BACHELOR'S THESIS / BIOMEDICAL ENGINEERING 2022

Dynamical analysis of gait motion in osteoarthritic women patients

Judith Torras Piedehierro

Universitat Pompeu Fabra
Barcelona

Dynamical analysis of gait motion in osteoarthritic women patients

Judith Torras Piedehierro

Bachelor's thesis UPF 2021/2022

Thesis supervisor(s):

Dr. Simone Tassani (DTIC, UPF)

M.Sc. Anaïs Espinoso (DTIC, UPF)

Acknowledgments

First of all, I would like to thank my tutors for all the help and support I received during this project. Thank you, Simone, for introducing me more into the world of biomechanics and giving me this opportunity. Thank you Anaïs for always being there when I needed you, for answering all my questions quickly and efficiently. Thank you for teaching me different ways of working and understanding things that I am sure will help me in the future.

I also wanted to thank the UPF and all the teaching staff for teaching me such a wonderful career. Of course, it has not been an easy path, but now I can say that it has been worth it because thanks to it, I have grown both personally and professionally.

Finally, I would like to thank my family and friends for their support during all this time. But most of all to my parents, as none of this would be possible without their constant trust in me and their unconditional love even on the worst days.

Summary/Abstract

Over 300 million people around the world, mainly women, suffer from Osteoarthritis (OA), a multifactorial disease affecting joints. It occurs most frequently in hands, hips, and knees. The most common solution is having a total knee replacement (TKR) placing a prosthesis on the patient. In the majority of these cases the decision of placing the prosthesis is based not only on objective radiographic measures but also on the pain felt by the patient and its perception, making this decision subjective.

Nowadays, studies of human motion dynamics have been frequently applied with biomechanical and computational models that use kinematic and kinetic parameters in order to help clinicians in treatment decision. Some dynamic approaches to gait analysis were also presented, but they were never performed over OA subjects.

Nonlinear time series analysis forms a group of algorithms and measures used to extract dynamical features underlying measured signals. It allows to describe dynamical systems where nonlinearities lead to complex time evolution. Unlike deterministic models that produce the same results for a particular set of inputs, stochastic models predict outcomes that account for certain levels of unpredictability or randomness. Using the nonlinear prediction error and a simple irregularity analysis measures we study how predictable the gait will be in the next steps.

In this study, human gait recordings of 13 women between 60 to 67 years old that suffer from OA will be analysed from which 6 subjects were referred to take a TKR while the others take a conservative treatment. The aim is to analyse differences in the predictability of the underlying dynamics and its irregularity between TKR and conservative patients. Our results show patients with TKR are more resilient and maintain more coherence compared to conservative patients who seem to present a more stochastic behaviour. Doing so, a quantitative analysis can help clinicians in the treatment decision.

Keywords

osteoarthritis, conservative, knee replacement, irregularity, predictability

Index

List of figures

List of tables

1. INTRODUCTION

1.1. Osteoarthritis

Osteoarthritis (OA), a multifactorial disease affecting joints, which involves degeneration of the articular cartilage, affects over 300 million people over the world [1]. It is the most common joint disease worldwide that affects to 10% men and 18% women over 60 years old and, 85% of all people between 55-65 have OA in one or more joints [2], [3]. With this disease, the cartilage within a joint begins to break down and the underlying bone begins to change, which develop slowly and get worse over time. OA most common effects are pain, stiffness, and swelling and, in some cases, it reduces functionality and disability decreasing their range of motion. Several factors like age and gender interact in a non-linear way [1], [4]. The general increase in life expectancy makes OA one of the leading causes of disability, being the hip and knee one of the most common joints affected by OA [2], [5]

The risk of developing OA increases with age and gender, especially after age 50 [2], [4]. Body mass index (BMI) is what determines if you suffer from obesity or not. People who weight more put more stress on joints, in particular on hips and knees and are more likely to develop OA. Moreover, genetics play an important role. Those people who have relatives that suffers from OA are more likely to develop it. Although not fully understood, its etiology is thought to be related to genetic, physical, and environmental factors [2], [5]

A way of defining the radiological progression of knee osteoarthritic is using the variation of the Kellgren-Lawrence (KL) [6], [7]. The KL grade proposed a five-grade classification scheme and examined plain radiographs of eight joints, including among them, hips, and knees [8]. Although, the KL classification is the most widely used clinical tool for the radiographic diagnosis of OA, the most suitable treatment for each patient it is still very unclear [6]. This grade seems not to be directly related to the pain felt by the patient so, it is still unclear whether KL grade or the functionality of the patients, in terms of pain, discomfort, or capability to perform daily activities should guide the treatment decision, the total knee replacement (TKR) or the conservative treatment [4].

There are two main treatments available to treat OA, one surgical and the other nonsurgical. Any nonsurgical procedure involves pharmacological treatment, exercise, weight loss or electrostimulation while the surgical implies a total knee replacement (TKR) surgery [1], [4]. Clinicians often have difficulties in which treatment they will choose for an OA patient. The most common solution is placing a prosthesis on the patient. In the majority of these cases the decision of placing the prosthesis is based not only on objective radiographic measures but also on the pain felt by the patient and its perception, making this decision subjective without any objective clue [7].

1.2. State of the art

Lower extremities, responsible for supporting the body, are subject to various loads during gait motion. Contact forces at the knee joint during gait can be estimated by using a rigid body model and inverse dynamics. In most cases, the contact pressure distribution for static poses can be obtained quantitatively by using finite element (FE) analysis considering the muscle force and ground reaction force (GRF) during gait [9].

Studies using dynamic simulation software such as OpenSim [10], LifeMod [11] and AnyBody [12] are often used only to obtain contact and muscle forces. Liu et al. [13] studied muscle activation according to a range of walking speeds to confirm the muscle contribution obtained from OpenSim. Kia et al. [14] evaluated contact forces at the knee joint and GRF with a musculoskeletal model using LifeMode's gait test. Wang et al. [15] analysed knee contact forces to study the effect of gait speed using Anybody. A study without the use of dynamic simulation software was also carried out. Simic et al. [16] and Taniguchi et al. [17] analysed joint torque or power through dynamic analysis based on changes in gait patterns or shoes. However, these studies are limited to the study of kinetic or kinematic effects and cannot obtain accurate contact pressure distributions at the knee joint. A method combining finite element (FE) analysis with rigid body Dynamics analysis was developed to obtain the contact pressure distribution of the knee and ankle joints during gait in Park et al. [9].

Another important study to consider is Vimieiro et al. [18] that proposes a computational model to analyse the dynamics of lower limb motion using a kinematic chain to represent the body segments and rotational joints linked to viscoelastic elements. This model analysed gait movement in different speeds (walking and running), but this model needs to be adapted if we want to analyse other movements like jump or squats. It is interesting because it could reproduce gait movement on the computer and be capable of identifying pathologies related to gait.

One of the most important studies to have a look in is Perc et al. [19]. They analyse human gait motion with a simple nonlinear time series. Using a short continuous recordings of human gait allows them to have a deeper look into the dynamics of the locomotory system. The conclusion extracted from this study was that the state of research of human gait is very similar as for human electrocardiography. Their study combined with the result of different studies, lead they to the conclusion that several vital functions of the human body are deterministic on short time scales whereas over long times, stochastic environmental influences affect the functioning, making it indistinguishable from randomness.

A study in which OA subjects were analysed, Simone et al. [4], consists of doing a multifactorial analysis of variance (MANOVA) in order to find relationship between clinical treatment options, gait function, and dynamics in patients with knee osteoarthritis. They found that the differences in gait between the two groups, TKR-referred and conservative treated, was moderated by a number of factors, like being female, older, and obese. These factors can reduce the variability in gait compression load.

1.3. Univariate signal analysis techniques

1.3.1. Deterministic nonlinear analysis

Nonlinear time series analysis form a group of algorithms and measures used to extract features from dynamical systems based on chaos theory. It allows one to describe dynamical systems where nonlinearities lead to complex time evolution. Importantly, this concept allows the extraction of information that cannot be resolved using classical linear techniques. The extraction of dynamics, entropy or predictability from a single signal could be done using univariate nonlinear measures [20], [21]. This kind of measures leads us to make predictions of what will happen in future steps taking present or past reference points.

Unlike deterministic models that produce the same exact results for a particular set of inputs, stochastic models are the opposite; the model presents data and predicts outcomes that account for certain levels of unpredictability or randomness. Using nonlinear prediction measures we can distinguish between purely stochastic, purely deterministic, and deterministic dynamics superimposed with noise [20], [22]. These methods were used in neurology, in a electroencephalographic recordings from epilepsy patients to help to understand the brain functions and malfunctions [21].

In this study the nonlinear prediction error (NPE) will be implemented. This measure shows the prediction error between the present state and the future state using information based on their neighbours [20]. Doing so, we wonder if we could quantify the predictability in gait dynamics.

1.3.2 Irregularity of phase velocity

Other univariate techniques allow us to analyse the irregularity in a single signal. Periodic signals tend to have less irregularity than noisy signals, so this type of measure it is useful to quantify the irregularity of a signal. Previous studies show that irregularity measures are useful in other fields such as in electroencephalographic recordings [23] or in fluid dynamics [24]. Both of them used these measures in order to finds the irregularity of their signals. In this study, the irregular analysis of the data is done to see how irregular is the signal extracted from gait motion. The sense of using this measure of predictability and irregularity in gait it will be good in terms that noise affects gait making the signal more irregular. Being irregular makes probably more difficult to make predictions, making it as an example of stochastic signal. Otherwise, deterministic signal varies less as they repeat periodically.

