A classification study of kinematic gait trajectories in hip osteoarthritis

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A B S T R A C T
The clinical evaluation of patients in hip osteoarthritis is often done using patient questionnaires. While this provides important information it is also necessary to continue developing objective measures. In this work we further investigate the studies concerning the use of 3D gait analysis to attain this goal. The gait analysis was associated with machine learning methods in order to provide a direct measure of patient control gait discrimination. The applied machine learning method was the support vector machine (SVM). Applying the SVM on all the measured kinematic trajectories, we were able to classify individual patient and control gait cycles with a mean success rate of 88%. With the use of an ROC curve to establish the threshold number of cycles necessary for a subject to be identified as a patient, this allowed for an accuracy of higher than 90% for discriminating patient and control subjects.

We then went on to determine the importance of each trajectory. By ranking the capacity of each trajectory for this discrimination, we provided a guide on their order of importance in evaluating patient severity. In order to be clinically relevant, any measure of patient deficit must be compared with clinically validated scores of functional disability. In the case of hip osteoarthritis (OA), the WOMAC scores are currently one of the most widely accepted clinical scores for quantifying OA severity. The kinematic trajectories that provided the best patient–control discrimination with the SVM were found to correlate well but imperfectly with the WOMAC scores, hence indicating the presence of complementary information in the two.

1. Introduction

Hip osteoarthritis is a chronic degenerative joint disease leading to the progressive destruction of the cartilage at the hip joint. Pain and stiffness are the key symptoms which lead to reduced joint mobility and gait dysfunction [1]. Among the several disease-specific questionnaires used to assess functional impairment in OA, the Western Ontario and McMaster Universities (WOMAC) index [2,3] is currently considered the gold standard for hip OA patient questionnaires [1,4]. While these patient-reported scores provide important information concerning the capacity for daily functioning, they can be criticized for not being objective and sufficiently sensitive to change [1,5].

One possible objective measure could come from radiographic analyses. Numerous studies however have reported that radiographic measures which are the recommended validated technique to assess OA structural anomalies, correlate poorly at the individual level with patient symptoms [6–8]. Such measures are also made in static conditions during which the principle deficits related to movement may not appear. A better measure of functional capacities may come from a tool that directly measures an important daily activity e.g. gait. Functional mobility is one of the important categories in the activities of daily living [9,10]. When compared to control subjects, 3D gait analysis has revealed differences in the gait of hip OA patients [1,11–13]. It therefore has the potential to be used as an objective functional measure of patient condition. A detailed gait analysis might also address the criticism of not being sufficiently sensitive. Alterations in gait may already be present in the patient before the appearance of clear functional disability [14]. 3DGA can also be useful for distinguishing fine grained differences that may exist between different types of treatment such as different protheses. Hip replacement surgeries are among the most successful procedures performed once other therapies such as physical therapy and pain medication have failed [15–17]. Only a detailed gait analysis would be able to evaluate and compare
different prostheses. The purpose of this project is to contribute to the objective characterization and evaluation of hip OA and its treatment.

Several questions however must be answered before the usefulness of 3DGA becomes more convincing for hip OA. After an extensive meta-analysis of hip and knee osteoarthritis 3DGA studies, Ornetti et al. [1] concluded that it was necessary to demonstrate the discriminant capacities of 3DGA before it becomes an established tool in the clinical setting. The first step taken in the study therefore was to demonstrate that sufficient information exists in the data gathered from 3DGA to discriminate hip OA patients and controls. Twelve kinematic trajectories were computed for each subject walking in a straight line at normal speed. We applied a classification paradigm in order to address the issues raised above i.e. We used a machine learning algorithm to identify from the kinematic trajectories whether a gait cycle belonged to a hip OA patient or to a control subject. Such algorithms use part of the data to find the hyperplane that best separates two data groups. The remaining data is then used for testing if the computed surface is able to separate previously unused examples. The machine learning technique applied was the support vector machine (SVM). The capacity of the SVM to classify gait cycles or subjects would demonstrate the presence of clinically relevant information in the gait data. Previous studies have shown that statistically significant differences are present between the gait variables of hip OA patients and controls [11–13]. None of these studies however have taken the step of then quantifying the discriminatory capacity that comes from the differences.

