Relevant Elderly Gait Features for Functional Fitness Level Grouping

Marta S. Santos[1], Vera Moniz-Pereira[2], André Lourenco[1,3], Ana Fred[1] and António P. Veloso[2]
[1]*Instituto de Telecomunicações,1049-001, Lisboa, Portugal.*
[2]*Univ Tecn Lisboa, Fac Motricidade Humana,CIPER, LBMF, P-1499-002 Lisboa, Portugal*
[3]*Instituto Superior de Engenharia de Lisboa, Lisboa, Portugal*

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Abstract: Locomotor tasks characterization plays an important role in trying to improve the quality of life of a growing elderly population. This paper focuses on this matter by trying to characterize the locomotion of two population groups with different functional fitness levels (high or low) while executing three different tasks - gait, stair ascent and stair descent. Features were extracted from gait data, and feature selection methods were used in order to get the set of features that allow differentiation between functional fitness level. Unsupervised learning was used to validate the sets obtained and, ultimately, indicated that it is possible to distinguish the two population groups. The sets of best discriminate features for each task are identified and thoroughly analysed.

1 INTRODUCTION

Fall-related morbidity and mortality rates are referred to as one of the most common and serious problems faced by the elderly, affecting around 30% of the population above 65 years (Todd and Skelton, 2004). Several risk factors have been associated with falls, of which lower limb muscle weakness and gait and balance deficit seem to have a preponderant role (Rubenstein, 2006). Accordingly, we have found, in a cohort of 647 Portuguese older adults, that falls might not be an inevitable consequence of ageing and that health, functional fitness and physical activity parameters were the most determinant factors for both episodic and recurrent falls (Moniz-Pereira et al., 2012). Further, we also verified that the majority of the falls occurred in an outdoor setting, and mainly while walking or climbing stairs. Thus, the biomechanical characterization of locomotor tasks in older people with different levels of functional fitness may have an important contribution for the prevention of falls and the improvement of quality of life in this population.

The particular case of locomotion data analysis presents several inherent difficulties (Chau, 2001a), such a: high-dimensionality (several kinetic and kinematic variables acquired through a period of time); temporal dependence (there's a quasi-periodic temporal dependence, being difficult to model); high variability (intrasubject and intersubject); data is typically composed by curves which are hard to correlate, and the relationships between variables are nonlinear.

Usually, gait data analysis is done through statistical studies (Horváth et al., 2001), (Prince et al., 1997) leading to a series of means and standard deviations of the parameters measured for pre-determined population groups, which can be hard to analyse and do not reflect the relative importance of the measures in the problem studied.

Pattern recognition systems have been explored as an alternative way of looking into gait data. Through the analysis of gait patterns it has been possible to detect gait pathologies (Kohle et al., Jun; Hausdorff et al., 1997), fatigue (Janssen et al., 2011), to evaluate the effects of medical procedures on gait (Ishii et al., 1996), or to detect subject's features (age group, fitness level) (Reid et al., 2010). These systems usually require the following sequence of steps: (1) sensing, (2) segmentation and data cleaning, (3) feature extraction, and (4) learning. Learning can be supervised (where training is required and performed using labelled samples) or unsupervised (where the system finds natural groups in data).

One of the steps required in pattern recognition systems is feature extraction. Most of the times, features are empirically defined by visualization of the

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signal, which can lead to a big amount of extracted features. Due to the "curse of dimensionality" problem (Raudys and Jain, 1991), classification error increases with the increase of the number of features for datasets with few observations. Feature selection is an optional step performed before (or during) learning, that eliminates irrelevant features and overcomes this problem, leading to improvements in the performance. As an example, (Begg and Kamruzzaman, 2005) used feature selection in gait data causing an increase on it's SVM classifier's accuracy; and (Chan et al., 2002) performed this as a pre-step of several classifiers, resulting in an increase of the classification rate.

In this work, we will use several kinetic and kinematic variables acquired from a group of elderly, to verify the possibility to distinguish between high and low functional fitness (FF) levels groups (Rikli and Jones, 1999; Rose et al., 2006) and which locomotion features are more relevant for the distinction of these two groups. Due to the small sample available and since we meant to approach the data in an exploring perspective, unsupervised learning techniques are used.

