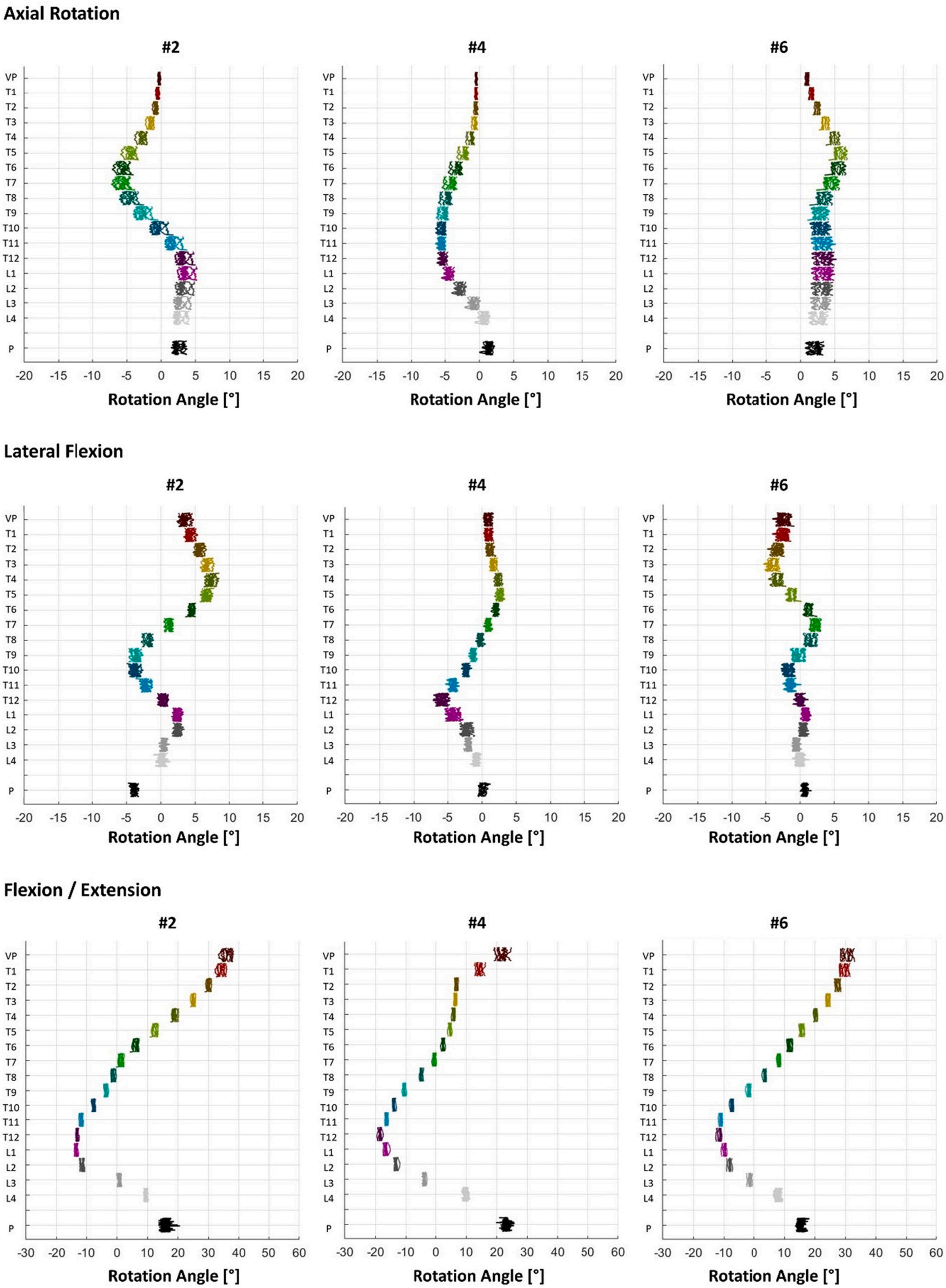

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Fig. 9. Inter-individual variation of rough orientational profiles (i.e. original data minus Log-Gabor filtered data) – for three different test persons walking at the same speed level (3 km/h). Top row: AxRot; middle row: LatFlex; bottom row: FlexExt. Parameters for the Log-Gabor filter were $\omega_0 = 10.0$ and $\sigma = 3.0$ for AxRot as well as LatFlex and $\omega_0 = 20.0$ and $\sigma = 6.0$ for FlexExt.

