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# A review on the coordinative structure of human walking and the application of principal component analysis☆

**Xinguang Wang[1, 2], Nicholas O'Dwyer[1, 3], Mark Halaki[1]**

1 *Discipline of Exercise and Sport Science, The University of Sydney, Australia*
2 *School of Science and Health, The University of Western Sydney, Australia*
3 *School of Human Movement Studies, Charles Sturt University, Australia*

## Abstract
Walking is a complex task which includes hundreds of muscles, bones and joints working together to deliver smooth movements. With the complexity, walking has been widely investigated in order to identify the pattern of multi-segment movement and reveal the control mechanism. The degree of freedom and dimensional properties provide a view of the coordinative structure during walking, which has been extensively studied by using dimension reduction technique. In this paper, the studies related to the coordinative structure, dimensions detection and pattern reorganization during walking have been reviewed. Principal component analysis, as a popular technique, is widely used in the processing of human movement data. Both the principle and the outcomes of principal component analysis were introduced in this paper. This technique has been reported to successfully reduce the redundancy within the original data, identify the physical meaning represented by the extracted principal components and discriminate the different patterns. The coordinative structure during walking assessed by this technique could provide further information of the body control mechanism and correlate walking pattern with injury.

Corresponding author: Xinguang Wang☆, Ph.D., Discipline of Exercise and Sport Science, The University of Sydney, NSW 2006, Australia, xinguang.wang@sydney.edu.au; chris.xg.wang@gmail.com.

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## Key Words
neural regeneration; reviews; human walking; coordinative structure; pattern, synergy; principal component analysis; dimension reduction; gender; walking speed; correlation; linear system analysis; coherence; neuroregeneration

## Research Highlights
(1) Numerous studies over the last decade have provided support for the idea of modular control of movement *via* muscle synergies or limb synergies. Such synergies have been proposed as building blocks that could simplify the construction of motor behavior.
(2) Principal component analysis is a powerful and elegant method of data analysis aimed at obtaining low-dimensional approximations of high-dimensional processes. It has been successful in capturing data redundancies by providing principal components that maximally preserves the variance.
(3) This review paper provides more complete information on the coordinative structure of human movement and the techniques used to identify the movement coordination.

## INTRODUCTION

The human body is a complex system which consists of hundreds of bones, joints and muscles. Human movement is composed of many moving segments which are powered by approximately 700 muscles and connected through about 300 joints with several rotation axes. During movement, therefore, the human body has a large number of degrees of freedom. A finely tuned and highly complex central nervous system is necessary to ensure skilled movements, such as walking, speaking and writing. As a task involving a large number of cyclically moving body segments, walking requires the appropriate coupling and coordinated movement of body segments to produce smooth motion, maintain balance, minimize energy expenditure and prevent injury.

Many researchers have identified the dimension during walking using dimension reduction techniques. The investigations on the degree of freedom provide a deeper understanding of the principles and theories behind the movements. In this paper, the degree of freedom and dimensional properties of walking were reviewed, and the popular techniques employed. The investigation on the coordinative structure during walking could provide deeper understanding about the human body movement control mechanism.

## CONTROL MECHANISM

Generally, during human walking, the central nervous system functions as the command center which is responsible for the integration and organization of the sensory and motor information in the control of movement. The sensory information formed by the neural signals from sensory receptors passes through the spinal cord to the brain. These signals then are integrated with the task requirements, and the resulting information is translated into commands that are sent to the motor units through the descending pathway and trigger the corresponding muscles to generate movement[1]. The motor unit is the final end of the transmission of the motor neural information to activate muscles and make a movement.

The phenomenon during walking could be explained in terms of the number of degrees of freedom. As an incredible complex system, the motor system exhibits large degrees of freedom during movement control. The motor control system must overcome the degrees of freedom problem in order to produce well-coordinated movement[2]. The total number of degrees of freedom is defined as the number of independent elements or components in a control system and the number of ways that each component can act. The control problem is solved by determining how to constrain the system's number of degrees of freedom in order to produce a specific result. During a movement, it was suggested that the brain reduces the number of degrees of freedom and only controls the position of joints. The slightly different pattern presented across subjects or across the individual repetition within one subject could be explained by the considerable flexibility of muscle activities[3].