The rest of the paper is organized as follows: section 2 gives a quick overview of related work; section 3 thoroughly explains the general methodology used in this work, from data collection, passing by feature extraction and selection and finally clustering and validation methods used; section 4 shows the results of applying the proposed methodology to our dataset; on section 5 the biomechanical meaning of the selected features is discussed; and section 6 draws the final conclusions.

2 RELATED WORK

Even though most of the gait pattern recognition investigation has been focused on supervised learning (Chau, 2001a) and (Chau, 2001b), some papers have reported the use of unsupervised learning techniques to investigate several gait characteristics. In (Xu et al., 2006), the authors tried to find underlying gait patterns among pathological and healthy gaits by applying k-means and hierarchical clustering algorithms (Jain and Dubes, 1988) to a series of features previously extracted. Cluster evaluation was done in terms of silhouette and mean square error (Halkidi et al., 2002).

In (Vaughan and O'Malley, 2005) fuzzy clustering is used to identity different walking strategies in children and young adults with cerebral palsy. In (Toro et al., 2007) hierarchical cluster analysis is used on sagittal kinematic gait data derived from children with and without cerebral palsy. Different walking strategies were distinguished by (Su et al., 2001) in patients with ankle arthrodesis using a fuzzy clustering technique. Non-hierarchical cluster analysis was used by (Mulroy et al., 2003) to classify the gait patterns of patients recovering from a stroke based on the temporal-spatial and kinematic parameters of walking. In (Jiang et al., 2010), affinity propagation clustering is used to better grouping of gait data based on the person's characteristics, and help to explain its relationship with human gait.

As shown there are several different clustering algorithms used for gait pattern recognition. In this study we apply the classical hierarchical clustering algorithms due to its simplicity and interpretability.

3 METHODOLOGY

Having as goal the separation of two populations (with high or low functional fitness level), the main focus of this work was to determine which features, from the acquired data, would be more relevant.

Several kinematic and kinetic variables were acquired from 3 different locomotor tasks, further described. The analysis is performed separately for each of the tasks, to systematically analyse the features involved, and because the tasks induce a different morphology in some variables.

The features were empirically determined by inspection of the signals, and selected using feature selection techniques. For the latter, we used a Wrapper method (Alelyani et al., 2013) combined with clustering. Finally, the obtained subsets of features were evaluated against the true label in order to verify the relevance of the features selected to our problem.

The methodology followed in this paper is systematized in figure 1.

3.1 Experimental Sets and Data Acquisition

A convenience sample of 27 participants over 65 years was selected from (Moniz-Pereira et al., 2012). None of them had any neurologic or orthopedic condition that would affect their gait pattern. Immediately prior to data collection, all participants were informed

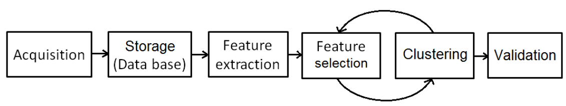


Figure 1: Methodology followed in this work.

about the study, accepted to participate and signed an informed consent. The Ethics Committee of Faculty of Human Kinetics approved the study protocol.

Functional fitness level was established according to a total score (TFFs) of 6 functional fitness tests (the 8 foot up and go, and the 30 second Chair Stand, from Senior Fitness Test battery (Rikli and Jones, 1999), and items 4 [step up and over] , 5 [tandem walk], 6 [stand on one leg] and 7 [stand on foam eyes closed] from the Fullerton Advanced Balance Scale (Rose et al., 2006)).

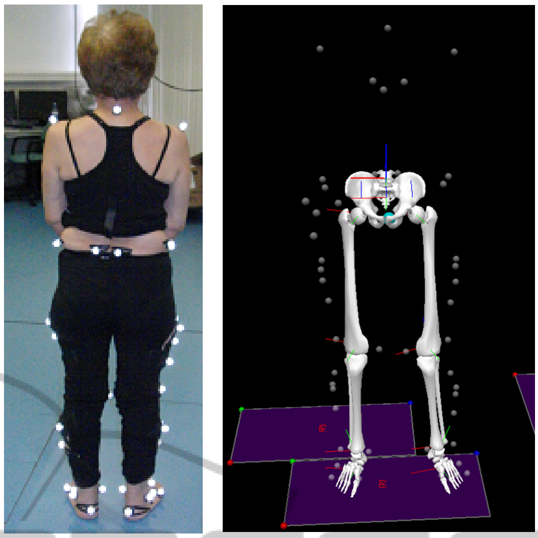
Three locomotor tasks were performed by each subject: gait (G), stair ascent (SA) and stair descent (SD). Several kinetic and kinematic variables were acquired relative to one gait cycle while performing each task. When performing the locomotor tasks, participants were barefoot and wore tight black shorts and t-shirts. Anthropometric measures (subjects body mass, stature and trochanteric height) were taken and the marker set used was based on the calibrated anatomical system technique (CAST) (Cappozzo et al., 1995), using a digitizing pointer for the ASIS markers 2(a).