1.4 Objective

Up to now, we have seen that human motion dynamics have been frequently applied with biomechanical and computational models that use kinematic and kinetic parameters. Although there are lots and different studies done about analysis of gait motion, none of them does consider osteoarthritic subjects. Following the work done by Tassani et al. in Ref. [4] functionality might discriminate better than loads between subjects requiring TKR and the other. So, in order to study the way in which the subjects move in a more comprehensive manner we try to implement nonlinear techniques to perform a dynamic analysis to complement their findings using the same database.

The main objective of this study is to analyse human gait dynamics in order to find if there is any irregularity in the different steps of the gait of osteoarthritis patients. This analysis would be performed in women that suffer from osteoarthritis to investigate the relationship between the choice of clinical treatment, gait functionality, and kinetics using dynamics techniques.

Taking 3D angle data about gait recordings of women that suffer from OA we will apply the nonlinear prediction error and a simple-analysis measure. Another point we want to investigate is the irregularity of this data analysing the irregularity in each point during gait. We expect to see significance differences between those who planned a TKR versus those who followed a conservative treatment. Differences between the two groups will help in treatment decision in OA patients. Applying easy to understand and compute signal analysis techniques we can contribute to the clinical decision of OA patients.

2. MATERIALS AND METHODS

2.1 Data collection

Data of this work comes from the HOLOA project, in which patients with knee OA were recruited to take gait recordings. This was done in collaboration with Hospital del Mar and UPF. In this thesis we will analyse gait recordings of thirteen women who suffer from OA. Six of them were planned TKR while the others followed a conservative treatment. Other influencing factors like age and BMI were fixed in 60-67 years old and non-obese, BMI <30. Gait recordings were performed using eight cameras BTS Smart-DX 700, 1.5 Mpixels 250 fps and two force plates BTS P-60000 500 Hz sampling (BTS S.p.A., Milan Italy). Helen Hayes marker protocol with medial markers was used [25] and each volunteer was asked to perform five valid gaits sequences which consisted of a series of heel-strike, toe-off and heel strike for each leg. The first heel strike of each leg was recorded in the moment in which the foot was touching the force plates [4]. One gait cycle starts when the heel strikes the ground and ends when the same heel touches the ground again. Fig. 1 and Fig. 2 shows the angles of hip during gait. Table 1 shows the characteristics of the patients, showing also, which leg did they have affected.

Table 1. Demographic information of patient's characteristics.

Num. Patient	Sex	Age	BMI	Treatment	Affected Side
1	Female	60-67	Non-obese (<30)	Conservative	Right
2	Female	60-67	Non-obese (<30)	Conservative	Left
3	Female	60-67	Non-obese (<30)	TKR-referred	Left
4	Female	60-67	Non-obese (<30)	Conservative	Right
5	Female	60-67	Non-obese (<30)	Conservative	Left
6	Female	60-67	Non-obese (<30)	TKR-referred	Left
7	Female	60-67	Non-obese (<30)	Conservative	Right
8	Female	60-67	Non-obese (<30)	TKR-referred	Left
9	Female	60-67	Non-obese (<30)	Conservative	Right
10	Female	60-67	Non-obese (<30)	Conservative	Left
11	Female	60-67	Non-obese (<30)	TKR-referred	Right
12	Female	60-67	Non-obese (<30)	TKR-referred	Right
13	Female	60-67	Non-obese (<30)	TKR-referred	Right

Angles of the different joints of the body such as pelvis, hip, knee, or ankle were extracted during gait motion. In this project, only hip will be analysed. Preliminary results are suggesting that knee kinematics does not present significative differences between TKR and conservative patient when a MANOVA was done. Regarding the analysis of angles, it suggests exploring the hip angle track motion, more specifically, the hip abduction-abduction and hip flexion-extension. The analysis was performed using a MANOVA for repeated measures implemented over 3 time points of gait cycle, as described in [4].

This project focuses on the hip abduction-adduction and flexion-extension movements. In Fig.1 and Fig.2 we can see exemplary signals from a patient who is going to follow a conservative treatment and from a patient with a TKR, respectively. Figures shows that the signal recorded from the movement from left and right sides are similar, however, there are some slight differences. The different analysis strategies presented here have the aim to find some numerical differences between them.

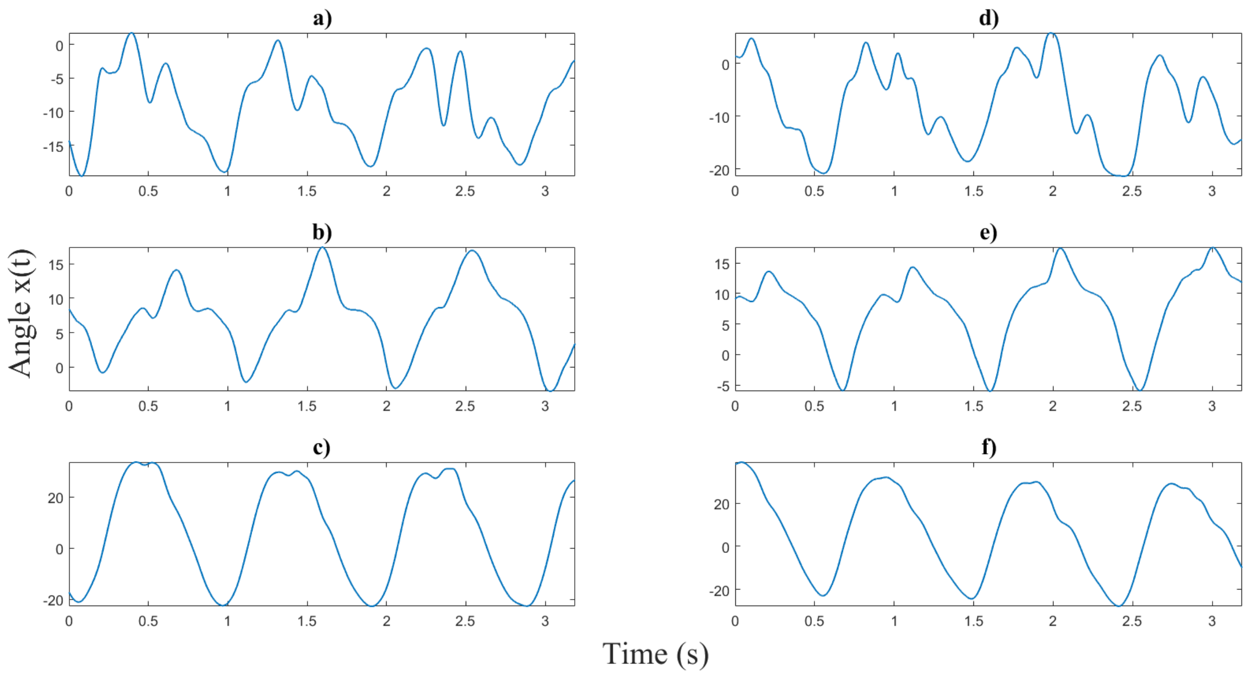

Fig.1. Signal of hip's angle of conservative patient 2 during gait. a)-c) angles from the affected or lateral side, a) intra-extra rotation, b) abduction-adduction and c) flexion-extension of the hip corresponding to x, y and z axis respectively of the affected side of the patient. d)-e) the same from a)-c) but for the contralateral or non-affected side which here corresponds to the left leg.

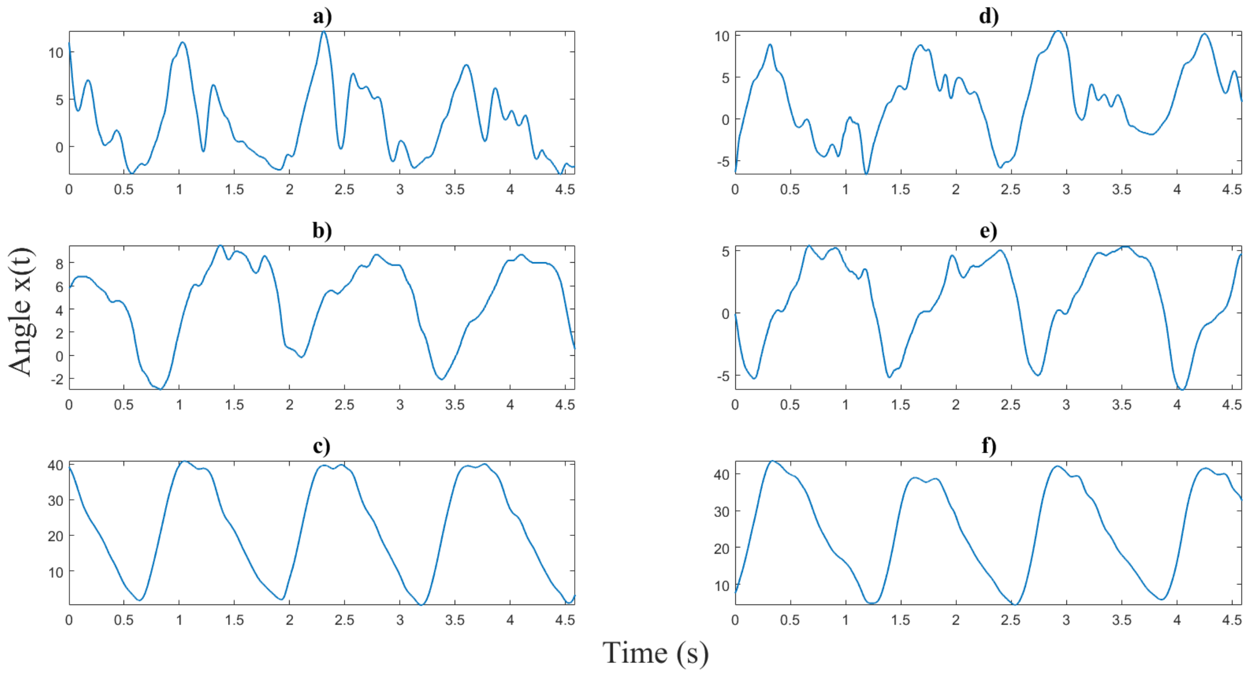

Fig.2. Same as Fig. 1 but for the TKR-referred patient 13. The affected side is the right leg.

