Non-age-related Gait Kinematics and Kinetics in the Elderly

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Non-age-related Gait Kinematics and Kinetics in the Elderly

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Abstract

Background: Non-age-related gait kinematics and kinetics are essential indicators for gait with normal function. They are instrumental in clinical evaluation and assistant device design. However, only a few studies focus on non-age-related gait analysis. This study aims to identify the non-age-related gait kinematics and kinetics by comparing their normalized time-varying waveforms in the healthy elderly and young groups.

Methods: Gait analysis for each gait cycle at self-paced is conducted from marker trajectories and ground reaction force. Pattern distance and percentage of significant difference between the young and elderly are calculated to represent the two sets of waveforms. The k-means clustering and elbow method are used to select and validate non-age-related kinematics and kinetics. The average waveforms with standard deviation are plotted for the comparison of the results.

Results: There is no significant difference in weight and height between two aging groups. The elbow point is where the k value equals two. The cluster centers of the two groups are 0.1417 and 0.3691 while total Euclidean distances are 0.001794 and 0.02750, respectively. The two critical values closest to the cutoff are 0.1593 and 0.3037. The average waveforms of the non-age-related group are highly overlapped with a minor standard deviation between healthy young and elderly groups but show lager variations between healthy and abnormal groups.

Conclusions: Ankle moment, knee angle, hip flexion angle, and hip adduction moment are identified as the non-age-related gait kinematic or kinetic features with distinguishing cutoff. These features are validated to reflect abnormal walking function, which is essential in the evaluation of mobility and functional ability of the elderly, and data fusion of the assistant device.

Keywords: Non-age-related gait analysis, kinematics, kinetics.

Background

The gait analysis of kinematics and kinetics is an important measurement for evaluating mobility quality and functional ability in the elderly[1-3], to be used for assessment of the effect of clinical treatments and physiotherapy interventions[4-6]. It is also a useful tool to investigate biomechanical mechanisms for developing novel assistant devices including various rehabilitation or

assistant robots[7-9]. It is noted that a lot of different gait patterns between healthy elderly and young adults at their self-selected speed have been reported age-related in previous studies[10-20]. However, a few studies focus on non-age-related kinematics and kinetics, which is as important as age-related gait analysis. When a kinematic or kinetic feature does not correlate with aging, this feature is essential to perform a defined activity for normal function.

To facilitate the evaluation of mobility quality and functional ability in the elderly, a normal reference of kinematic and kinetic features in the healthy population should be established. Generally, the healthy elderly data is not as easily collected as the young because the risk of getting diseases increases with age. In this case, the determined non-age-related gait kinematics and kinetics are impactful to identify the representative key features and prompt the data fusion of the elderly and young groups. In addition, therapists could pay more attention to these features to evaluate whether different motion patterns are abnormal or caused by individual and age variation, because the age-related waveforms are in worse intragroup and intergroup consistency.

Considering the age-related gait features, elderly individuals tend to walk at a slower speed, take shorter step length and stride length, and spend more time on the double support phase[10-13]. It is widely reported that they adopt altered kinematics and kinetics as a compensation strategy due to muscle weakness or actuator impairment[14, 15], including a larger hip extension angle and moment, lower ankle plantarflexion, and a smaller range of motion (ROM)[16-18]. Although speed is also taken into consideration for its impact on the waveforms, variation persists[19-21]. In this study, we introduce a time series analysis approach to select non-age-related kinematics and kinetics. We calculate the pattern distance[22] and the percentage of significant difference for healthy groups on each joint. Then we determine and validate the classification by the k-means algorithm and elbow method[23]. The selected no-age-related features are also compared and evaluated to the elderly with mild walking issues.

Methods

A. Subjects

A total of 22 subjects were recruited for this study. There were 12 healthy young adults under 55 years old in the young group, 8 healthy elderly adults over 55 years old in the elderly group, and 2 elderly adults with mild walking issues in the abnormal group. The healthy groups were screened by an online self-reported questionnaire. The inclusion criteria were self-reported healthy with normal daily activity ability and no walking difficulty. The exclusion criteria included a history of orthopedic diagnosis, joint pain, neurological disease, and memory or cognitive problems with mobility impairment[24]. Women with pregnancies were excluded as well. In the abnormal group, one subject was in bilateral knee pain, especially when walking downstairs and the other had right patella fracture surgery in Jan. 2017. This study was performed in accordance with the Declaration of Helsinki and approved by the Ethics Committee of The University of Hong Kong - Shenzhen Hospital (2021-032).