Kinematic and kinetic data was collected with a Qualisys Track Manager system (Qualisys AB, Gothenburg, Sweden) with 8 infrared, high speed cameras (Qualisys Oqus 300, Qualisys AB, Gothenburg, Sweden) working at a frequency of 200 Hz and synchronized with two Kistler force plates (9281B e 9283U014 Kistler Instruments Ltd, Winterthur, Switzerland). For the stairs trials, a wooden staircase with three steps was built. Each step had 15 cm of height and 27 cm of depth. The last step was extended (80 cm depth) in order to avoid deceleration during stair climbing.

Two force platforms were used. The first was embedded on the floor in front of the staircase, while the second was covering and securely fixed on the first step. This step was built ensuring an extreme rigidity of the structure. Each force platform was independent of the surrounding wooden pieces to ensure adequate measures.

Participants were asked to walk at their comfortable pace. Prior to data collection, training trials were allowed so that the subjects would become comfortable with each task. Three trials from each task were collected, and the order of the tasks (walking and stairs) was randomized.

A seven segments (feet, shanks, thighs and pelvis) model was built for each subject 2(b) and optimized through inverse kinematics (Lu and O'Connor, 1999) to minimize the effect of soft tissue artefact. The joints were modelled as spherical joints, i.e. rotational motion was allowed in the 3 axis, but translations were restricted.



(a) Instrumented suject. (b) Subject based 7 segment 3D model.

Figure 2: Aquisition set.

A fourth order Butterworth low pass filter at 10Hz was used for both kinematic and kinetic data. Gait variables included: (1) foot and pelvis absolute angles, (2) lower limb joint angles (using a XYZ Cardan sequence), (3) ground reaction forces, (4) lower limb joint moments and powers (determined through inverse dynamics). Kinetic data was normalized to subjects body mass. As all variables were computed for the 3 planes of motion (X sagital plane, Y frontal plane and Z transverse plane), a total of 34 variables were analysed

All the aforementioned data processing was performed through a continuous pipeline developed under Visual 3D software (Professional Version v4.80.00, C-Motion, Inc, Rockville, USA).

3.2 Feature Extraction

Each *acquisition* comprises a total of 34 kinetic and kinematic variables acquired during one gait cycle performing a certain task. The data set contained 3 acquisitions of the same task per individual (from a total of 27 individuals). The individuals were divided in two groups according to their total functional fitness score (TFFs) - High FF level (HFFl) and Low FF level (LFFl). The median of the TFFs was 21 and the subjects were classified as having a Low FF score (TFFs range from 17 to 21 in a total of 14 subjects) and High FF score (TFFs range from 22 to 24 in a total of 13 subjects).

Due to limitation of the acquisition setup, in gait and stair descent tasks, a gait cycle (GC) is consid-

Table 1: Total functional fitness score of the population of this study. Low TFFs range: 17-21; High TFFs range: 22-24.

TFFs	17	18	19	20	21	22	23	24
Freq.	1	1	1	4	7	2	3	8

ered from toe off to toe off, and in stair ascent from heel strike to hell strike. Also, the signal morphology varied considerably for some variables from task to task. So, it is not possible to simply compare the variables when acquired during different tasks, and, therefore, the acquisitions are further separated by task performed.

The features extracted included the signals' mean, standard deviations, maxima, minima, area under the curve and skewness. Through visual analysis of each variable, a set of characteristics was extracted resulting in a total of 33, 31 and 37 features extracted for the G, SA and SD tasks, respectively. The features were then normalized in amplitude per task.

3.3 Feature Selection

One of the main problems in machine learning is the selection of relevant features from a set of extracted features. The feature selection can be divided in two main tasks: subset selection and subset evaluation.