The second step in the study dealt with the important question of identifying the most pertinent gait variables for the discrimination. The vast quantity of data generated in 3DGA remains an obstacle to its use in the clinical as well as research setting. What measures could be used to select the most pertinent variables? One way to do this would be to rank the individual kinematic angles in the order of their capacities to discriminate patients and controls. The previously cited gait studies did not take this step. By using the SVM to do this, we provide two important points of departure from previous methods of analyzing data from 3DGA. 1) Rather than hand picking a few variables that we consider to be important, we analyze the entire dataset to objectively uncover the important discriminatory variables. This takes into account the fact that even disorders at isolated points in the lower limbs are likely to have ramifications for all the interconnected body segments involved in gait. It cannot at all be ruled out that greater discriminatory differences may in fact lie at points distal to the original dysfunctional joint. 2) Since the SVM is able to carry out a trial by trial analysis of the data, we are able to take into account the high variability of patient gait rather than compute averages that may not convey accurate information.

The final step taken was to ask how the parameters from gait analysis compared with the WOMAC index. Since this is the gold standard for hip OA patient questionnaires [1,4], it is necessary when proposing any new tool, to relate it to the WOMAC index. It should be noted that the study does not seek to replace the WOMAC scores with the results from 3DGA but rather to probe the relationship between the variables from the two studies. Would 3DGA provide answers that just reflect what is already available from the patient questionnaires? Or would the 3DGA provide information that is supplementary to what is available in the WOMAC index and hence correlate imperfectly with the patient questionnaires?

2. Methods

The study was carried out by placing markers on the joints of subjects who walked in a straight line at normal speed. Twelve kinematic trajectories were computed for each subject. An SVM classification paradigm was then applied to the kinematic trajectories in order to 1) find out if sufficient information was available in the kinematic data to discriminate patients and subjects 2) rank the discriminatory capacities of the individual kinematic angles to carry out the discrimination.

2.1. Subjects

Patient and control characteristics are displayed in Table 1. Patients with hip OA were diagnosed by an experienced rheumatologist (PO). Patients aged 40–80, with unilateral symptomatic hip OA, defined using the American College of Rheumatology criteria [18] were included. Other inclusion criteria were Kellgren and Lawrence stages II, III, or IV on the X-ray and no indications of surgical procedure as defined by an experienced rheumatologist. All patients were in the mild to moderate stage of hip OA: 70% of the subjects were at stage 2 of the Kellgren and Lawrence scores while 30% were in stage 3. Control participants were subjects aged 40–80 without symptomatic joint rheumatism. Exclusion criteria for all participants were secondary hip OA, inflammatory hip OA, significant painful ankle, knee or foot disorders, chronic back pain, Alzheimer’s disease, Parkinson’s disease, motoneuronal disorders, non-stabilized diabetes mellitus, cardiac or respiratory insufficiency and inability to understand the procedure. The rheumatologist also evaluated the WOMAC scores for each patient. Each subsection of the WOMAC scores had a range from 0 to 100.

The study protocol was approved by the local ethics committee (CPP Est I, Dijon, France). It was conducted in compliance with the principles of Good Clinical Practise and the Declaration of Helsinki. All patients signed an informed consent form.

2.1.1. Procedure

Gait analyses were carried out by a single experienced investigator (DL), blinded to previous measurements. Body kinematics were recorded during barefoot walking along a 4-m-long straight pathway indicated by a path drawn on the floor. The participants were given the instruction (given orally by the examiner at the beginning of each session) to walk at the most comfortable speed (“as if you were in the street”). They performed 10 trials, and were then asked if they had experienced any difficulties during the test.

2.2. Three dimensional gait analysis

For the gait analysis, the body was represented as an interconnected chain of rigid segments, and kinematics were recorded at a rate of 120 Hz using a 3-dimensional computerized movement analysis device (Smart, e-Motion, Italy). The device was made up of eight video-based cameras with infrared strobes. Retro-reflective markers were always attached to the skin over the following body landmarks (Fig. 1): acromion, anterior superior iliac spines, posterior superior iliac spines, femur, lateral epicondyles, tibia, lateral malleoli, distal head of the second metatarsals, heels. In order to minimize the risk of cross-talk, each participant performed an initial trial to check the position of the thigh markers. Blankevoort et al. [19] and Lafortune et al. [20] have shown that the ab/adductor motion of

