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Original Research

Artificial Intelligence Approach in Biomechanical Analysis of Gait

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ABSTRACT

The objective of the current investigation was to conduct a biomechanical analysis of human gait based on the Unsupervised machine learning – Artificial Intelligence approach. Twenty-eight junior active males participated in the study. Following the placement of the markers, the participants were asked to complete the gait task in a 10-meter gateway where the dominant leg contact was placed on the third step and non- non-dominant leg on the fourth step. The task was executed in two separate attempts, first by the preferred speed of the participants and second with a steady speed of 100BPM. The Hierarchical approach consisting of Nearest Neighbor and the utilization of Z score was employed to discern uniform gait biomechanical patterns of the entire participant according to the values of joint angles and joint moments in both conditions - preferred and steady speeds by SPSS software version 26 ($p<0.05$). Considering a combination of both kinematics and kinetics parameters, in preferred speed, the hip and knee in the vertical direction for both dominant and non-dominant limbs are classified in one cluster, but in a steady speed, the hip in mediolateral direction and knee in the vertical direction for both dominant and non-dominant limbs are presented in one cluster. The kinematic and kinetic variables are useful in gate clustering to categorize gait patterns. These variables can be subdivided into homogeneous subgroups for a more detailed understanding of human locomotion.

Keywords: Artificial Intelligence, Gait, Biomechanics, Machine learning, Clustering

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INTRODUCTION

Gait, being crucial elements of human existence, are commonly evaluated through the utilization of biomechanical gait analysis as a means of assessing abnormal gait patterns and scrutinizing athletic prowess [1]. This is of paramount importance in detecting gait irregularities, identifying postural abnormalities, and evaluating clinical modalities and rehabilitation regimens [1, 2]. It is of considerable significance to acknowledge that the examination of gait entails a substantial quantity of mutually reliant variables, which can be difficult to interpret due to the vast amount of data and their inter-relations [1]. However, significant progress in motion capture equipment, research methodologies, and data analysis techniques has led to abundance of investigations being conducted, which have contributed to the enhancement of our comprehension of gait biomechanics. Such studies have provided invaluable insights into the intricate mechanisms that govern human gait, and have paved the way for further advancements in this field of research.

The investigation of the mechanical properties of the human body, commonly referred to as gait analysis, is designed to measure the variables that impact the efficacy of the lower extremities. The researchers envision the implementation of gait analysis as a tool for both diagnosis and treatment selection. However, they have encountered considerable obstacles in this endeavor due to intricacies such as the sheer volume of data involved and the lack of distinct correlations between an individual's gait and their condition [3, 4].

The escalating volume of data in the realm of biomechanics research has significantly amplified the significance of enlisting innovative methodologies such as artificial intelligence that possess superior capabilities in managing large-scale data, called “big data”[4]. As a result, the progression of data science techniques will broaden the understanding of examining novel hypotheses concerning biomechanical risk factors and performance-linked variables linked with the biomechanics of walking and running gait [4]. A bipedal locomotion or gait pattern may be subdivided into the stance and swing phases, which are distinguished by the occurrence of initial contact and toe-off instance. Kinetic and kinematic parameters are capable of identifying gait patterns throughout the process of gait progression [5].

The study carried out by Farah and colleagues established that the identification of gait phases can be executed through the utilization of machine learning techniques [6]. As a result of the aforementioned, it is clear that the application of artificial intelligence (AI) methods would bring about advantageous outcomes for the field of gait analysis [1]. These methodologies exhibit sufficient capability in managing data that is high-dimensional, temporal, and complex [7, 8]. In order to achieve intelligent behavior, the construction of models that possess the capability of automatic learning from databases that are available, and the ability to make precise predictions, is paramount [9, 10]. Machine learning (ML) is currently being widely utilized across various domains, including medical diagnosis [11-14], pattern recognition [15, 16], image processing [17, 18], classification [19, 20], clustering [4, 21], prediction analysis[1, 22, 23], monitoring [24], therefore, making them suitable for gait studies. Machine learning methodologies have been effectively utilized in diverse gait-related domains, namely, to interpret gait disorders [20, 25, 26], to anticipate timely measures for mitigating fall-associated hazards resulting from physical impairments or advanced age [9, 12], to determine motor recovery tasks [27, 28], or in planning a rehabilitation or therapeutic modalities [29-31].

In the present research, an unsupervised methodology is embraced to categorize gait patterns into various groups. To achieve this, the feature set, which has been extracted by a gait matcher, is subjected to a clustering scheme. Assuming the feasibility of clustering gait patterns into distinct groups, our aim is to ascertain (a) the existence of any correlation between individual clusters and the physical attributes of the individual in question, and (b) the extent to which these correlations are consistent across various gait matchers. Examining the clustering tendency of gait feature sets has multiple advantages. Firstly, within the framework of a gait-based surveillance system, the quest for a particular identity can be restricted to designated clusters that are grounded on the input gait data, thus leading to a reduction in search time. Secondly, concerning an identification-at-a-distance system that is open set, clustering gait patterns may prove to be valuable in constructing a physical "profile" of an observed identity that is not present in the existing database. Consequently, the amalgamation of such matchers at a higher level is expected to enhance the overall recognition accuracy. Previous research has exhibited unique groupings of ambulatory patterns in both healthy and pathological cohorts, implying that diverse techniques of motion may be manifested [4]. However, these studies have used discrete time point variables and usually focused on only one specific joint and plane of motion.