In this work we used three techniques for subset selection (Molina et al., 2002): forward, backward and floating forward feature selection.

Forward feature selection (FS) is a bottom up method, i. e., it begins with an empty set and the best features are added at each step. The best features are the ones that, together with the rest of the subset of features already selected, will result in a better score according to some evaluation criteria.

Backward feature selection (BS) is similar to FS only it uses a top-down perspective, i. e., it begins with a full set and deletes the less relevant features. The less relevant features are the ones which exclusion will lead to a set of features with the highest score, according to some evaluation criteria.

The main disadvantage of the forward and backward feature selection methods is that they converge to local maxima of the evaluation function. To avoid this, and since we have a small number of features and samples, we have evaluated all the of possible cardinalities of the feature subset. This means that we have studied/evaluated the subsets resulting from setting all the possible values of *Min. no. of features* as a stopping criterion. This will return the full behaviour of the evaluation function allowing us to choose its global maximum.

Sequential floating forward feature selection (FFS) (Pudil et al., 1994) starts with an empty subset of features as in FS. However, the number of features does not increase monotonously. The algorithm involves both adding and deleting features. In this way nesting of feature sets is avoided.

In this study the application of the feature selection step is evaluated a clustering validity index over the clusters obtained using the subset of features under evaluation. We used the Ward's hierarchical method in combination with two clustering validity indexes: Adjusted Mutual Information score (AMI) (Vinh et al., 2010);Consistency Index (CI) (Fred, 2001).

3.4 Clustering

Unsupervised learning refers to the problem of finding hidden structure on the data. In this study Ward clustering (Murtagh and Legendre, 2011) (Jain and Dubes, 1988) is used and is, therefore, described in the next subsection. The last subsection, explains the validation methods used.

Other clustering methodologies, such as k-means, where used. However their results were worse than the ones obtained with Ward clustering therefore, and due to space constrains, these results are not presented nor this methodology is detailed.

3.4.1 Ward Method

Ward minimum variance method is an hierarchical clustering method that aims to minimize the sum of squared differences within the clusters (Murtagh and Legendre, 2011). It starts by considering each sample as a single cluster (singleton). Then, it will find the two clusters that, after merging, will lead to the minimum increase in the total within cluster variance. At each step, the clusters obeying this condition will be merged until a pre-defined total number of clusters is reached.

3.4.2 Subset Evaluation and Clustering Validation

After obtaining the natural clustering partitions of the data, we need to check if the partitions revealed are correlated with the parameter we want to investigate,the functional fitness level. This is done by comparing the partitions obtained with the data's true label using a validation method. The validation method will return a score that is a measure of the similarity between the partitions obtained and the true label.

We used two external criteria: Adjusted Mutual Information score (AMI)(Vinh et al., 2010) and Consistency Index (CI) (Fred, 2001) to compare the obtained results with the ground truth information.

As a Mutual Information function, AMI measures the agreement of the two assignments, ignoring permutations. Furthermore, it is normalized against chance. It is bounded between 0 and 1. Values close to 0 indicate random or largely independent labels, while values close to one indicate significant agreement. Also, it is invariant to cluster shape so it can be used with any clustering algorithm.

Let U and V be two clusters, $H(U)$ (eq. 1) and $H(V)$ (analogous to eq. 1) the entropy of the clusters, $I(U,V)$ the mutual information between the two clusters (eq. 2), and $E[I(U,V)]$ the expected mutual information between the two clusters. The AMI score is given by equation 3.

$$H(U) = \sum_{i=1}^{|U|} P(i) log(P(i)) \qquad (1)$$

$$I(U,V) = \sum_{i=1}^{|U|} \sum_{j=1}^{|V|} P(i,j) log(\frac{P(i,j)}{P(i)P(j)}) \qquad (2)$$

$$AMI(U,V) = \frac{I(U,V) - E[I(U,V)]}{max H(U), H(V) - E[I(U,V)]} \qquad (3)$$

The consistency index (CI) reflects the fraction of shared samples in matching clusters in two data partitions, over the total number of samples. It is an iterative procedure that, in each step, determines the pair of clusters having the highest matching score, given by the fraction of shared samples. As AMI, it ignores permutations, is bounded between 0 and 1 (0 means no matching at all, 1 means perfect match). CI can be generally expressed by:

$$CI = \frac{1}{n} \sum_{i=1}^{min\{nc_1, nc_2\}} n\_shared_i \qquad (4)$$

where nc_i the number of clusters in partition i and n_shared_i is the number of samples shared for the i^{th} clusters. One can say that the CI score is the clustering equivalent to an accuracy measure since it reflects the fraction of well classified samples.