2.2 Embedding theorem

The first step to apply the nonlinear prediction error is to apply the embedding theorem. This method enables the reconstruction of the phase space from a single observed signal. The signal vectors need to be delayed in order to apply this theorem. In order to do so, we use the method of delay coordinates to obtain an estimate of the underlying dynamics.

$$x(t)_i = (x_i, x_{(i-\tau)}, \dots, x_{i-(m-1)\tau}) \qquad (1)$$

Being x_i our vector of the signal delayed, with embedding dimension m and delay τ for i=*1*+(m-1)τ,…,N being N = n…N the number of samples and n = 1+(m-1)τ the embedding window. Before the implementation of this, it is needed to determine proper values for the embedding parameters m and τ. A suitable τ must fulfil two criteria. First, it has to be large enough to be relevant and significantly different from the information we already have, and second, it should not be larger than the typical time in which the system loses memory of its initial state. Being τ too large, the embedding space would look more like a random signal. Fulfilling these two criteria, it will be possible to gather enough information about the system to reconstruct the whole phase space with a reasonable choice of m. In order to accomplish these criteria, we used m = 3 and different values of τ (τ = 5 and τ = 10) that can be seen in Fig.3.

The orientation of adjacent trajectory systems can be used as a criterion to distinguish deterministic and stochastic dynamics. When adjacent trajectories are aligned, similar current states lead to similar recent states. Conversely, when trajectories intersect and adjacent segments are misaligned, similar current states generally do not lead to similar future states, meaning this will be a stochastic dynamic [19], [20].

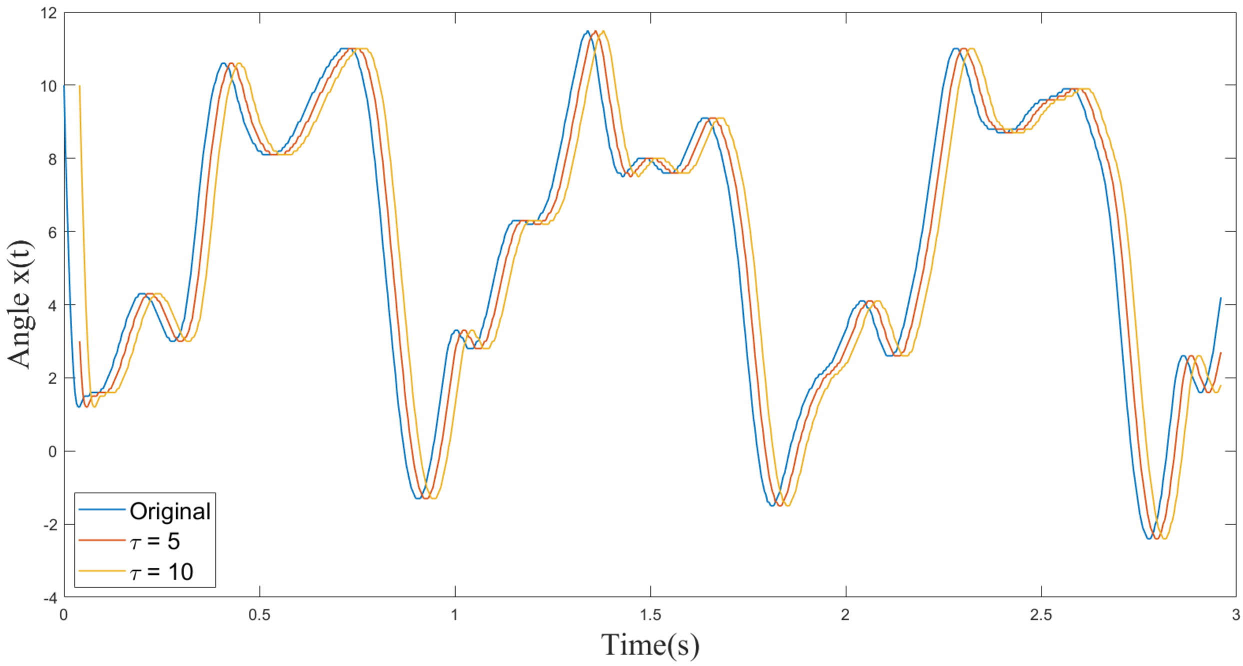

Fig.3. Two delay coordinates with the original signal from patient 1.

With all these parameters the embedding theorem was applied in data in order to see the attractors and find out if these signals follow more deterministic or stochastic structures.

2.3 Nonlinear Prediction Error (NPE)

Nonlinear prediction error is a measure to quantify the degree of alignment mentioned in the previous section. High values of NPE means that the trajectories are less aligned, and the prediction of the next step is low while low values mean that trajectories are more aligned, and the next step is more predictable. Measure NPE it is neither normalized to one or bounded from above.

Firs of all, the normalization of time series data was done. Then, we applied delay coordinates to x_i as explained in Section 2.2. To calculate the nonlinear prediction error with h horizon, the distance we want to look at or predict, we take x_{i0} as a reference point and look up to the time indices of the k nearest neighbours of the reference point (x_{ig}). The neighbours are those points that have smaller distances to our point in the reconstructed phase space. The Theiler correction W is needed to avoid basing the prediction in the previous or forward section of the trajectory of the reference point and basing it in the neighbour's trajectory. So, with this method we use the future states of the neighbours to predict the future state of our reference point and quantify the error made [20].

$$\varepsilon_{i0} = x_{i0} + h - \frac{1}{k} \sum_{g=1}^{k} x_{ig} + h \qquad (2)$$

$$NPE = \sqrt{\frac{1}{N-h-n+1} \sum_{i0=n}^{i0=N-h} \varepsilon_{i0}^{2}} \qquad (3)$$

2.3.1. Parameter selection

Parameters depending on nonlinear prediction error (NPE) need to be fixed previously. In order to find them we used the same NPE to find where these values vary less and are more constant. Since most of the data was normalized, in some cases we were looking at that values that are around to zero.

First, we want to fix the number of neighbours k in our data. To do so, we fix the rest of the parameters. In literature it has been found that h, the horizon, was fixed in $h = 5$ and Theiler correction in $W = 30$ [19], [20]. These values were used in NPE to see how k behave, starting from 1 to 20 in steps of 1. The NPE goes to very high values for more than 20 neighbours, since predicting the future state of a reference point with a high number of points is not appropriate for the algorithm. Fig. 4 shows the dependence of NPE against the number of neighbours k.

The NPE was performed in every patient, TKR-referred and conservative. Taking the mean of all the values that were around to 0 we conclude that $k = 8$. Once, neighbours were fixed, the next parameter to find was h, the horizon wanted to base the prediction. In order to do so, the same procedure mentioned above was done. Taking $k = 8$ and $W = 30$, we analysed h from 1 to 30 in steps of 1. Fig. 5 shows the dependence of NPE against the horizon h.

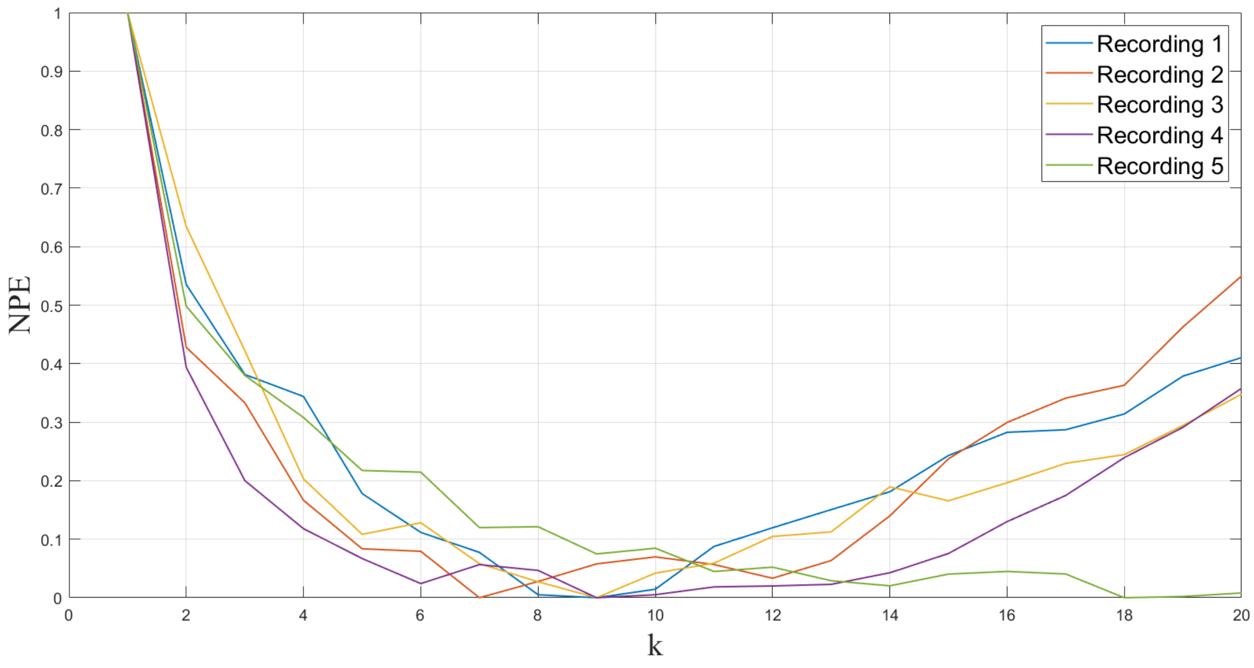

Fig.4. NPE in dependence of nearest neighbours k from the TKR patient 11.