B. Motion Capture

The motion capture system was Vicon (Oxford, UK) at 100 Hz with 12 cameras and two force plates (AMTI, USA). We placed 39 spherical markers with 14 mm diameter on the anatomical joints in accordance with the Plug-in full limb model[25]. And we calibrated the system till the world error of all cameras was less than 2 mm. Each subject performed at least one trial of static pose and ten to fifteen trials of self-selected speed barefoot walking at a 10 m even walkway.

C. Data Processing and Gait Measurement

We preprocessed the gait data of each subject on Vicon to select one to three valid trials. Notably, we regarded the trials with two whole feet on the force plates separately during walking as valid trials. For each valid trial, we selected two representative gait cycles (left gait cycle and right gait cycle) based on the force plate feedback and output marker trajectories and force data for further processing. To be specific, we got 66 gait cycles for the young, 32 for the healthy elderly and 6 for the abnormal group.

OpenSim 4.1[26] was adopted for the analysis. The measurement of gait kinematics and kinetics was performed on Gait2354[27] (Fig. 1). In this model, the hip, knee and ankle was defined in three, one and one degrees of freedom, respectively. We attached 16 virtual markers in accordance with the Plug-in lower limb marker placement on this model and additionally added the 10th thoracic vertebrae marker on the trunk. For each subject, we scaled the skeleton model using their static pose to match their anthropometry by minimizing the different locations between the experimental and corresponding virtual markers. We adjusted the location of virtual markers based on the static pose videos to reduce the maximum marker error until less than 4 cm and the root mean square marker error until less than 2 cm. Then for each representative gait cycle, we used an inverse kinematics algorithm[26] with marker trajectories to reproduce the gait of the subject and recorded the kinematic results of each joint. An inverse dynamics algorithm[26]

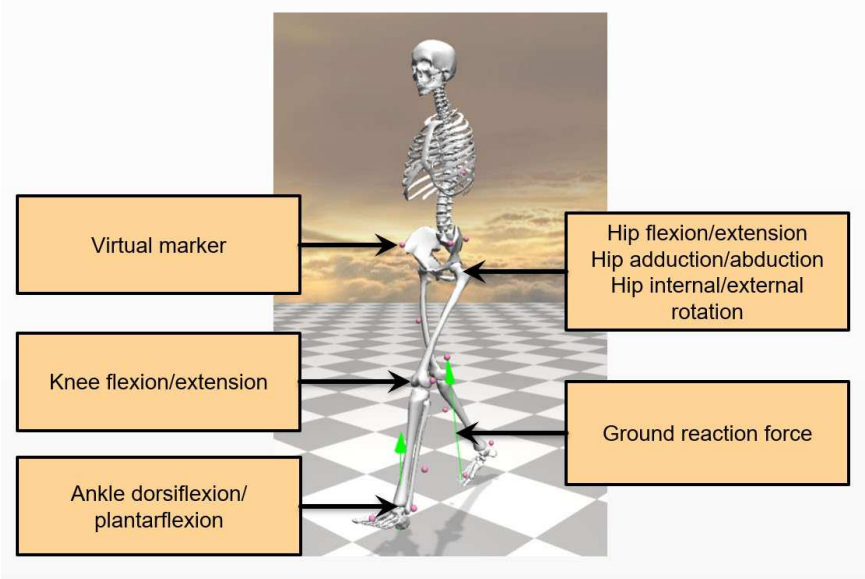

Fig.1. Visualization of Gait2354 model on OpenSim. The joints of interest are noted, including hip, knee and ankle. Pink balls are virtual makers that we set to drive the skeleton. Green arrows denote ground reaction force obtained from the force plates during walking.

was applied with ground reaction force on each foot to estimate the joint torques that reproduced the gait kinematics. We adopted a 1-D interpolation fast Fourier transform method[28] to normalize the waveforms to the same time length and marked the gait cycle from 0 to 100%. The amplitude of moment-related waveforms was normalized by their height and weight. To be specific, ankle angle, ankle moment, knee angle, knee moment, hip flexion angle, hip flexion moment, hip adduction angle, hip adduction moment, hip rotation angle, and hip rotation moment are measured.