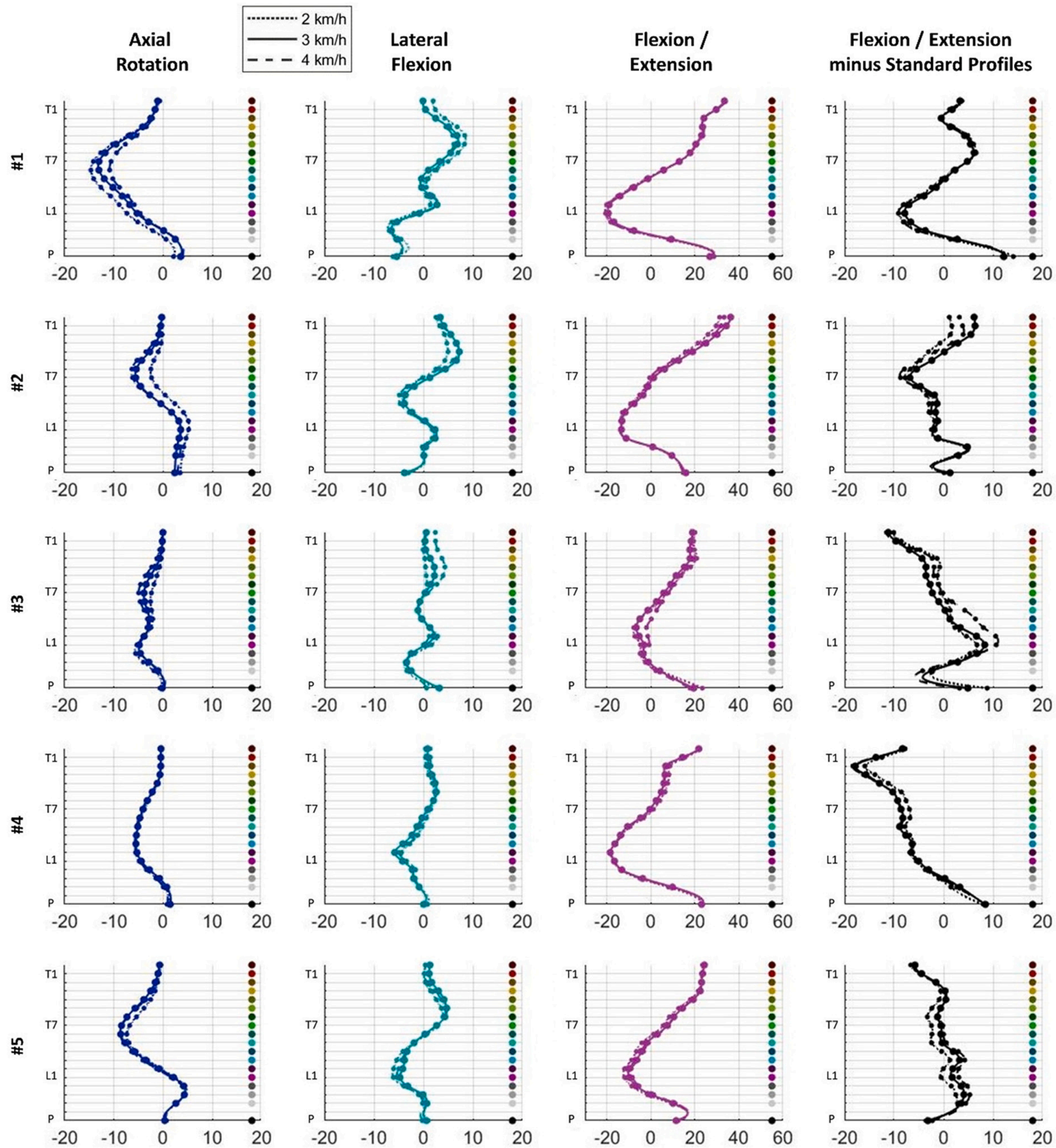

Fig. 10. Full comparison of neutral profiles – test persons #1 - #5 using the representation introduced in Fig. 5. The first three columns represent the rotation directions AxRot, LatFlex, and FlexExt. In the 4th column, the average sagittal profiles across all test persons are subtracted from the FlexExt values to better show the deviation from a standardized orientation in this direction. The