From Fig. 5 we can see that with increasing values of horizon h we get higher values of the prediction error. This is clear since the error will increase as we are far away from the reference point. To select the parameter h, we need a sufficient low number to avoid a lot of error, so following the literature, h = 5 [20].

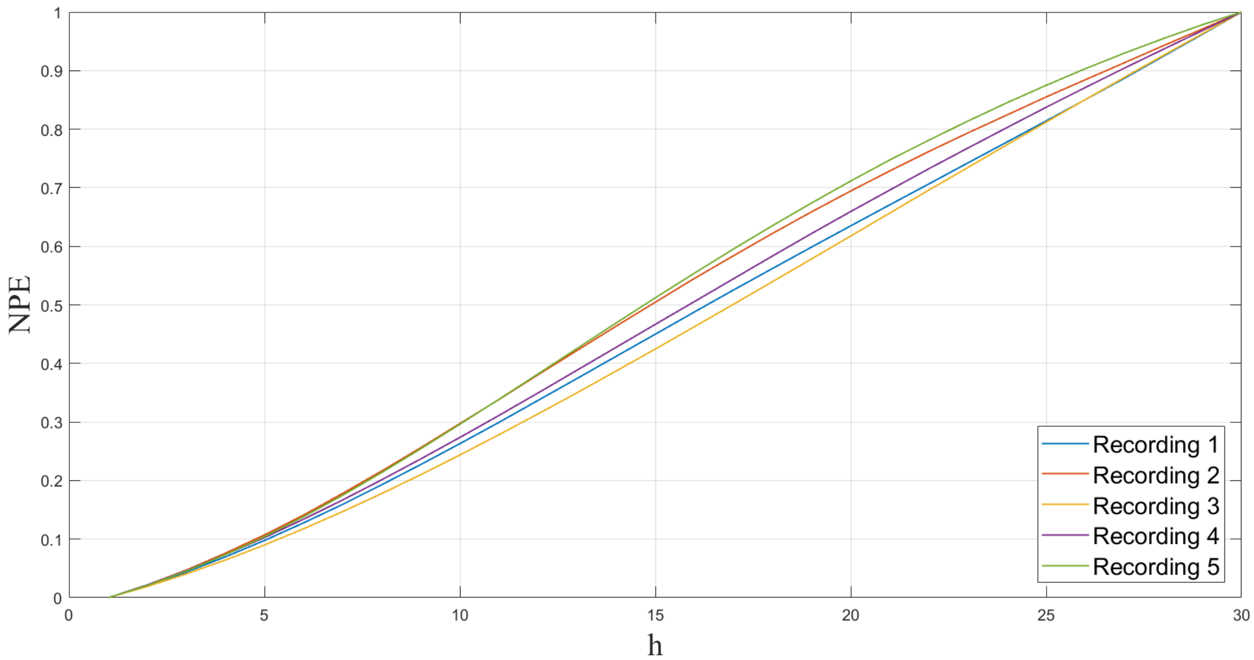

Fig.5. NPE in dependence of horizon *h* from the conservative patient 8.

The last parameter to be fixed is the Theiler correction, *W*. This correction was necessary to avoid predicting the trajectory based on the previous or forward part of the reference point. The last step was to create the Theiler vector to see which value fits most to data. Fig. 6 shows the dependence of NPE against the Theler correction *W*.

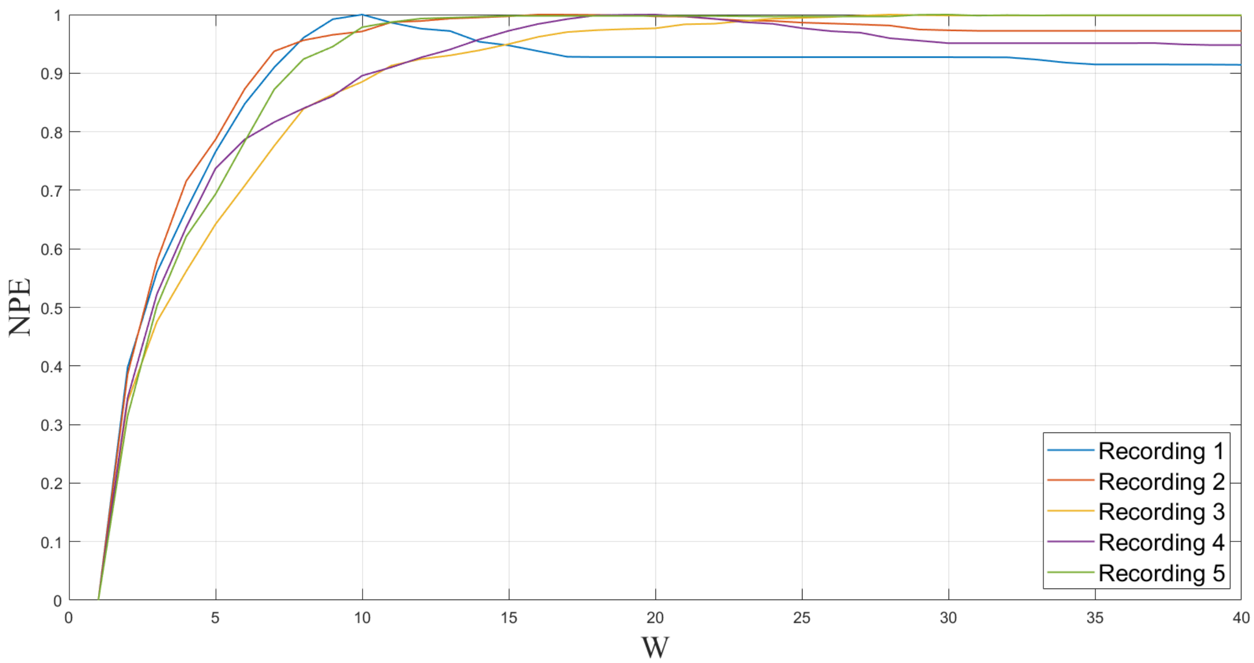

Fig.6. NPE in dependence of Theiler correction *W* from the conservative patient 4.

Looking at Fig. 6 it can be seen that when the error stays more constant is around 20. Although it seems to take higher values, we should not forget that this data was normalized, and the non-normalized values were low values of NPE. So, for Theiler correction we took $W = 20$.

Eventually, the parameters of NPE were the following: embedding dimension was fixed in m=3, the number of neighbours were k = 8, the horizon h = 5 samples, and Theiler correction in W = 20. The delay used was equal to the previous section, embedding theorem, τ = 5 (Table 2). The selection of patients in Fig 4, 5 and 6 was done arbitrary but rest of the patients follow the same tendency. The selection was done to show some examples only.

Table 2. Selected parameters of NPE after the study of parameter selection using gait dynamics.

Embedding dimension (*m*)	**Neighbours (*k*)**	**Horizon (*h*)**	**Theiler correction (*W*)**	**Embedding delay (τ)**
3	8	5	20	5

2.4 Irregularity measure (S)

The last measure applied in this study is the phase velocity standard deviation *S*, which calculates how our data varies [23]. To determine numerically the measure *S*, we consider our data as a discrete time series of N samples. The discrete times *i* for *i = 0,...,N-1*. In order to compute this measure, the standard deviation of the derivative computed as the difference between two subsequent points.

$$\dot{x}(t)_{t_i} = \frac{x(t_{i+1}) - x(t_i)}{\Delta t} \quad (4)$$

$$S = \sigma(\dot{x}(t))_{i=0,\ldots,N-1} \quad (5)$$

In the equation above, the standard deviation (σ) of the derivative of the signal x(t) is calculated. Doing so, we will be able to see how much our data changes during all the recordings to determine if gait recordings has more or less irregularity. Measure S, it is neither normalized to one nor bounded from above. Since measure is a standard deviation, it cannot be negative. For higher values of S, the irregularity of the data is more while for low values of S, the irregularity is less.

Statistical analysis describes the comparison in the affected leg and in the contralateral or non-affected. Performing a t-test was needed to analyse significant differences. This kind of statistical analysis shows if the result has a statistically significant difference between the groups. Because of repeated measure a correction was implemented, and p-value given by the t-test was deemed significant for a value $p<0.025$. The lower the p-value is, the more reliable the result will be.

3. RESULTS

3.1 Embedding theorem

In this study we use the embedding analysis to see the predictability from the pattern of the gait motions from OA patients. In this kind of analysis, from a purely periodic signal without noise we expect to have a pure deterministic signal. When noise is added this results in a stochastic signal. In Fig. 7 we represent a pure periodic signal and the same signal adding Gaussian white noise. Fig. 8 shows how these signals were delayed using delay coordinates. Fig. 9 shows the attractor from the purely periodic signal all the trajectories aligned, in contrast, in the attractor from noisy signal we have that those trajectories are crossing each other. If trajectories do not cross each other mean that similar present states will have similar future states (deterministic). In contrast, when trajectories are not aligned from a similar present state, we can observe different future states (stochastic). Other examples used in literature are those analysing dynamical systems as the Lorenz dynamics, used as a deterministic system, and the autoregressive process, used as a stochastic system [20].

