كشف الاختلافات في المشية بين الأشخاص الأصحاء والمبتوري الأطراف باستخدام تحليل المكونات الأساسية والخرائط ذاتية التنظيم

حسام حنا [1،2،*]، صالح مسعود [1]، ابراهيم اسماعيل [3]

[1] كلية الهندسة الطبية الحيوية، جامعة الأندلس للعلوم الطبية، طرطوس، سورية.

[2] مركز الأطراف الاصطناعية والأجهزة التقويمية، مستشفى حمص الكبير، حمص، سورية.

[3] قسم الطب والجراحة، جامعة بارما، بارما، إيطاليا.

البريد الالكتروني: ح.ح. hh6@au.edu.sy؛ ص.م. sm2@au.edu.sy؛ ا.ا. ebrahim.ismaiel@unipr.it

الملخص:

تقدم هذه الدراسة نهجاً لتحليل وكشف التباين في المشية بين الأفراد الأصحاء والمبتورين فوق الركبة مع أطراف اصطناعية سفلية باستخدام تحليل المكونات الأساسية (PCA) وشبكة الخرائط ذاتية التنظيم (SOM). تبدأ المنهجية باستخراج المكونات الأساسية لتغيرات الحركة الزاوية لكل من الورك والركبة والكاحل لالتقاط أنماط الحركة الأكثر أهمية أثناء المشي على المستوى السهمي. ثم يتم استخدام هذه المكونات الأساسية أو الحركات الأساسية كمدخلات لشبكة SOM. يكمن دور SOM في تصنيف البيانات وكشف الاختلاف بشكل آلي بين الأشخاص الأصحاء والمبتورين بالاعتماد على العناصر الأساسية للحركة. من خلال نتائج تصنيف شبكة SOM للمكونات الأساسية، أظهرت الدراسة إمكانية توظيف شبكة SOM في كشف وتحديد الاختلافات بين الأشخاص الأصحاء ومبتوري الأطراف الذين يرتدون أطرافهم الاصطناعية، بما في ذلك أنماط بسط وقبض مفاصل الأطراف السفلية الثلاث (الكاحل والركبة والورك). تشير النتائج إلى إمكانية توظيف طريقة تحليل العناصر الأساسية للمشية مع تقنية SOM في بناء نظام تشخيصي يفيد في دعم القرار الطبي وتحديد الاختلاف في العناصر الأساسية للحركة باستخدام الشبكات العصبونية. بالإضافة الى امكانية ذلك في تحسين تصميم الأطراف الاصطناعية وتصميم برامج إعادة التأهيل لاستعادة آليات المشي الطبيعية لدى مبتوري الأطراف.

الكلمات المفتاحية: تحليل المشي، تحليل المكونات الأساسية (PCA) ، الخرائط ذاتية التنظيم (SOM)، مبتوري الأطراف، الأطراف الاصطناعية.

Detecting Differences in Gait Between Healthy individuals and Amputees Using Principal Component Analysis and Self-Organizing Maps

Hussam Hanna [1,2,*], Saleh Massoud [1], Ebrahim Ismaiel [3]

[1] Faculty of Biomedical Engineering, Al-Andalus University for Medical Science, Tartous, Syria.

[2] Prosthetics and orthotics Center, Homs Grand Hospital, Homs, Syria.

[3] Department of Medicine and Surgery, University of Parma, Parma, Italy.

Emails: H.H.: hh6@au.edu.sy; S.M.: sm2@au.edu.sy; E.I.: ebrahim.ismaiel@unipr.it

* Indicate the research to communicate with regarding the research, regardless of his/her numbering.