different test persons (here #1 - #5) are shown in the particular lines. In each diagram, all three speed levels are shown in parallel (intra-individual comparison). They are presented using different line styles as given in the in the uncolored legend at the top.

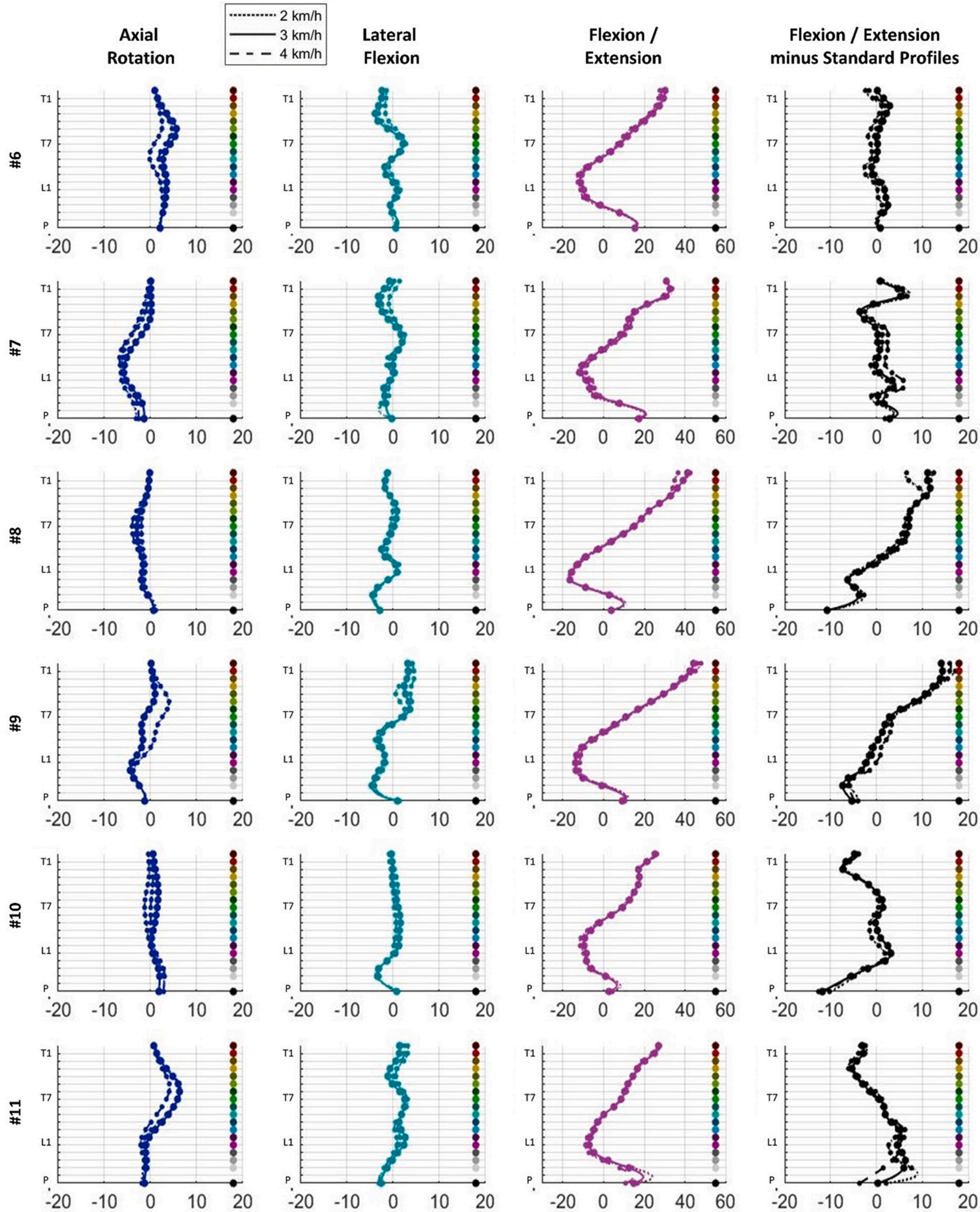

Fig. 11. Full comparison of neutral profiles – remaining test persons #6 - #11. See Fig. 10 for a description of the diagrams.