The fundamental objective of the present research is to meticulously scrutinize the phenomenon of clustering on joint biomechanics of lower limbs concerning limb dominancy. The ultimate goal is to ascertain whether or not these variables have a discernible influence on the clustering mechanism. Henceforth, the primary objective of this investigation was to ascertain whether the gait patterns of individuals with sound health could be demarcated into homogeneous subcategories based on three-dimensional kinematic data gathered from the ankle, knee, and hip joints. The secondary aim was to pinpoint differences in joint Biomechanics amongst the aforementioned groups.

MATERIAL AND METHODS

Participants

The current study is an observational cross-sectional study. Twenty-eight junior active males (age: 19.56±2.34 years, height: 185.21±15.94 cm, body mass: 65.44±8.45 kg) participated in the study according to the G-power® considering 80% of power level including an effect size of 0.80 and alpha of 0.05. The criteria for exclusion comprised the existence of any disorder pertaining to the neurological or musculoskeletal system, which impeded the movement of the subjects. Additionally, the utilization of any assistive device was also considered as grounds for exclusion. This study was approved by the ethical Committee of the Sport and Science Research institute (IR/ssri.rec.2023.14178.2035) and written and informed consent was obtained from each individual before participating in the study.

Equipment

The subject was introduced to the laboratory and a brief explanation was given about the experimental methods. Demographic characteristics of subjects including height and body mass were measured. 21 anatomical reflective markers were used (Figure 1). The gait kinematics were collected via a 3D motion-capture system with 6 cameras having 4 Mb of resolution and the Cortex 6.0 software (Raptor-4, Motion Analysis, Vicon). Two force platforms manufactured by AMTI were utilized during the gait analysis to gather kinetic data pertaining to the subject's gait pattern. The participant stated warming up and getting familiar with the test. The laboratory coordinate system used for the study was considered as X-axis in the direction of walking and positive forward, Y-axis in lateral direction of Gait and positive to the right, and Z-axis in the vertical direction and positive upward.

After the placement of the markers, the individuals were instructed to accomplish the gait task within a 10-meter walkway whereby the leg that was dominant made contact with the third step while the non-dominant leg made contact with the fourth step. The calibration space was designed in such a meticulous manner that it facilitated an optimal environment for the task at hand. It is imperative to provide a precise explanation of the calibration area, which was meticulously crafted to ensure that the participants were able to complete the task with utmost accuracy and precision.

The task was executed in two separate attempts, first by the self-selected speed of the participants and second one with steady state walking speed of 100BPM.

Figure 1. The present discourse presents an extended perspective of the Laboratory of Biomechanics with a focus on the walkway. The walkway is equipped with a sophisticated motion-capture system that includes state-of-the-art cameras and force plates.

Protocol

Data processing and analysis

Data of the markers and ground reaction force (GRF) were subjected to filtration utilizing a fourth-order low-pass Butterworth filter. The cut-off frequency employed in the filtration process was 10 Hz. The instances of heel contact and toe off were deduced based on the point at which the vertical GRF crossed a threshold level of 20 N. According to the magnitude of GRF on force platform, stance phase of gait in two different conditions: 1). Preferred speed and 2). Constant speed 100BPM were extracted. Additionally, 3D hip, knee, and ankle angles were computed by means of Cardan angles. The joint moments were represented in the joint-coordinate system, ascertained using a inverse-dynamics methodology and were normalized with respect to the participant's body mass.

Procedure of cluster analysis

The present study utilized a connectivity-based clustering technique, namely the hierarchical clustering analysis (HCA) approach, to accurately exhibit homogeneous biomechanical patterns of gait in the entirety of the participant cohort or objects. This was accomplished by thoroughly investigating the dominant and non-dominant joints in three planes, and formulating a cluster tree, or dendrogram. To initiate the collective HCA on a data set, extremum values of joints angles and joints moments in both conditions - preferred and steady speeds - were diligently considered for input. Firstly, the selected kinematics and kinetics were separately inputted to comprehensively discern the clustering and classifications of the joints based on dominant and non-dominant limbs. It is of paramount significance to acknowledge that the selection of the squared Euclidean distance as the metric for this analysis was executed with great care and precision. Additionally, the conscientious adoption of Ward's linkage method was undertaken with utmost diligence and attention to detail. In addition, the nearest neighbor and Z score were judiciously considered for clustering method and transform values. Furthermore, the subsequent analysis consisted of k-means clustering by carefully inputting all the variables, including maximum and minimum in both angles and moments. ANOVA statistical analysis was conducted to elucidate the significance of the variables entered in the clustering process. The SPSS software version 26 was employed for the purpose of constructing the clustering model while the alpha level was set at 0.05.

