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Identification of movement strategies during the sit-to-walk movement in patients with knee osteoarthritis

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Abstract

Patients with osteoarthritis of the knee commonly alter their movement to compensate for lower limb weakness and alleviate joint pain. Movement alterations may lead to weight-bearing asymmetries, and potentially in the progression of the disease. This study presents a novel numerical procedure for the identification of sit-to-walk strategies and differences in movement habits between control adults and persons with knee osteoarthritis.

Ten control and twelve participants with osteoarthritis performed the sit-to-walk task in a motion capture laboratory. Participants sat on a stool, height adjusted to 100% of their knee height, then stood, and walked to pick up an object from a table in front of them. Different movement strategies were identified by means of hierarchical clustering. Trials were also classified as to whether the left and right extremities used a bilateral or an asymmetrical strategy. Participants with osteoarthritis used significantly more asymmetrical arm strategies ($p = .034$), while adopting the pushing through the chair strategy more often than the control subjects ($p = .015$).

The results demonstrated that the two groups favour different sit-to-walk strategies. Asymmetrical arm behaviour possibly indicates a compensation for the weakness of the affected leg. The proposed procedure may be useful to rapidly assess post-operative outcomes and developing rehabilitation strategies.

***Keywords*:** Hierarchical clustering, movement asymmetries, motion analysis

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Introduction

Movement alterations and neuromuscular adaptations in activities of daily living in patients with knee osteoarthritis are well documented. Studies have reported such changes in level walking,[1-3] stair ascent and descent[4,5] and sit-to-stand.[6-12] The main reason suggested for the movement alterations is to unload the affected joint while keeping the pain experienced to a minimum.[13-15] Yet, such asymmetric adaptations can lead to the progression of the disease, and even knee replacements in the contralateral joints in patients with end-stage osteoarthritis.[16,17]

The biomechanics of the sit-to-stand and sit-to-walk movement, in people with disabilities, has been previously reported.[18-21] The identification of movement strategies, or the study of their effects has been achieved via questionnaires, video observation and motion analysis.[22-26] Pushing through the armrest, pushing through the knees, scooting forward, leaning forward, thorax flexion and obliquity, feet backward, and no arms used have all been identified as categories of movement strategy.[22,23,25] However, to the authors' knowledge, there are no studies describing numerical tools to identify and classify the standing movement, potentially facilitating rapid analysis of motion capture data with minimal visual inspection.

We propose the use of hierarchical clustering, to categorise sit-to-walk strategies. Cluster analysis is a statistical technique used to identify structure in a series of objects by organizing the objects into groups, or so called, clusters.[27,28] Clustering has been used in a wide range of applications, from the mapping of the brain activity[29] to discovering patterns from stock markets[30] and earthquake applications.[31] Motion patterns of human movement have been elucidated by clustering indices of joint angle trajectories of people performing goal-directed tasks: Ait El Menceur et al and Lempereur et al identified movement strategies during the car ingress movement, whilst Park et al discerned stoop and squat lifting motions.[32-34]

This paper explores the use of hierarchical clustering to classify the sit-to-walk movement and detect asymmetries in the movements of people with and without physical disabilities of the lower limbs. Even though trials are grouped through the clustering process, the movement strategy prescribed to each cluster needs to be identified through observation. Nevertheless, a reliable procedure will allow the identification of the strategy attributed to each cluster by visually inspecting only a fraction of the cluster's trials. This, combined with the advantages of a process utilizing quantitative data and statistical methods over observational techniques, will allow the fast and consistent identification of movement strategies in bulky motion analysis data libraries.

Methods

Participants: This paper reports a subgroup analysis of the study "Biomechanical Assessment of a High Congruency Knee Bearing" registered at www.clinical trials.gov as NCT02422251. Ten young adults and twelve persons with osteoarthritis (Table 1) were recruited from community groups and the Golden Jubilee National Hospital in Clydebank, Scotland, respectively. The study had the ethical approval of the Strathclyde University Ethics and the West of Scotland Research Ethics Committee 5. Control participants with abnormal lower limb function, previous lower limb surgery and musculoskeletal, neurological or sensory deficit were excluded. Patients with osteoarthritis were scheduled for a primary unilateral total-knee replacement one to two weeks after their sit-to-walk session took place. All participants gave written informed consent for the study.

