Explainable Artificial Intelligence in Movement Sciences

Zheng, Xiaoping

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Appendix A

Summary

Walking is one of the most common daily physical activities. Gait serves as a window into health by reflecting the intricate coordination of the musculoskeletal, cardiorespiratory, and nervous systems. The advent of wearable sensor technologies, such as accelerometers, enables the recording of gait performance in daily living environments. Artificial Intelligence (AI), applied in gait analysis, has shown success in monitoring the gait of older adults and analyzing complex conditions, such as back pain. AI-driven gait analysis exhibits accuracy levels that are comparable with trained clinicians. However, these achievements are accompanied by increasing the complexity of AI models which are lack of explainability. The black-box nature makes clinical experts and patients hard to trust the AI-driven gait analysis, and it may fail to meet the law requirements and ethical standards. Thus, explainable AI (XAI) has emerged to address these challenges by enhancing the transparency and interpretability of AI models. It may help to establish trust between AI-driven gait analysis and their users. Additionally, XAI could offer valuable insights into movement expertise for human movement scientists and clinical experts by explaining the knowledge extracted from data by these black-box AI models. Therefore, the aim of this thesis was to enhance the understanding of movement, especially gait, in healthy older adults and patients with back pain by leveraging insights from XAI (**Chapter 1**).

Conventional machine learning (CML) is commonly used for classifying various gait patterns based on gait outcomes. However, these gait outcomes are handcrafted, and the process of their design and selection are labor-intensive. Additionally, the computation of gait outcomes is usually offline, implying that such approaches may not be suitable for real-time applications such as monitoring the gait of older adults in daily living environments. Hence, the study described in **Chapter 2** aimed to eliminate the need for handcrafted gait outcomes and improve the performance of age-related gait pattern classification by employing deep learning (DL) based on accelerometer data collected from 3-minute walking. This chapter compared the performance of five DL models (using accelerometer signal data as input) with four CML models (using handcrafted gait outcomes as input). The results showed that all DL models surpassed CML models, achieving an area under the curve (AUC) greater than 0.94, compared to the highest AUC of 0.83 achieved by the best CML model. These findings not only highlighted the superiority of DL, but also suggested that DL has learned valuable gait outcomes reflecting age-related changes in gait, which had been overlooked by CML. In addition, this chapter presented an investigation into the effects of different window sizes on classification performance, as varying window sizes result in different numbers of consecutive gait cycles being used as DL input. It was observed that convolutional neural network (CNN) was capable of using single stride data to differentiate between adults and older adults, while recurrent neural network (RNN) might depend on the distinctions and connections among various gait cycles for classification.

Building on the insights from Chapter 2, the study described in **Chapter 3** aimed to investigate what DL models had learned from data in classifying adults and older adults, utilizing XAI. The findings indicated that accelerometer signal data spanning from the terminal swing to the loading response phase, especially data around heel contact, contributed most to the classification process. These findings suggested that DL captured different acceleration and deceleration patterns to differentiate the gait of older adults from adults. Additionally, the study revealed that variations in acceleration and deceleration within a single stride were adequate for CNN to classify (achieving an AUC of 0.89). RNN classified based on subtle differences and relationships in acceleration and deceleration patterns across multiple strides, attaining an AUC of 0.94. These results implied that RNN considered the postural control ability of older adults. Notably, XAI revealed that DL primarily utilized data in the vertical and anterior-posterior directions for classification, rather than data in the mediolateral direction, which is more closely related to balance.