RESULTS

Clustering of the variables consist of three joints × three planes × limb dominancy is presented in table 1. According to the different conditions of preferred and steady- state walking speed, in both preferred and steady speed, biomechanics of dominant and non-dominant knee in vertical direction classified in one cluster while considering only kinematics gait pattern. Also, hip joint Biomechanics, both in dominant and non-dominant limbs, in vertical direction would be classified in one cluster considering kinetics parameters only (figure 2). Considering a combination of both kinematics and kinetics parameters, in preferred speed, hip and knee in vertical direction for both dominant and non-dominant limbs are classified in one cluster, but in steady speed, the hip in mediolateral direction and knee in vertical direction for both dominant and non-dominant limbs are presented in one cluster (Table 1). Considering preferred speed, Hip joint Biomechanics, both in dominant and non-dominant limbs, in vertical direction would be classified in one cluster considering kinetics parameters only. Considering a combination of both kinematics and kinetics parameters, in preferred speed, hip and knee in vertical direction for both dominant and non-dominant limbs are classified in one cluster, but in steady speed, the hip in mediolateral direction and knee in vertical direction for both dominant and non-dominant limbs are presented in one cluster.

Figure 2 & 3 present dendrogram of the hierarchical cluster analysis. Linkage distance is shown on the horizontal axis, and three-dimensional joints on the vertical axis for both conditions of self-selected walking speed and steady-state walking speed.

Table 1. Result of HCA for preferred and steady speed in separation according to the selected kinematics, kinetics and a combination of both of the kinematics and kinetics

variables	Preferred speed			Steady speed		
	cluster by kinematics	cluster by kinetics	total	cluster by kinematics	cluster by kinetics	total
Hip X Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Hip Y Dominant	**1**	**1**	**2**	**1**	**1**	**2**
Hip Z Dominant	**1**	**2**	**1**	**1**	**2**	**1**
Hip X non-Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Hip Y non-Dominant	**1**	**1**	**2**	**1**	**1**	**2**
Hip Z non-Dominant	**1**	**2**	**1**	**1**	**2**	**1**
Knee X Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Knee Y Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Knee Z Dominant	**2**	**1**	**1**	**2**	**1**	**2**
Knee X Non-Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Knee Y Non-Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Knee Z Non-Dominant	**2**	**1**	**1**	**2**	**1**	**2**
Ankle X Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Ankle Y Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Ankle Z Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Ankle X Non-Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Ankle Y Non- Dominant	**1**	**1**	**2**	**1**	**1**	**1**
Ankle Z Non-Dominant	**1**	**1**	**2**	**1**	**1**	**1**

Green color: the second cluster formed by kinematics only, yellow color: the second cluster formed by kinetics and blue color: the first cluster formed by combination of kinematics and kinetics together.