## COORDINATION

Coordination was defined as a problem of mastering the very large number of degrees of freedom involved in a particular movement by reducing the number of independent variables to be controlled[2]. The control of human movement is simplified by organizing actions into linkages or couplings between limb segments known as "synergies"[2] or, a more elaborate notion, "coordinative structures"[4-5]. In a technical context, synergy or coordinative structure is defined as a construct or collection of different elements working together to produce results not obtainable by any of the elements alone. While the concept of synergies has frequently been applied to kinematic modules, it must be recognized that the term synergy has been defined loosely in the motor control literature[6] and different notions of synergies exist[7]. During human movement, the musculoskeletal and neural elements become linked and operate as one functional unit to reduce the dimensionality of executive control. Many biomechanical studies have supported the existence of such functional units and demonstrated that multi-segmental movements are highly coupled and correlated for a variety of tasks[8-14].

As a complex task, it is difficult to fully understand the pattern, kinematic and kinetic properties of human walking. Recent studies have tried to detect the coordinative structure of walking and answer the question that how the nervous system controls gait mechanics[15-21]. It was suggested that walking patterns appear to be remarkably simple and consistent when gait is considered at a whole body level of analysis rather than that of the patterns of individual muscles[15, 22-25]. This phenomenon could be explained by synergies for inter-segmental coordination at the whole body level. These couplings and correlations were suggested to lead to a reduction in the number of degree of freedom in gait mechanics[15].

To detect the pattern and coordination of movements, great research efforts have been directed toward understanding the mechanisms associated with multi-segmental movements. The coordinative structure of human walking has been explored from both theoretical and experimental aspects[26]. Modelling approaches ranging from neuromodulation of coupled oscillators[27-28] to synergetics[29-30], group-theory[31], and topological dynamics[32-33] have been used to describe gait and it has been suggested that excess degrees of freedom are constrained by neural control. As a result, limb dynamics are confined to an attractor space of lower dimensionality than that of the original parameter space. Experimental studies have been conducted to collect both kinematic and kinetic data from different tasks in order to provide evidence for coordinative structures that lead to a reduction of dimensionality. The elevation angles of the thigh, shank and foot were found to be correlated during walking[15]. An investigation on the co-variance between limb segments in human locomotion showed that the temporal changes of the elevation angles of lower limb segments with respect to the vertical and forward directions were highly coupled and correlated. This planar covariation of leg segment angles was confirmed in several other studies[26, 34-37].

## TECHNIQUES OF MEASUREMENT AND ANALYSES

As defined by the notion of synergy, the elements within a multi-element system co-vary their outputs to preserve the coordinative pattern and deliver a stable movement. Many computational approaches such as principal component analysis, independent components analysis and nonnegative matrix factorisation have been applied to quantify the relationship between the elements during specific tasks[38]. To be specific, this paper reviewed the recent studies that focused on the application of principal component analysis on human movement.

### What is principal component analysis

Principal component analysis is one of the most common methods used by data analysts to investigate the number of degrees of freedom in an action because of its potential for data reduction and explanation[39]. It is a multivariate, non-parametric statistical technique that can reveal hidden structure within a complex data set while simultaneously filtering out noise. The main purpose of principal component analysis is to summarize the most important information in the data by representing the variation of a limited number of components which explain the maximal amount of variance.

Mathematically, principal component analysis is an orthogonal transformation which converts the original variables into a new set of uncorrelated principal components. The number of these principal components is much less than the number of variables in the original data. The majority of variation within the original dataset can be explained by the first several principal components. The remaining principal components, which account for a small amount of variation, can be dropped or associated with noise in the signals, and therefore, a reduction in dimensionality is achieved[40-41]. Because residuals are defined as the difference between the original data and that estimated from the inverted principal component mode, the residuals should represent information of random noise. Thus, principal component analysis could decrease the effect of random noise in the original data[42].

### Why principal component analysis is used

In studies of human movement, principal component analysis has been used to reduce the dimensionality of complex data sets by determining the most important factors that contribute to the sources of variation in movement patterns. Due to the redundancy within human movement data, principal component analysis can be applied to extract the principal information, reduce the dimensionality and recognize patterns. Principal component analysis can define a new set of variables that correlate with the original variables. This new set of variables can be divided into two groups, principal components that account for large amount of total variance and principal components that account for small amount of total variance. The principal components that account for large amount of total variance can represent the original data with the majority of variation, which is suggested to be related to the control signal outputs of spinal pattern generators under the influence of descending information[43]. The principal components that account for small amount of total variance are normally considered to indicate random noise within the system[42]. The number of components in either group is affected by the criteria of principal component selection. As the first several principal components normally account for the most variance, the original data can be approximated by using the first several eigenvectors.