Hierarchical clustering: The basic input for most clustering applications is a multivariate data matrix $n \times p$ where each row contains multiple measurements describing each object to be clustered. Then, a measure of similarity (e.g. Euclidean distance, city block distance, Pearson correlation) is used to transform the $n \times p$ matrix into an $n \times n$, the elements of which give a measure of similarity (or dissimilarity) between pairs of objects. Values of the $n \times p$ and $n \times n$ matrices may also be transformed allowing procedures such as value standardization (e.g. z-scores or range 0 to 1), or converting an exponential dissimilarity relationship to a linear one (logarithmic transformation). Next, the technique proceeds to a series of mergers of objects into groups. Initially, each object n, occupies a single cluster. Then, the selected measure of similarity between each and every pair of objects can be used to cluster two objects together resulting in a $n-1$ cluster solution. The grouping is made on the basis of keeping the within-group dissimilarity at minimum. A clustering algorithm (e.g. nearest neighbor, centroid clustering, Ward's method) is used to measure the similarity between clusters when one or both clusters contain two or more objects. Differences among clustering algorithms arise from the way the distance (i.e. similarity) between two groups is defined. The procedure continues by combining two clusters at each stage until all objects belong in a single cluster. The end product of the hierarchical clustering method is the combination of the objects in a tree of clusters, the dendrogram.[28]

Different measures of similarities and hierarchical clustering algorithms may produce very diverse results on the same data set. As addressed by Everitt et al, apart from general observations regarding the properties of each clustering approach, no recommendations can be made in an absolute sense. Even so, several authors[36-38] provide a discussion over the choice of the similarity measure given the nature of the data, or provide remarks about typical clustering algorithms.[35]

The most critical issue of the clustering process is determining the number of clusters most representative for the group of objects.[39] Even though there are no standard techniques, a trend in a measure of dissimilarity, the agglomeration schedule coefficient, can be used as an indicator. Yet, as addressed by Hair et al,[39] this approach will most often result in a two-cluster solution due to the high increase of the dissimilarity measure when going from a two to one cluster solution. Unlike clustering of static data, time series clustering can be notably challenging, especially in long time series with dissimilar lengths.[40] In those cases, authors have resorted to approaches of capturing the behaviour of the curve by means of first and second-order decompositions, such as the mean value, standard deviation and trend.[40]

Data collection: All measurements were made in a motion capture laboratory using a six T-160 and six T-40S camera system (©Vicon Motion Systems Ltd) at a sampling rate of 100 Hz. Male participants wore tight fitting Lycra shorts and trainers; female participants additionally wore a Lycra sports bra. Reflective markers (diameter 14mm) were attached using double-sided adhesive ring tape to thirty-five anatomical landmarks as part of the full-body Plug-In Gait model. The markers were positioned on the left and right temple and on the back of the head in the horizontal plane defined by the front head markers with a sports headband, 7th cervical vertebra, 10th thoracic vertebra, suprasternal notch, xiphoid process of the sternum, middle of the right scapula, acromioclavicular joints, lateral epicondyles of humerus, laterally and medially of the wrists, below the head of the second metacarpals, bilaterally to the anterior and posterior superior iliac spine, lateral epicondyles of the femurs, thighs, tibias, lateral malleoli, over the second metatarsal heads and mid heels.[41] Subjects' anthropometrics were measured for the model scaling.

Yet, a subset of seven markers is required for the clustering analysis: the suprasternal notch, the metacarpals, the lateral malleoli and the lateral epicondyles of the femurs, denoting the position of the torso, hands, feet and knees respectively. The full-body Plug-In Gait model was adopted to facilitate the analysis of a series of different tasks, including the sit-to-walk, which the participants of this study performed during the same motion capture session. Additionally, the processed full-body model aided the validation of the classification results, by allowing the visual inspection of the trials in the Vicon Nexus 3D perspective workspace.