impact of specific pathological conditions or demographics on motion patterns could not be determined. The measurements for each single test person were performed on one day. Thus, the variation due to measurement artifacts caused by the setup were not included in the intra-individual data sets. The individual motion characteristics also may vary from day to day. Additionally, no direct quantitative assessment was included.

Table 1
Results of *k*-means clustering algorithm applied to rough orientational profiles (ROP) as well as neutral profiles (NP) for all rotation directions. The success of the algorithm as well as the number and types of misclassifications are listed. Parameters for the Log-Gabor filter were $\omega_0 = 10.0$ and $\sigma = 3.0$ for AxRot as well as LatFlex and $\omega_0 = 20.0$ and $\sigma = 6.0$ for FlexExt.

Rotation direction	Signal type	***k*-means:** success / misclassifications
AxRot	Rough orientational profiles (ROP)	One larger bundle of groups (test persons) mixed up: #3, #4, #7, #9
	Neutral profiles (NP)	Two bundles of groups (test persons) mixed up: one larger bundle with #3, #4, #7, #9, #11 and one smaller bundle with #6, #10
LatFlex	Rough orientational profiles (ROP)	One bundle of groups (test persons) mixed up: #3, #10
	Neutral profiles (NP)	Fully correct assignment
FlexExt	Rough orientational profiles (ROP)	Fully correct assignment
	Neutral profiles (NP)	Fully correct assignment