Many studies have applied principal component analysis to kinematic, kinetic or electromyography data in order to reveal underlying coordinative structures in the correlated patterns of variation among joints or body segments. Principal component analysis has been applied to the coordination of complex movement such as walking[20, 40, 44-46], grasping tasks[47], dancing[48], wrestling[49], swinging[50], juggling[51], hula-hooping[52] and instrument playing[53]. These studies all successfully reduced the dimensionality of the data which identified the pattern.

**How to conduct principal component analysis**

In general, to conduct a principal component analysis on human walking data, the first step is to compute either the covariance or the correlation matrix of the dataset variables (*e.g*. joint angles). After the correlation (covariance) matrix is obtained, principal component analysis can be performed to calculate:

(1) Eigenvectors, the directions of the orthogonal axes, which account for most of the dataset variance;
(2) Eigenvalues, the scalar components of each eigenvector, which indicate the fraction of the total variance accounted for by each eigenvector;
(3) Principal component or factor scores, the dot product of the original data and eigenvectors, which represent the waveforms associated to each eigenvector/ eigenvalue;
(4) Weighting coefficients or factor loadings, which represent the Pearson correlation coefficients between the principal components and the original data so that the original signal can be reconstructed by the weighted sum of the principal components.

Either a correlation matrix or a covariance matrix between all pairs of signals in the data set has been used to find the relationships between each pair of variables[40, 54]. The correlation matrix consists of the Pearson product-moment correlation coefficients between each pair of signals, which is a measure of the strength of linear dependence between two signals. The covariance matrix is composed of the covariance between signal pairs and describes how much the variance of one signal changes with the other signal. Because the Pearson correlation is obtained by dividing the covariance of the two signals by the product of their standard deviations, Pearson correlation and covariance are mathematically closely related measures of the relationship between two signals. In fact, they are equivalent measures if the signals have unit variance.

Both correlation and covariance have been used to find the relationships between each pair of variables, however, the two methods focus on different aspects of analysis. From the definitions of correlation and covariance, the covariance matrix gives greater weight to signals that vary over a larger range, whereas using the correlation matrix is equivalent to normalizing the amplitude of the signals and ensures that the analyses are not dominated by the largest signals. Therefore, principal components extracted from a covariance matrix will be dominated by signals with larger amplitudes, whereas those extracted from a correlation matrix will be influenced only by the temporal relationships among the original time-series[55]. It has been suggested that the matrix utilized could affect the percentage of cumulative power represented by the first several eigenvectors[46]. A recent study applied dynamic linear system analysis to identify the correlation in frequency domain which could overcome the limitation of phase difference and amplitude ratio[56-57]. Coherence matrix generated from the dynamic linear system analysis was employed in principal component analysis instead of correlation or covariance matrix. As more information carried by coherence matrix, the performance of principal component analysis was enhanced in terms of detecting principal component.

There are a variety of rules to estimate the number of components[58]. The performance of the rules is largely dependent on whether the data contain uncorrelated variables and on the size of the correlation matrix[59]. For human movement studies, the eigenvalue and the variance explained are frequently used in determination of the principal component number. The Kaiser-Guttman method is a popular stopping rule to determine the number of principal components[60-61]. In this method, eigenvalues > 1 are retained because these components summarize more information than any single original variable. However, this rule has been criticized by other researchers[62] because a principal component analysis of randomly generated, uncorrelated data will produce eigenvalues exceeding one. Therefore, another method which uses the percentage of total variance accounted for has been proposed to determine principal component numbers. In this method, the number of principal components needed to adequately describe a data set is found using criteria which are based on the portion of explained variation[63-64]. Normally, the first several principal components that account for over 90% of total variance are identified from a scree plot (where the variance accounted for by each additional principal component is plotted according to decreasing amounts of contribution) and selected. In order to explain the variance within kinematic and kinetic data of human locomotion, both of these methods have been applied widely[40, 65-68].

**Outcomes of human movements studies using principal component analysis**

Many human locomotion studies have applied principal component analysis to interpret human movement data and increase understanding of the complex coordination of locomotion. In these studies, principal component analysis has been used to determine redundancies[22, 40, 46], identify patterns of coordination[21, 54, 65, 68-69] and discriminate different activities[16, 20, 42-43, 66, 70].

***Redundancy determination***

Basically, principal component analysis is used to detect the redundancy within the data, reduce the dimensionality effectively and separate invariant structure and variance in data sets. Most previous studies stated that the dimensionality of gait data could be reduced to 3–5 principal components that could account for most of the variance within the data, depending on the number of dimensions measured and the relative complexity of the behaviour analysed[15, 20, 22, 40, 65-66].