| Table 1: Characteristics of subjects included in the study. |
|----------------|----------------|
| N              | 20             | 20             |
| Age            | 63.82 ± 6.55   | 62.23 ± 6.24   |
| BMI            | 26.02 ± 4.35   | 24.07 ± 4.03   |
| WOMAC pain     | 60.81 ± 21.04  | NA             |
| WOMAC stiffness | 53.75 ± 25.03  | NA             |
| WOMAC function | 55.05 ± 21.59  | NA             |
the knee is physiologically limited to approximately 7° due to the restrictions imposed by knee geometry and the collateral ligaments. The position of the thigh markers was corrected if the knee add/abduction range of motion during initial trials was higher than 10°. The trunk segment was defined by the shoulder (two acromion markers), and one virtual marker calculated as the mean of the iliac spine segments [21–23]. According to iSB recommendations the trunk was defined by these three markers allowing a calculation of the trunk segment reference frame. Kinematic data were then interpolated with a Woltring polynomial then

\[ \mathbf{x}_{\text{trunk}} = \mathbf{F} \left( \mathbf{X}_{\text{markers}} \right) \]

and a scalar \( \mathbf{F} \) that defines the sequencing function. The higher the penalty associated with misclassification, the higher the penalty associated with misclassification. The larger the \( C \) value, the higher the penalty associated with misclassification. In SVM, nonlinear classification problems are solved by mapping the original data into a higher dimensional feature space by means of a kernel function and then construct a linear OSH between the two classes in the new feature space. Thus, although it uses linear learning methods due to its nonlinear kernel function, it is in effect a nonlinear classifier. A complete formulation of support vector machines can be found in a number of publications [29–32]. Here, the brief theory of SVMs for nonlinear classification will be presented.

Let us consider a supervised binary classification problem. Let us assume that the training set consists of \( N \) vectors from a \( d \)-dimensional feature space \( \mathbf{x}_i \in \mathbb{R}^d (i = 1, 2, \ldots, N) \). A target \( y_i \in \{-1, +1\} \) is associated with each vector \( \mathbf{x}_i \). Searching an OSH in the original input space is too restrictive in most practical cases. In SVM, nonlinear classification problems are solved by mapping the original data \( x \) into a higher dimension feature space \( F \) by \( z = \phi(x) \) via a nonlinear mapping \( \phi : \mathbb{R}^d \rightarrow F \), in which the mapped data are linearly separable. Considering the case when the data are linearly nonseparable in \( F \), there exists a vector \( \mathbf{w} \in F \) and a scalar \( b \) that define the separating hyperplane as \( \mathbf{w} \cdot \mathbf{z} + b = 0 \) such that

\[ y_i (\mathbf{w} \cdot \mathbf{z}_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad \forall i \]  

where \( \xi_i \) are the slack variables introduced to account for the nonseparability of data.

\[
\begin{align*}
\text{minimize: } & \frac{1}{2} \| \mathbf{w} \|^2 + C \sum_{i=1}^{N} \xi_i \\
\text{subject to: } & y_i (\mathbf{w} \cdot \mathbf{z}_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad \forall i
\end{align*}
\]

The constant \( C \) represents a regularization parameter that controls the penalty assigned to errors. The larger the \( C \) value, the higher the penalty associated with misclassified samples. This optimization problem can be translated into a dual problem using a Lagrangian formulation as follows:

\[
\begin{align*}
\text{maximize: } & \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \mathbf{K}(\mathbf{x}_i, \mathbf{x}_j) \\
\text{subject to: } & \sum_{i=1}^{N} \alpha_i y_i = 0 \text{ and } 0 \leq \alpha_i \leq C, \quad \forall i
\end{align*}
\]

where \( \alpha_i \) are the nonnegative Lagrangian multipliers. The data points \( \mathbf{x}_i \) corresponding to \( \alpha_i > 0 \) are the support vectors. It is worth noting that, in the nonseparable case, two kinds of support
vectors coexist: (a) margin support vectors that lie on the hyperplane margin and (b) nonmargin support vectors that fall on the “wrong” side of this margin. The kernel function 
\( K(x_i, x_j) = \Phi(x_i) \Phi(x_j) \) satisfies Mercer’s condition [29] and can be computed without having explicit knowledge of \( \Phi(.) \). For any test vector \( x \in \mathbb{R}^d \), the output is then given by

\[
y = f(x; \alpha) = \text{sgn} \left( \sum_{i=1}^{N_S} \alpha_i y_i K(s_i, x) + b \right)
\]

where \( s_i \) are the \( N_S \) support vectors. To build an SVM classifier, the user needs to tune \( C \) and \( \varepsilon \) to find a kernel function and its parameters. A linear kernel was found to be optimal for this particular study. The SVM analysis was carried out with a MATLAB program that had been written and utilized in previous studies [33–35].