To complete the sit-to-walk task, subjects were instructed to sit on a standard armless, backless chair, height adjusted to 100% of knee height. If a participant was unable to rise to a standing position, the chair was re-adjusted to 115% of knee height. Apart from a single participant whose chair was re-adjusted, all other subjects performed the task with the chair at 100% of knee height. Similarly to Dolecka et al and Farquhar et al,[22,42] a table with a target object was placed three meters in front of the chair. The participants were instructed, on the count to three, to stand up, approach the table and pick up the target object. Participants were asked to perform the task in a natural manner similar to standing up from a chair at home to pick up a glass of water from the table in front of them. No other instructions were given. Up to five trials of the task were recorded per participant.

Data processing: For each recorded trial, two frames, $f1$ and $f2$, were chosen to characterise the initiation and endpoint of the movement strategy. Frame $f1$ depicted the participant preceding the sit-to-walk movement, whilst frame $f2$ was chosen to reveal the strategy that the participant used between $f1$ and $f2$. Frame $f2$ exists before gait initiation, discounting changes due to side dominance, i.e. left or right leg first to walk. Whole-body centre of mass trajectory and vertical velocity along with the mediolateral ground reaction force may be used to identify the phases of the continuous sit-to-walk movement[43] and select the desirable frame(s) $f1$ and $f2$. In this study, the drop in the vertical centre of mass trajectory at the beginning of the movement was used to determine the aforementioned frames $f1$ and $f2$. Marker trajectories were filtered using a 4^{th} order Butterworth filter with a cut-off frequency of 6 Hz.

Global coordinates of the markers were determined at $f1$ and $f2$ for all trials. The following variables were calculated between $f1$ and $f2$: the angle of the trajectory of the torso marker projected in the sagittal plane with respect to the horizontal; the horizontal distance moved by each foot marker in the sagittal plane normalised by body height; the horizontal distance moved by each hand marker in the sagittal plane normalised by body height; the relative x, y and z position of each hand with respect to the lateral epicondyle of the ipsilateral knee normalised by body height. Normalising functions under the assumption that segment lengths are analogous to total body height.[44]

The variables were organized into four separate matrices corresponding to the torso angle (2×61), foot movement (2×122), hand movement (2×122), and the relative position of hands with respect to the knee (4×122). The first row of each matrix contained a concatenation of the participant identifier (A-J: control group, K-V: osteoarthritis group), trial number $(1 - 5)$ and, except for the torso matrix, sidedness $(L\ or\ R)$.

Matrices were submitted to HC (IBM SPSS) separately. Ward's method and Euclidian distance were chosen as the agglomerative algorithm and distance measure respectively. The combination of strategies each subject used to complete the sit-to-walk movement derives from summation of the strategies identified from each distinct HC. Fisher Exact tests were used to compare the two groups for strategy preference and to assess the level of movement symmetry in each group. Significance was set at $p = .05$.

Results

The dendrogram obtained from the clustering of the torso matrix suggests the existence of two major clusters separated by a dashed line (Figure 1). This is confirmed by the change in the agglomeration schedule coefficient (horizontal axis, scaled from 1 to 25). Cluster 1 contains 48 subjects and cluster 2 contains 13. Visual inspection of the trials in the Vicon Nexus 3D perspective workspace indicates that the subjects in cluster 1 use the leaning forward (LF) strategy.

The existence of two clusters, each for feet (Figure 2) and hands (Figure 3), is similarly supported by the increase in the scaled agglomeration coefficients (horizontal axes) in the last stage of each HC. Cluster 2 from the foot progression clustering contains 27 lower extremities and corresponds to the foot backward (FB) strategy while the elements in cluster 1 refer to rather motionless lower extremities. Similarly, cluster 2 from the clustering of the hands contains 29 upper extremities related to the arm forward (AF) strategy.