Principal component analysis was used to investigate the complex coordinated movement of walking and stepping over obstacles[22]. Eight angles from the trunk, thigh, lower leg and foot angles were collected in this study. Three principal components that accounted for over 95% of angles changes were extracted from principal component analysis, which meant that the changes in the raw angle data could be adequately approximated by varying only three principal components. Another study reported that the first four modes generated from principal components covered about 90% of walking signals that had 90 dimensions and thus could be assumed to cover most relevant features of the data[40]. Similarly, Daffertshofer *et al* [40] applied principal component analysis to reduce the dimensionality of each subject’s set of postures. The results showed that a low-dimensional space spanned by the first four eigenpostures could account for 98% of variance within the original data set that had a dimensionality of 1 400.

It is not only kinematic data that can be reduced in dimensionality by principal component analysis. Electromyography data also have been successfully processed by principal component analysis during walking. Five principal component waveforms have been identified to account for about 90% of the total waveform variance across different muscles during normal gait[71]. Similar results have been reported in another studies[46, 54, 68] which indicated that first few principal components were retained as features to represent the original electromyography data.

***Pattern identification***

Further investigation of principal components can help to identify the synergies or patterns during human motion. As already indicated, Daffertshofer *et al* [40] reported that four principal components could cover about 90% of the variance of walking signals that had 90 dimensions. A closer look at these principal components revealed that the first and third principal components primarily reflected the arm and foot movements, including all the phase-locked components that oscillated at the stride or walking frequency (*e.g*., knee and hip positions). In contrast, the second and fourth principal components appeared to oscillate at twice the basic movement frequency (*i.e*., the step frequency), reflecting knee and ankle bending as well as body sway. It was also found that all the phase-locked components that oscillated at this double frequency contributed to the second and fourth principal components.

Das *et al* [65] applied principal component analysis to normal human limb angles during gait. The first four principal components were extracted and analyzed. It was found that the first two components captured the phase of the gait (*i.e*. stance and swing) and accounted for about 70% of the variance; while the third and fourth components were useful in discriminating between running and walking. All the data points were further projected onto the plane defined by the first and second principal components, as well as the third and fourth principal components, respectively. The phase information (temporal cues) was captured by the first two principal components, while the gait pattern (spatial cues) was differentiated by plotting all the data points onto the third and fourth principal components. Temporal cues from the first two principal components contained information that could identify the phase of the gait cycle; spatial cues from the third and fourth principal components were useful for recognizing running and walking.

Davis and Vaughan[69] conducted a study to investigate activation patterns of 16 lower limb muscles during gait using principal component analysis. Four factors were found to account for 91.5% of the variance in the original data set. Further analysis of the factor loading matrix showed that certain muscle groups acted in a similar manner. The muscle groups could be divided into those that act at the times of 1/ heelstrike, 2/ single limb loading response, 3/ propulsion phase, or else 4/ acted in a biphasic manner.

***Discrimination of different activities***

Principal component analysis has also been employed to investigate motor control patterns and has been suggested to be able to identify differences in gait pattern between groups. To assess the walking performance of asymptomatic elderly subjects, kinematic and kinetic gait data of the knee joint (*e.g*. joint angles, net reaction moments and bone-on-bone forces) were collected and four principal components were extracted using principal component analysis[42]. The difference between the original data and that estimated from the inverted principal component model was defined as residuals. The residuals calculated from the gait data of normal subjects and patients were compared to detect statistically significant differences. The outcomes of the analysis of residuals were shown to agree with the clinical findings. This indicated that the principal component models were able to quantify differences from normal with statistical significance.

In order to evaluate hip diseases, principal component analysis was conducted and a “gait evaluation plane” was formed by the first two principal components[70]. The four quadrants defined by the gait evaluation plane explained different characteristics of gait in terms of high or low gait ability, symmetry and activity. The distribution of the subjects on the gait evaluation plane was distinguished by different clinical treatment procedures. Specifically, patients with total hip replacement, internal fixation and prosthetic reconstruction were distributed in the 1st and 2nd quadrants, which showed low activity. Patients with hip fusion and arthroplasty were in the 3rd and 4th quadrants, which showed low symmetry. Patients undergoing conservative treatment and osteotomy were distributed throughout the plane. Thus, it was suggested that the position in the gait evaluation plane showed good agreement with clinical gait characteristics.

Ivanenko *et al* [43] conducted a study using principal component analysis to detect differences in walking pattern between normal individuals and patients with spinal injury. A basic set of five temporal components accounted for most of the variance of the electromyography activity across recorded muscles. The shape of the five components was generally similar in both controls and patients but the weights of the five components differed between groups. It was therefore suggested that even though the fundamental signals expressed by the five temporal components were preserved after a spinal lesion, their distribution to α motor neurons pools was re-wired, which could presumably be considered as an adaptation of lesion or training.

