Computational Intelligence Generation of Subject-Specific Knee and Hip Healthy Joint Angles Reference Curves

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Abstract. Backpropagation Neural Network (BNN) and Extreme Learning Machine (ELM) can generate subject-specific joint angle reference profiles based on a subject's height, weight, age and walking speed. These reference profiles are useful in various fields such as biomechanics and medicine, for detection of gait pathologies and rehabilitation. A common procedure used to identify abnormal gait is comparing an individual's knee and hip curves against healthy reference curves. These reference curves are usually obtained from a heterogeneous sample of healthy subjects and might lack the specificity required to obtain accurate results. It is why the generation of reference curves according to an individual's height, weight, age and gait speed shall result in a better comparison and diagnosis. The main objective of the present study is to observe which of the two Computational Intelligence (CI) methods, BNN and ELM, present more accurate results when used to generate reference curve profiles based on subject height, weight, age and gait speed for the knee and hip joint angles.

Keywords: BNN · ELM · Human gait · Subject-specific profiles

1 Introduction

Gait is one of the most basic, fundamental human characteristics. The way we walk allows us to have mobility and live life as we know it. Nevertheless, some pathologies can arise at an early age, during or towards the end of our life, as a result of mental impairments, physical injuries and/or neurodegenerative diseases [1–3]. Independently of its cause, gait pathologies can severely affect our quality of life [4, 5].

Gait analysis and assessment is used to detect abnormalities in human gait, propose a treatment and observe its effectiveness [6]. Traditional methods based themselves in the qualitative clinician observation [7], but a plethora of methods based on the

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quantitative measurements such as spatiotemporal, kinetic and kinematics have been applied in the identification and classification of pathological gait [2, 8–10]. With the fast growth of hardware computational power, the application of CI methods in broader fields, including biomedical engineering, were made possible [11]. CI methods offer the capability of modeling complex systems such as the human body [12] in a fast-inexpensive way, having by now demonstrated to be capable of identifying and classifying gait pathologies [13, 14].

A common procedure used to identify gait pathologies is comparing the kinematic data, obtained using vision acquisition systems and body markers on a subject walking to a healthy-standard joint angle curve [15, 16]. The lower body joint angles profile, namely the hip and knee, are crucial and commonly used in several different marker placements [17, 18] both in visual acquisition systems and wearable technologies.

The generation of the reference healthy joint angle curve is based on very distinct subjects in such way that it can serve as a standard joint angle curve and so it lacks the specificity necessary for an accurate comparison, seen that subject specific features such as weight, height and age influence gait pattern [19–22]. Furthermore, such reference profile does not commonly take in consideration the gait speed, which is known to have great impact on joint angle's profile [23, 24].

CI can generate healthy joint angle curve based on subject specific parameters. Luu et al. [25] used anthropometric data and gait parameters of subjects to feed a Generalized Regression Neural Network (GRNN) which was trained to target Fourier coefficients of joint angle's waveform. Posteriorly, inverse Fourier transform can be applied to obtain the lower limb joint angle waveform.

Alaskar et al. [8] used signals from force sensitive resistors of continuous walk from healthy subjects and with Parkinson's Disease (PD). Multilayer neural network, trained with backpropagation using the Levenberg-Marquardt optimization, was used to detect if subjects had PD. Classification was performed using statistical and frequency features from data, clinical information (age, height, gait speed, weight and gender), and a mixture of both, resulting in the following classification accuracies of 64%,81% and 91% respectively.

Yoo et al. [13] described a method for human recognition through gait using BNN. The 2D human skeleton trajectory is extracted from dataset of indoor and outdoor walking subjects. The mean and variation of the gait angles for single sequence of each subject are extracted as features. After being trained, BNN is used as a classifier, identifying if the individual is recognized, acting as a biometric system.

Rani et al. [9] used ELM in multicategory classification of gait abnormalities in children, obtaining accuracies of 97.98% when using Principal Component Analysis (PCA) and 99.21% accuracy when used T-Test.

Utomo et al. [14] showed that ELM performed better as a generalization classifier model, when compared with BNN in diagnosing breast cancer. ELM resulted in sensitivity, specificity and accuracy results of 94.8%, 97.4%, 96.4% respectively. Meanwhile, BNN showed considerably lower sensitivity (84.3%) and accuracy (92.1%) and slightly higher specificity (98%).

Ma et al. [26] used Swarm Particle Optimization (SPO) to choose input bias, weights and number of neurons of hidden layer and trained the ELM algorithm to identify falls, among other activities, out of low-cost Kinect depth camera. This strategy denominated by the author as variable-length particle swarm optimization was able to achieve up to 86.83% fall detection accuracy.