Trials in cluster 1 of the hand movement matrix were submitted to the final hierarchical clustering: the fourth matrix corresponding to the relative position of the hands was diminished from 4×122 to 4×93, by removing the elements of the matrix following the arm forward strategy. The dendrogram (Figure 4) implies the existence of two to four major clusters. Visual inspection of the trials in Vicon Nexus 3D perspective workspace revealed that extremities belonging in cluster 1, 2 and 3 use the push knee (PK), no arms (NA) and push chair (PC) strategies respectively. Clustering results may also be illustrated by plotting the relative position of the extremities (Figure 5). Extremities adopting the arm forward strategy seem to overlap with other clusters at $f2$ since the distinction of the arm strategies resulted from the progression of the hands throughout the sit-to-walk motion and not from the spatial position at a single frame.

The strategy each subject used to complete the task, derives from the accumulation of the various extremity strategies identified through the clustering process (Table 2). Bilateral strategies, where the left and right extremities used a matching strategy, are noted with a subscript B. In the last clustering of the position of the hands, irregular movement strategies were classified and clustered among the three major clusters of the three-cluster solution. At trials A3, A4 and Q5, participants kept their hand(s) close to the seat at the height of their pelvis until completion of the standing movement. As a result, the trials were clustered as if the subjects were pushing through the chair. Similarly, during trials N1 and R1 the hands floated over their knees, hence, those movements were linked to the push knee strategy.

Patient participants adopted the push chair strategy more frequently than the control group ($p = .015$) (Table 3). Conversely, control participants potentially have a tendency to favour the push knee strategy however, the difference between groups was non-significant ($p = .097$). There was no difference between groups in the frequency of use of such feet strategies, ($p = .205$). On the other hand, patients with osteoarthritis used considerably more asymmetrical arm strategies ($p = .034$), while the control group adopted more bilateral arm strategies (Table 3).

Discussion

A novel numerical procedure was used to identify movement patterns and dissimilarities in the behaviour of control participants and patients with osteoarthritis of the knee. The results obtained in this study are in agreement with the findings in the observation study of older adults and people living with dementia performing the sit-to-stand movement by Dolecka et al.[22] Leaning forward was the most common movement strategy, used in 88.5% of the trials by the control group in this study compared to 100% previously reported.[22] The foot backward strategy was observed in 34.6% of the control trials in this study compared to 33.3% reported by Dolecka et al.[22] Other similar strategies are observed in this, and the abovementioned study[22] with similar frequencies: pushing through knees in 46.2% and 36.6% of the control trials; no arms used in 23.1% and 20%. The scoot forward may also make the task easier, [22,25,45,46] however, this type of movement was not adopted by healthy older adults.[22] Our analysis cannot identify this strategy since the progression of the pelvis was not considered when constructing the matrices. Nevertheless, this strategy is infrequent and can be excluded if it is considered an adjustment in the starting position of the participant. Apart from the five strategies detected, the leaning forward, foot backward, push knee, no arms and push chair, the hierarchical clustering of the hands progression matrix additionally revealed the arm forward strategy.

The increased use of the push chair strategy by the osteoarthritis group may indicate a need to assist the sit-to-walk movement by decreasing the loading on the affected knee. Persons with osteoarthritis also prefer more asymmetrical arm strategies; those two findings reveal an insightful pattern in their movement behaviour: pushing through the chair with the arm ipsilateral to the affected knee decreases the demand on lower limb extensors,[47] while the contralateral arm may assist the movement by the use of the arm forward or push knee strategies. Such patterns might ease the pain on the affected joint by transferring the weight-bearing on other joints, increasing though, the risk of injury at the hip and ankle.[48] The identification of such compensation mechanisms and movement strategies may strengthen and accompany the biomechanical analysis of motion capture by providing a depiction of the manner participants perform the movement, act as an indicator of the rehabilitation process of subjects with movement disabilities, or correlate the effect of treatment methods on the outcome of the therapy.