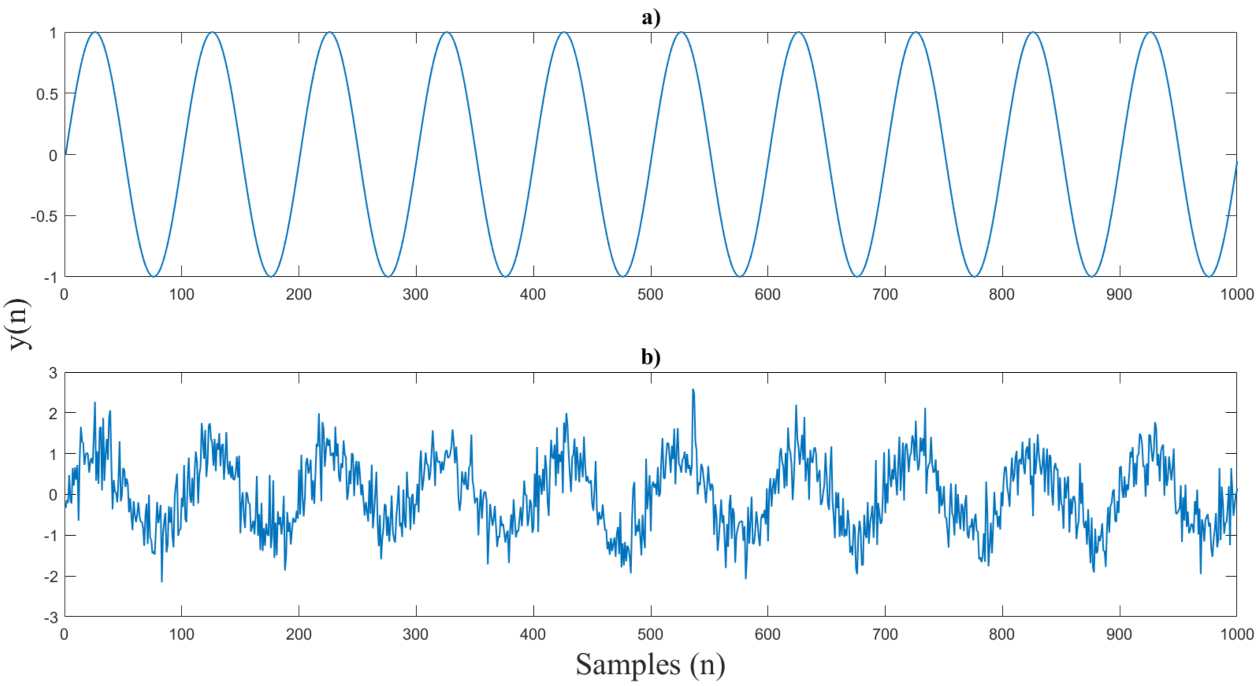

Fig.7. Simulated signals to explain the embedding theorem, a) sinusoid signal with frequency 10 Hz and b) the same sinusoid signal with noise added. In a) we can see that this signal is purely periodic and b) that it is like a random or stochastic signal.

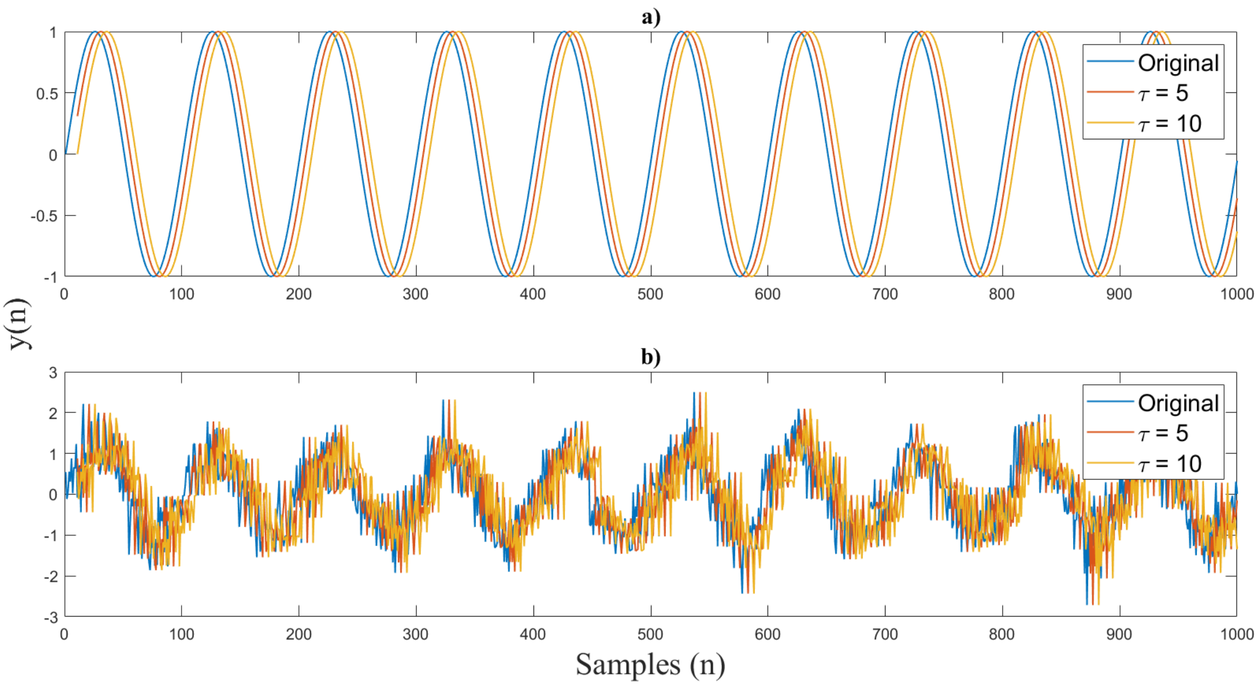

Fig.8. Sinusoid signals in Fig. 7 with delay coordinates using different τ.

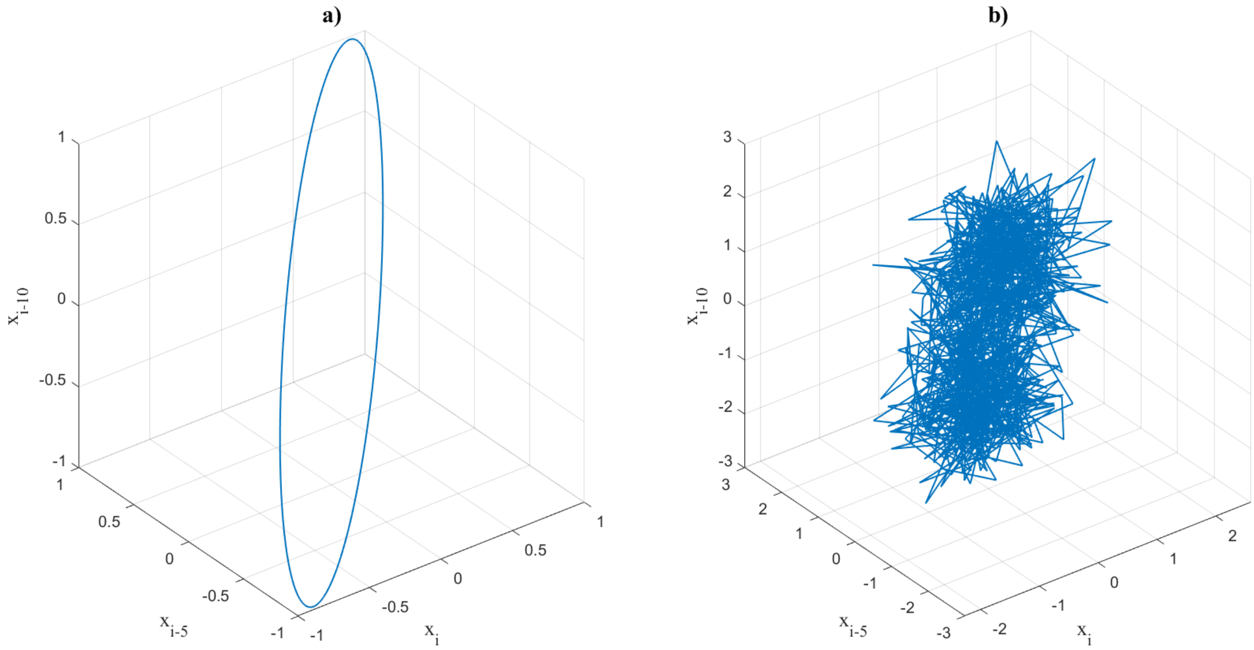

Fig.9. Attractors of the sinusoid signals in Fig. 7 to show the embedding theorem. In a) the sinusoid free-noise signal and in b) the noisy sinusoid signal. The x axis shows the original signal, the y axis delayed with τ = 5 and the z axis with τ = 10. The values of τ used here are the same as the ones used in the OA data for the embedding theorem analysis.

The results of an exemplary TKR patient and one treated with a conservative treatment are shown in Fig. 10 and Fig. 11, respectively. Parallel lines presented in the embedding diagram identify region of the gait characterized by mainly deterministic behaviour. When parallel trajectories are lost the behaviour tends to be more stochastic. In general, in our results seem that patients with TKR are more resilient and maintain more coherence when embedding increases compared to conservative patients which seems to present a more stochastic behaviour. However, this occurs in most cases but not in all patients. And also, it can be seen that there are some slightly differences between the affected side in comparison with the non-affected or contralateral. But, the most important difference is between the two groups of study, between TKR and conservative ones.