Abstract:

This study presents an approach for analyzing and detecting variations in gait between healthy individuals and above-knee amputees with lower-limb prosthetics using principal component analysis (PCA) and self-organizing maps (SOM). The methodology begins with the extraction of principal components from the angular movements of the hip, knee, and ankle joints to capture the most significant movement patterns observed during walking in the sagittal plane. The SOM network then uses these principal components, or principal movements, as inputs. The role of the SOM is to classify the data and automatically discern differences between healthy individuals and amputees based on the principal movement elements. Through the classification results of the SOM network for the principal components, the study demonstrates the potential of using SOM to detect differences due to prosthetic limbs, including distinctive movement patterns in the extension and flexion patterns of the three lower extremity joints (ankle, knee, and hip). The findings suggest that employing the principal component analysis of gait with SOM technology can aid in constructing a diagnostic system that supports medical decision-making and uses the variance in principal movement elements for rapid identification through neural networks. Furthermore, this method could improve lower limb prosthetic design and rehabilitation programs to restore natural gait mechanisms in amputees.

Keywords: Gait analysis, Principal component analysis (PCA), Self-Organizing Maps (SOM), amputee gait, prosthesis.

Received:
Accepted:

1. Introduction:

Human movement is a complex process coordinated by a motor system with an abundance of degrees of freedom, making it a central challenge in biomechanics and motor control research (Bernstein, 1967). Traditional approaches focus on single outcome variables like the Center of Mass or Center of Pressure (Quijoux et al., 2020; Mehdizadeh et al., 2021), but this has been criticized for oversimplifying the complexity of a multi-dimensional system (Federolf et al., 2021). Principal component analysis (PCA) has emerged as an alternative, allowing for the decomposition of high-dimensional movement data into principal components (PCs) that explain the system's variance (Troje, 2002; Federolf, 2012). PCA breaks down complex signals into PCs, each explaining a portion of variance. Studies often use body-segment markers to feed into PCA, creating high-dimensional inputs (Federolf et al., 2012; Ross et al., 2018). The first PC captures the largest variance, followed by subsequent PCs. Lower-ranked PCs often represent important movement strategies, such as postural control strategies in bipedal movements (Federolf et al., 2013b). In gait studies, a few principal movements (PMs) often explain most of the variance (Ó'Reilly, 2021; Promsri, 2022), with just two PMs covering over 90% of movement variance during treadmill walking (Federolf et al., 2012). PCA offers several advantages: it supports a non-reductionist view of biomechanical analysis, allowing for a more holistic understanding of movement (Federolf et al., 2021; Bolt et al., 2021). Furthermore, it is data-driven and minimizes investigator bias. However, a key limitation is that PCA studies are often confined to controlled environments, making it unclear if findings can generalize to field settings with wearable sensors. Differences in marker sets and measurement systems may affect PCA outcomes, but the extent of this impact remains unknown.

In this study, we aim to utilize self-organizing maps (SOMs) to detect and visualize the most significant differences in gait between healthy individuals and amputees by clustering principal components of joint angles. The approach begins by calculating the PCs of the hip, knee, and ankle joint angles for both groups. These PCs reduce data complexity while preserving the most significant movement patterns. These principal components are then used as input to the SOM, which is particularly effective for clustering and visualizing high-dimensional data. By projecting this data onto a lower-dimensional grid, the SOM preserves the topological structure of the movement variability between the two groups. As an unsupervised learning method, the SOM clusters similar patterns based on the PCs. Significant differences in movement patterns between healthy individuals and amputees will result in distinct clusters on the SOM grid. Comparing the clusters formed by healthy individuals to those of amputees allows us to detect which principal components show the most divergence between the two groups. The SOM net highlights the PCs, or combinations of PCs, that differ the most between healthy and amputee subjects, providing insights into movement patterns and compensatory strategies used by amputees. This method will help identify the key movement clusters that differentiate the two groups based on the principal component analysis of joint angles.

2. Material and Methods:

2.1. Data collection

The biomechanics dataset by Hood et al. (2020) includes data from 18 individuals with unilateral above-knee amputations walking at various speeds, with subjects divided into K2 and K3 groups based on their ability to comfortably walk at 0.8 m/s. The K2 group walked at speeds ranging from 0.4 to 0.8 m/s, while the K3 group walked at speeds between 0.6 and 1.4 m/s. Full-body biomechanics data was collected using a 10-camera motion capture system and a fully instrumented treadmill. The dataset aims to help clinicians understand the biomechanical demands of walking with a prosthesis at different speeds, provide researchers with insights into amputee gait deviations, and assist engineers in improving prosthesis design.