Considering different body segments independently, which in reality act in concert, has its own merit. When dealing with motion capture data, it is anticipated that repeated recordings of the same participant are clustered together due to an increased resemblance of the majority of the segments behavior. By considering each segment separately, the proposed procedure was shown to accurately discern strategies independently of the individual adopting them (Table 2). Additionally, by only including five body segments and two or four strategies per segment, the whole-body behaviour can be described by 128 possible whole-body variations. Alternatively, if all body segments were clustered simultaneously, the optimum numerous cluster solution would have been challenging to detect and validate, with differences among clusters being possibly trivial. What is more, by including further descriptive layers of movement, the suggested clustering process would exponentially increase the number of whole-body strategies while making sure that the results are comparable and descriptive.

A limitation of the study may arise from the trial exclusion, resulting in an uneven distribution of the included trials among participants. Although the strategy classification process requires the trajectories of only seven anatomical landmarks at two single time frames, entire trials had to be processed in order to facilitate the validation of the clustering results, and estimate the whole-body centre of mass trajectory which was used for the selection of frames $f1$ and $f2$. As a result, marker obstruction, more often in trials of obese participants, was the primary reason for trial exclusion. A second potential limitation of this study is associated with the heterogeneity of the characteristics of the two groups in question. In addition to the age contrast, the mean BMI of the control and patient participants (Table 1), sets the groups into two distinct weight classes: normal weight and obese persons respectively. Previous studies[49-51] have shown that both age and BMI influence the performance when rising from a chair. Presumably in the present study, the movement dissimilarities that were detected between people with and without knee osteoarthritis, may be credited to both age and obesity, and their association in the progression of joint disorders.[52] Nevertheless, the presence of asymmetric behaviour in the movement of people with knee osteoarthritis (Table 3), is most likely attributed to the negative impact of pain in the degenerative joints of the patient participants.

The selection of the similarity measure and the clustering algorithm can also be viewed critically. The Euclidean distance as a measure of similarity between a pair of objects can be interpreted as the physical distance between two points in the Euclidean space.[35] In an example of measuring the similarity between the progressions of extremities in an axis of motion, the Euclidean distance has the fitting property that the pair of extremities with the smallest dissimilarity have moved almost equally on that axis. As regards the clustering algorithm, Ward's method performs well when the data contain clusters of approximately the same size[35] which fits the dichotomous nature of this study's data set, i.e. mobility impaired and healthy individuals.

In conclusion, the proposed procedure managed to classify the participants based on the combination of distinct movement techniques used to fulfill the sit-to-walk movement. By means of the proposed methodology, it was possible to identify the five major strategies already reported through observation by Dolecka et al while detecting an additional sixth, the arm forward, which was likely reported combined with the no arm used trials. Other studies either classified movement strategies through observation without quantifying the degree of progression of the participants' extremities[22,25] or set a movement distance threshold without accounting for variation due to participants' anatomy.[26] Movement classification by the proposed procedure occurs based on quantitative data and statistical calculations, classifying a set of subjects into clusters according to their movement preferences while taking into consideration the body segment lengths. The key advantage of this procedure is the reduced processing time of the required dataset input: instead of processing (gap filling, filtering, modeling, etc.) the entire length of each recorded trial, processing two frames suffice for the entire analysis. Matching a strategy to each cluster requires the inspection of a small number of trials at each distinct cluster. Although the proposed classification process is not entirely free from the observational aspect, it may be employed as a practical and reliable tool to process large datasets in minimal time.