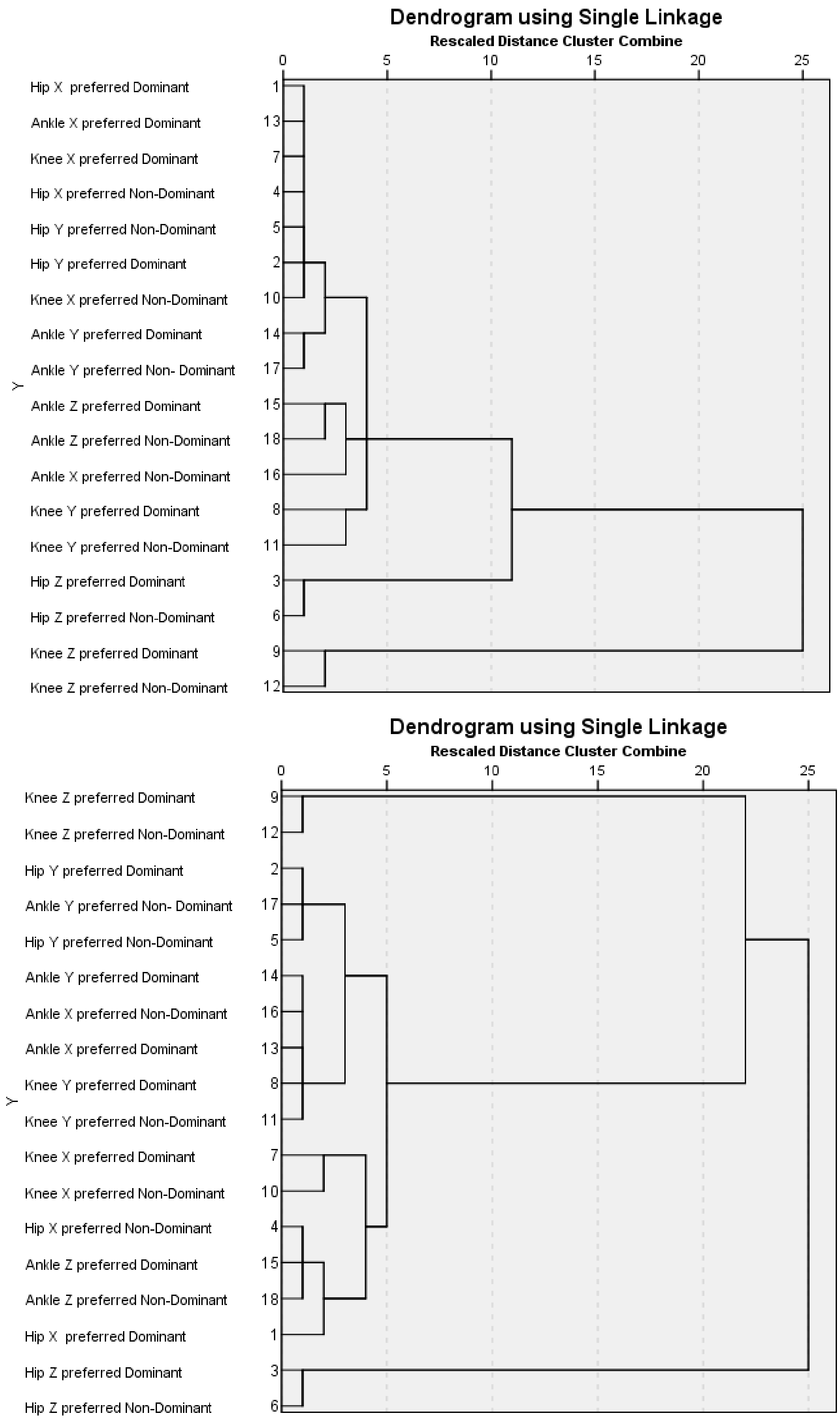

Figure 2. A dendrogram resulting from the implementation of a hierarchical cluster analysis. Linkage distance is shown on the horizontal axis, and three-dimensional joints on the vertical axis for preferred speed

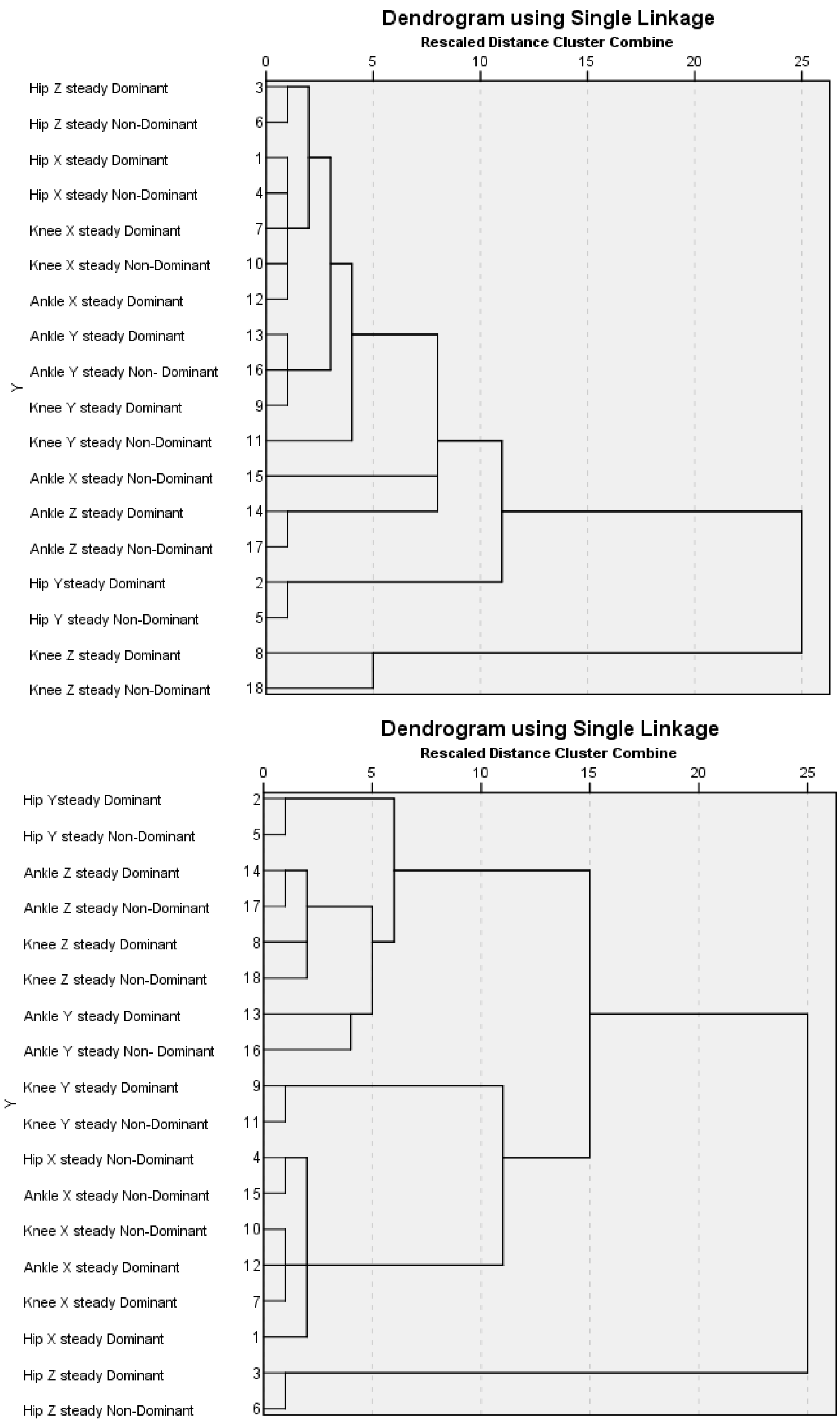

Figure 3. A dendrogram resulting from the implementation of a hierarchical cluster analysis. Linkage distance is shown on the horizontal axis, and three-dimensional joints on the vertical axis for steady speed.