2.3.2. Input vectors
Input vectors for the SVM consisted of the entire time series from one gait cycle (200 points) for any kinematic angle. In the case where all the 12 kinematic angles were utilized, the input vector was created by linking the individual vectors together to create a vector of size \( 12 \times 200 \). We will refer to this as the total kinematic vector. The vectors were normalized so as to give equal importance to each kinematic angle and to preserve information regarding amplitude differences between the two subject groups [33,35,36].

2.3.3. Cross validation
The classification tasks were done using 5-fold cross validation [33,35]. This ensured that the data used in the training was not used for testing. The percentage of correct classifications was verified for each subject when they were in the test case i.e. what percentage of the 10 gait cycles associated with each individual was attributed to the correct class? Accuracy rates were reported as the mean \( \pm \) SEM of the number of gait cycles correctly classified over all 40 subjects.

2.4. ROC curve
Each subject is associated with 10 gait cycles. As is the case with many clinical tests, not all the gait cycles from one subject get labelled the same way. It is therefore necessary to establish the percentage of gait cycles that would have to be identified as “patient gait cycles” before a subject is identified as a patient. In clinical work, this is normally done with the use of a receiver operator characteristic (ROC) curve. We constructed an ROC curve to follow how the percentage of subjects identified as patients changed with this threshold. This was done by plotting the true positive rate (sensitivity) along the y-axis and the false positive rate (1-specificity) along the x-axis [37].

2.5. Statistics
Accuracy rate comparisons were done using a repeated measures ANOVA and a Tukey HSD post-hoc test. Linear relationships between variables were probed using Pearson uni- and multi-correlation coefficients. Results were taken to be significant if \( p < 0.05 \).

3. Results
The first part of this section is devoted to the analysis of the kinematic trajectories using the SVM. It should be noted that the classification success is evaluated in terms of gait cycles rather than in terms of subjects i.e. what percentage of gait cycles for each subject is identified as correctly belonging to a patient or a control subject? This was done in order to provide a finer analysis of the capacities of each kinematic trajectory. Only once, in Section 3.1, following the use of the ROC curve do we report on what the classification success of the gait cycles translates to in terms of classifying subjects.

3.1. Discriminating patients and control gait cycles using the SVM
Kinematic trajectories were obtained from subjects who walked at comfortable speeds in a straight line (Fig. 2).

Our first test involved the use of the total kinematic vector i.e. all the kinematic trajectories for one gait cycle (Fig. 3) to identify if a gait cycle belonged to a patient or a control. The percentage of gait cycles correctly identified as belonging to patient or control was on average 88 \( \pm \) 2% per subject (first column of histogram, Fig. 3).

Our next step consisted of transforming the above results reported in terms of gait cycles into an identification of subjects as patients or controls. For this step we constructed an ROC curve. We define \( P_{\text{thresh}} \) as the percentage of cycles that must be identified by the SVM as belonging to a patient before a subject is identified as a patient. Subjects were assigned to the correct group (patient or control) with percentages of 97%, 97%, 95% or 93% for \( P_{\text{thresh}} \) values of 50%, 60%, 70% and 80% respectively. Most of the errors made were due to a decrease in sensitivity i.e. patients incorrectly identified as controls.

3.2. The identification of the discriminating kinematic trajectories
Next we ranked the classification capacities of each kinematic trajectory. This is displayed in decreasing order in Fig. 3. The best gait cycle classification was obtained with three sagittal and one frontal trajectory. The sagittal trajectories were the thigh, shank and foot trajectories (accuracy 85.8 \( \pm \) 3%, 73.2 \( \pm \) 4%, 72.3 \( \pm \) 4% respectively). The frontal angle was the foot frontal angle (accuracy 74.5 \( \pm \) 4%). These trajectories provided gait cycle discriminations with mean accuracies greater than 70%. The performances of the remaining kinematic trajectories were poorer. These include all the computed trunk and pelvic trajectories.

The thigh sagittal angle was found to be the most valuable when classifying patient and control gait cycles. The classification success using this trajectory alone was not significantly different from that of all the kinematic trajectories combined (first column of histogram, Fig. 3) (\( p > 0.05 \), repeated measures ANOVA, Tukey HSD post-hoc).