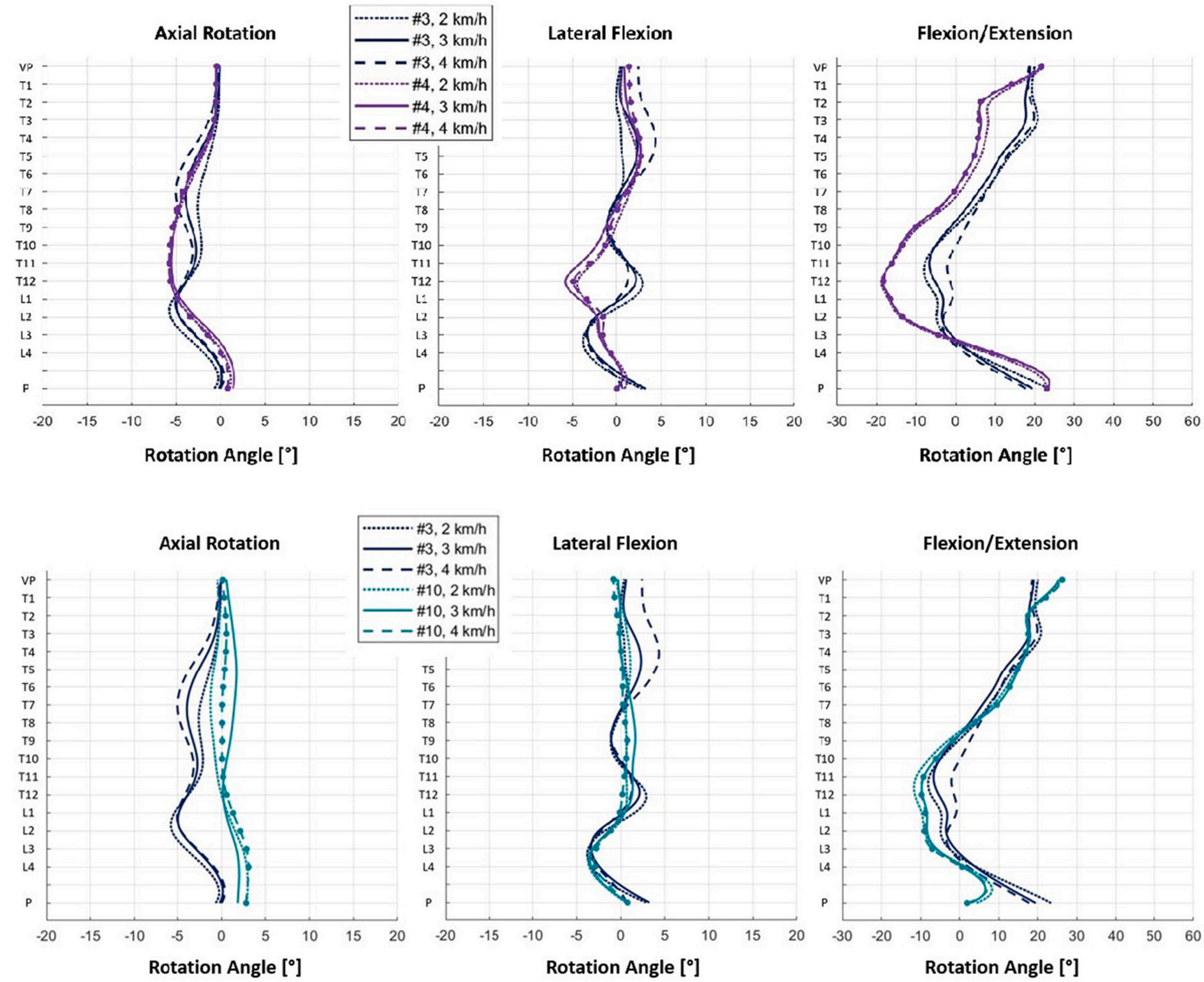

Fig. 12. Comparison of neutral profiles for critical cases – with respect to the discrimination between test persons: upper row – cases #3 and #4 where the separation failed for AxRot, bottom row – cases #3 and #10 where LatFlex had issues to discriminate the individuals (in particular, with respect to the rough orientational profiles). In both cases, the other motion directions could be utilized to achieve a proper discrimination.

A further limitation of our study is that no detailed validation of dynamic ST measurement data is available in the current literature, to the best of our knowledge. In particular, this applies to a detailed analysis of the full range of intervertebral motion. Basically, this is due to the missing gold standard (e.g. x-ray based measurements) for this type of data. However, the reliability and reproducibility of dynamic ST measurements has already been proven, as discussed in the introduction. Additionally, consistency with other references has been shown, e.g. in (Betsch et al., 2013) with respect to a marker-based measurement technique and a dedicated synthetic model in (Betsch et al., 2011). For example, marker detection at 3 km/h occurs with an accuracy of 0.03 mm (± 0.79 mm) as demonstrated in (Betsch et al., 2013). Even without proven accuracy in comparison to a gold standard, the reproducibility of ST measurements serves as a basis for analyzing inter- and intraindividual variation. Here, relative comparisons and not absolute accuracy are the key elements for the analysis. Additionally, not the comparison to a gold standard but the relation to clinical effects is most relevant when using motion analysis techniques for identifying important characteristics of spinal motion.

The results of our study could provide basic steps in this direction. Important motion characteristics could be identified that characterize individual test persons and were found to be robust with respect to the repetition of gait cycles as well as the variation of speed levels. The presented methods allow further insights into the kinematic behavior of the spine during specific motion tasks like gait. The analysis in this paper provides some prospects for further research. First, a systematic analysis regarding the combination of different motion directions of the spine should be performed. Within the given paper, the *k*-means algorithm was only applied to single motion directions. The extended analysis could also include an analysis of specific parts of the spine, e.g. lumbar, lower / upper thoracic spine, or even particular vertebrae. Second, it should be assessed how the methods perform when only three gait cycles are recorded, since this rather reflects the standard protocol of the ST system, which is subject to data processing limitations. This would also allow to apply the methods to other studies with a similar setup. The study at hand utilized an extended set of 10 cycles which allowed a more extensive assessment of variation. In general, an extension of the number of test cases / other studies should be addressed to provide a confirmation of the findings in our study. Additionally, the sequence of speed levels could be randomized to exclude habituation or fatigue effects for the higher speed levels. Third, a true quantitative assessment of the relationship between intra- and inter-individual variation would be beneficial to provide more detailed insights, e.g. about the statistical robustness of the study results. This could also be used to rate the contributions of the particular motion directions and spinal regions more precisely. Further on, a step back from the neutral profiles, i.e. only a single value per vertebra, towards an analysis of more detailed motion patterns would be helpful. The methods developed in this study provide a useful basis to address such extensions. This could be useful to identify specific groups of pathologies like pain, instabilities, arthritis, or patients after spondylodesis in a more detailed way. Finally, it could help to better understand the relation between vertebral motion and their impact on clinical findings.