Table 2 represent the result of k-mean clustering based on ANOVA. According to the table, in preferred speed, angle maximum and moment minimum include the most significant role in classification of the clusters (F=53.250, p=0.000) and (F=40.736, p=0.000), respectively. In steady speed, angle maximum and angle minimum play the most significant role in clustering the data (F= 68.663, p=0.000) and (F=6.119, p=0.025), respectively. in preferred speed condition, angle minimum and moment maximum contained the least effect on clustering (F=4.23, p=0.057) and (F=4.319, P=0.054) but in steady speed condition, moment maximum has the least effect (F=3.132, p=0.096).

Table 2. ANOVA test in separation in both preferred and steady speed

variables	preferred speed						steady speed					
	Cluster		Error		F	Sig.	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df			Mean Square	df	Mean Square	df		
Angle maximum	10462.881	1	196.487	16	53.250	**.000***	20336.753	1	296.182	16	68.663	**.000***
Angle minimum	269.572	1	63.842	16	4.223	.057	505.858	1	82.666	16	6.119	**.025***
Moment maximum	3.327	1	.770	16	4.319	.054	5.157	1	1.646	16	3.132	.096
Moment minimum	1.175	1	.029	16	40.736	**.000***	.181	1	.235	16	.773	.392

*Significant difference (P<0.05)

DISCUSSION

The purpose of the present research endeavor was to meticulously investigate and analyze the phenomenon of clustering on the lower joints' biomechanics in order to classify biomechanical parameters of the gait. In essence, the preliminary phase of this scholarly inquiry necessitated the precise and detailed measurement and evaluation of the kinematic and kinetic parameters associated with the maximum and minimum lower extremities joints angle and moment, respectively. The process was performed at both the preferred speed and constant speed of gait by utilizing the technique of clustering. The results of this research showed that taking into consideration a conflation of kinematics and kinetics parameters, when in a state of preferred speed, hip and knee joints performance in vertical direction for both of the dominant and non-dominant limbs are grouped together in a cluster. However, when in a state of steady speed, the hip in the mediolateral direction and the knee in the vertical direction for both the dominant and non-dominant limbs are presented in a cluster. Also, the research findings indicate that the maximum angle exhibited the most prominent impact and this effect is statistically significant. in preferred speed, angle maximum and the moment minimum show that is statistically significant.

In fact, the results showed that in the preferred speed, the kinematic variable only in the knee joint and in the vertical axis and the kinetic variable in the hip joint and in the vertical axis had an effect on clustering, and also in the steady speed, it was shown that the same joints in the kinematic and kinetics are effective in the vertical axis, but in general, with the change of speed, the effect in the hip joint changed from the vertical axis to the mediolateral direction, which can indicate balance.

On the other hand, considering the effect of moments and angles, it can be said that the maximum angle has the greatest effect on clustering.
Previous studies have reported the presence of multiple gait patterns in healthy individuals [32-34]. This phenomenon may induce a diversity of movement patterns within a control group, thus potentially confounding the outcomes of the research. One potential strategy to tackle the aforementioned issue could involve employing cluster analyses to effectively identify and classify individuals according to their distinct movement patterns [35]. Prior research endeavors have employed a hierarchical cluster analysis (HCA) as a means of categorizing the various gait patterns exhibited by individuals afflicted with cerebral palsy [36, 37], Charcot-Marie-Tooth disease [38] and chronic stroke [39], and as well healthy individuals [33, 34, 40]. Mezghani et al., (2013) undertook an investigation on a cohort of 111 asymptomatic subjects and delineated four discrete ambulatory patterns. Nevertheless, the authors confined their study to solely the kinematic data of the knee joint in the frontal plane, condensed using principal component analysis (PCA) [32].
Although previous studies have identified distinct gait patterns in individuals, it is important to note that only one recent study has explored the existence of consistent subcategories for running gait patterns in healthy individuals [41]. The investigations that have attempted to classify uniform sub-categories founded on the kinematic data of running gait are not inevitably representative of the broader population, and they do not encompass the entirety or complexity of the patterns of lower limb running gait.
The methodology of utilizing a connectivity-based clustering or the hierarchical cluster analysis (HCA) approach was employed to ascertain the presence of homogeneous gait patterns of the entire participant group or objects, predicated on the PC scores, through the creation of a cluster tree or dendrogram. Using the Ward's linkage method, binary clusters were formed by pairing individual subjects based on distance information [42], the newly established clusters were subsequently merged to generate larger clusters, culminating in the formation of the dendrogram.
The conclusive clustering solution was established through a quantitative approach [36, 38, 39] the aforementioned determination was substantiated via a comprehensive visual scrutiny of the dendrogram [43, 44]. A coefficient of inconsistency was computed through a comparison between the link distance in a dendrogram and the mean distance of all links situated underneath it in the tree. A coefficient of substantial magnitude indicates that unique clusters have been properly segregated.