4 RESULTS

As a baseline approach, we applied the clustering algorithm directly to the extracted features, without performing feature selection. A total of 33, 31 and 37 features were used for clustering in the gait (G), stair ascent (SA) and stair descent (SD) tasks, respectively. As a result, we obtained a CI score of 0.667 for the G and SD tasks, and 0.556 for the SA task, indicating that the features selected, as a group, did not allow a good differentiation between the locomotion of the subjects belonging to the two functional fitness levels.

Table 2: CI score and number of features of the subsets obtained with the different feature selection configurations. The results were obtained with the classical feature selection algorithms, column "Typical", and our adapted version to find the global maximum of the subset evaluation function, column "Global max". Best results are highlighted.

		AMI		CI	
		Typical	Global max	Typical	Global max
BS	G	**0.827 (13)**	**0.827 (13)**	0.741 (22)	0.741 (22)
	SA	0.827 (23)	0.79 (4)	0.852 (14)	0.859 (11)
	SD	0.778 (21)	0.815 (16)	0.704 (15)	0.778 (3)
FS	G	0.679 (1)	0.802 (5)	0.802 (5)	0.802 (5)
	SA	0.79 (2)	0.889 (17)	**0.889 (4)**	**0.889 (4)**
	SD	0.802 (6)	0.815 (16)	0.802 (3)	0.815 (10)
FFS	G	0.679 (1)	-	0.802 (5)	-
	SA	0.78 (2)	-	0.889 (6)	-
	SD	**0.852 (7)**	-	0.802 (3)	-

In order to investigate which features would be relevant for this purpose, we experimented several feature selection configurations. As referred in the previous sections, three subset search methods where used (forward, backward and floating forward feature selection), combined with two subset evaluation measures (AMI and CI scores), resulting in 6 different feature selection configurations. Also, we tried the typical BS and FS approach in which the only stopping criteria is "no improvement in the evaluation criteria" versus a search for the global maximum of the evaluation function. We present these results in table 2.

Results improved with feature selection. Also, as expected, results were generally better with the global max method; there are few situations where the first maximum coincided with the global maximum of the evaluation function.

The best CI scores obtained were of 0.827, 0.889 and 0.852 for the G, SA and SD tasks. These results indicate that the the features identified by the feature selection algorithms allow to distinguish the subjects of each group with a reasonable degree of confidence and it is worth to analyse the subsets in detail, which will be done in the next section.

5 SELECTED FEATURES DISCUSSION

For the results presented in the table 2 we defined *best result* as a higher CI score or a lower number of selected features. However, in a biomechanical context, fewer variables can mean results that are very difficult to interpret. Indeed, other configurations presented subsets with the same score but with a higher number of features. For the G and SA tasks 3 and 14 configurations, respectively, presented a score equal to the one selected as best. For the SA task, the best subset only contained 4 features, which is not enough for the biomechanical analysis, so we were forced to look into other frequently selected features present in the subsets with the same score as the best one. The maximum score for the SD task corresponded to a selection of features with small locomotor relevance, so we investigated the features frequently chosen by subsets with the second higher score for this task - 0.815.

In the next subsections we describe and discuss the features that are both frequently chosen by high score subsets and relevant to the locomotor task.

5.1 Gait Task

The group of elderly subjects with lower functional fitness level (LFFl) walked with the hip more flexed throughout the stance (figure 3(a)). (DeVita and Hortobagyi, 2000) have detected the same difference when comparing young with elderly subjects. In their work, the authors suggested that the increased hip flexion in elderly gait pattern was probably a postural adjustment in order to be able to produce larger extensor hip joint moment during stance and to compensate for the lower plantarflexor joint moment exerted. Although in this study we have not found differences in the hip extensor joint moment, the ankle plantaflexor joint moment peak showed to be lower in the LFFl group, meaning that these subjects have a significant less vigorous push off. Other authors (Prince et al., 1997); (Winter, 1991) have also reported a reduction in peak plantarflexor moment when comparing elderly with young subjects. These differences are also in accordance with the lower ground reaction force vertical peak showed by the LFFl peak during the push-off phase.