Walking and running are the two most common forms of human gait. Although they share some basic kinetics and kinematics, the two gaits are obviously different. The differences between them were assessed by applying principal component analysis to the kinematics and to electromyography data from 32 muscles[16]. The timing of muscle activation was accounted for by the same five basic temporal activation components during running as found previously for walking[71] and in patients[43]. The major difference between walking and running in terms of muscle activation was found at stance phase. One component was found to shift to an earlier phase in the step cycle during running.

**Other techniques**

In addition to principal component analysis, other statistical methods such as independent components analysis and nonnegative matrix factorisation[72] have been developed to assess linear decomposition of data sets based on different assumptions[38]. The differences between principal component analysis and nonnegative matrix factorisation arise from the constraints imposed on the matrix factors. Principal component analysis constrains the analysis to orthogonal (uncorrelated) factors, while nonnegative matrix factorisation constrains the temporal components and weighting coefficients to be nonnegative. Compared to the orthogonal factors yielded by principal component analysis, independent components analysis aims at extracting unknown hidden components from multivariate data based on the assumption that the unknown components are mutually independent[73].

These different analyses (principal component analysis, independent components analysis, and nonnegative matrix factorisation) have been applied to find common components in the electromyography patterns across muscles in both animal locomotion[38] and human walking[17] and running[16]. Normally, different sets of components were extracted because the statistical approaches applied different restrictions on the outcomes. The results of these studies, however, showed that the three methods gave essentially the same result--they reduced the dimensionality of the data to the same number of components. The different algorithms converged to a similar solution about the temporal structure of the electromyography activation patterns. The total variance explained by the basic temporal components was also close for each method. Therefore, different statistical methods have similar performance in terms of detecting movement control mechanisms, reduction of dimensionality and component extraction.

**Reconstruction**

Since the principal components extract most of the information contained in the original data set, the original data can then be reconstructed using a linear combination of the principal components. Several studies have successfully reconstructed the original data using this method[20, 40, 42, 46]. Wootten *et al* [46] applied principal component analysis to an electromyography data set, extracted several principal components and suggested that principal component analysis was very efficient in the reconstruction of the original electromyography waveforms. Kinematic data of human walking also have been reconstructed using the principal components extracted from principal component analysis[40, 42], the first several principal components being sufficient to reconstruct the original kinematic signals.

Generally, there exists an arbitrary number of vector sets $\{\overrightarrow{Vec}^{(k)}\}$ that can express the *N*-dimensional original vector set $\vec{X}(t)$ as $\vec{X}(t)=\sum_{k=1}^{N}P_k(t)\overrightarrow{Vec}^{(k)}$. In this equation, the $\overrightarrow{Vec}^{(k)}$ reflects an N-dimensional vector. When the vectors within $\{\overrightarrow{Vec}^{(k)}\}$ are independent and orthogonal, they are the same as the eigenvector outputs from the principal component analysis. The eigenvector, $\{\overrightarrow{eigVec}^{(k)}\}$, from principal component analysis can therefore be used to reconstruct the original data. After running a principal component analysis on the original data $\vec{X}(t)$, $P_k(t)$ is the scalar product of the original data and the corresponding eigenvector, that is $P_k(t)=\overrightarrow{eigVec}^{(k)}\vec{X}(t)$. As the first M (M < N) components can account for the majority of variance within the original data $\vec{X}(t)$, $\vec{X}(t)$ can be approximated by $\vec{X}(t)\approx\vec{X}^{(M)}(t)=\sum_{k=1}^{M<N}P_k(t)\overrightarrow{eigVec}^{(k)}$. In this way, the original data can be reconstructed by using the first M components while keeping its main features [40].

**Injuries**

To investigate the mechanism of injury, many experimental models have been used in biomedical research include animal, live human and human cadavers and computational modelling. The computer model of walking is getting more popular for studying injury during walking. An injury during walking could be considered to result from the external perturbation which would be detected as an extra degree of freedom by using the technique reviewed in this paper.

## CONCLUSION

Human walking movements and control mechanism have long been of great interest to investigators. This paper summarized both the dimensional properties of human walking and the popular techniques employed in detecting the dimension of movement and further provided more complete information of the coordinative structure of human walking and the techniques used to identify the movement coordination. The coordinative structure of walking may further increase the understanding of injury.

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