In corroboration with our conjecture, the HCA methodology proved to be efficacious in delineating two discrete and uniform running gait patterns predicated on 3D kinematic data obtained from the hip, knee, and ankle joints. These findings are in alignment with previous research that has explored the walking and running gait patterns of fit individuals and has also noted the presence of homogeneous clusters or distinct gait patterns in healthy individuals [32-34, 40, 41]. Hence, the findings of the current investigation propose that an elevated level of inconsistency in gait kinematic data may exist amid a specific assemblage [45].
Furthermore, the findings of this study provide corroboration for earlier research that highlights the intricate nature of the classification and differentiation of gait kinematics. It is evident that this task is a multifaceted classification predicament that is inherently interdependent upon the relationships that exist amongst numerous kinematic variables [46-49].
previous research utilizing the HCA methodology has primarily directed its focus towards the gait patterns of unaffected individuals in a singular plane. An illustration of this is demonstrated in Simonsen and Alkjaer's (2012) study which discovered noteworthy disparities between two groups

of pedestrians, predicated on their sagittal plane knee kinematics during heel contact and peak flexion angles. These findings bear a resemblance to the present study's results. Additionally, Mezghani et al., (2013) directed their research towards examining the kinematics of the knee in the frontal plane. The input variables for the hierarchical clustering analysis were the first two principal components. Their scrutiny revealed the presence of four distinct clusters, with noticeable dissimilarities in both the stance and swing phases of the walking gait cycle [32]. Nevertheless, additional investigation is warranted in order to augment and elaborate upon this discovery.

Acknowledgement of the limitations of the present research study is imperative. The outcome of the cluster analysis is subject to the sample of data employed, and in the event that there is a utilization of data from an entirely different healthy cohort, the resultant grouping may differ, consequently modifying the concluding cluster solution. As a result, it becomes necessary to undertake further research aimed at determining the stability and robustness of the PCA and HCA methods. precautions must be made that the precise positioning of markers has the potential to exert an influence on the accuracy of kinematic variables pertaining to planes [50]. Regardless, we have opted to scrutinize these variables as they possess significant relevance in the analysis of individuals' gait, owing to the crucial role that kinematics and kinetics variables play in this regard.

Conclusions

The outcomes of this study indicate that the observed fluctuations in gait patterns may be attributed to the presence of diverse gait strategies that are represented within the sample. In this study, we investigated and analyzed the clustering phenomenon on the biomechanics of the lower joints in order to cluster the biomechanical parameters of gait.

It can be posited that the kinematic and kinetic variables, which are distinct components of human motion, have been shown to be highly efficacious in the task of gate clustering, a procedure that involves the categorization of gait patterns into discrete subgroups. It is worth noting that these variables, owing to their unique properties, can be further subdivided into homogeneous subgroups, which allows for a more nuanced and comprehensive understanding of the underlying mechanisms that govern human locomotion.

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Institutional Review Board Statement: The current research methodology has received endorsement from the ethics committee at the Research Institute of Physical Education and Sports Sciences, with the assigned identification number of IR.SSRI.REC-1402-2035.

Informed Consent Statement: All participants involved in the research study provided informed consent.

Conflicts of Interest

The authors hereby declare their absence of any conflict of interest, thereby indicating their impartiality and lack of bias towards any particular entity or group.

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REFERENCES

1. Khera P, Kumar N. Role of machine learning in gait analysis: a review. Journal of Medical Engineering & Technology. 2020;44(8):441-67.
2. Molavian R, Salehi M, Alizadeh R. A Comparison of Kinematic Symmetry of Lower Limbs during Running at Different Speeds. Journal of Clinical Physiotherapy Research. 2021,6(4):e4, https://doi.org/10.22037/jcpr.v6i3.34467.
3. Fatahi A, Molaviaan R. Comparison of Kinematics and kinetics Symmetry of Lower Limbs during running. Journal of Exercise Science and Medicine. 2020;12(2) : 217-225. doi: 10.32598/JESM.12.2.10.
4. Phinyomark A, Petri G, Ibáñez-Marcelo E, Osis ST, Ferber R. Analysis of big data in gait biomechanics: Current trends and future directions. Journal of medical and biological engineering. 2018;38:244-60.
5. Izhar CAA, Hussain Z, Maruzuki M, Sulaiman MS, Abd Rahim A. Gait cycle prediction model based on gait kinematic using machine learning technique for assistive rehabilitation device. IAES International Journal of Artificial Intelligence. 2021;10(3):752-763. DOI:10.11591/ijai.v10.i3.pp752-763.
6. Farah JD, Baddour N, Lemaire ED, editors. Gait phase detection from thigh kinematics using machine learning techniques. 2017 IEEE International Symposium on Medical Measurements and Applications (MeMeA); 2017: IEEE.
7. Dolatabadi E, Taati B, Mihailidis A. An automated classification of pathological gait using unobtrusive sensing technology. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2017;25(12):2336-46.
8. Lai DT, Begg RK, Palaniswami M. Computational intelligence in gait research: a perspective on current applications and future challenges. IEEE Transactions on Information Technology in Biomedicine. 2009;13(5):687-702.
9. Paulo J, Peixoto P, Amorim P. Trajectory-based gait pattern shift detection for assistive robotics applications. Intelligent Service Robotics. 2019;12:255-64.
10. Kutilek P, Hozman J, editors. Prediction of lower extremities movement using characteristics of angle-angle diagrams and artificial intelligence. 2011 E-Health and Bioengineering Conference (EHB); 2011: IEEE.
11. Farah JD, Baddour N, Lemaire ED. Design, development, and evaluation of a local sensor-based gait phase recognition system using a logistic model decision tree for orthosis-control. Journal of neuroengineering and rehabilitation. 2019;16(1):1-11.
12. Begg R, Kamruzzaman J. Neural networks for detection and classification of walking pattern changes due to ageing. Australasian Physics & Engineering Sciences in Medicine. 2006;29:188-95.
13. Lau H-Y, Tong K-Y, Zhu H. Support vector machine for classification of walking conditions using miniature kinematic sensors. Medical & biological engineering & computing. 2008;46:563-73.
14. Faraji B, Khezri D. Ultra-Local Model Control of Parkinson's Patients Based on Machine Learning. Journal of Advanced Sport Technology. 2021;5(1):1-16.
15. Souza AdMe, Stemmer MR. Extraction and classification of human body parameters for gait analysis. Journal of Control, Automation and Electrical Systems. 2018;29:586-604.
16. Shim H-m, Lee S. Multi-channel electromyography pattern classification using deep belief networks for enhanced user experience. Journal of Central South University. 2015;22(5):1801-8.
17. Wei W, McElroy C, Dey S, editors. Human Action Understanding and Movement Error Identification for the Treatment of Patients with Parkinson's Disease. 2018 IEEE International Conference on Healthcare Informatics (ICHI); 2018: IEEE.
18. Leightley D, McPhee JS, Yap MH. Automated analysis and quantification of human mobility using a depth sensor. IEEE journal of biomedical and health informatics. 2016;21(4):939-48.
19. Van Gestel L, De Laet T, Di Lello E, Bruyninckx H, Molenaers G, Van Campenhout A, et al. Probabilistic gait classification in children with cerebral palsy: A Bayesian approach. Research in Developmental Disabilities. 2011;32(6):2542-52.
20. Mu T, Pataky TC, Findlow AH, Aung MS, Goulermas JY. Automated nonlinear feature generation and classification of foot pressure lesions. IEEE Transactions on Information Technology in Biomedicine. 2009;14(2):418-24.
21. Khezri D, Eslami M, Yousefpour R. Clustering healthy runner based on 3-D kinematics patterns of pelvic during running using hierarchical method. Journal of Applied Exercise Physiology. 2019;14(28):227-40.