The complete dataset by Moreira et al. (2021) includes raw and processed data from 16 healthy participants walking on a flat surface at seven controlled speeds (1.0 to 4.0 km/h). The raw data comprises 3D joint trajectories of 24 markers, ground reaction forces, force plate moments, center of pressures, and EMG signals from selected muscles. Processed data includes gait cycle-normalized information, such as filtered EMG signals, 3D ground reaction forces, joint angles, and torques.

2.1. Methodology

In this study, we apply PCA and SOM to analyze and visualize differences in gait patterns between healthy individuals and amputees. The methodology involves several key components, which are described in detail below:

1. PCA:

The joint angles of the hip, knee, and ankle for both healthy and amputee groups are first processed through PCA. The latter reduces the dimensionality of the original gait data, transforming it into a set of orthogonal PCs that account for the maximum variance in the dataset. Mathematically, PCA computes the eigenvectors of the covariance matrix *C* of the joint angle data, where:

$$C = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)(x_i - \mu)^T \qquad (1)$$

where x_i represents the joint angle data, and μ is the mean of the dataset. The eigenvectors corresponding to the largest eigenvalues are selected as the principal components, capturing the most significant patterns of joint movement in a reduced form. These PCs are used to represent the primary modes of variability between the two groups, allowing for a simplified yet informative comparison of gait patterns.

2. Input to Self-Organizing Maps:

The principal components derived from PCA are used as input features for the SOM. SOMs are particularly effective at handling high-dimensional data and project it onto a lower-dimensional grid (typically 2D) while preserving the topological relationships within the data. The SOM algorithm maps each input vector *x*, which is represented by its PCs, to a specific node on the grid based on the similarity of the input data. Each node in the SOM is associated with a weight vector www, which is updated during training to match the input patterns. The update rule is given by:

$$w(t+1) = w(t) + \alpha(t) \cdot h_{ci}(t) \cdot \left(x(t) - w(t)\right) \qquad (2)$$

where *α(t)* is the learning rate, and $h_{ci}(t)$ is the neighborhood function that ensures nearby nodes in the grid are updated similarly to maintain topological relationships. By using the PCs as input, the SOM clusters the gait data from healthy and amputee individuals based on underlying movement patterns.

3. Clustering for Differences:

As an unsupervised learning method, the SOM clusters the input data into distinct regions on the map. Each region represents similar patterns of movement, as captured by the PCs. If significant differences in gait exist between healthy individuals and amputees, their PCs will form distinct clusters on the SOM grid. The clusters representing healthy individuals can be spatially compared with those representing amputees, providing a clear visualization of which principal components—reflecting key aspects of gait variability—differ the most between the two groups.

4. Visualization of SOM Clusters:

The resulting SOM grid provides a visual representation of the relationships between the PCs for both groups. Each point on the grid corresponds to a specific gait pattern, with clusters of points indicating similar movement strategies. By examining the grid, we can observe which combinations of PCs lead to distinct movement behaviors in healthy individuals versus amputees. This visualization helps in identifying key differences, such as compensatory strategies used by amputees, and reveals the underlying biomechanical adaptations captured by the PCs.

3. Results and Discussion:

Starting with the difference in gait patterns between a healthy individual and an amputee with a prosthesis, Figure 1 reveals significant variations in joint trajectories. The healthy gait pattern on the left, shown in blue, exhibits smoother and more symmetrical movements, with a wider range of motion. In contrast, the amputee's gait on the right, depicted in pink, shows more constrained and asymmetric patterns, particularly in the hip and knee regions. The prosthetic gait demonstrates reduced flexion-extension, likely due to compensatory strategies for balancing and propulsion, indicating biomechanical adaptations necessary for the amputee's locomotion. These differences highlight the impact of the prosthesis on gait efficiency and coordination. All graphical data were produced using the first subject in both datasets.

