GAIT Analysis: Methods & Data Review

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Abstract - **The physiotherapists analyse gait patterns to recognize normal and pathological gait movements. The difficulty of the gait analysis can be high due to patterns' complexity and variability. The gait patterns are affected by the characteristics of the individual (gender, age, weight and height) and the walking speed.**

In this paper, it is proposed a Machine Learning (ML) algorithm to generate knee angle patterns in sagittal plane, which is one of the joints used during the walk. The ML algorithm can generate a specific reference of normal knee pattern depending on individual's characteristics and walking speed. This specific reference provides a personalized gait analysis. To this end, three ML approaches are compared: an Artificial Neural Network (ANN), an Extreme Learning Machine (ELM) and a Multi-output Support Vector Regression (MSVR). Using the patterns of healthy people collected by a vision system, authors show that ELM outperforms ANN and MSVR. The ELM can generate specific reference knee patterns for female and male gender.

The reference knee patterns generated by the ELM can be used by a gait analysis system which the team proposes to future work. The main goal of the gait analysis system is to evaluate and classify the severity of gait pathology through the comparison of the real pattern of an individual with the specific reference pattern generated by the ML approach. The proposed gait analysis system can help physiotherapy team in the gait pathology diagnosis and evaluation of future pathologies.

Index Terms - **ANN, FBNN, ELM, MSVR, gait analysis, knee pattern**

I. INTRODUCTION

The human gait is a cyclic pattern composed by a set of complex movements which are executed by several parts of the body [1]. The gait cycle, repeated over the person's gait, begins with the first touch of the heel on the floor and ends when the same heel touch on the floor by the second time [2].

The analysis of the human gait can be applied in different fields such as physiotherapy and identification of people for forensics [3] and security purposes [4]. The physiotherapy area analysis the gait limitations caused by sports activities, and musculoskeletal and neurological diseases, such as Parkinson disease [5]. The rehabilitation team uses the gait analysis to recognize normal and pathological gait patterns [6] which is important for gait pathology diagnosis and evaluation of future pathologies.

The complexity of the gait and the large number of joints involved in the gait make the work team select the knee as the first joint to be analysed. The joint knee is easy affected by problems that degrades the gait quality such as sport injuries.

In gait analysis, the physiotherapist compares the knee joint angle pattern of the patient with a reference healthy knee pattern. Normally, the reference healthy knee pattern is a literature knee joint pattern which describes the knee pattern of people without any type of gait disease. However, this comparison of patterns is not specific for each patient who has personal characteristics (gender, age, weight, height and gait speed) [7]. The personal characteristics affect the knee joint pattern and the literature pattern does not take them into account.

The ML algorithms were been used to generate reference knee pattern for an individual with specific characteristics [8]. The use of the pattern generated by the ML algorithm improves the results of the gait analysis.

A visual comparison between the patient's pattern and the pattern generated by the ML algorithm can result in a weak classification of the gait severity. The gait pathology severity can be quantified using gait indices. Gait indices compare the knee patterns using multivariate statistic methods.

In authors investigation work, they pretend to develop an innovative gait analysis system. The development of the system will have an incremental process where the study methods lead the team for the study of new methods. This incremental process allows the development of a reliable gait analysis system with better medical results and low cost than the current state-of-the-art.

In this paper, it is proposed the generation of reference knee joint pattern for specific individuals (with various height, weight, age, gender and gait speed) using ML algorithms. After training and testing three ML algorithms (ANN, ELM and MSVR) with gait data of people without gait limitations (healthy people), the authors select the ML algorithm with best results in generation of gait patterns.

In future work, the proposed innovative gait analysis system will use gait indices to compare the real patterns of patients with the specific reference gait patterns generated by the selected ML algorithm. The proposed system can be a great help in rehabilitation and physiotherapy processes providing a personalized analyse for each patient.

This paper is organized as follows. Section II presents a review of ML methods for gait analysis. Section III is dedicated to the methodology where data collection, data processing, and ML train and test processes are described. Section IV shows the experimental results of the study ML algorithms. In section V is described the evaluation of the experimental results. Section VI presents the proposes for the future work plan of the authors. The concluding remarks are drawn in section VIII.

II. BACKGROUND

In gait analysis, physiotherapists use measure parameters such as angles of joints movements and pressure distribution under feet [9].