D. Data Analysis

Independent two-sample t-tests were adopted to evaluate the amplitude difference in the healthy elderly and young groups. We statistically analyzed whether a significant difference existed at every time point of the waveform. Then we counted the percentage where there were significant differences of each waveform and considered it as percentage t-test. We also calculated the mean value and standard deviation of the waveforms and ROM in each group.

In order to fully consider the temporal information, especially the trend change in the waveform, we calculated the pattern distance[22] between two healthy groups. We used piecewise linear representation to divide the waveform into pieces along the timeline based on slope. To be specific, the cutoff of each piece was the peak in the waveform. For each piece， it was marked as 1 with positive slope, -1 with negative slope, and 0 with no slope). Followed by this, a waveform W_1 with peak number of i could be represented as:

$$W_1 = \{(s_{11}, t_{11}), (s_{12}, t_{12}), \dots, (s_{1i}, t_{1i})\}$$

where $s_{1i} \in S = \{1, -1,\ 0\}$ denotes the slope and t_{1i} are peak times including the start and end points. For two average waveforms, all peak times were found and ordered. Then we divided them into pieces in the same amount. The distance $D_{W_1W_2}$ could be calculated as:

$$D_{W_1W_2} = \sum_{j=1}^{k} t_{Nj} * |s_{1j} - s_{2j}|$$

where k is the total peak number, $t_{Nj} = \frac{t_j}{t_N}$, t_j denotes time period of piece j, and t_N denotes the total time of the waveform. Afterward, we normalized $D_{W_1W_2}$ to [0 , 1] by dividing the theoretical maximum value 2.

For each waveform, the mean value of the percentage t-test and pattern distance was set as a parameter to indicate the degree of difference in amplitude and temporal change. Closer to 1 indicates a greater difference. Then we adopted k-means clustering algorithm to categorize these waveforms into two groups. The non-age-related group was those with values closer to 0. The elbow method[23] was also used to validate whether two classes were the most proper k value to conduct the clustering. To be specific, we used the sum of Euclidean distance as a function of the number of clusters, and picked the elbow of the curve as the number of clusters to use.

Results

The young group contains 3 males and 9 females with an average age of 28.7 (SD=5.17) in a range from 22 to 40 years old. Subjects in the young group were measured with a bodyweight of 58.7 (SD=10.27) kg and a height of 1.66 (SD=0.07) meters. The elderly group contains 4 males and 4 females with an average age of 63.6(SD=6.14), ranging from 56 to 72 years old. Subjects in the elderly group were measured with a bodyweight of 57.6 (SD=11.78) kg and a height of 1.63 (SD=0.10) meters. There is no significant difference in weight and height between two healthy groups with p values of 0.829 and 0.599 according to the t-test result. The abnormal group includes 2 females with the age of 71 and 73. They are measured with bodyweights of 55.9 and 56.3 kg a height of 1.67 and 1.58 meters.

Table 1. is arranged according to the values of Mean (percentage t-test, pattern distance) from the smallest to largest. The clustering results indicate that the first four waveforms are in non-age-related group and the rest are in age-related group. The cluster centers of two groups are 0.1417 and 0.3691 and total Euclidean distances are 0.001794 and 0.02750, respectively. Fig. 2

TABLE 1. RESULTS OF PERCENTAGE T-TEST, PATTERN DISTANCE AND THEIR MEAN VALUES

Kinematics and Kinetics	percentage t-test	pattern distance	Mean (percentage t-test, pattern distance)	Clustering Results
Ankle Moment	0.1926	**0.2222**	0.1074	Non-age-related
Hip Flexion Angle	0.2593	**0.2222**	0.1407	
Knee Angle	**0.3111**	0.0074	0.1593	
Hip Adduction Moment	0.1778	0.1407	**0.1593**	
Hip Flexion Moment	0.5037	0.1037	**0.3037**	Age-related
Knee Moment	0.5556	**0.0593**	0.3074	
Hip Rotation Moment	**0.4222**	0.2148	0.3185	
Ankle Angle	0.6740	0.1037	0.3889	
Hip Adduction Angle	0.6593	0.1481	0.4037	
Hip Rotation Angle	0.7778	0.2074	0.4926	

This table shows the results of three methods we used in the data analysis. Orders of the results are arranged according to the values of Mean (percentage t-test, pattern distance) from the smallest to largest. The first four lines are non-age-related group based on the k-means clustering results and the rest are age-related group. The bold value denotes the largest and smallest values in the non-age-related and age-related groups respectively.