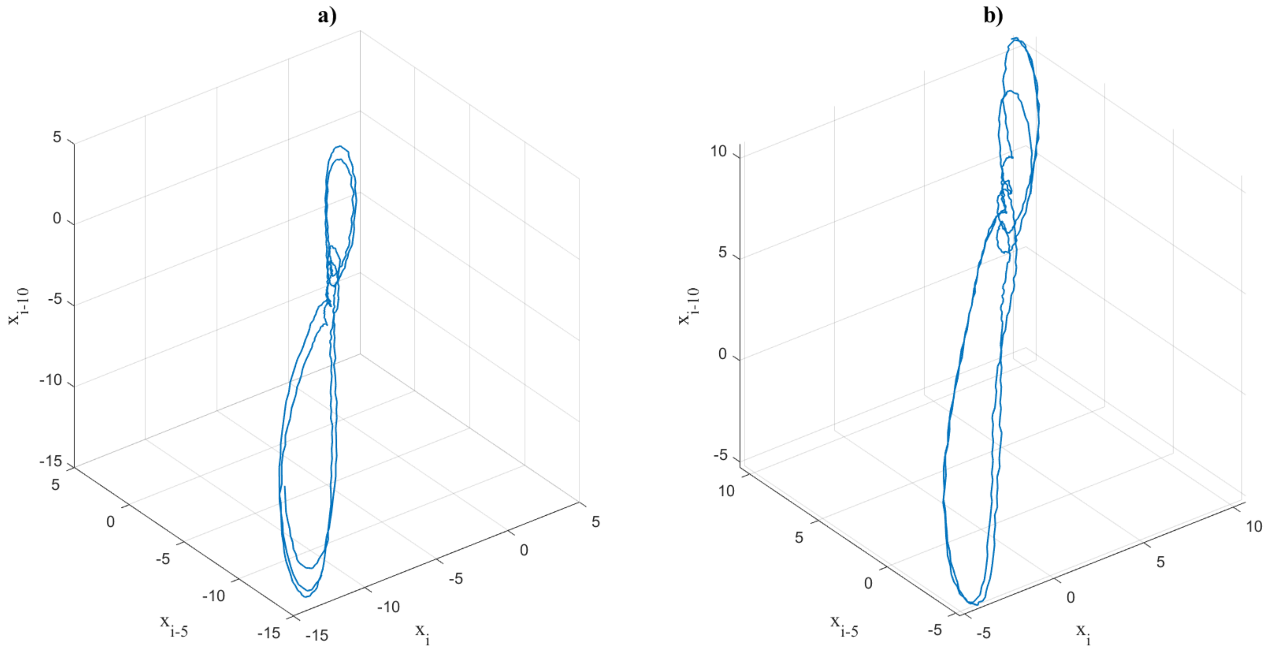

Fig.10. Embedding theorem diagram of the hip abduction-adduction of a TKR-referred patient 12 being a) the right leg and the affected one and b) the left one being the non-affected or contralateral.

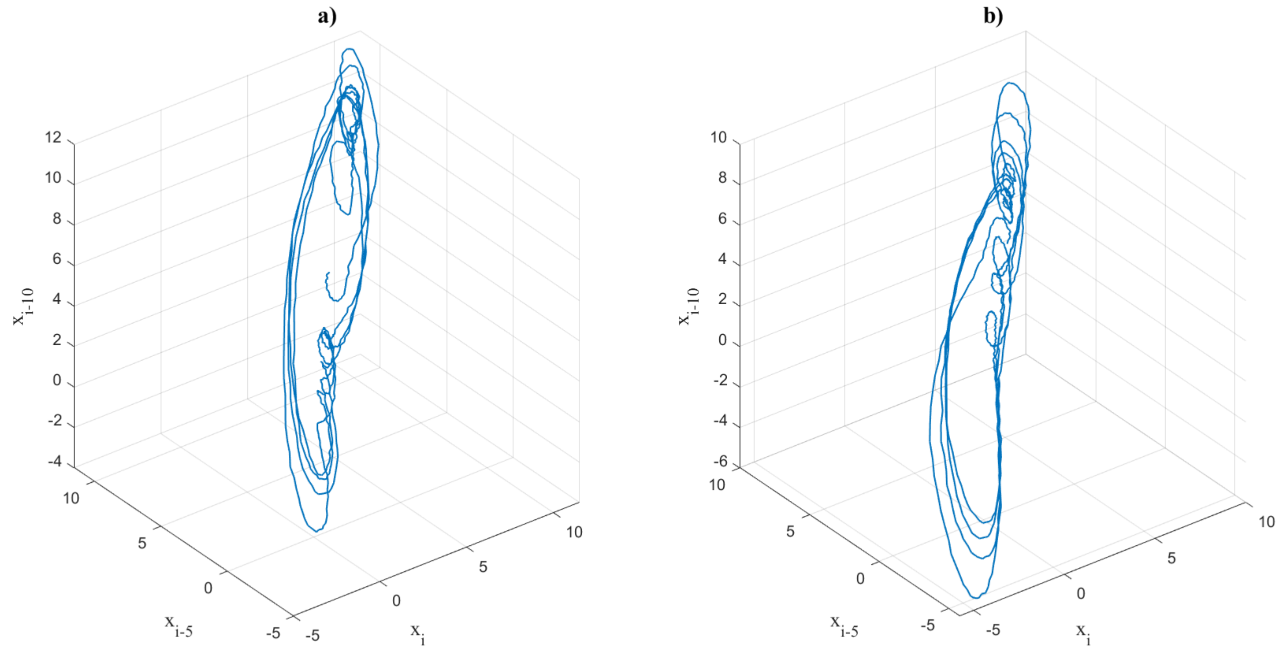

Fig.11. Embedding theorem diagram of the hip abduction-adduction of a conservative patient 1 being a) the right leg and the affected one and b) the left one being the non-affected or contralateral.

3.2 Nonlinear Prediction Error (NPE)

With NPE we could quantify the predictability of the data shown graphically with attractors in Section 3.1. In this section, we show the results of NPE from the left and right hip of flexion extension movement in Fig. 12 and Fig. 13, respectively. Moreover, we show in Fig. 14 and Fig. 15 the same but for a hip abduction adduction. Table 2 shows the results of the NPE differentiating between affected and contralateral sides in the two main groups. Every point is the result of a gait recording, every patient has five recordings except from patient 1 who only have four.

In Table 3 and Table 4 it can be seen that the TKR patients have a lower value of the standard deviation, this means that the conservative patients have more variability in its gait. Regarding as the mean we can see that although having the same values for the two groups, TKR-referred have, in general, lower values than conservative patients. Since it is known which is the affected leg with OA, in the statistics analysis (t-test) of the results we separate the results between affected and contra-lateral knee in order to find more significant differences (Table 5 and Table 6).

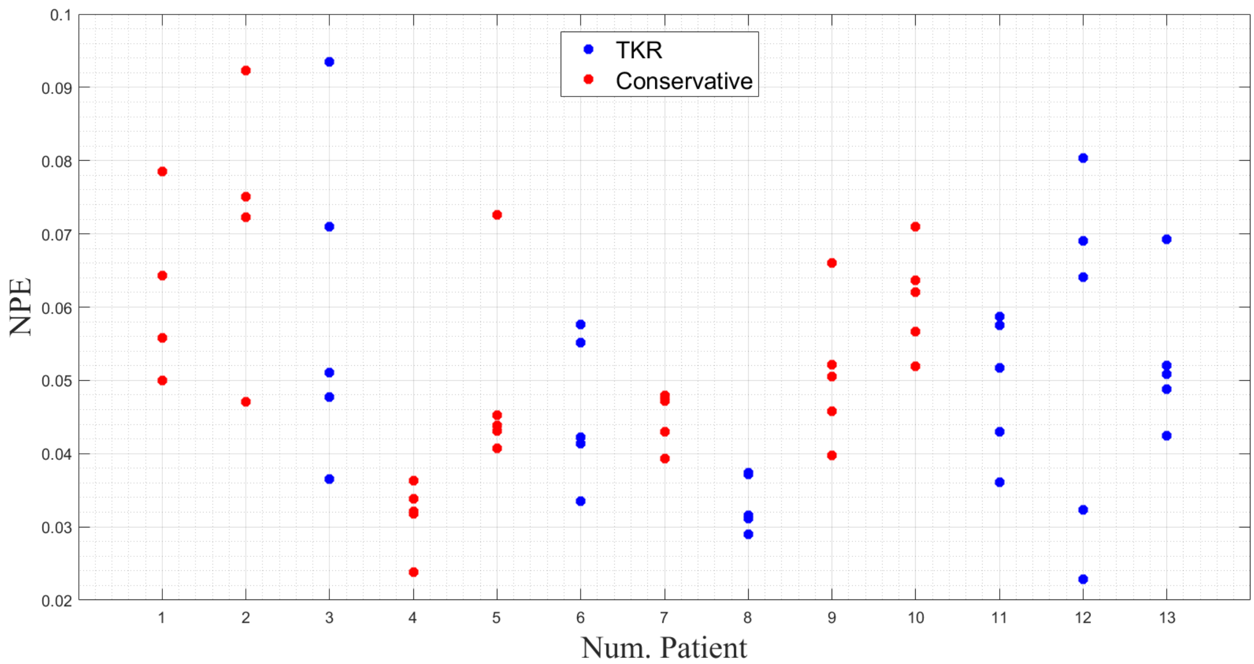

Fig.12. NPE results of the left hip flexion extension of each patient.