The available systems to collect gait parameters are video tracking [10], force plates [11], treadmills [12, 13], insoles [14, 15] and instrumented shoes [16, 17]. The presents work starts by collecting the angles of joints movements using the low vision system composed by a treadmill, two cameras and several passive marks. The vision system is described in Subsection A of Section III.

A. ML Algorithms for Gait Analysis

ML algorithms can extract important information from a large gait dataset [18].

Shallow and deep architectures are two class of ML algorithms used in gait analysis publications. Shallow architectures have few levels of representation. In opposition, deep ML are composed by multi levels of representation.

a) Shallow ML for gait analysis

M. Rani and G. Arumugam [19] compared the performance of ELM and Support Vector Regression to classify the children abnormal gait. The study concluded that the ELM has better classification accuracy, a reduced training time and a simpler implementation.

T. P. Luu *et al.* [20] proposed a General Regression Neural Network (GRNN) to generate healthy gait patterns. The method used the inverse transform to convert the coefficients of Fourier generated by the GRNN into a gait pattern.

Kong *et al.* [21] used ANN to classify the human gait into six different gait stages.

C. Prakash *et al.* [22] presented a multi-model technique for subject identification. The silhouette image of healthy people was used to train three ML: ANN, Random Forest (RF) and Linear Discriminant Analysis (LDA), along with Principal Component Analysis. RF and LDA generated values were used to train one Support Vector Machine (SVM) with Radial Function Basis Kernel. The SVM output were the subject identification.

b) Deep ML for gait analysis

M. Alotaibi and A. Mahmood [23] developed a specialized deep Convolutional Neural Network (CNN) architecture for gait recognition which it was used to identify persons taking into account their style and manner of walk.

K. Shiraga *et al.* [24] used a model named GEINet for human gait recognition over view variations and covariate conditions, such as clothing and carrying situations. The GEINet model is a CNN trained with Gait Energy Image (GEI).

B. M. Nair and K. D. Kendricks [25] presented a method for real-time detection of threats on surveillance videos. The deep regression-based neural network correlates the latent features generated by Deep Belief Network (DBN) to the inverse kinematic model. After, it was used the K-Nearest Neighbour classifier to classify gait signatures where a threat is a person wearing a loaded vest.

J. Triloka *et al.* [26] proposed a multilayer feed-forward neural networks for walking gait pattern identification.

M. Rauf *et al.* [27] presented a Fully Connected Network (FCN) tested in human gait recognition tasks. The FCN development uses the gait data and a weight matrix generated by a deep CNN model.

In the present paper, it is study three shallow ML to generate the knee joint patterns: ANN, ELM and MSVR.

III. METHODOLOGY

The work development follows an incremental strategy. Which starts is the test of the capability of three ML algorithms, with shallow architectures, to generate reference gait patterns for specific individuals: ANN, ELM and MSVR.

A. Data Collection

The vision system developed by P. Ferreira *et al.* [28] is used to collect the gait patterns. The vision system is composed by a treadmill, two cameras and 20 passive marks. Each camera positioned in one side of the treadmill is characterised by a CMOS 640x480 (VGA) sensor, maximum of 30 frames/sec. and USB 2.0 interface. The alignment and the calibration of the system were done according to P. Ferreira *et al.* [28]. The passive marks were positioned in the joints of each side of the individual, as represented for the right side in Fig. 1: shoulder, elbow, wrist, pelvis, leg, knee, ankle, heel and two extremities of the finger toes. After the measurement of the distances between the marks to know the depth was realized the pelvis calibration. The pelvis calibration gives the pelvis position taking into account the relationship between leg, knee and pelvis marks. The pelvis mark, represented in Fig. 1 with triangle was removed before the gait record because it would be occluded by upper limb of the individual.

Fig. 1: Position of passive marks during the gait record

The vision system was used to collect data from a group of individuals with healthy gait composed by 14 females and 11 males. The low number of specimen used is acceptable for a prototype system. Table I presents physical characteristics intervals, mean and standard deviation of the healthy group. Gait pattern are affected by the gender, age, weight and height of the individual and by the gait speed.