TABLE 2. RANGE OF MOTION IN KINMETICS AND KINETICS FOR YOUNG AND ELDERLY GROUP

Kinematics and Kinetics	Young	Elderly
Ankle Angle	36.297(9.753)	28.701(5.574)
Knee Angle	62.066(4.186)	57.707(5.589)
Hip Flexion Angle	41.432(5.811)	**44.335(4.109)**
Hip Adduction Angle	14.626(3.004)	**15.580(4.007)**
Hip Rotation Angle	11.652(4.420)	**14.780(4.787)**
Ankle Moment	0.878(0.076)	0.845(0.084)
Knee Moment	0.458(0.122)	0.418(0.083)
Hip Flexion Moment	0.664(0.140)	**0.780(0.168)**
Hip Adduction Moment	0.519(0.099)	**0.540(0.103)**
Hip Rotation Moment	0.101(0.035)	0.095(0.032)

This table shows the average range of motion and corresponding standard deviation of each waveform of kinematics or kinetics. We bold the greater value in the elderly group compared with the young group.

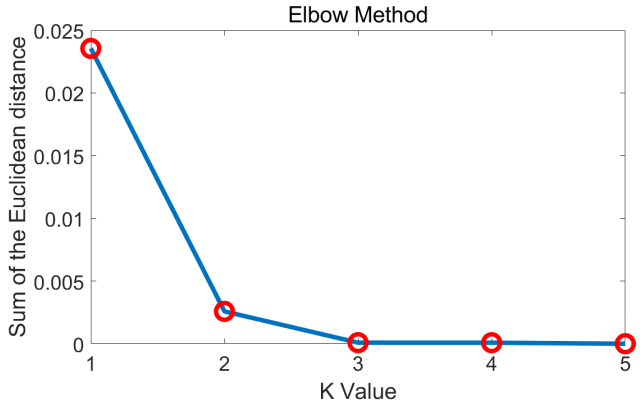

Fig. 2. Results of elbow method. The horizontal axis is k value we set for the k means clustering and the vertical axis is the corresponding sum of the Euclidean distance. The elbow cut-off point is where k value equals 2.