The insights and methodologies from these two chapters could shed light on the gait analysis of other conditions, such as back pain. Gait analysis in patients with chronic low back pain (CLBP) reported conflicting evidence, supporting the idea that CLBP is a heterogeneous condition. The presence of human assumed central sensitization (HACS) in CLBP might contribute to this heterogeneity. In **Chapter 4**, it was hypothesized that different levels of HACS (low or high) could be related to the gait patterns of patients with CLBP, and these differences could be effectively classified using CML. Additionally, XAI could be used to interpret these differences in gait patterns. By analyzing accelerometer data collected from daily living environments for about one week, the results of this chapter confirmed that patients with CLBP and with low or high levels of HACS (CLBP- and CLBP+, respectively), could be effectively classified by CML (e.g., Random Forest), achieving an accuracy of 84.4%. XAI revealed that patients in CLBP- group exhibited a higher smoothness and better stability in gait, whereas patients in CLBP+ group showed a more regular, less variable, and predictable gait pattern. These findings suggested that CLBP- and CLBP+ patients might adopt different motor control strategies, namely “loose control” and “tight control”. The loose control strategy, characterized by reduced trunk movement control, could explain the gait patterns in CLBP-, while the tight control strategy, with enhanced trunk movement control, could explain those in CLBP+. These findings emphasize the need for personalized treatment approaches.

Building on the findings from Chapter 4, the study described in **Chapter 5** delved into the physical activity intensity (PAI) patterns in patients with CLBP, where inconsistent evidence was also observed, based on the accelerometer data collected from daily living environments over a period of approximately one week. This study employed unsupervised CML with XAI

(Hidden semi-Markov Model, HSMM) to explore PAI patterns in CLBP- and CLBP+ groups. While traditional methods using preset cut-points failed to detect statistical differences in overall PAI between CLBP- and CLBP+ groups, HSMM can learn the PAI patterns from data. HSMM identified distinct PAI patterns in these two groups. CLBP- group tended to segment tasks into smaller bouts, interspersed with frequent and short rests. CLBP+ group exhibited prolonged periods of activity and rest. PAI patterns in CLBP+ group could be explained by the endurance response pattern, characterized by overuse and overload of physical structures, despite experiencing pain. PAI patterns in CLBP- might not align with the fear-avoidance response pattern, as there was no evidence indicating fear belief in this group. The insights from Chapters 4 and 5 contributed to a better understanding of CLBP, movement, and HACS, paving the way for personalized treatment strategies in the future.

In Chapters 4 and 5, the low and high levels of HACS were determined using the central sensitization inventory (CSI) questionnaire, based on a predefined cut-off value of 40. However, it has been reported that the cut-off value for CSI may vary according to different pain conditions, as well as different cultural and national contexts. It is notable that there is no universally accepted gold standard for assessing HACS. Based on the data patterns and structure within gender and clinical outcomes (questionnaires reflecting pain, physical status, and psychological status), the objective of **Chapter 6** was to utilize unsupervised CML with XAI to investigate subgroups related to HACS among patients with CLBP. The results identified two distinct subgroups within the CLBP population. One subgroup, characterized by higher pain, greatest disability, worse psychological status, and higher CSI values, was assigned to higher levels of HACS, while the other represented lower levels of HACS. Based on these subgroups, a new cut-off value of 35 was established for the Dutch-speaking population with CLBP. The methodology used in this chapter provided new understanding in identifying HACS-related patterns and contributes to setting more accurate cut-off values.

Chapter 7 provided a summary of the main findings in this thesis and discussed potential future directions. Using the thesis as a case study, it provided guidelines for selecting appropriate AI models for movement analysis, elaborating on their advantages and disadvantages. By underscoring the potential of XAI in human movement analysis, this chapter highlighted the need for ongoing improvements to make XAI more reliable, understandable, and user-friendly. Despite acknowledged limitations, this chapter presented the view that the potential of AI, particularly XAI, in movement analysis, holds promise for AI-driven human movement analysis in the future. Furthermore, this advancement will aid clinical experts and movement scientists in deciphering knowledge extracted from data by AI models.