In contrast with the previously referred studies, however, we have found that subjects with a LFFl had a higher knee extensor joint moment peak at the beginning of the stance, during the weight acceptance phase. As the LFFl subjects also presented a higher degree of knee flexion (figure 3(b)) during this phase, a larger knee extensor moment may be necessary to control knee flexion and thus to properly support the body.

Data concerning the other planes of motion is scarce in the literature for this population. Nevertheless, the higher external rotation of the hip, ankle adduction joint moment (figure 3(c)) and knee abductor angular impulse seem to suggest a higher effort to control medio-lateral body stability in the LFFl group.

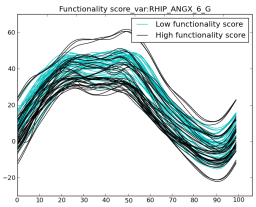
5.2 Stair Ascent Task

When compared to the HFFl group, the LFFl group also showed to adopt a different strategy to deal with the SA task. The higher hip and pelvis flexion angles (figures 3(d) and 3(e)) and a higher abduction hip angle may be a strategy of the subjects with low functional fitness level in order to guarantee a safe clearance of the swing leg through the intermediate step. Also, as mention before for the walking task, a more flexed hip during the stance may also be a postural adjustment in order to produce a larger extensor moment of the hip during the stance (DeVita and Hortobagyi, 2000). In fact, the subjects from the LFFl group seem to compensate their lack of plantarflexor joint moment during the stance, with a higher extensor hip moment. This was also verified by (Novak and Brouwer, 2011), when comparing young and older subjects. Furthermore, subjects higher functionality showed, not only to use more their plantarflexors, but also to produce more knee extension power during the weight acceptance phase.

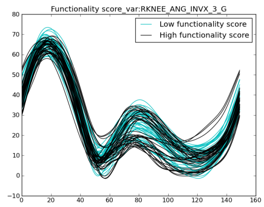
On the contrary of what has been reported when comparing young with older subjects (Novak and Brouwer, 2011), the LFFl group showed a lower hip abductor joint moment (figure 3(f)) when compared to the HFFl group. It could be hypothesize that due to the higher task demand, the subjects with a lower functional fitness level were not able to rely as much as the HFFl subjects on the hip abductor muscles to control the body lateral stability.

5.3 Stair Descent Task

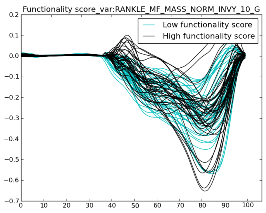
Finally, for the SD task the more significant features obtained to distinguish the LFFl group from the HFFl group were difficult to interpret in a biomechanical point of view. However, if we consider the features belonging to the second highest score subsets, it is interesting to verify that in accordance to what was verified in the previous tasks, the LFFl group had a more flexed hip (figure 3(g)) during the SD task and produce a higher hip extensor joint moment. Further, similar to what we have found for the SA task, the subjects with lower functionality produced a lower



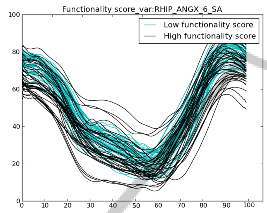
(a) Hip's angle in X (G). Feature: mean.



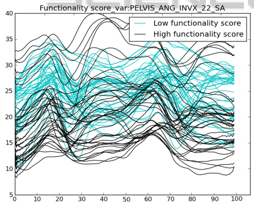
(b) Knee's angle in X (G). Feature: 2nd max



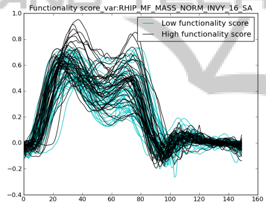
(c) Ankle's joint moment in Y (G). Feature: maximum (40% to 60% of GC), minimum and mean on the second third of the signal



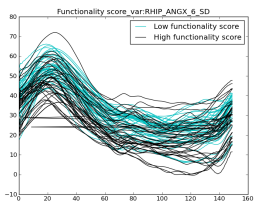
(d) Hip's angle in X (SA). Features: mean (till 20% of the GC)



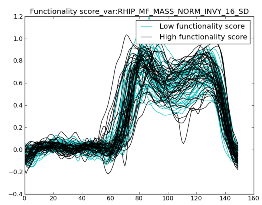
(e) Pelvis' angle in X (SA). Feature: mean.