ELM was chosen due to its simplicity and fast results when compared to commonly used regression algorithms, while BNN served as baseline [26]. Support Vector Machine (SVM) was not included in the comparison, since results showed to be slower in such applications [9, 28, 29].

2 Dataset

A public dataset from the Laboratory of Biomechanics and Motor Control at the Federal University of ABC, Brazil [18] was used. The dataset is composed by raw and processed lower-body kinematic data of 42 healthy volunteers, 24 young adults and 18 older adults obtained through a motion-capture system with 12 cameras (Raptor-4; Motion Analysis Corporation, Santa Rosa, CA, USA) on 10 meters over-ground walk and using dual-belt, instrumented treadmill (FIT; Bertec, Columbus, OH, USA).

Overground trials were made at 3 different speeds: self-selected comfortable speed, slow (30% slower) and fast (30% slower). Each participant's comfortable speed was determined during the 10 meters overground walking familiarization period. The 45 healthy subjects' characteristics (age, height, weight) are displayed in Table 1. The Young/Older groups division was employed by dataset authors and comprises the ranges of 27–37 and 50–84 years old, respectively.

Table 1. Subjects characteristics.

Age group	Gender	Number of persons	Mean age	Mean height (cm)	Mean weight (kg)
Older	F	8	60.1	154.76	61.094
Older	M	10	64.8	167.49	71.58
Young	F	10	25.9	162.91	58.915
Young	M	14	28.8	176.92	75.171

Figure 1 shows the anatomical markers used for obtaining kinematic data.

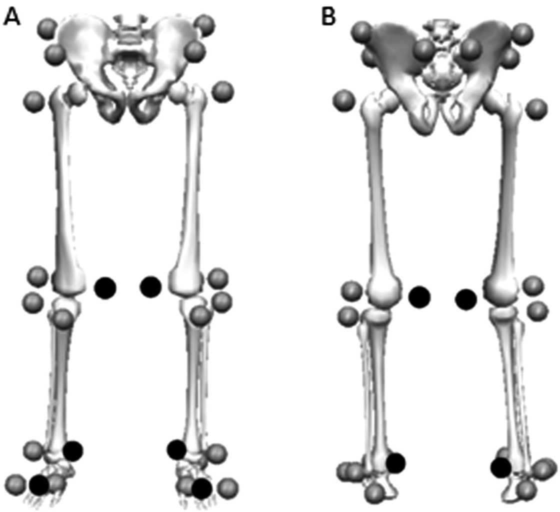

Fig. 1. Markers protocol. Anterior (A) and posterior (B) views. Markers shown black are removed during for the trial recording. Image from [18].

3 CI Methods and Training Procedures

3.1 BNN

An artificial neural network is composed of several layers containing multiple neurons per layer. Every neuron has a weight, bias and chosen activation function. The weight and bias are used to calculate a weighted sum of the input of the neuron which is then applied to the activation function.

The hidden layer neurons have non-linear activation functions, while input and output are usually chosen linear. Initially the weights, as well as the bias of the hidden neurons are attributed randomly. The neural network training consists in feeding inputs to the network and comparing the output results with the expected results. The error of every iteration is used to change the weights for the next iteration in the attempt of improving results. This procedure is referred as backpropagation and consists of a gradient descendent optimization algorithm [30, 31]. In this particular case the regression algorithm used for networks was the Levenberg Marquardt.

Deep Neural Network (DNN) comprises an extended number of hidden layers and neurons. This type of network can learn more complex data relations than NNs however, they require high processing power and memory [32]. Nevertheless, single hidden layer neural networks, with sufficient hidden units, can attain high accuracies and model complex problems [33, 34]. Figure 2 shows the structure of the single hidden layer neural network where θ_0 to θ_{100} represents the angle values from 0% to 100% of the gait cycle. One typical angle curve is represented in Fig. 3.

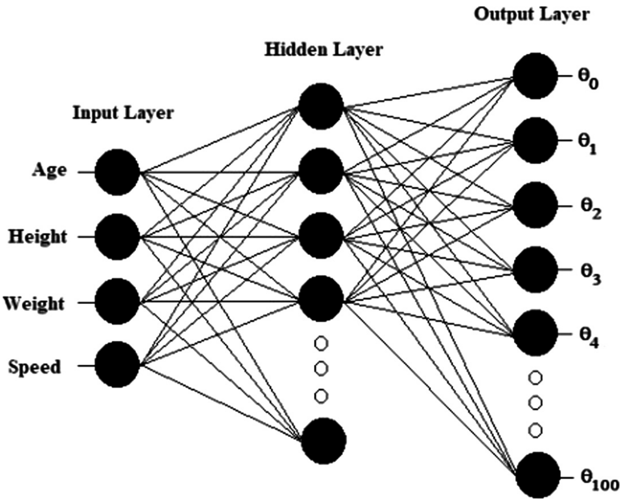

Fig. 2. Single hidden layer neural network structure.