Samenvatting

Lopen is een van de meest voorkomende dagelijkse fysieke activiteiten. Het loopgedrag geeft inzicht in de gezondheid doordat het de coördinatie van het musculoskeletale-, het cardiorespiratoire systeem en het zenuwstelsel weerspiegelt. Met de komst van draagbare sensortechnologieën, zoals accelerometers, is het mogelijk geworden om het lopen in de dagelijkse leefomgevingen te registreren. Met gebruik van data analysemethoden en artificiële intelligentie (AI) kan uit de accelerometer signalen informatie worden gehaald, waarmee inzicht wordt gekregen over veranderingen in het lopen als gevolg van het ouder worden of door lage rugklachten. AI-gestuurde loopanalyse heeft een nauwkeurigheidsniveaus die vergelijkbaar is met die van getrainde clinici. De prestaties van de voorspelling en nauwkeurigheid gaat echter gepaard met een toenemende complexiteit van de AI-modellen waarbij het lastig is te beschrijven op grond waarvan het model tot zijn uitkomst komt. Deze zogenoemde "black-box" maakt de toepassing er van in de kliniek lastig. Klinische experts en patiënten zullen moeite hebben om de AI-gestuurde loopanalyse te vertrouwen omndat niet altijd duidelijk is hoe de uiteindelijke resultaten tot stand zijn gekomen. Daarnaast is wetgeving omtrent het gebruik van AI in de zorg nog in ontwikkeling. Explainable AI (XAI), een recente ontwikkeling beoogt deze uitdagingen aan te pakken en de transparantie en interpreteerbaarheid van AI-modellen te verbeteren. Het kan bijdragen aan het creëren van meer inzicht in de achtergrond van de uitkomst van de modellen en bijdragen aan het vertrouwen tussen AI-gestuurde loopanalyses en de gebruikers. Daarnaast kan XAI waardevolle inzichten en kennis genereren over het begrijpen van veranderend bewegen als gevolg van leeftijd en aandoeningen. Daarom was het doel van dit proefschrift om het begrip van beweging, met name het loopgedrag, bij gezonde oudere volwassenen en patiënten met rugpijn te verbeteren, door gebruik te maken van inzichten uit XAI (**hoofdstuk 1**).

Conventionele Machine Learning (CML) wordt vaak gebruikt voor het classificeren van verschillende looppatronen op basis van een grote verscheidenheid aan loopparameters, zoals spatio-temporele parameters (stap lengte, stap tijd, snelheid) en dynamische parameters (stabiliteit, vloeiendheid, frequentie) van het lopen. Deze loopparameters worden afzonderlijk berekend vanuit accelerometer signalen, en dit is doorgaans een arbeidsintensief proces met veel voorbewerkingen. Bovendien wordt de berekening van de loopparameters meestal offline gedaan, waardoor real-time toepassingen zoals het monitoren van het looppatronen van oudere volwassenen in dagelijkse leefomgevingen, met directe terugkoppeling niet mogelijk is. **Hoofdstuk 2** heeft als doel om te onderzoeken of met Deep Learning (DL) modellen, op basis van accelerometer signalen van drie minuten lopen, de noodzaak van het vooraf berekenen van aparte loopvariabelen voor classificatiemodellen kan worden vermeden. De prestatie van modellen voor de classificatie van looppatronen van mensen met verschillende leeftijd wordt in dit hoofdstuk vergeleken. De prestaties van vijf DL-modellen (met het 'ruwe' accelerometer signaal als invoer) is vergeleken met vier CML-modellen (met afzonderlijke loopvariabelen). De resultaten toonden aan dat alle DL-modellen de CML-modellen overtroffen, met een area under the curve (AUC) van meer dan 0,94, vergeleken met de hoogste AUC van 0,83 van het beste CML-model. Deze bevindingen benadrukten niet alleen de superioriteit van DL, maar suggereerden ook dat DL waardevolle loopuitkomsten heeft geleerd die leeftijdsgerelateerde veranderingen in het lopen weerspiegelen, welke door de CML niet werden geïdentificeerd. Daarnaast beschrijft het hoofdstuk de effecten van verschillende venstergroottes van data selectie op de classificatieprestaties. Verschillende venstergroottes resulteren in verschillende aantallen van opeenvolgende loopcycli die gebruikt worden als input voor het DL-model. Er werd geconstateerd dat Convolutionele Neurale Netwerken (CNN) in staat waren om op basis van een enkele loopcycli onderscheid te maken tussen volwassenen en oudere volwassenen, terwijl Recurrent Neural Network (RNN) de relaties over de tijd tussen loopcycli meeneemt in de classificatie.