3.3. Correlation of kinematic variables with WOMAC scores
We investigated the correlations of the “best” kinematic trajectories identified above with the WOMAC scores. The amplitude of extension or flexion either in passive stretching or during gait is a variable that is clinically important. We therefore found the maximum amplitude (\( \text{trajectory}_{\text{max}} - \text{trajectory}_{\text{min}} \)) for each kinematic trajectory. It is to be recalled that all the kinematic trajectories in the study were normalized. The maximum amplitude assigned to each subject was the mean of the 10 trials for each subject. No correlation with the kinematic variables was obtained using the WOMAC stiffness score (Table 2). Depending on the kinematic variables used, significant correlations were sometimes observed with the WOMAC pain and function scores. Since it was the trajectory that provided the best patient control discrimination, we first examined the correlations with the thigh angle alone before carrying out a multivariate correlation with the three remaining discriminating angles i.e. foot sagittal, shank sagittal and foot frontal angles. The best correlations were always obtained with the WOMAC function scores. With the thigh angle alone this correlation was significant (\( r = 0.46, \ p < 0.05 \)). The correlations were found to be improved by performing a multivariate
correlation with four of the above mentioned angles as the independent variables. The correlations with the WOMAC pain scores became significant \( r = 0.63, p < 0.05 \) and correlation with the WOMAC function score increased to \( r = 0.74 (p < 0.05) \).

4. Discussion

In this study we further investigated the potential of 3DGA as a tool in the evaluation of hip osteoarthritis. An original aspect of the study was the direct evaluation of the capacity of the data for discriminating gait cycle or subject categories with the use of an SVM. The high percentage of success by the algorithm for distinguishing patients and controls shows that the necessary information for performing this essential task is available in the kinematic data from 3DGA. This study therefore forms part of a growing movement to detect and distinguish gait patterns through the use of nonlinear combinations of gait variables [38–42]. Such techniques had not been previously applied to hip OA.

By examining kinematic trajectories that extend all the way from the trunk to the foot, the study also takes a position that is quite different from several of the previous gait analysis studies on hip OA [11,13,43] which had largely restricted their analyses to variables around the affected joint. Our investigation shows how the SVM can then be used to identify the most discriminative kinematic trajectories and hence set aside those that do not provide as much information. The capacity to discriminate is

<table>
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<th>Table 2</th>
<th>Univariate and multivariate correlation coefficients between kinematic variables and WOMAC scores.</th>
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<td>Correlation coefficient with thigh sagittal angle</td>
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<tr>
<td>WOMAC pain</td>
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<tr>
<td>WOMAC stiffness</td>
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<td>WOMAC function</td>
<td>0.46 ( p &lt; 0.05 )</td>
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highly indicative of what is the most significantly altered in patient gait. The predominance of the thigh sagittal angle in this regard is in keeping with the location of the joint degradation in hip OA. Significant differences in hip extension and flexion have been observed in this patient population [11,13,43]. Once the thigh sagittal trajectory is altered, it is to be expected in a well-coordinated system [44] that there would be anomalies in the other kinematic trajectories of the leg as well. Hence it is not totally unexpected that we would find alterations in the shank and foot sagittal angles as well. The high capacity of the foot frontal trajectory for discrimination is a little more surprising. It might be due to compensatory lateral movements of the foot that are made to reduce torques in the lower limb. This might then reduce the extension of the hip during the late phase of stance. Eitzen et al. [12] had expressed the need to examine gait alterations in the frontal plane for hip OA subjects. We have therefore produced a result that responds to this question. Next to the thigh sagittal angle, the gait cycle classifications were more poorly performed using the pelvic and trunk trajectories. A better classification with the trunk trajectories may have been obtained with a more detailed trunk model. The mean performance using pelvic obliquity was 58% while it was 61% using pelvic tilt. Especially given the ROC thresholds required to distinguish patients and controls, this does not mean that there would not be significant differences in these kinematic trajectories between patients and controls. Indeed Watelain et al. [11] had reported that pelvic tilt and obliquity are significantly different between hip OA patients and controls. Our study however shows that the thigh sagittal trajectory is a better variable for gait cycle classification. This is also in agreement with one of our previous studies showing that the pelvic obliquity and tilt trajectories showed a poor test re-test reliability in 3DGA done on arthritic patients [21]. A glance at the kinematic trajectories of Fig. 2 also provides an explanation for the differences in the discrimination capacities of these kinematic trajectories. There is more variability in the trunk and pelvic variables than in the sagittal spatial angles or the foot frontal trajectory.