(f) Hip's joint moment in Y (SA). Features: mean.



(g) Hip's angle in X (SD). Features: mean.



(h) Knee's momentum force in Y (SD). Feature: mean.

Figure 3: Plot of some of the gait cycle variables from which features where selected as most distinctive. Individuals with low functionality score are plotted in blue, and high functionality scores in black.

hip abduction joint moment (figure 3(h)) during this task showing therefore not to rely, as much as the HFFl group, on hip abductors to control the medial lateral stability of the body.

6 CONCLUSIONS

This paper summarizes the potential of different kinetic and kinematic features, acquired using an 7 segments model (feet, shanks, thighs and pelvis), to distinguish different functional fitness levels in an sample of elderly population. Unsupervised learning methodologies were used, and evidence was found favouring the natural separation of elderly population groups according to this parameter. Feature selection has proven to be an effective tool in revealing interesting variables increasing the discriminative capacity.

A set of best distinguishing features for each task is presented along with an analysis of the features selected and their meaning for the elderly locomotion. The results showed that some of the differences observed between groups are similar to the ones reported in the literature when studying differences between young and old subjects. In general, LFFl subjects adopted a more flexed hip posture during the analysed taskstasks. Additionally, they seem, not only to redistribute joint moments and compensate their lack of plantarflexor moment with a higher hip extensor moment, but also not to rely on the hip abductors, as much as the HFFL group, to control medio-lateral stability in more challenging tasks (SA and SD). These changes may increase the predisposition to fall in the LFFl group. Further, this could mean that changes in gait pattern may not be only a consequence of ageing, but also be caused by losses in functionality. The further investigation of these different gait patterns is therefore important for the establishment of exercise programs, aiming to improve functionality and therefore to prevent falls, for this population.

Future work includes trying different learning methods and feature selection methods and an extensive evaluation of the approach for larger data sets.

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REFERENCES

Alelyani, S., Tang, J., and Liu, H. (2013). Feature selection for clustering: A review. *Data Clustering: Algorithms and Applications*, CRC Press

Begg, R. and Kamruzzaman, J. (2005). A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data. *Journal of biomechanics*, 38(3):401–408.

Cappozzo, A., et al. (1995). Position and orientation in space of bones during movement: anatomical frame definition and determination. *Clin Biomech (Bristol, Avon)*, 10(4):171–178.

Chan, K., et al. (2002). Comparison of machine learning and traditional classifiers in glaucoma diagnosis. *Biomedical Eng, IEEE Trans on*, 49(9):963–974.

Chau, T. (2001a). A review of analytical techniques for gait data. part 1: fuzzy, statistical and fractal methods. *Gait & Posture*, 13(1):49–66.

Chau, T. (2001b). A review of analytical techniques for gait data. part 2: neural network and wavelet methods. *Gait & Posture*, 13(2):102–120.

DeVita, P. and Hortobagyi, T. (2000). Age causes a redistribution of joint torques and powers during gait. *J. Appl. Physiol.*, (88):1804–1811.

Fred, A. L. (2001). *Multiple Classifier Systems*, chapter Finding consistent clusters in data partitions. Springer.

Halkidi, M., Batistakis, Y., and Vazirgiannis, M. (2002). Cluster validity methods: Part i. *SIGMOD Record*.

Hausdorff, J., et al.(1997). Altered fractal dynamics of gait: reduced stride-interval correlations with aging and huntingtons disease. *J Appl Physiol*, 82(1):262–9.

Horváth, M.,et al. (2001). Kinematic and kinetic analyses of gait patterns in hemiplegic patients. *Facta univ-series: Physical Edu and Sport*, 1(8):25–35.

Ishii, Y.,s et al. (1996). Influence of total knee replacement (tkr) design on screw-home movement: Comparison of five designs for total knee replacement prostheses. *Journal of Orthopaedic Science*, 1:313–317.

Jain, A. K. and Dubes, R. (1988). *Algorithms for Clustering Data*. Prentice Hall.

Janssen, D., Schllhorn, W., et al. (2011). Diagnosing fatigue in gait patterns by support vector machines and self-organizing maps. *Hum Mov Sci*, 30(5):966–75.