TABLE I
CHARACTERISTICS OF HEALTHY GROUP

Gender	*Characteristic*	*Minimum*	*Maximum*	*Mean*	*Standard Deviation*
Female	Height (m)	1.59	1.69	1.64	0.03
	Age (years)	18	58	33	16
	Weight (kg)	47	90	65	13
Male	Height (m)	1.69	1.90	1.78	0.07
	Age (years)	19	55	35	13
	Weight (kg)	58	120	81	19

Each individual walked five different speeds on the treadmill. The value of the speeds corresponds to 25%, 50%, 75%, 100% and 125% of the comfortable speed. The comfortable speed is the velocity appropriated for a individual with a specific gender, age and weight, as proposed by R. W. Bohannon [29]. The future objective of the work is the development a method to analysis the gait of individual with gait pathologies which gives priority to the study of the lower gait speeds. The selection of maximum and minimum speeds was limited by the vision system characteristics: minimum treadmill speed of 0.28 m/s and maximum speed for a good accuracy 1.53 m/s.

This work only used the data of the knee joint for realize the gait analysis.

B. Data Processing

Before the knee joint patterns was fed to the MLs, it was performed a set of 5 processing steps, illustrated in Fig. 2. First the temporary walking instabilities caused by the begin (first step) and the end (last 5 steps) of the treadmill movement was removed from the knee joint data. In the second processing step was removed the steps which increases the standard deviation of the patterns and it was calculated the mean pattern for each knee of an individual at a specific gait speed. Steps 3, 4 and 5 made some adjustments to allow patterns comparison: vertical shift for the minimum of the pattern becomes zero; horizontal shift for abscissa of the maximum of the pattern becomes 75% of the gait cycle; and filtration and realignment of left knee joint pattern to remove the disruption of some patterns caused by previous step, respectively.

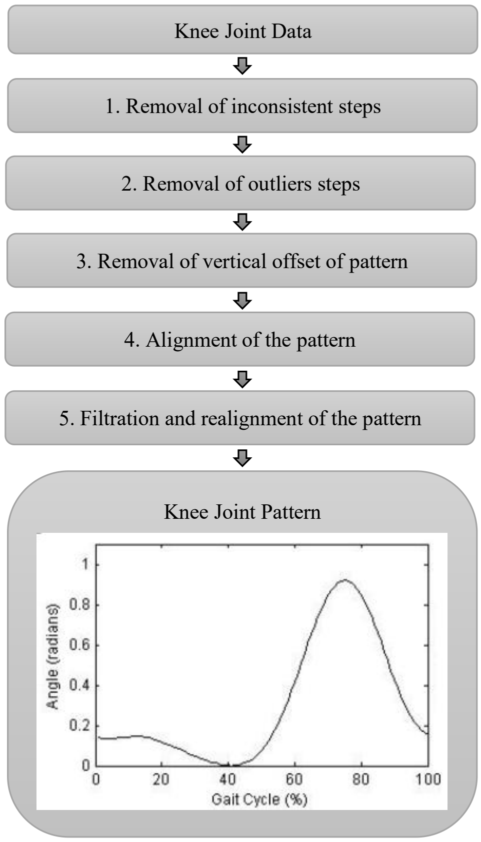

Fig. 2 : Flowchart of the processing of the knee joint data recorded by the vision system

C. Generation of Knee Joint Pattern

Input and output matrices, for the ML algorithms, grouped the processed knee joint patterns in function of the gender, i.e. each gender has an input and an output matrices. Women and men present different gait pattern because they walk with different styles and present different physical characteristics (such as height and weight).

The knee dominance (right or left) was not considered in the data division due to two reasons:

1. It is expected that healthy individuals present similar right and left knee patterns which was proved by the collected data. The difference measured between the maximum value of the left and right knee is small (about 0.04 rad). Furthermore, this difference is close to the vision system calibration error value (0.035 rad).

2. The reference literature for knee joint pattern [30] used in this work as comparison base also join the right and left knee patterns.

The input matrices had one line for each physical characteristic (height, age and weight) and one line for the gait speed. The number of columns of input matrix resulted of the multiplication of the number of gait speeds by the number of individuals and the number of knees. The ML algorithms only generate accurate patterns for input features with values within the range limited by the input matrices, described in Table I for each gender. The output matrices had 100 lines (percentage of gait cycle) and the same number of columns than the input matrices.