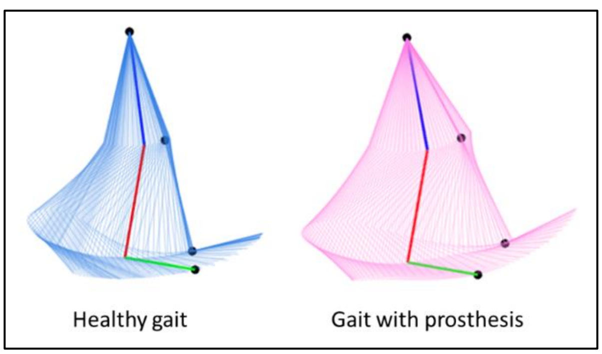

Figure 1 – Gait patterns of healthy and amputated subjects.

The PMs of a healthy gait, derived through PCA, are illustrated in Figure 2. Each panel represents a different principal movement, ordered by the amount of variance explained in the gait data. PM1 captures the most significant variance, depicting overall gait dynamics involving major limb movements. Subsequent PMs (PM2 through PM9) show progressively smaller contributions to the total variance, focusing on finer gait details, such as minor adjustments in joint angles. These principal movements collectively offer a reduced-dimensional view of the gait cycle, highlighting how the most critical elements of motion can be simplified and understood through PCA. As the variance explained decreases with each PM, the movements depicted become more subtle, focusing on specific adjustments within the gait pattern that are less critical to overall movement but still important in the comprehensive biomechanical analysis.

The PMs of an amputee's gait with a prosthesis derived through PCA are illustrated in Figure 3. Similar to the analysis of healthy gait, each panel represents a principal movement, ordered by the variance explained. PM1, which captures the largest portion of variance, shows more constrained and asymmetric movements compared to a healthy gait, particularly in the range of motion of the prosthetic limb. Subsequent PMs (PM2 through PM9) reveal smaller and more localized patterns of movement. These movements are characterized by compensatory strategies due to the prosthesis, such as reduced joint flexibility and altered postural adjustments. The decomposition of the gait into principal components highlights how the prosthetic limb impacts overall movement, with the lower-ranked PMs indicating subtle biomechanical differences that contribute to the overall gait adaptation.

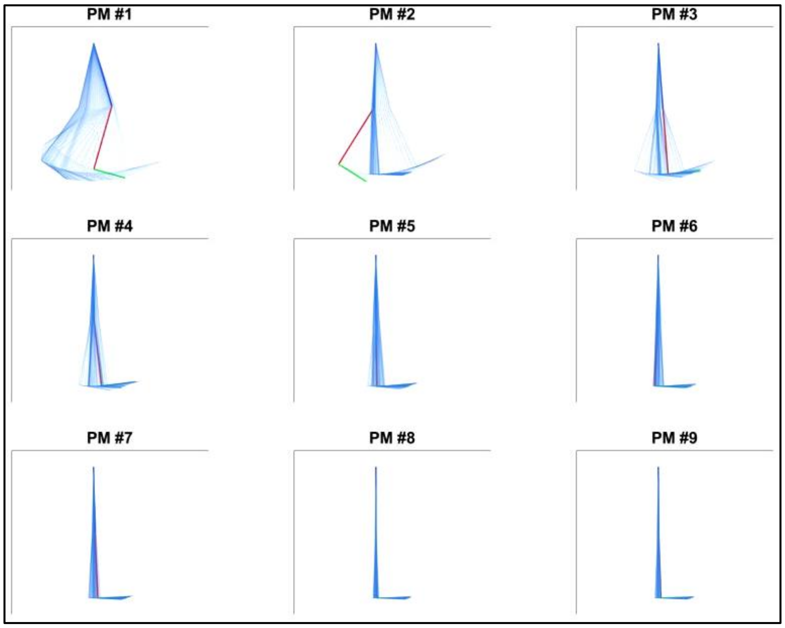

Figure 2 - PMs of healthy gait derived using PCA. Each panel (PM1 to PM9) represents a principal movement, ordered by the amount of variance explained.