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CRediT authorship contribution statement

Martin Haimerl: Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Validation, Project administration, Supervision, Writing – original draft. **Iman Nebel:** Methodology, Software, Visualization. **Alina Linkerhägner:** Investigation, Data curation. **Jürgen Konradi:** Conceptualization, Methodology, Validation, Project administration, Supervision, Writing – review & editing. **Claudia Wolf:** Methodology, Data curation, Formal analysis, Validation, Project administration, Writing – review & editing. **Philipp Drees:** Resources, Supervision. **Ulrich Betz:** Conceptualization, Methodology, Supervision.

Data availability

Data will be made available on request.

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Studies in humans and animals

The data used in this paper were obtained in a fully anonymized way as a part of a quality assurance step performed by the manufacturer of the used DIERS 4D motion® Lab / DIERS formetric 4D system. According to the responsible ethics committee of the medical chamber Rhineland-Palatinate (2021.03.11), there were no objections to statistically evaluate and publish them as anonymous results.

References

Applebaum, A., Ference, R., & Cho, W. (2020). Evaluating the role of surface topography in the surveillance of scoliosis. *Spine Deformity*. Advance online publication https://doi.org/10.1007/s43390-019-00001-7.

Betsch, M., Wild, M., Johnstone, B., Jungbluth, P., Hakimi, M., Kühlmann, B., & Rapp, W. (2013). Evaluation of a novel spine and surface topography system for dynamic spinal curvature analysis during gait. *PLoS One, 8*(7), Article e70581. https://doi.org/10.1371/journal.pone.0070581.

Betsch, M., Wild, M., Jungbluth, P., Hakimi, M., Windolf, J., Haex, B., Horstmann, T., & Rapp, W. (2011). Reliability and validity of 4D rasterstereography under dynamic conditions. *Computers in Biology and Medicine, 41*(6), 308–312. https://doi.org/10.1016/j.compbiomed.2011.03.008.

Bridge, C. P. (2017). Introduction to the monogenic signal. March 27 http://arxiv.org/pdf/1703.09199v1.

Christe, G., Kade, F., Jolles, B. M., & Favre, J. (2017). Chronic low back pain patients walk with locally altered spinal kinematics. *Journal of Biomechanics, 60*, 211–218. https://doi.org/10.1016/j.jbiomech.2017.06.042.

Ćuković, S. M., Taylor, W. R., & Ghionea, I. G. (2019). Technology-enhanced systems in idiopathic scoliosis 3D diagnosis and screening. In I. Karabegović (Ed.)*, vol. 42*. *Lecture notes in networks and systems: Vol. 42. New technologies, development and application* (pp. 271–278). Springer International Publishing. https://doi.org/10.1007/978-3-319-90893-9_33.

Degenhardt, B. F., Starks, Z., & Bhatia, S. (2020). Reliability of the DIERS formetric 4D spine shape parameters in adults without postural deformities. *BioMed Research International, 2020*, 1796247 https://doi.org/10.1155/2020/1796247.

Dindorf, C., Konradi, J., Wolf, C., Taetz, B., Bleser, G., Huthwelker, J., Werthmann, F., Drees, P., Fröhlich, M., & Betz, U. (2021). Machine learning techniques demonstrating individual movement patterns of the vertebral column: The fingerprint of spinal motion. *Computer Methods in Biomechanics and Biomedical Engineering*, 1–11. https://doi.org/10.1080/10255842.2021.1981884.