Jiang, S., et al. (2010). Gait symmetry analysis based on affinity propagation clustering. In *Computer and Inf Tech (CIT), IEEE 10th Int Confe on*, 1673–1678.

Kohle, M., et al. Clinical gait analysis by neural networks: issues and experiences. In *Computer-Based Medical Systems., 1997. Proc., 10th IEEE Symp on*, 138–143.

Lu, T. and O'Connor, J. (1999). Bone position estimation from skin marker co-ordinates using global optimisation with joint constraints. *J Biomech*, 32(2):129–34.

Molina, L. C., Belanche, L., and Nebot, A. (2002). Feature selection algorithms: A survey and experimental evaluation. In *Proceedings of the 2002 IEEE International Conference on Data Mining*, ICDM '02, pages 306–, Washington, DC, USA. IEEE Computer Society.

Moniz-Pereira, V., Carnide, F., et al. (2012). Falls in portuguese older people: procedures and preliminary results of the study biomechanics of locomotion in the elderly. *Acta Reumtol. Port.*, 37:324–332.

Mulroy, S., Gronley, J., et al. (2003). Use of cluster analysis for gait pattern classification of patients in the early and late recovery phases following stroke. *Gait & Posture*, 18(1):114 – 125.

Murtagh, F. and Legendre, P. (2011). Ward's hierarchical clustering method: Clustering criterion and agglomerative algorithm. *CoRR*, abs/1111.6285.

Novak, A. and Brouwer, B. (2011). Sagittal and frontal lower limb joint moments during stair ascent and descent in young and older adults. *Gait Posture*, 33(1):54–60.

Prince, F., Corriveau, H., et al. (1997). Gait in the elderly. *Gait & Posture*, 5(2):128–135.

Pudil, P., Novovičová, J., and Kittler, J. (1994). Floating search methods in feature selection. *Pattern recognition letters*, 15(11):1119–1125.

Raudys, S. J. and Jain, A. K. (1991). Small sample size effects in statistical pattern recognition: Recommendations for practitioners. *IEEE Tran. on pattern analysis and machine intelligence*, 13(3):252–264.

Reid, S. M., et al. (2010). Differentiation of young and older adult stair climbing gait using principal component analysis. *Gait & Posture*, 31(2):197 – 203.

Rikli, R. E. and Jones, C. J. (1999). Development and validation of a functional fitness test for community-residing older adults. *IEEE Trans Pattern Analysis and Machine Intelligence*, (7):129–161.

Rose, D., Lucchese, N., and Wiersma, L. (2006). Development of a multidimensional balance scale for use with functionally independent older adults. *Arch. Phys. Med. Rehabil.*, (87(11)):14781485.

Rubenstein, L. Z. (2006). Falls in older people: epidemiology, risk factors and strategies for prevention. *Age and Ageing*, 35 Suppl 2:ii37ii41.

Su, F.-C., Wu, W.-L., Cheng, Y.-M., and Chou, Y.-L. (2001). Fuzzy clustering of gait patterns of patients after ankle arthrodesis based on kinematic parameters. *Medical Engineering & Physics*, 23(2):83 – 90.

Todd, D. and Skelton, C. (2004). What are the main risk factors for falls amongst older people and what are the most effective interventions to prevent these falls? *Copenhagen: WHO Regional Office for Europe*.

Toro, B., Nester, C. J., and Farren, P. C. (2007). Cluster analysis for the extraction of sagittal gait patterns in children with cerebral palsy. *Gait & Posture*, 25(2):157–65.

Vaughan, C. L. and O'Malley, M. J. (2005). A gait nomogram used with fuzzy clustering to monitor functional status of children and young adults with cerebral palsy. *Dev Med Child Neurol*, 47(6):377–83.

Vinh, N., Epps, J., and Bailey, J. (2010). Information theoretic measures for clusterings comparison: Variants, properties, normalization and correction for chance. *J. Mach. Learn. Res.*, pages 2837–2854.

Winter, D. (1991). *The Biomechanics and Motor Control of Human Gait: Normal,Elderly and Pathological*. Waterloo: University of Waterloo Press.

Xu, G., Zhang, Y., and Begg, R. (2006). Mining gait pattern for clinical locomotion diagnosis based on clustering techniques. In *Proc of the 2nd int conf on Adv Data Mining and Appl*, 296–307. Springer-Verlag.