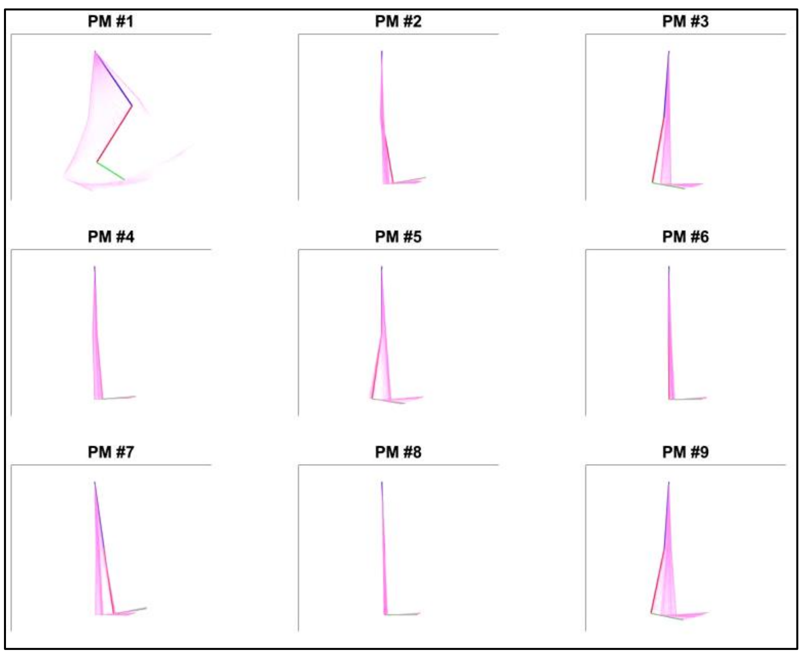

Figure 3 - PMs of an amputee's gait with a prosthesis.

In Table 1, we address the outcomes of a SOM analysis applied to the PCs derived from gait data of healthy individuals and amputees. The principal components, ranked by the percentage of variance they explain in the dataset, highlight key differences in movement patterns between the two groups. These differences are visualized through the SOM grid, which clusters movement patterns based on the PCs. For PC1, which explains 40% of the variance, the healthy individuals exhibit smooth, coordinated anterior-posterior leg and arm swings. In contrast, the amputee subjects show reduced swing and asymmetric leg movements. The SOM grid reflects these differences through a larger spread of clusters for amputees, indicating greater variability in their compensatory strategies. This suggests that the prosthesis significantly alters their overall gait mechanics.

Table 1. Table: SOM outcomes comparing principal components of gait between healthy and amputee subjects, highlighting key movement clusters and differences in the SOM grid.

PM	Variance Explained (%)	Key Movement Cluster (Healthy)	PM Cluster (Amputee)	Notable Differences (SOM Grid)
PM1	40%	Smooth anterior-posterior leg and arm swing	Reduced swing, asymmetric leg movements	Larger spread in SOM cluster for amputees, indicating greater variability in compensatory strategies
PM2	20%	Hip and knee flexion-extension in sync	Limited hip flexion, exaggerated knee flexion	Distinct clusters in SOM showing altered coordination patterns for prosthetic leg
PM3	15%	Balanced body posture with minimal adjustments	Shifts in trunk posture, compensating for prosthesis	Clustering shows increased postural adjustments in amputees, especially during stance phase
PM4	10%	Stable ankle dorsiflexion during swing phase	Reduced dorsiflexion, compensatory foot movement	Amputee SOM cluster exhibits more variability in foot positioning
PM5	7%	Coordinated arm movement during stride	Less coordinated arm movement, asymmetry	SOM clusters highlight decreased upper-body movement coordination in amputee subjects
PM6	5%	Minor adjustments in knee rotation	Increased knee rotation, compensatory torque	More dispersed SOM clusters for amputees, indicating irregular knee rotation patterns
PM7	3%	Fine adjustments in ankle inversion/eversion	Restricted inversion, altered foot angle	Amputee clusters show constrained foot adjustments, highlighting limited flexibility