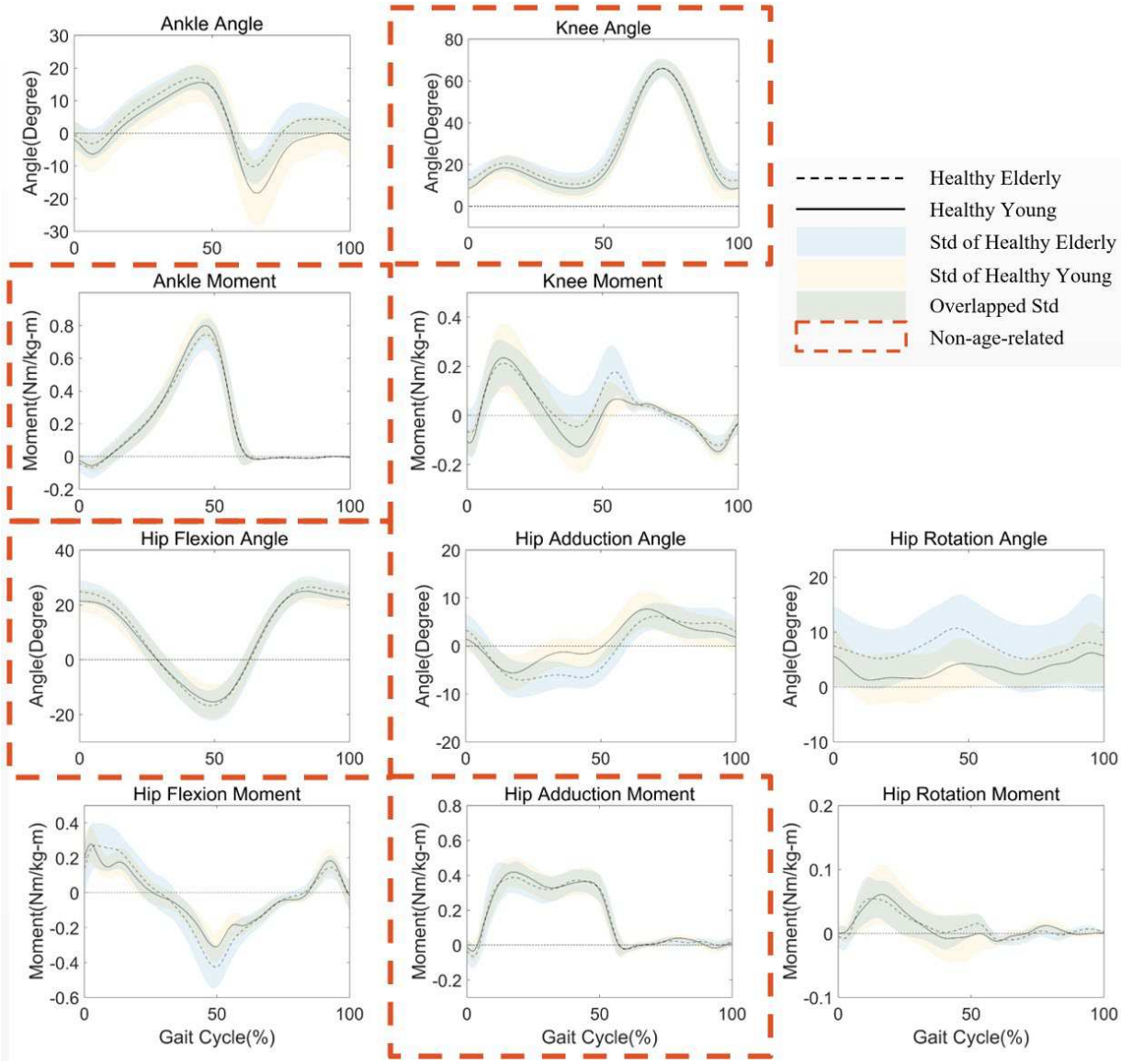

Fig. 3. Results of average waveforms with standard deviation for the healthy young and elderly group, including kinematics and kinetics of interested joints. The horizontal axis is normalized to one gait cycle in percentage from 0 to 100. The black dashed line in each subplot denotes the average waveform of the healthy elderly group and the black solid line denotes the young group. The standard deviation of the healthy elderly group is blue area and that of the young group is in yellow. The overlapped area is in green. Subplots with red dashed contours are determined as the non-age-related group by final k means clustering, which contains ankle moment, knee angle, hip flexion angle and hip adduction moment.