In train and test process of ML algorithms was used the data of 10 women and 9 men of the healthy group. The data of the other individuals (4 woman and 2 men) will be used in future work to calculate the reference gait indices of healthy gait.

The female matrices had the following dimensions: input 4×100 and output 100×100. The dimension of input matrix was 4×90 and output matrix was 100×90 for the male gender.

a) ML Algorithms

This work compared the capability, to generate the reference knee joint pattern for specific individuals, with various height, weight, age, gender and walking speed, of three ML models: ANN, ELM and MSVR. Training and testing of the ML models was performed in a PC 2 GB RAM, 2.16 GHz.

The ANN architecture was a Feedforward Backpropagation Neural Network (FBNN) with 4 inputs, one hidden layer and 100 outputs. The hidden layer was composed by a number of neurons ranging from 4 to 22. Taking into account the existence of random variables (weights and biases) each number of neurons was train, test and validate in more than 7 FBNN. The samples for training (70%), testing (25%) and validation (5%) phases were randomly selected from the processed data. As activation function it was used the sigmoidal which is indicated for regression function [31].

The ELM was constituted by one input layer with 4 inputs, one hidden layer with a number of neurons ranging from 4 to 22 and one output layer with 100 outputs. Each number of neurons was tested in more than 11 ELM networks to change the random values (weights and biases). The sigmoid activation function was used. A right comparison of results requests the use of the same inputs by the different ML algorithms. The ELM train matrices had the training and validation samples of the FBNN, and the ELM test matrices the same samples than the FBNN test matrices. As requested by the ELM algorithm the input matrices were normalized in the interval between -1 and 1.

In this work, the MSVR algorithm used the Radial Basis Function, a tolerance value of $1e^{-20}$ and the following parameters intervals: C= {1, ..., 10000}; ε= {10^{-6}, ..., 10}; and ϒ= {0.01, ..., 1000}. Intervals selection were based in the results of [32], [33] and [34]. Since MSVR does not have random variables each set of parameters only was used one time in the 9800 MSVR tested for each gender. The MSVR used the same matrices than the ELM.

b) ML Evaluation Scheme

Evaluation of the studied ML algorithms was based on three criteria of pattern analysis: accuracy, similarity and behaviour.

The accuracy criterion considered three statistical parameters: Mean Squared Error (MSE), Correlation Coefficient (ρ) and Dynamic Time Warping (DTW). The ML algorithm selected to generate the knee patterns was the one with better statistical results. The selected ML should present: a low MSE value which indicates a low generation error; if possible a high ρ value that indicates similarity between generated and real knee patterns; and a low DTW_{ML}, the zero value of this parameter indicates a similarity of 100% between generated and real patterns.

The similarity criterion compares the results of DTW_{ML} and DTW_{LIT}. The DTW_{LIT} is the DTW between the Literature [30] and the real patterns. The patterns used as reference in gait analysis should be as similar as possible with the reality which is described by a low value of DTW.

The behaviour criterion analysis the knee pattern and its dependence with the gait speed. In the knee pattern analysis, it was realized a visual comparison between profile of the generated pattern and the expected one described by A. Gomes *et al.* [35]. The best ML has the higher similarity between the patterns. According to T. Oberg *et al.* [36] the amplitude of knee joint pattern grows with the increasing of the gait speed. The present work analysis the variation of the knee pattern with the speed through the calculation of the DTW between generated and literature [30] knee patterns, named as DTW_{SPEED}. Once the literature pattern describes the knee pattern for a single high gait speed, it is expected that the DTW_{SPEED} values, calculated for each gait speed, decreases with the gait speed increases.

IV. EXPERIMENTAL RESULTS

Table II shows the statistical results and the parameters of three ML models which shows better results, for female and male gender.

The similarity between reference and real patterns was measured using the DTW parameter: DTW_{ML} uses as reference the generated pattern and DTW_{LIT} uses as reference literature pattern [30]. Table III presents the average of DTW_{ML} and DTW_{LIT} calculated with different gait speeds, for 6 healthy individuals of each gender.