Voortbouwend op de inzichten uit hoofdstuk 2, heeft het onderzoek dat in **hoofdstuk 3** wordt beschreven als doel om te onderzoeken wat DL-modellen hadden geleerd van de data bij het classificeren van volwassenen en oudere volwassenen, met behulp van XAI. De resultaten lieten zien dat het accelerometer signaal tijdens de late zwaaifase tot aan het neerzetten van de voet binnen een loopcyclus, met name het moment rond het hielcontact, het meest bijdroeg aan het classificatieproces. Deze bevindingen suggereren dat DL verschillende versnellings- en vertragingspatronen identificeert die het looppatroon van oudere volwassenen onderscheidt van dat van volwassenen. Daarnaast toont het onderzoek aan dat variaties in versnelling en vertraging binnen enkele schrede voldoende is voor CNN om te classificeren (met een AUC van 0,89). Recurrent Neural Network (RNN) methoden, classificeert daarentegen op basis van relaties in versnellings- en vertragingspatronen over verschillende loopcycli, waarbij een AUC van 0,94 werd bereikt. De resultaten impliceerden dat RNN rekening houdt met dynamische veranderingen over de tijd, die gerelateerd zijn aan de houdingscontrole. Echter, opmerkelijk was dat XAI liet zien dat DL voornamelijk datagegevens in de verticale en anterolaterale richtingen gebruikte voor de classificatie in plaats van datagegevens in de mediolaterale richting, die sterker gerelateerd zijn aan balans.

De inzichten en methodologieën uit deze twee hoofdstukken kunnen gebruikt worden om inzicht te krijgen in het looppatroon van mensen met aandoeningen, zoals rugklachten. Studies naar het looppatroon bij patiënten met chronische lage rugpijn (CLBP) laten tegenstrijdige resultaten zien. Dit komt overeen met het beeld dat er is van van CLBP als een heterogene aandoening. De aanwezigheid van 'human assumed central sensitization' (HACS) in CLBP zou kunnen bijdragen aan deze heterogeniteit. In **hoofdstuk 4** wordt de hypothese getest dat verschillende niveaus van HACS (laag of hoog) gerelateerd zijn aan de looppatronen van patiënten met CLBP, en dat deze verschillen effectief geclassificeerd kunnen worden met behulp van CML. Daarnaast zou XAI gebruikt kunnen worden om deze verschillen in looppatronen te interpreteren. Door de accelerometer signalen van één week uit de dagelijkse leefomgeving te analyseren, bevestigden de resultaten, gepresenteerd in dit hoofdstuk, dat patiënten met CLBP en met lage of hoge niveaus van HACS (respectievelijk CLBP- en CLBP+) effectief geclassificeerd konden worden door CML (bijvoorbeeld met Random Forest), met een nauwkeurigheid van 84,4%. XAI liet zien dat patiënten in de CLBP-groep een grotere soepelheid en een betere stabiliteit in loopgedrag vertoonden, terwijl patiënten in de CLBP+ groep een regelmatiger, minder variabel en voorspelbaarder looppatroon vertoonden. Deze bevindingen suggereren dat CLBP- en CLBP+-patiënten mogelijk verschillende motorische controle strategieën aannemen, namelijk "losse controle" en "strakke controle". De "losse controle" strategie, gekenmerkt door verminderde controle over de rompbewegingen, zou de looppatronen in CLBP- kunnen verklaren, terwijl de "strakke controle" strategie, met verbeterde controle over de rompbewegingen, de looppatronen in CLBP+ zou kunnen verklaren. Deze bevindingen benadrukken de noodzaak van een gepersonaliseerde behandeling.