PC2, explaining 20% of the variance, shows that healthy subjects have synchronized hip and knee flexion-extension, whereas amputees display limited hip flexion and exaggerated knee flexion. This leads to distinct clusters in the SOM grid, highlighting altered coordination patterns in amputees, particularly affecting their prosthetic leg. For PC3, which accounts for 15% of the variance, healthy individuals maintain balanced body posture with minimal adjustments, whereas amputees exhibit changes in trunk posture as a compensatory strategy for the prosthesis. This results in increased postural adjustment clusters in the SOM grid for amputees, particularly during the stance phase of gait. PC4, contributing 10% of the variance, demonstrates that healthy subjects exhibit stable ankle dorsiflexion during the swing phase. In contrast, amputees show reduced dorsiflexion and compensatory foot movements. The SOM clusters for amputees show more variability in foot positioning, indicating challenges in achieving the same degree of stability and flexibility in their gait. For PC5, with 7% variance explained, healthy individuals exhibit coordinated arm movements during the stride, while amputees show less coordinated and more asymmetric arm movements. This is reflected in the SOM grid, where decreased upper-body coordination in amputees is highlighted by the distinct cluster formations. PC6, explaining 5% of the variance, captures minor adjustments in knee rotation in healthy individuals, while amputees display increased knee rotation, likely as a compensatory response. The SOM grid shows more dispersed clusters for amputees, reflecting irregular knee rotation patterns that could contribute to altered gait dynamics.

Finally, PC7, accounting for 3% of the variance, shows that healthy subjects make fine adjustments in ankle inversion and eversion. In contrast, amputees exhibit restricted inversion and altered foot angles, with the SOM grid showing constrained foot adjustments. This highlights the limited flexibility in the amputees' gait, likely due to the prosthesis. These findings have significant implications for understanding amputee biomechanical adaptations. The SOM analysis effectively clusters the principal movements that differ between healthy and amputee subjects, providing insight into compensatory strategies used by amputees. These differences, particularly in PCs related to overall movement coordination and stability, highlight the challenges amputees face in replicating natural gait patterns, shedding light on areas for potential improvement in prosthetic design and rehabilitation strategies.

4. References:

1. Bernstein, N. (1967). The coordination and regulation of movements. Pergamon Press.
2. Bolt, K. J., Oldham, S. M., & O'Brien, T. D. (2021). Movement variability in sports performance: Applications of principal component analysis. International Journal of Sports Science & Coaching, 16(3), 558-570.
3. Federolf, P., Roos, L., Nigg, B. M., & von Tscharner, V. (2012). The analysis of movement variability using PCA in sports biomechanics: Theoretical framework and practical implementation. Sports Biomechanics, 11(4), 419–441.
4. Federolf, P., Tecante, K., & Nigg, B. M. (2013b). A holistic approach to study the temporal variability in movement control. Journal of Biomechanics, 46(6), 1129–1135.
5. Hood, S., Ishmael, M. K., Gunnell, A., Foreman, K. B., & Lenzi, T. (2020). A kinematic and kinetic dataset of 18 above-knee amputees walking at various speeds. Scientific data, 7(1), 150.
6. Mehdizadeh, S., & Sanjari, M. A. (2021). A critical review of center of pressure measures. Gait & Posture, 85, 251-263.
7. Moreira, L., Figueiredo, J., Fonseca, P., Vilas-Boas, J. P., & Santos, C. P. (2021). Lower limb kinematic, kinetic, and EMG data from young healthy humans during walking at controlled speeds. Scientific data, 8(1), 103.
8. Ó'Reilly, M. (2021). Whole-body movement variability during gait. Journal of Biomechanics, 125, 110591.
9. Promsri, A. (2022). Principal component analysis of walking movements. Gait & Posture, 96, 65–72.
10. Quijoux, F., Houx, L., Lempereur, M., Jolivet, E., Osseby, G.-V., Moreau, T., & Duret, C. (2020). Center of mass and center of pressure interaction in postural control of older adults. Gait & Posture, 82, 275–281.
11. Troje, N. F. (2002). Decomposing biological motion: A framework for analysis and synthesis of human gait patterns. Journal of Vision, 2(5), 371-387.