22. Yoo TK, Kim SK, Choi SB, Kim DY, Kim DW, editors. Interpretation of movement during stair ascent for predicting severity and prognosis of knee osteoarthritis in elderly women using support vector machine. 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2013: IEEE.
23. Xiong B, Zeng N, Li H, Yang Y, Li Y, Huang M, et al. Intelligent prediction of human lower extremity joint moment: An artificial neural network approach. IEEE Access. 2019;7:29973-80.
24. Zeng W, Ismail SA, Pappas E. Classification of gait patterns in patients with unilateral anterior cruciate ligament deficiency based on phase space reconstruction, Euclidean distance and neural networks. Soft Computing. 2020;24(3):1851-68.
25. Alaqtash M, Sarkodie-Gyan T, Yu H, Fuentes O, Brower R, Abdelgawad A, editors. Automatic classification of pathological gait patterns using ground reaction forces and machine learning algorithms. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2011: IEEE.
26. Devanne M, Wannous H, Daoudi M, Berretti S, Del Bimbo A, Pala P, editors. Learning shape variations of motion trajectories for gait analysis. 2016 23rd International Conference on Pattern Recognition (ICPR); 2016: IEEE.
27. Costa Á, Iáñez E, Úbeda A, Hortal E, Del-Ama AJ, Gil-Agudo A, et al. Decoding the attentional demands of gait through EEG gamma band features. PLoS one. 2016;11(4):e0154136. https://doi.org/10.1371/journal.pone.0154136.
28. Goh SK, Abbass HA, Tan KC, Al-Mamun A, Thakor N, Bezerianos A, et al. Spatio–spectral representation learning for electroencephalographic gait-pattern classification. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2018;26(9):1858-67.
29. Paulo J, Peixoto P, Nunes UJ. ISR-AIWALKER: Robotic walker for intuitive and safe mobility assistance and gait analysis. IEEE Transactions on Human-Machine Systems. 2017;47(6):1110-22.
30. Liu D-X, Du W, Wu X, Wang C, Qiao Y, editors. Deep rehabilitation gait learning for modeling knee joints of lower-limb exoskeleton. 2016 IEEE international conference on robotics and biomimetics (ROBIO); 2016: IEEE.
31. Thongsook A, Nunthawarasilp T, Kraypet P, Lim J, Ruangpayoongsak N, editors. C4. 5 decision tree against neural network on gait phase recognition for lower limp exoskeleton. 2019 First International Symposium on Instrumentation, Control, Artificial Intelligence, and Robotics (ICA-SYMP); 2019: IEEE.
32. Mezghani N, Fuentes A, Gaudreault N, Mitiche A, Aissaoui R, Hagmeister N, et al. Identification of knee frontal plane kinematic patterns in normal gait by principal component analysis. Journal of Mechanics in Medicine and Biology. 2013;13(03):1350026-13.
33. Simonsen EB, Alkjær T. The variability problem of normal human walking. Medical engineering & physics. 2012;34(2):219-24.
34. Vardaxis VG, Allard P, Lachance R, Duhaime M. Classification of able-bodied gait using 3-D muscle powers. Human Movement Science. 1998;17(1):121-36.
35. Phinyomark A, Osis S, Hettinga BA, Ferber R. Kinematic gait patterns in healthy runners: A hierarchical cluster analysis. Journal of biomechanics. 2015;48(14):3897-904.
36. Roche N, Pradon D, Cosson J, Robertson J, Marchiori C, Zory R. Categorization of gait patterns in adults with cerebral palsy: a clustering approach. Gait & Posture. 2014;39(1):235-40.
37. Toro B, Nester CJ, Farren PC. Cluster analysis for the extraction of sagittal gait patterns in children with cerebral palsy. Gait & posture. 2007;25(2):157-65.
38. Ferrarin M, Bovi G, Rabuffetti M, Mazzoleni P, Montesano A, Pagliano E, et al. Gait pattern classification in children with Charcot–Marie–Tooth disease type 1A. Gait & posture. 2012;35(1):131-7.
39. Kinsella S, Moran K. Gait pattern categorization of stroke participants with equinus deformity of the foot. Gait & posture. 2008;27(1):144-51.
40. Watelain E, Barbier F, Allard P, Thevenon A, Angué J-C. Gait pattern classification of healthy elderly men based on biomechanical data. Archives of physical medicine and rehabilitation. 2000;81(5):579-86.
41. Hoerzer S, von Tscharner V, Jacob C, Nigg BM. Defining functional groups based on running kinematics using Self-Organizing Maps and Support Vector Machines. Journal of biomechanics. 2015;48(10):2072-9.
42. Ezugwu AE, Ikotun AM, Oyelade OO, Abualigah L, Agushaka JO, Eke CI, et al. A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges, and future research prospects. Engineering Applications of Artificial Intelligence. 2023;56:6439-6475. https://doi.org/10.1007/s10462-022-10325-y.
43. Saxena A, Prasad M, Gupta A, Bharill N, Patel OP, Tiwari A, et al. A review of clustering techniques and developments. Neurocomputing. 2017;267:664-81.
44. Ruff L, Kauffmann JR, Vandermeulen RA, Montavon G, Samek W, Kloft M, et al. A unifying review of deep and shallow anomaly detection. Proceedings of the IEEE. 2021;109(5):756-95.