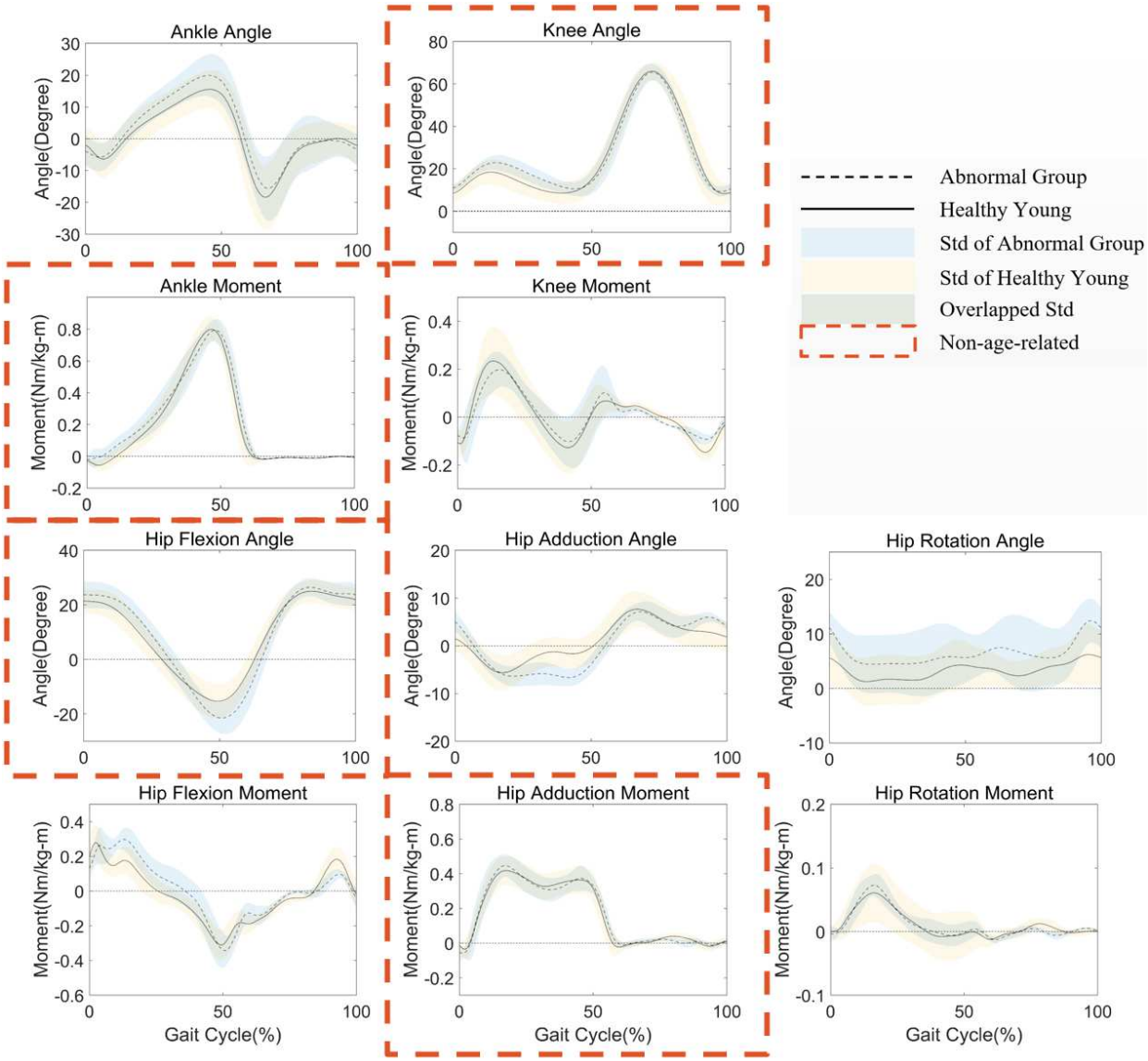

Fig. 4. Results of average waveforms with standard deviation for the healthy young and abnormal group. Each subplot is set the same as in Fig. 3. The black dashed line in each subplot denotes the average waveform of the abnormal group and the black solid line denotes the young group. The standard deviation of the abnormal group is blue area and that of the young group is in yellow. The overlapped area is in green. Subplots with red dashed contours are determined as the non-age-related group.

shows the elbow point is where the k value equals 2, which means the most proper number of clustering classes are two. The average waveforms of the healthy groups with standard deviation are shown in Fig. 3. Four waveforms with red dashed contours are determined as the non-age-related group by clustering. They are ankle moment, knee angle, hip flexion angle, and hip adduction moment. As the comparison, Fig. 4 shows the average and standard deviation in abnormal and young groups. The ROM in kinematics and kinetics for the healthy young and elderly groups is in Table. 2 and the larger values in the healthy elderly group are bolded.

Discussion

Non-age-related kinematics and kinetics are essential to evaluate gait in normal function. This study aims to identify them by comparing normalized waveforms in the elderly and young groups. OpenSim is adopted to analyze kinematics and kinetics from Vicon marker trajectories and AMTI ground reaction forces. We use percentage t-test and pattern distance to describe the waveforms. Then k-means clustering and elbow method are utilized to find and validate the cutoff point of the non-age-related group. Eventually, ankle moment, knee angle, hip flexion angle, and hip adduction moment are categorized into the non-age-related group. This result is supportive of the conclusion in [29] that sagittal plane joint angles are not different between healthy groups at the hip or knee. It is also important for clinical evaluation and data fusion. Therapists could focus on them to differentiate the abnormal gait patterns and individual or age variation, and evaluate the treatment and intervention effect. Mobility devices for the elderly such as exoskeleton robots, assistive robots, and prosthetics, etc., could be designed similar to the young in non-age-related kinematics and kinetics.