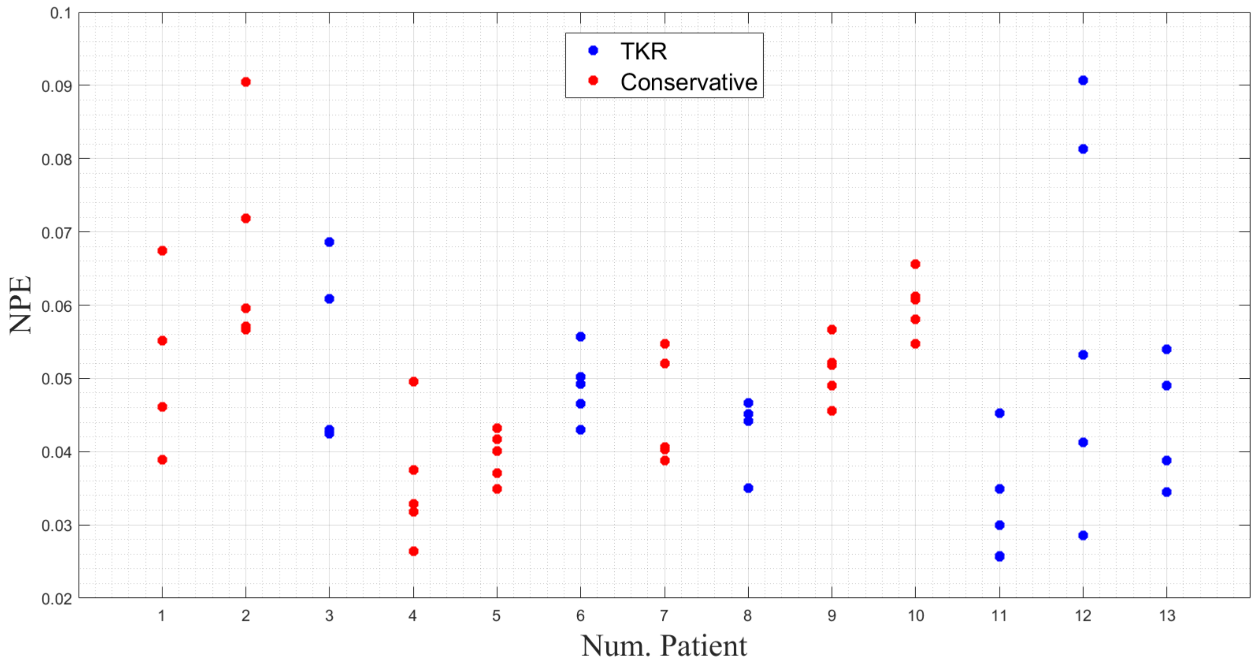

Fig.13. Same as Fig. 12 but for the right hip flexion extension.

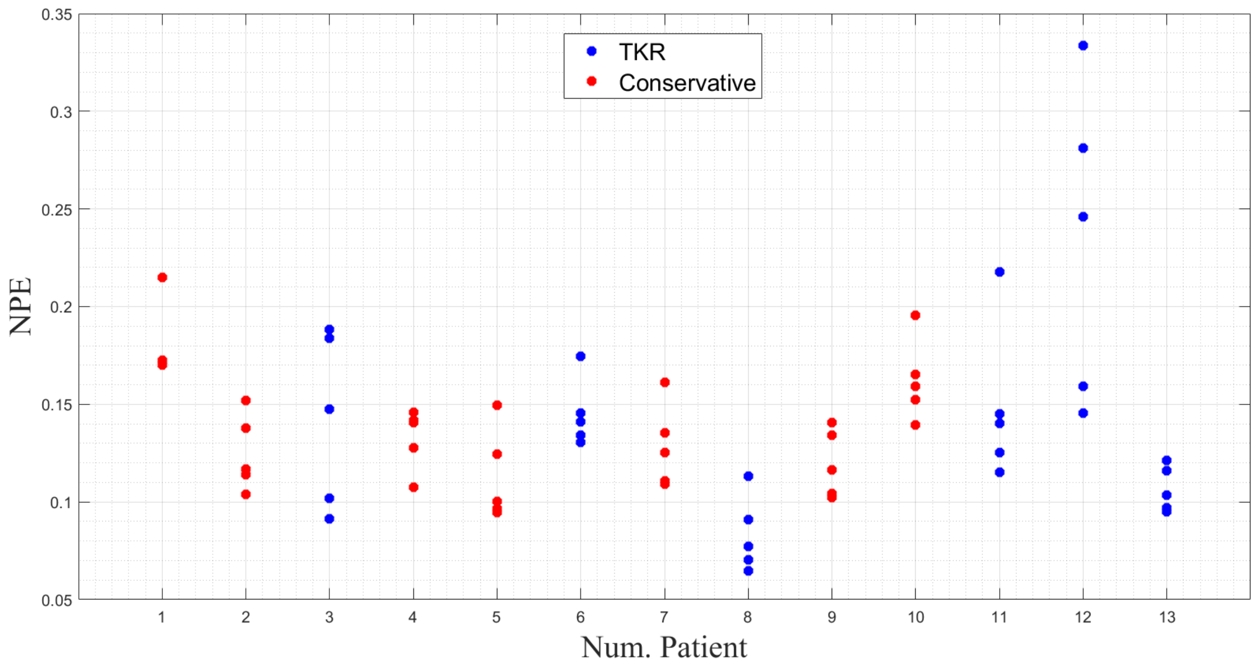

Fig.14. Same as Fig. 13 but for the left hip abduction adduction.

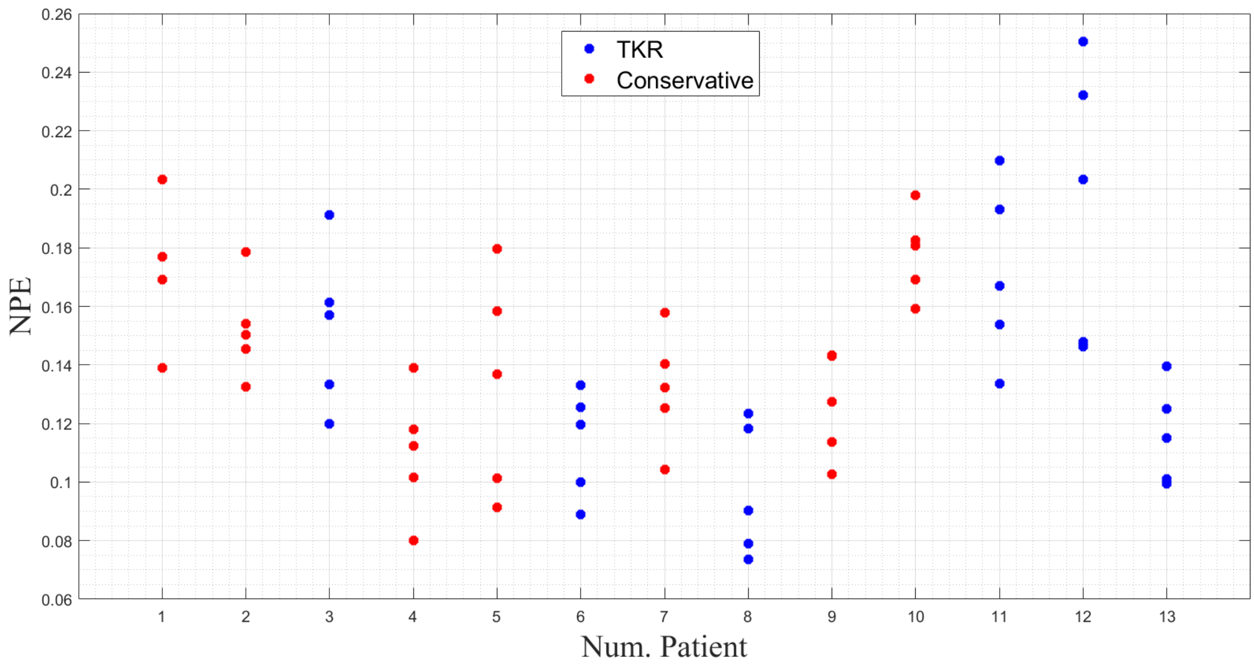

Fig.15. Same as Fig. 14 but for the right hip abduction adduction.

Table 3. NPE results between conservative and TKR patients of hip abduction-adduction.

NPE Results	*TKR*		*Conservative*	
	Affected	Contralateral	Affected	Contralateral
Mean	0,1424	0,1419	0,1342	0,1467
Standard Deviation (STD)	0,0295	0,0334	0,0215	0,0207

Table 4. NPE results between conservative and TKR patients of hip flexion-extension.

NPE Results	*TKR*		*Conservative*	
	Affected	Contralateral	Affected	Contralateral
Mean	0,0456	0,0499	0,0528	0,0509
Standard Deviation (STD)	0,0132	0,0110	0,0103	0,0075

Table 5. T-test results (p-value) of the NPE between affected and contra-lateral legs of hip abduction-adduction.

NPE Results	*Affected*	*Contra-lateral*
Mean	0,669	0,837
Standard Deviation (STD)	0,224	0,274

Table 6. T-test results (p-value) of the NPE between affected and contra-lateral legs of hip flexion-extension.

NPE Results	*Affected*	*Contra-lateral*
Mean	0,313	0,854
Standard Deviation (STD)	0,498	0,345

As it can be seen in Table 5 and Table 6 the results have no significance difference in this analysis measure between the affected leg with OA and the contra-lateral using NPE. Although in Table 4 it can be observed that the standard deviation of conservative patients seems to be a little bit lower, meaning that this data has less variability with regard the results of the different recordings.

3.3 Irregularity measure

As it is mentioned before, this measure shows the irregularity of the data, in this study the gait recordings about hip abduction-adduction and flexion-extension of the hip were analysed. In Table 7 and 8, show the results of the S measure. Table 9 and Table 10 shows the statistical analysis.

Table 7. S (irregularity) results between conservative and TKR patients of hip abduction-adduction.

S Results	*Conservative*		*TKR*	
	Affected	Contralateral	Affected	Contralateral
Mean	0,1654	0,1595	0,1186	0,1247
Standard Deviation (STD)	0,0090	0,0113	0,0076	0,0096

Table 8. S (irregularity) results between conservative and TKR patients of hip flexion-extension.

S Results	*Conservative*		*TKR*	
	Affected	Contralateral	Affected	Contralateral
Mean	0,4127	0,4130	0,3370	0,3523
Standard Deviation (STD)	0,0124	0,0150	0,0155	0,0141

Table 9. T-test results (p-value) of the NPE between affected and contra-lateral legs of hip abduction-adduction. Where (*) means that there is significance difference.

S Results	*Affected*	*Contra-lateral*
Mean	0,025*	0,051
Standard Deviation (STD)	0,669	0,792

Table 10. T-test results (p-value) of the NPE between affected and contra-lateral legs of hip flexion-extension.

S Results	*Affected*	*Contra-lateral*
Mean	0,079	0,160
Standard Deviation (STD)	0,467	0,785

Table 9 shows that we have a statistically significance difference in the affected side versus the contralateral, which was close to be significative but is was not, when the T-test was done. The higher is the value of S, the higher is the irregularity of the data, meaning that if it has more variability, the patient is not charging the same point every step he takes.