Drerup, B. (2014). Rasterstereographic measurement of scoliotic deformity. *Scoliosis, 9*(1), 22. https://doi.org/10.1186/s13013-014-0022-7.

van Emmerik, R., & Wagenaar, R. C. (1996). Effects of walking velocity on relative phase dynamics in the trunk in human walking. *Journal of Biomechanics, 29*(9), 1175–1184. https://doi.org/10.1016/0021-9290(95)00128-X.

Gipsman, A., Rauschert, L., Daneshvar, M., & Knott, P. (2014). Evaluating the reproducibility of motion analysis scanning of the spine during walking. *Advances in Medicine, 2014*, Article 721829. https://doi.org/10.1155/2014/721829.

Guidetti, L., Bonavolontà, V., Tito, A., Reis, V. M., Gallotta, M. C., & Baldari, C. (2013). Intra- and interday reliability of spine rasterstereography. *BioMed Research International, 2013*, Article 745480. https://doi.org/10.1155/2013/745480.

Haimerl, M., Nebel, I., Linkerhägner, A., Konradi, J., Wolf, C., Betz, U., & Drees, P. (2022). Comprehensive visualization of spinal motion in gait sequences based on surface topography. *Human Movement Science, 81*, Article 102919 (In press).

Huber, P. J., & Ronchetti, E. M. (2011). *Robust statistics (2. Aufl.). Wiley series in probability and statistics: v.693*. Wiley. http://www3.interscience.wiley.com/cgi-bin/homepage/?isbn=9780470434697. https://doi.org/10.1002/9780470434697.

Knott, P., Sturm, P., Lonner, B., Cahill, P., Betsch, M., McCarthy, R., Kelly, M., Lenke, L., & Betz, R. (2016). Multicenter comparison of 3D spinal measurements using surface topography with those from conventional radiography. *Spine Deformity, 4*(2), 98–103. https://doi.org/10.1016/j.jspd.2015.08.008.

Kouwenhoven, J.-W. M., Vincken, K. L., Bartels, L. W., & Castelein, R. M. (2006). Analysis of preexistent vertebral rotation in the normal spine. *Spine, 31*(13), 1467–1472. https://doi.org/10.1097/01.brs.0000219938.14686.b3.

Kovesi, P. (2000). Phase congruency: A low-level image invariant. *Psychological Research, 64*(2), 136–148. https://doi.org/10.1007/s004260000024.

Lamoth, C., Beek, P. J., & Meijer, O. G. (2002). Pelvis–thorax coordination in the transverse plane during gait. *Gait & Posture, 16*(2), 101–114. https://doi.org/10.1016/S0966-6362(01)00146-1.

Liu, X., Yang, X. S., Wang, L., Yu, M., Liu, X. G., & Liu, Z. J. (2019). Usefulness of a combined approach of DIERS Formetric 4D® and QUINTIC gait analysis system to evaluate the clinical effects of different spinal diseases on spinal-pelvic-lower limb motor function. *Journal of Orthopaedic Science : Official Journal of the Japanese Orthopaedic Association*. Advance online publication https://doi.org/10.1016/j.jos.2019.09.015.

Mieritz, R. M., Bronfort, G., Jakobsen, M. D., Aagaard, P., & Hartvigsen, J. (2014). Reliability and measurement error of sagittal spinal motion parameters in 220 patients with chronic low back pain using a three-dimensional measurement device. *The Spine Journal : Official Journal of the North American Spine Society, 14*(9), 1835–1843. https://doi.org/10.1016/j.spinee.2013.10.030.

Mohokum, M., Schülein, S., & Skwara, A. (2015). The validity of rasterstereography: A systematic review. *Orthopedic Reviews, 7*(3), 5899. https://doi.org/10.4081/or.2015.5899.

Needham, R., Naemi, R., Healy, A., & Chockalingam, N. (2016). Multi-segment kinematic model to assess three-dimensional movement of the spine and back during gait. *Prosthetics and Orthotics International, 40*(5), 624–635. https://doi.org/10.1177/0309364615579319.