45. Grau S, Maiwald C, Krauss I, Axmann D, Horstmann T. The influence of matching populations on kinematic and kinetic variables in runners with iliotibial band syndrome. Research quarterly for exercise and sport. 2008;79(4):450-7.
46. Hreljac A, Ferber R. A biomechanical perspective of predicting injury risk in running. International SportMed Journal. 2006;7(2):98-108.
47. Ferber R, Hreljac A, Kendall KD. Suspected mechanisms in the cause of overuse running injuries: a clinical review. Sports health. 2009;1(3):242-6.
48. Fukuchi RK, Stefanyshyn DJ, Stirling L, Duarte M, Ferber R. Flexibility, muscle strength and running biomechanical adaptations in older runners. Clinical Biomechanics. 2014;29(3):304-10.
49. Phinyomark A, Hettinga BA, Osis ST, Ferber R. Gender and age-related differences in bilateral lower extremity mechanics during treadmill running. PloS one. 2014;9(8):e105246.
50. Osis ST, Hettinga BA, Macdonald SL, Ferber R. A novel method to evaluate error in anatomical marker placement using a modified generalized Procrustes analysis. Computer methods in biomechanics and biomedical engineering. 2015;18(10):1108-16.

رویکرد هوش مصنوعی در تحلیل بیومکانیکی راه رفتن

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چکیده

هدف از مطالعه حاضر انجام یک تحلیل بیومکانیکی راه رفتن بر اساس رویکرد یادگیری ماشینی بدون نظارت – هوش مصنوعی بود. بیست و هشت مرد جوان فعال در این مطالعه شرکت کردند. پس از قرار دادن مارکرها، از شرکت کنندگان خواسته شد تا عملکرد راه رفتن را در یک مسیر ۱۰ متری که تماس پای غالب در قدم سوم و پای غیر غالب در قدم چهارم قرار می گیرد، تکمیل کنند. این کار در دو تلاش جداگانه، اول با سرعت ترجیحی شرکت کنندگان و دوم با سرعت ثابت BPM۱۰۰ اجرا شد. فرآیند خوشه‌بندی بر اساس رویکرد HCA شامل NN و امتیاز Z برای شناسایی الگوهای بیومکانیکی راه رفتن همگن کل شرکت‌کننده با توجه به مقادیر حداکثری زاویه مفاصل و گشتاور مفاصل در هر دو شرایط - سرعت‌های ترجیحی و ثابت توسط نرم‌افزار SPSS نسخه ۲۶ استفاده شد ($p<0.05$). با در نظر گرفتن ترکیبی از پارامترهای کینماتیک و کینتیک، در سرعت ترجیحی، هیپ و زانو در جهت عمودی برای هر دو اندام غالب و غیر غالب در یک خوشه طبقه‌بندی می‌شوند، اما در سرعت ثابت، لگن در جهت میانی و زانو در جهت عمودی برای هر دو اندام غالب و غیر غالب در یک خوشه ارائه شده اند. متغیرهای کینماتیکی و کینتیکی در خوشه بندی پارامترهای راه رفتن برای دسته بندی الگوهای مورد نظر مفید هستند. این متغیرها را می توان به زیر گروه های همگن برای درک دقیق تر حرکت انسان تقسیم کرد.

واژه‌های کلیدی: هوش مصنوعی، راه رفتن، بیومکانیک، کلاسترینگ، یادگیری ماشین