The advantages of our analysis methods are shown in the full consideration of the spatial-temporal information and slope changes, and making all the kinematics and kinetics comparable. In some studies, the maximum and minimum values, and ROM are utilized for the comparison[17, 30]. These approaches do not take into account the temporal information of the waveforms. Some researchers divide the gait cycle into several pieces based on the key events and phases[31], while this method can't assess the similarity of the waveforms as a whole. In [29, 32], they select principal component analysis to reduce the dimension of gait data and identify the differences between the elderly and young groups. Some works apply t-tests on waveforms and plots h-values along the timeline to indicate the variation[21]. Although these two methods consider the temporal aspect of waveforms, they don't make full use of the amplitude and trend changes over time, which is directly correlated to the interpretation of spatial-temporal gait analysis. In comparison, we use t-test to calculate percentage that shows significant difference between the young and elderly in each kinematics and kinetics. This method could differentiate amplitude variations very well at every time point. Then we calculate the pattern distance along gait cycle axis to extract the trend difference. This approach compensates the temporal information to percentage t-test and reduces the impact of the absolute amplitude value. Therefore, the kinematics and kinetics are comparable even though the angle values are generally much greater than the moment value. And the mean value of these two normalized results is used for the final classification by k means clustering.

In the results, the cutoff point of non-age-related group is very clear and validated by elbow method. And the selected kinematics and kinetics show high consistency in the two healthy groups. We bold the largest value in no-age-related group and the smallest value in age-related group in Table 1. The smallest four values of the percentage t-test are in non-age-related group, which is evidence to a consistent conclusion. However, two values close to the cutoff (0.3111 and 0.4222) are not in significant variance compared with the Mean (percentage t-test, pattern distance) method (0.1593 and 0.3037). Age-related group contains smaller pattern distance values than those in the non-age-related group while they are with apparent standard deviation. The obvious turning

point in Fig.2 strongly supports that our approach has successfully found the non-age-related kinematics and kinetics. In Fig. 3, the waveforms in the non-age-related group show lower intragroup and intergroup variation. The average waveforms are with relatively higher consistency in both amplitude and temporal changes considering the range of motion. And the standard deviation areas are also smaller, and highly overlapped. The hip rotation angle shows the worst performance in both percentage t-test and Mean (percentage t-test, pattern distance) method. We could observe from the waveform that it shows large deviation in both young and elderly groups and the value of mean waveform has a significant difference. As a comparison, the ankle moment performs best in Mean (percentage t-test, pattern distance). Its intragroup deviation is small and mean waveforms are highly overlapped. These results indicate that non-age-related waveforms are consistent with age and individual. In Fig. 4, the non-age-related features shows clear variation between the healthy young and abnormal elderly group compared with those in Fig. 3, especially knee angle, ankle moment and hip flexion angle. And the age-related features are remained large difference. These results prove that non-age-related features are able to reflect abnormal walking function, which is valuable to the clinical evaluation. Moreover, we also find that the values showing larger ROM in the elderly group are all relevant to the hip in Table 2, which could be explained by elderly adults has a greater hip extensor recruitment during gait as a compensation strategy[33].

Conclusions

Some kinematic and kinetic features in gait analysis are found identical in healthy young and elderly groups. Ankle moment, knee angle, hip flexion angle and hip adduction moment are identified as the non-age-related gait kinematics and kinetics. We find these features are able to reflect abnormal walking function, which has been validated on abnormal elderly. This study result is essential in the evaluation of mobility quality and functional ability of the elderly, and data fusion of the mobility device.

List of abbreviations

ROM: Range of motion.

Declarations

Ethics approval and consent to participate

The study was performed in accordance with the Declaration of Helsinki and approved by the Ethics Committee of The University of Hong Kong - Shenzhen Hospital [2021] 032. All study participants gave full informed written consented to take part.

Consent for publication

Not applicable.

Availability of data and materials

The data collected and analyzed in the present study are not publicly available due to ethical restrictions but are available from the corresponding author upon request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

All authors were involved in the design of the study protocol. Y. L and Y. H were the principal investigators in this project and the contact person responsible for ethical approval. Y. L, T. X and X. C were responsible for the subject recruitment and data collection. Y. L, T. X and S. Q conducted the outcome measures and data processing. Y.L and S. Q were responsible for the statistical analysis. Y. L, E. Y and Y. H evaluated the outcome. The writing of the manuscript was guided by Y. H. All authors contributed to parts of the manuscript and have read and approved the final manuscript.

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Not applicable.

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