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Tables

Table 1. Participant characteristics

Characteristic	Control Group (n=10)	Osteoarthritis Group (n=12)
Gender (n), female/male	4/6	6/6
BMI (kg/m^2), mean ±SD	23.56 ±3.04	32.54 ±3.96
Age ($years$), mean ±SD	46 ±7.4	70 ±5.3
Chair height (cm), mean ±SD	50.40 ±2.93	49.85 ±4.25

Table 2. Distribution of strategies identified for the recorded trials

Subj.	1st trial	2nd trial	3rd trial	4th trial	5th trial
A	LF+AF$_B$	LF+NA$_B$	LF+**PC$_B$**	LF+**PC$_B$**	
B	LF+PK$_B$	LF+PK$_B$			
C	AF$_B$				
D	LF+FB$_R$+PK$_B$	LF+FB$_R$+PK$_B$	LF+FB$_R$+PK$_B$		
E	LF+FB$_L$+NA$_B$	LF+FB$_L$+AF$_B$			
F	LF+NA$_B$	LF+FB$_L$+NA$_B$	FB+NA$_B$	LF+AF$_B$	
G	LF+PK$_B$	LF+PK$_B$			
H	LF+PK$_B$	LF+PK$_B$	LF+PK$_B$		
I	LF+PK$_B$	LF+AF$_L$+PC$_R$	LF+FB$_L$+PC$_B$		
J	LF+FB$_R$+NA$_B$	PK$_B$			
K	LF+PK$_B$				
L	AF$_B$	AF$_B$			
M	LF+FB$_B$+AF$_B$	LF+FB$_B$+PK$_B$			
N	**PK$_B$**	FB$_B$+AF$_B$			
O	LF+PC$_B$	LF+PK$_B$	LF+PK$_B$	LF+PC$_B$	
P	LF+FB$_L$+PC$_B$	LF+PC$_B$	LF+FB$_B$+AF$_R$+PC$_L$	LF+FB$_L$+PC$_B$	LF+FB$_R$+PC$_B$
Q	LF+NA$_B$	LF+FB$_R$+NA$_B$	LF+FB$_R$+PC$_B$	LF+FB$_B$+NA$_R$+PC$_L$	LF+FB$_B$+NA$_R$+**PC$_L$**
R	LF+**PK$_B$**	AF$_B$			
S	LF+AF$_R$	LF+NA$_B$	LF+AF$_B$	LF+NA$_B$	
T	LF+PK$_B$				
U	LF+AF$_B$	LF+PC$_B$			
V	AF$_R$+PC$_L$	PK$_R$+PC$_L$	AF$_R$+PC$_L$	AF$_R$+PC$_L$	AF$_R$+PC$_L$

In bold: irregular movement strategies.

Abbreviations used: LF: leaning forward; FB: foot/feet backward; AF: arm(s) forward; NA: no arm(s); PC: arm(s) pushing through the chair; PK: arm(s) pushing through the knee(s); $_{B/R/L/}$: both/right/left.

Table 3. Strategies and asymmetries among groups.

Strategies	Control group (n =26 trials)	Osteoarthritis Group (n =35 trials)	$p-value$
Leaning forward, n trials (%)	23 (88.5%)	25 (71.4%)	.128
Foot/feet backward,[a] n trials (%)	9 (34.6%)	11 (31.4%)	.999
Arm(s) forward,[a] n trials (%)	5 (19.2%)	13 (37.1%)	.163
Pushing through the chair,[a] n trials (%)	**4 (15.4%)**	**16 (45.7%)**	**.015**
Pushing through the knee(s),[a] n trials (%)	12 (46.2%)	8 (22.9%)	.097
No arm(s),[a] n trials (%)	6 (23.1%)	6 (17.1%)	.746
Asymmetries			
Feet asymmetries, n trials (%)	8 (30.8%)	5 (14.3%)	.205
Hands asymmetries, n trials (%)	**1 (3.8%)**	**9 (25.7%)**	**.034**

In bold: Statistically significant difference between groups.

[a]Each type of strategy refers collectively to all possible bilateral and asymmetrical variations observed.

Figures

Figure 1 – Torso progression dendrogram.

Figure 2 – Feet progression dendrogram.

Figure 3 – Hands progression dendrogram.

Figure 4 – Hands spatial position dendrogram.

Figure 5 – Spatial position of the hand extremities with respect to the lateral epicondyle of the ipsilateral knee, adopting the push chair (PC), push knee (PK), no arms (NA), and arms forward (AF) strategies at frame f_2.