Voortbouwend op de bevindingen uit hoofdstuk 4, onderzocht het in **hoofdstuk 5** beschreven onderzoek de intensiteit van fysieke activiteit patronen bij patiënten met CLBP, gemeten in de dagelijkse omgeving met een draagbare accelerometer gedurende ongeveer één week. Dit onderzoek maakte gebruik van CML zonder gebruik te maken van XAI (Hidden semi-Markov Model, HSMM) om patronen van fysieke activiteit van patiënten met CLBP- en CLBP+- te onderzoeken. Terwijl traditionele methoden die gebruik maken van vooraf ingestelde afkapwaarde van het acceleratiesignaal er niet in slaagden om verschillen in algemene fysieke activiteit intensiteit tussen CLBP- en CLBP+ -groepen statistisch significant vast te stellen, kan HSMMM de PAI-patronen vanuit de datagegevens leren. HSMM identificeerde zo verschillende PAI-patronen in deze twee groepen. CLBP- groepen hadden de neiging om taken op te splitsen in kleinere periodes, afgewisseld met frequente en korte rustpauzes. De CLBP+ groep vertoonde langere periodes van activiteit en rust. Fysieke activiteit patronen in de CLBP+ groep kunnen verklaard worden door een persisterende respons patroon, die gekenmerkt wordt door overmatig gebruik van fysieke structuren, ondanks het ervaren van pijn. De fysieke activiteitenpatronen in de CLBP-groep komen mogelijk niet overeen met het angst-vermijdingsrespons patroon, aangezien er geen aanwijzingen waren voor angstovertuiging in deze groep. De inzichten uit hoofdstuk 4 en 5 droegen bij aan een beter begrip van CLBP, beweging en HACS, en maken de weg vrij voor gepersonaliseerde behandelstrategieën in de toekomst.

In de hoofdstukken 4 en 5 werden de lage en hoge niveaus van HACS bepaald met behulp van de Central Sensitization Inventory (CSI) vragenlijst, op basis van een vooraf gedefinieerde afkapwaarde van 40. Er is echter gerapporteerd dat de afkapwaarde voor CSI kan variëren door zowel verschil in pijnconditie als verschil in culturele en nationale context. Het is opmerkelijk dat er geen universeel geaccepteerde gouden standaard is voor het beoordelen van HACS. Gebaseerd op de patronen en structuren in de datagegevens van mensen met hetzelfde geslacht en dezelfde klinische uitkomsten (vragenlijsten over pijn, fysieke status en psychologische status), was het doel van het in **hoofdstuk 6** beschreven onderzoek om CML zonder toezicht van XAI te gebruiken voor het onderzoeken van HACS-gerelateerde subgroepen binnen patiënten met CLBP. Uit de resultaten werden twee verschillende subgroepen binnen de CLBP-populatie geïdentificeerd. De ene subgroep, die gekenmerkt werd door meer pijn, de grootste invaliditeit, slechtere psychologische status en hogere CSI-waarden, werd toegewezen aan hogere HACS-niveaus, terwijl de andere subgroep lagere HACS-niveaus vertegenwoordigde. Op basis van deze subgroepen werd een nieuwe afkapwaarde van 35 vastgesteld voor de Nederlandstalige populatie met CLBP. De methodologie die in dit hoofdstuk gebruikt werd, gaf nieuw inzicht in het identificeren van HACS-gerelateerde patronen en draagt bij aan het vaststellen van nauwkeurigere afkapwaarden.

Hoofdstuk 7 geeft een samenvatting van de belangrijkste bevindingen in dit proefschrift en bespreekt mogelijke richtingen voor toekomstig onderzoek. Door het proefschrift als casestudy te gebruiken, worden richtlijnen gegeven voor het selecteren van geschikte AI modellen voor bewegingsanalyse, waarbij de voor- en nadelen worden besproken. Door de potentie van XAI voor de bewegingswetenschappen te onderstrepen, benadrukte dit hoofdstuk de noodzaak van voortdurende verbeteringen om XAI betrouwbaarder, begrijpelijker en gebruiksvriendelijker te maken. Ondanks de erkende beperkingen, toont het hoofdstuk wat de potentie is van AI, met name XAI, voor de (klinische) bewegingsanalyse van verschillende patiëntengroepen. Deze ontwikkeling zal klinische experts en bewegingswetenschappers kunnen ondersteunen in het inzicht krijgen in veranderingen in het bewegingen tijdens dagelijkse activiteiten in verschillende patiëntengroepen.