The ability of the proposed ML models was tested with the generation of knee patterns for an unknown individual of each gender, with five different gait speeds: 0.28, 0.67, 1.03, 1.33 and 1.53 $m.s^{-1}$. The unknown individuals presented physical characteristics with values contained in the ranges of the Table I, which ensures the reliability of the pattern generated by the ML models. The woman had the following characteristics: 22 years old, height of 1.60 m and weight of 59 kg. The man of 33 years old presented a height of 1.80 m and a weight of 80 kg.

TABLE II
STATISTICAL RESULTS AND PARAMETERS OF THE BEST ML FOR EACH GENDER

	Model		*Statistical Parameters*				
Gender	*Algorithm*	*Parameters*	*Train MSE (rad)*	*Validation MSE (rad)*	*Test MSE (rad)*	*ρ (%)*	*DTW_{ML} (rad)*
Female	FBNN	5 nodes	0.13	0.22	0.14	98.31	1.65
	ELM	12 nodes C=80	0.18	without	0.11	98.63	1.66
	MSVR	ε=10 ϒ=1000	0.20	without	0.12	98.63	1.64
Male	FBNN	10 nodes	0.08	0.18	0.09	98.94	1.37
	ELM	12 nodes C=100	0.12	without	0.11	98.74	1.32
	MSVR	$\varepsilon=10^{-6}$ ϒ=500	0.14	without	0.13	98.47	1.42

TABLE III
AVERAGE OF DTW_{ML} AND OF DTW_{LIT} FOR 12 INDIVIDUALS OF THE HEALTHY GROUP

Individual	*DTW_{ML} (rad)*			*DTW_{LIT} (rad)*
	FBNN	*ELM*	*MSVR*	
Female #1	1.61	1.42	1.66	5.07
Female #2	0.97	1.00	1.70	3.13
Female #3	1.89	1.31	1.55	7.20
Female #4	1.43	1.44	1.55	6.51
Female #5	1.76	1.78	1.61	3.09
Female #6	2.53	2.48	2.50	5.78
Mean (female)	1.70	1.57	1.76	5.13
Male #1	1.30	1.41	1.52	4.16
Male #2	1.15	1.00	1.29	4.30
Male #3	1.89	1.64	1.87	3.35
Male #4	1.59	1.71	1.79	4.03
Male #5	1.01	1.01	0.92	5.78
Male #6	1.25	1.07	1.27	5.71
Mean (male)	1.37	1.31	1.44	4.56

Fig. 3, 4 and 5 represent the knee pattern generated by the best FBNN, ELM and MSVR, respectively, for the unknown woman at different gait speeds and the literature pattern [30].

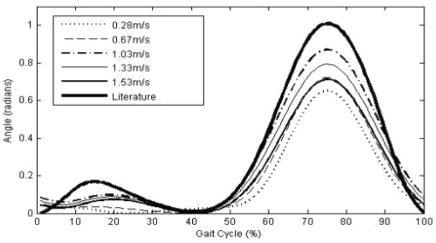

Fig. 3: Knee joint patterns of five gait speeds generated by the selected FBNN for the new female characteristics, and literature knee pattern [30].

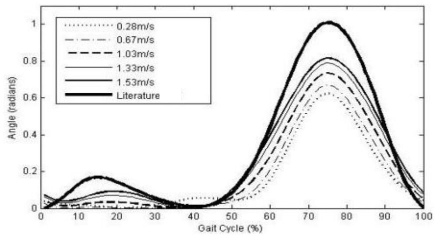

Fig. 4: Knee joint patterns of five gait speeds generated by the selected ELM for the new female characteristics, and literature knee pattern [30].

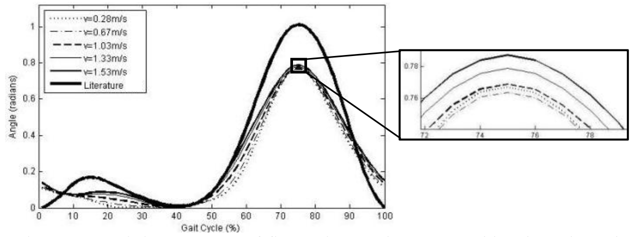

Fig. 5: Knee joint patterns of five gait speeds generated by the selected MSVR for a the new female characteristics, and literature knee pattern [30].

The knee pattern generated to the unknown man, by FBNN, ELM and MSVR, selected to the male gender, are represented in Fig. 6, 7 and 8.