4. DISCUSSION

This study shows a method to analyse data extracted from OA patients in order to find differences between the two main groups, those who will have a total knee replacement (TKR) and the ones that will follow a conservative treatment. Following the literature, when MANOVA was done in order to find relationship between clinical treatment options, gait function, and dynamics in patients with knee osteoarthritis the knee had not significant differences between the two main groups [4]. In order to extend this study, it was suggested to study the hip abduction-adduction and flexion-extension in order to find more significance differences between the two main groups of the study since knee kinematics was not identified as significantly different by the preliminary analysis.

The analysis techniques applied were from two different points of view. One of them which looks more to the topological part trying to differentiate if the dynamics from measured signals resembles a more stochastic or deterministic behaviour. The other technique was focused more on the phase velocity of our angles in hip to see the irregularity of the data.

First of all, we applied the embedding theorem in order to graphically observe if the signals of hip abduction-adduction follow a deterministic or stochastic behaviour. In the analysis, TKR-referred and conservative treatment patients were divided into two groups. This kind of analysis shows graphically the behaviour of a signal, being parallel lines characterized by a deterministic behaviour and when these parallel lines are lost, the behaviour tends to be more stochastic. See in Fig. 9a one purely deterministic signal and in Fig. 9b a stochastic one. Fig. 10 and Fig. 11 show that, in general, patients with TKR-referred are more resilient and maintain more coherence when embedding increases compared to conservative patients which seem to present a more stochastic behaviour. Also, it can be seen that there some slightly differences between the affected side in comparison with the non-affected or contralateral side. Although, the most important difference is between the two groups of study, between TKR and conservative ones. However, this occurs in most cases but not in all patients.

In the next part of the analysis, the nonlinear prediction error was computed. This technique allows to quantify the degree of alignment of the trajectories seen in the embedding theorem. First, we compute the NPE to see which parameters fits best to our signals. Once the parameters were found (Table 2), we computed the NPE from the wanted signal. Table 3 shows that the standard deviation of TKR-referred of hip abduction-adduction is lower in the affected side versus the contralateral side. This make sense in a way that if it has less variability with regard to NPE, the patient is charging all the time the same points, if a charge is load in the same points, it is more likely to take a TKR. Charging more different points is better to give time to the other points to recover. In conservative patients it seems to be more or less the same variability. We could find some relationship in this way but looking at Table 5 we cannot significantly see differences between the two main groups.

The last measure applied was the irregularity of phase velocity S, the irregularity of the data. This measure shows numerically how irregular is the input signal. Remember that variability is what is given by the standard deviation from the result of S, and S is the measure of irregularity. In our context, more irregularity means more variability, and more variability, as it is mentioned before, means less charge in the same point. Looking at Table 7 and Table 8 we can see that in general the affected side of each group of patients have less standard deviation, meaning that is less variable in time. This corroborate what it has been said with the results of NPE. And if we take a look at Table 9, which shows the results of the T-test, we can find some statistically significant differences between the affected side versus the contralateral side in the hip abduction adduction meaning that this analysis could be clinically significative. However, this does not occur in the flexion-extension movement.

This study has some limitations since the group studied is based only in thirteen women suffering OA and only two kinds of movements were analysed. These techniques need to be applied in more than one joint and in the three axes in order to lead to a truthful conclusion. For future work, the group need to be extended with the oldest group from 67-75 and with the obese (BMI > 30) or performing the analysis of the knee and pelvis as it they were suggested joints to study in literature [4] . Also, it can be extended including men to increase the analysis group of study and have more resilient results.

5. CONCLUSIONS

Nonlinear prediction error (NPE) and irregularity of phase velocity (S) measures are useful to find differences in patterns from data. Previous work suggested that hip was needed to investigate and that is what is done in this study. Making a dynamic analysis using the nonlinear technique and the irregularity measure, we corroborate that the TKR-referred patient has less variability in their steps during gait than those who followed a conservative treatment. Also, TKR patients seemed to have more predictable data in the performed analyses, meaning that it could be easier to predict how the future steps during gait will look like. All these statements suggest that having less variability means charging load in the same point more often without having time to be totally recovered.

BIBLIOGRAPHY

[1] "Osteoarthritis (OA)," Arthritis, CDC. https://www.cdc.gov/arthritis/basics/osteoarthritis.htm (accessed May 21, 2022).

[2] Glyn-Jones, S., Palmer, A. J. R., Agricola, R., Price, A. J., Vincent, T. L., Weinans, H., & Carr, A. J. (2015). Osteoarthritis. Lancet, 386(9991), 376–387. https://doi.org/10.1016/s0140-6736(14)60802-3

[3] Wilson, W., Van Donkelaar, C. C., Van Rietbergen, R., & Huiskes, R. (2005). The role of computational models in the search for the mechanical behavior and damage mechanisms of articular cartilage. Medical engineering & physics, 27(10), 810-826.

[4] Tassani, S., Tio, L., Castro-Domínguez, F., Monfort, J., Monllau, J. C., Ballester, M. A. G., & Noailly, J. (2022). Relationship Between the Choice of Clinical Treatment, Gait Functionality and Kinetics in Patients With Comparable Knee Osteoarthritis. Frontiers in bioengineering and biotechnology, 10.

[5] B. Kidd, "Mechanisms of Pain in Osteoarthritis," HSS Journal, vol. 8, no. 1, pp. 26–28, Feb. 2012, doi: 10.1007/s11420-011-9263-7.

[6] Braun, H. J., & Gold, G. E. (2012). Diagnosis of osteoarthritis: imaging. Bone, 51(2), 278-288.

[7] Oosthuizen, C. R., Takahashi, T., Rogan, M., Snyckers, C. H., Vermaak, D. P., Jones, G. G., ... & Pandit, H. (2019). The knee osteoarthritis grading system for arthroplasty. The Journal of Arthroplasty, 34(3), 450-455.

[8] Kellgren, J. H., & Lawrence, J. (1957). Radiological assessment of osteo-arthrosis. Annals of the rheumatic diseases, 16(4), 494.

[9] Park, S., Lee, S., Yoon, J., & Chae, S. W. (2019). Finite element analysis of knee and ankle joint during gait based on motion analysis. Medical Engineering & Physics, 63, 33-41.

[10] Delp, S. L., Anderson, F. C., Arnold, A. S., Loan, P., Habib, A., John, C. T., ... & Thelen, D. G. (2007). OpenSim: open-source software to create and analyze dynamic simulations of movement. IEEE transactions on biomedical engineering, 54(11), 1940-1950.

[11] Huynh, K. T., Gibson, I., Jagdish, B. N., & Lu, W. F. (2015). Development and validation of a discretised multi-body spine model in LifeMOD for biodynamic behaviour simulation. Computer methods in biomechanics and biomedical engineering, 18(2), 175-184.

[12] Damsgaard, M., Rasmussen, J., Christensen, S. T., Surma, E., & De Zee, M. (2006). Analysis of musculoskeletal systems in the AnyBody Modeling System. Simulation Modelling Practice and Theory, 14(8), 1100-1111.

[13] Liu, M. Q., Anderson, F. C., Schwartz, M. H., & Delp, S. L. (2008). Muscle contributions to support and progression over a range of walking speeds. Journal of biomechanics, 41(15), 3243-3252.

[14] Kia, M., Stylianou, A. P., & Guess, T. M. (2014). Evaluation of a musculoskeletal model with prosthetic knee through six experimental gait trials. Medical engineering & physics, 36(3), 335-344.

[15] Wang, X., Ma, Y., Hou, B. Y., & Lam, W. K. (2017). Influence of gait speeds on contact forces of lower limbs. Journal of healthcare engineering, 2017.

[16] Simic, M., Wrigley, T. V., Hinman, R. S., Hunt, M. A., & Bennell, K. L. (2013). Altering foot progression angle in people with medial knee osteoarthritis: the

effects of varying toe-in and toe-out angles are mediated by pain and malalignment. Osteoarthritis and cartilage, 21(9), 1272-1280.
[17] Taniguchi, M., Tateuchi, H., Takeoka, T., & Ichihashi, N. (2012). Kinematic and kinetic characteristics of Masai Barefoot Technology footwear. Gait & Posture, 35(4), 567-572.
[18] Vimieiro, C., Andrada, E., Witte, H., & Pinotti, M. (2015). A computational model for dynamic analysis of the human gait. Computer Methods in Biomechanics and Biomedical Engineering, 18(7), 799-804.
[19] Perc, M. (2005). The dynamics of human gait. European journal of physics, 26(3), 525.
[20] Andrzejak, R. G. (2011). Nonlinear time series analysis in a nutshell. Epilepsy: The Intersection of Neurosciences, Biology, Mathematics, Engineering and Physics, 125-138.
[21] Andrzejak, R. G., Schindler, K., & Rummel, C. (2012). Nonrandomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients. Physical Review E, 86(4), 046206.
[22] Kantz, H., & Schreiber, T. (2004). Nonlinear time series analysis (Vol. 7). Cambridge university press.
[23] Espinoso, A., & Andrzejak, R. G. (2022). Phase irregularity: A conceptually simple and efficient approach to characterize electroencephalographic recordings from epilepsy patients. Physical Review E, 105(3), 034212.
[24] Inouye, T., Shinosaki, K., Sakamoto, H., Toi, S., Ukai, S., Iyama, A., ... & Hirano, M. (1991). Quantification of EEG irregularity by use of the entropy of the power spectrum. Electroencephalography and clinical neurophysiology, 79(3), 204-210.
[25] Perc, M. (2005). Nonlinear time series analysis of the human electrocardiogram. European Journal of Physics, 26(5), 757.