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About the Author

Xiaoping Zheng (郑潇平) was born on April 8, 1993, in Shantou, China. From 2012 to 2016, he pursued his Bachelor's degree in Information Engineering at the Chinese University of Geosciences in Wuhan, over 1,000 km away from his hometown. He continued at the same university for his Master's in Software Engineering, completing it in 2019. This education laid a foundation in computer science for him. In October 2019, Xiaoping embarked on a new journey over 10,000 km away from hometown, to study a new subject, Human Movement Science, at the University of Groningen. His 4-year PhD program was supported by the China Scholarship Council-UG Joint Scholarship (Grant No. 201906410084).

Xiaoping's PhD research revolved around exploring artificial intelligence in studying human movement characteristics. Working within a multidisciplinary team, he collaborated with data scientists to apply advanced techniques in extracting insights from complex data collected from movements. He cooperated closely with movement scientists, aiding in the interpretation of data-driven findings and their implications in human movement. Furthermore, he liaised with clinicians and rehabilitation experts to translate these findings into clinically relevant applications. In this research, he contributed as a bridge, bridging the gap between data science and practical applications, making complex data understandable and useful across various disciplines.

Currently, Xiaoping continues to explore the relationship between movement and health by utilizing artificial intelligence at the Chinese University of Hong Kong. After his PhD, he will officially commence his Postdoctoral research at the same institution.

Scientific Output

Journal Publications

Zheng, X., Reneman, M., Echeita, J., Schiphorst Preuper, R., Kruitbosch, H., Ottem, E., and Lamoth, C., Association between central sensitization and gait in chronic low back pain: Insights from a machine learning approach. Computers in biology and medicine, 144 (2022): 105329. doi.org/10.1016/j.compbiomed.2022.105329

Zheng, X., Reneman, M., Schiphorst Preuper, R., Ottem, E., and Lamoth, C., Relationship between physical activity and central sensitization in chronic low back pain: Insights from machine learning. Computer Methods and Programs in Biomedicine, 232 (2023): 107432. doi.org/10.1016/j.cmpb.2023.107432

Submitted for Publication

Zheng, X., Wilhelm, E., Reneman, M., Ottem, E., and Lamoth, C., Age-related gait patterns classification using deep learning based on time-series data from one accelerometer. doi.org/10.36227/techrxiv.22643314.v1

Zheng, X., Reneman, M., Ottem, E., and Lamoth, C., Explaining deep learning models for age-related gait classification based on acceleration time series. doi.org/10.48550/arXiv.2311.12089

Zheng, X., Lamoth, C., Timmerman, H., Ottem, E., and Reneman, M., Establishing central sensitization inventory cut-off Values in patients with chronic low back pain by unsupervised machine learning. doi.org/10.48550/arXiv.2311.11862

Conference Contributions

Oral Presentations

Zheng, X., Reneman, M., Ottem, E., and Lamoth, C., Explaining deep learning models for age-related gait classification based on time-series acceleration. ISB 2023, Fukuoka, Japan.

Zheng, X., Wilhelm, E., Reneman, M., Ottem, E., and Lamoth, C., Deep learning for age-related gait patterns classification based on raw accelerometer signal from 3 minutes walking. ISPGR 2023, Brisbane, Australia.

Zheng, X., Reneman, M., Schiphorst Preuper, R., Ottem, E., and Lamoth, C., Physical activity patterns of patients with chronic low back pain and central sensitization: insights from a machine learning method. BME 2023, Egmond aan Zee, The Netherlands.

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