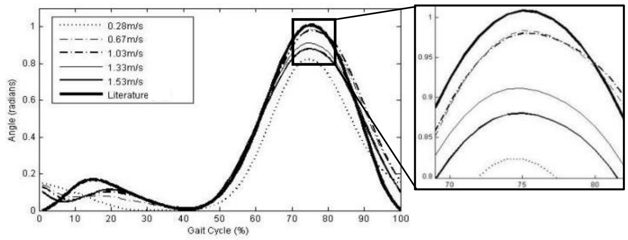

Fig. 6: Knee joint patterns of five gait speeds generated by the selected FBNN for a the new male characteristics, and literature knee pattern [30].

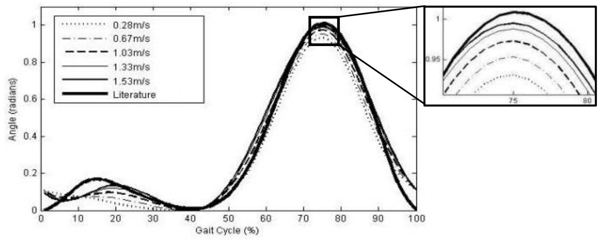

Fig. 7: Knee joint patterns of five gait speeds generated by the selected ELM for a the new male characteristics, and literature knee pattern [30].

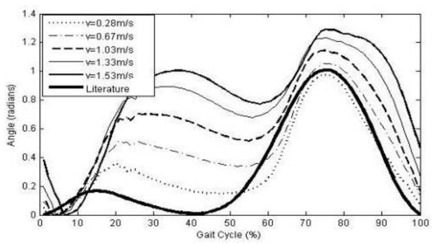

Fig. 8: Knee joint patterns of five gait speeds generated by the selected MSVR for the new male characteristics, and literature knee pattern [30].

Table IV shows the DTW_{SPEED} results for the unknown woman and man, calculated in function of the gait speed.

TABLE IV
DTW_{SPEED} FOR FEMALE AND MALE CHARACTERISTICS UNKNOWN BY THE SELECTED ML MODELS

Gender	*Gait Speed (m/s)*	DTW_{speed} (rad)		
		FBNN	ELM	MSVR
Female	0.28	7.92	8.66	5.06
	0.67	6.34	7.69	5.04
	1.03	3.09	6.47	4.96
	1.33	4.29	4.73	4.85
	1.53	5.96	3.97	4.79
Male	0.28	4.07	2.60	19.40
	0.67	2.34	2.44	13.09
	1.03	2.39	2.18	10.91
	1.33	2.53	1.70	11.14
	1.53	2.86	1.49	11.16

V. DISCUSSION

The authors propose an analysis system for gait pathology diagnosis and evaluation of future pathologies. In the present paper, it is discussed the first part of the development of the analysis system: generation of a reference knee joint pattern for an individual with specific characteristics (height, weight, age, gender and gait speed).

For each gender (female and male), the performance of three ML models to generate the reference knee joint pattern for an individual is compared: FBNN, ELM and MSVR. The analysis of the performance is based on three criteria: accuracy, similarity and behaviour of the knee patterns. As result, this analysis indicates the best ML model to generate the patterns for each gender.

Starting with the analysis of ML results for the female data. According to Table II, the ELM has the lowest test MSE and the MSVR has the lowest DTW_{ML}. However, the small difference between the statistical parameters of the ELM and MSVR, makes the accuracy criterion insufficient for selection of the best ML model. The similarity criterion compares the reference patterns with the real patterns. Table III shows that the proposed ML models generate patterns more similar with the real pattern than the pattern of the literature, once $DTW_{ML} < DTW_{LIT}$. Among the ML models, the FBNN presents the lowest DTW_{ML} value for three women and the ELM the lowest DTW_{ML} for the other three. However, the mean DTW_{ML} of the six women suggests the ELM as the method able to generate patterns more identical with the real pattern. The behaviour criterion, for female data, presents as results Fig. 3, 4 and 5, and Table IV. The three figures show that the three models can generate patterns similar with the pattern described by the knee joint [37]. The DTW_{SPEED} result of Table IV shows that maximum of the pattern generated by the FBNN do not increase with gait speed, in opposition to the results of T. Obert *et al.* [36]. The difference of the MSVR results is too small to describe the expected dependence. The DTW_{SPEED} of the ELM describe the correct dependence between knee pattern and gait speed. Taking into account the criteria results, the ML model, more indicated to generate the pattern for the women, is the ELM.