Papi, E., Bull, A. M. J., & McGregor, A. H. (2019). Spinal segments do not move together predictably during daily activities. *Gait & Posture, 67*, 277–283. https://doi.org/10.1016/j.gaitpost.2018.10.031.

Scheidt, S., Endreß, S., Gesicki, M., & Hofmann, U. K. (2018). Using video rasterstereography and treadmill gait analysis as a tool for evaluating postoperative outcome after lumbar spinal fusion. *Gait & Posture, 64*, 18–24. https://doi.org/10.1016/j.gaitpost.2018.05.019.

Schinkel-Ivy, A., & Drake, J. D. M. (2015). Which motion segments are required to sufficiently characterize the kinematic behavior of the trunk? *Journal of Electromyography and Kinesiology : Official Journal of the International Society of Electrophysiological Kinesiology*, 239–246. https://doi.org/10.1016/j.jelekin.2014.12.008.

Schmid, S., Bruhin, B., Ignasiak, D., Romkes, J., Taylor, W. R., Ferguson, S. J., Brunner, R., & Lorenzetti, S. (2017). Spinal kinematics during gait in healthy individuals across different age groups. *Human Movement Science, 54*, 73–81. https://doi.org/10.1016/j.humov.2017.04.001.

Schroeder, J., Reer, R., & Braumann, K. M. (2015). Video raster stereography back shape reconstruction: A reliability study for sagittal, frontal, and transversal plane parameters. *European Spine Journal : Official Publication of the European Spine Society, the European Spinal Deformity Society, and the European Section of the Cervical Spine Research Society, 24*(2), 262–269. https://doi.org/10.1007/s00586-014-3664-5.

Tabard-Fougère, A., Bonnefoy-Mazure, A., Hanquinet, S., Lascombes, P., Armand, S., & Dayer, R. (2017). Validity and reliability of spine rasterstereography in patients with adolescent idiopathic scoliosis. *Spine, 42*(2), 98–105. https://doi.org/10.1097/BRS.0000000000001679.

Tan, P.-N., Steinbach, M., & Kumar, V. (2014). *Introduction to data mining (First edition, Pearson new international edition)*. Pearson.

Tsang, S. M. H., Szeto, G. P. Y., Li, L. M. K., Wong, D. C. M., Yip, M. M. P., & Lee, R. Y. W. (2017). The effects of bending speed on the lumbo-pelvic kinematics and movement pattern during forward bending in people with and without low back pain. *BMC Musculoskeletal Disorders, 18*, 157. https://doi.org/10.1186/s12891-017-1515-3.

Wessel, J., Pierrynowski, M. R., Pennell, K., & Woodhouse, L. J. (2013). Reliability and validity of spinal coordination patterns during treadmill walking in persons with thoracic spine pain–a preliminary study. *BMC Musculoskeletal Disorders, 14*, 345. https://doi.org/10.1186/1471-2474-14-345.

Wolf, C., Betz, U., Huthwelker, J., Konradi, J., Westphal, R. S., Cerpa, M., Lenke, L., & Drees, P. (2021). Evaluation of 3D vertebral and pelvic position by surface topography in asymptomatic females: Presentation of normative reference data. *Journal of Orthopaedic Surgery and Research, 16*(1), 703. https://doi.org/10.1186/s13018-021-02843-2.

Yun, W.-S., Kim, H., Ahn, J. H., Park, Y.-B., & Park, Y.-J. (2015). Individual characteristics of reliable lumbar coupling motions. *European Spine Journal : Official Publication of the European Spine Society, the European Spinal Deformity Society, and the European Section of the Cervical Spine Research Society*, 1917–1925. https://doi.org/10.1007/s00586-015-4081-0.

Zwambag, D. P., Beaudette, S. M., Gregory, D. E., & Brown, S. H. M. (2019). Distinguishing between typical and atypical motion patterns amongst healthy individuals during a constrained spine flexion task. *Journal of Biomechanics, 86*, 89–95. https://doi.org/10.1016/j.jbiomech.2019.01.047.