This is the first study to evaluate the application of machine learning to kinematic data in hip OA patients. Some form of machine learning has already been applied to knee OA data [39,40]. There are differences in the algorithms and the data pre-processing applied in the two previous studies. Deluzio and Asthen [39] applied linear discriminant analysis (LDA) to data whose dimensionality had been reduced using PCA (Principal components analysis). We applied an SVM rather than the LDA algorithm because previous studies have shown the former algorithm to be more efficient [36,41,45]. In comparison to some of the previous studies, we had neither extracted any particular features from the data [41] nor reduced the data dimensionality using a PCA [39]. Avoiding such a reduction in the dimensionality of the data has the potential of making it easier later to identify the discriminating features.

Compared to more traditional forms of statistics, the use of the SVM allowed for the coupling together of several kinematic trajectories and more importantly the use of the entire kinematic trajectory. The latter step helps to avoid the use of arbitrary definitions such as “the start of stance” unless they are necessary. We observed in a previous study that the entire time series of a measured variable was more efficient for classification than vectors created from pertinent extracted features [35]. This once again is another example of a global approach compared to previous studies where specific phases of the gait cycle were picked for analyses [11–13,43].

A final point to be discussed is the correlation that was observed between the kinematic variables and the validated WOMAC score. Previous studies on this relationship have produced contradictory results. Lindemann et al. [46] found the correlation between the gait parameters and the WOMAC scores to be poor. This is in contrast to the report by Boardman et al. [47]. Both studies had been carried out on patients following hip replacements. Our study like the Eitzen et al. study [12] on the other hand, examines the correlations before hip replacement. They therefore demonstrate the potential of 3DGA in pre-operational decisions. As in the case of the Eitzen et al. [12] study, there was a significant but imperfect correlation between some of the kinematic trajectory modifications in the sagittal plane, and the WOMAC scores, hence indicating the presence of complementary information coming from the two techniques. The imperfect correlation between the two scores should not come as a surprise. Patient feelings on their condition may not correspond perfectly to an objective reality. Their impressions remain nevertheless important to the clinician. Patient scores are also a global score that may take into account other factors that may not be measured during gait such as the difficulties with tying shoe laces. 3DGA provides information concerning the deviation of patient gait from normal gait. Since gait is a crucial daily activity, this remains important information even if the correlation between the two scores is not perfect. Our results support the arguments of Ornetti et al. [1], who had concluded that the best outcome measure would come from a combination of the patient self-assessment scores and the objective 3DGA. In our study, the best correlations between the objective gait data and the subjective patient scores were found to be with the WOMAC function score (Table 2). The poorest were for WOMAC stiffness. This is perhaps not so surprising as the stiffness subscale has been found to have a poorer construct validity and reliability than the WOMAC pain or function scores [4].

There are several steps that should be taken in further extensions of this investigation. Perhaps the one that would be the most pertinent in a clinical framework would be the use of the SVM to provide a composite index of gait performance. This could most likely be done using the function in Eq. (4) that computes the distance of any test vector from the separating hyperplane. Another useful step to be taken would be to perform a classification using separate phases of the gait cycle in order to identify the phases which are the most altered in hip OA patients.

5. Conclusion

In this study we further investigated the potential of 3DGA as an objective outcome measure for hip OA patients. The association of the SVM a machine learning algorithm to the 3DGA allowed us to directly evaluate the capacity of 3DGA for discriminating patients and controls. Using the kinematic trajectories generated from the 3DGA, we were able to discriminate gait cycles with a mean success of 88%. With an ROC curve, this led to an accuracy of higher than 90% for discriminating patients and controls. This demonstrates the relevance of gait analysis in the clinical setting. The large amount of data gathered during 3DGA remains an obstacle to its use in the clinical setting. We show in this study how the SVM can be used to identify the most pertinent kinematic trajectories for the population at hand. We found that the thigh, shank and foot sagittal as well as the foot trajectory provided the best discrimination. This suggests that these are important trajectories to take into consideration for evaluating the loss of functional capacities in hip OA patients. The relevance of the kinematic trajectories obtained from 3DGA is also highlighted by the good correlation of the maximum amplitudes of the above mentioned trajectories with the WOMAC function score.

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