Table II presents the accuracy criterion results for the healthy men. The FBNN has the best test MSE and the ELM the best DTW_{ML}. The small difference between the statistical results of this two ML models and the importance of the DTW_{ML} parameter suggest the ELM as the best ML. Table III shows the following distribution of best DTW_{ML} results: MSVR 1 man, FBNN 2 men and ELM 3 men. Once the ELM also has the best mean DTW_{ML} value, the similarity criterion also suggests the ELM as the best ML. Fig. 8 shows that the MSVR generates knee patterns with incorrect profiles for the new man. Fig. 6 and 7 prove the ability of FBNN and ELM, respectively, to generate correct knee joint patterns. However, Table IV shows that the patterns generated by the FBNN not describe the correct dependence with the gait speed, because the DTW_{SPEED} only decreases until the second gait speed. Once the patterns generated by the ELM present the correct profile and right gait speed dependence (Table IV), the behaviour criterion indicates the ELM as the best ML. The knee joint patterns for the men can be generated by the ELM as indicated by the three criteria.

VI. FUTURE WORK

This section realizes a link between the preformed work described in the paper and the open questions proposed by the work team for the next work plan.

A. Data collection

The future work includes the increases of number of specimens of the healthy people database. A higher number of samples and a large range of physical characteristics diversity improve the generalization of the conclusions for a possible application of the system in real situations.

To evaluate the potential impact of the proposed system, the experimental results drew from the collected databases need to be compared in the system results for a benchmark dataset.

Other future task is the advantage analysis of crossing data collect by two systems: vision system presented in this paper and instrumented shoe registered by the team in national patent entitled “Instrumented shoe for gait analysis” [38]. The instrumented shoes measure vertical and horizontal forces during the gait.

B. Generation of reference gait pattern

In opposition to the shallow algorithms presented in this paper (FBNN, ELM and MSVR), the deep learning algorithms are composed by multi levels of representation. The deep algorithms are robust against the overfitting problems and can automatically extract high-level feature hierarchies from high-dimensional data [39] which give it a higher representational power. Some publications in the area of human gait analysis [40, 41, 42, 43] show that the deep learning algorithms outperform the shallow algorithms. The studies [44] and [45] use the DBN as a deep learning algorithm for gait analysis. So, the authors intend to develop a new ML algorithm constituted by unsupervised DBN layers to extract the features of the data and a supervised ELM on top layer. The performance of the new algorithm will be compare with the results of the algorithms presented in this paper.

C. Approach to evaluate and classify the gait severity

The authors intend to investigate an innovative approach to evaluate and classify the severity of gait pathology, indicating: severity level, affected joint and gait speed limitation. This approach will compare the real pattern of a patient with the reference pattern generated by the selected ML algorithm. The patterns comparison will use gait indices developed by the work team and indices presented by state-of-the-art for the gait analysis as the Gait Variable Score (GVS) [46]. The team pretends to develop a global index to quantify the gait severity of patient and several partial indices to indicate the dynamic and static balance levels and the level of the pathology severity in each joint.

To evaluate the proposed approach will be necessary to create a database with the gait patterns collected from patients with gait limitations or pathologies.

Additionally, the authors pretend to develop a contextual adaptation model to evaluate future gait pathologies. This model will use: gait indices; muscle strength test and analysis of gait pathology achieved by medical team; and DBN-ELM approach with data from the more frequent gait pathologies.

VII. CONCLUSIONS

In this manuscript, it is compared the performance of ANN, ELM and MSVR in generation of knee joint angles patterns. The three ML algorithms use the characteristics of the individual (gender, age, weight and height) and the gait speed to generate a specific healthy reference knee pattern. The ELM outperforms ANN and MSVR.

The use of the knee patterns generated by the ELM as reference of healthy gait can provides an objective gait pathology analysis instead of a subjective one resulted of the use of a literature pattern which is generic for people with different characteristics.

As future work, the work team proposes the development of an innovative gait analysis system to provide gait pathology evaluation and classification focused on the individual. This system can be a useful in clinical analysis. The results presented in this paper will be included in the proposed gait analysis system.

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