3.2 ELM

ELM algorithm consists, in a simplistic way, of a BNN, where the input layer, weights and bias of hidden neurons are attributed randomly and kept fixed. This method uses the least squares solution and the Moore-Penrose generalized inverse matrix to obtain the weights between the hidden layer and the output (see Eq. 1).

$$\widehat{\omega}_o = H^{\dagger} T \tag{1}$$

$\widehat{\omega}_o$ is the smallest least square solution of the linear system $H\omega_o = T$ and represents the output weights. T represent the targets and $H^{\dagger}$ the Moore-Penrose generalized inverse of the hidden layer output matrix [27].

ELM can be used for classification and regression achieving the smallest training error, being a clear advantage when comparing with backpropagation algorithms that stop at local minimums. Besides its simplicity, applications in several areas have shown that ELM is much faster when compared with gradient based algorithms and produces good generalization [27, 35–37].

3.3 Training Procedures

Kinematic data, specifically the knee and hip angles, of male subjects (young and older) on overground walking for 3 different speeds (slow, comfortable and fast) was used as target to train the BNN and ELM. This data consisted on a target matrix of 42 columns (14 young males × 3 speeds) by 101 rows (marker angles normalized to 101 points) for the younger group and 54 columns (18 males × 3 speeds) by 101 rows for the older group.

The inputs fed to the CI's were age, height, weight and speed of the subject trial, all normalized between 0 and 1. The amplitudes of the marker's angles were normalized for improved results in CI methods and reliable comparison.

The accuracy was measured in terms of Mean Squared Error (MSE) for both algorithms and consists in the average squared error between the BNN output and the target. Since both network output and target are angular curves, MSE will be the mean of the angular distance between BNN results and targets. It's given by:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{101}\sum_{k=0}^{100}\left(\theta_{t,k} - \theta_{CI,k}\right)^2\right) \tag{2}$$

Where N is the number of test samples and $\theta_{t,k}$ and $\theta_{CI,k}$ are respectively, the target value and the CI output at k% of the gait cycle.

Table 2 shows the data division used for the two methods and resumes the previous given information.

Table 2. Data normalization ranges.

Method	Input range	Target range		Accuracy measurement	Data division		
		Knee	Hip		Train (%)	Test (%)	Validation (%)
BNN	[0,1]	[0,1]	[–1,1]	MSE	70	25	5
ELM	[0,1]	[0,1]	[–1,1]	MSE	75	25	–

Different networks were generated for dominant/non-dominant limb, younger/older group for both knee and hip angles.

The CI's were implemented using MATLAB in a computer with an Intel i7-6700, 2.90 GHz processor and 16,0 GB RAM. For the neural network's creation was used the Deep Learning Toolbox™ and for ELM a self-written script.

The BNN number of hidden units was iterated from 4 to 50 and each network topology was trained and tested 3 times. For ELM the number of hidden neurons were iterated from 4 to 50 and trained/tested 50 times.

In both algorithms the activation function of the hidden layer neurons used, was the sigmoid and the output activation functions were kept linear.

4 Results and Discussion

The most accurate results for the BNN and ELM are shown in Tables 3 and 4 for young and older man dominant limb and young and older man non-dominant limb respectively.

Table 3. BNN's and ELM best accuracies, young and older man dominant limb.

Limb	Method	Age group	Train accuracy MSE	Test accuracy MSE	Validation accuracy MSE
Knee	BNN	Young Older	**0.0001** **0.0010**	**0.0022** **0.0022**	0.0009 0.0027
	ELM	Young Older	0.0036 0.0045	0.0061 0.0089	- -
Hip	BNN	Young Older	**0.0015** **0.0025**	**0.0069** 0.0784	0.0023 0.0027
	ELM	Young Older	0.0463 0.0330	0.0215 **0.0349**	- -

Table 4. BNN's and ELM accuracies, young and older man non-dominant limb.

Limb	Method	Age group	Train accuracy MSE	Test accuracy MSE	Validation accuracy MSE
Knee	BNN	Young Older	**0.00004** **0.00008**	**0.0010** **0.0011**	0.0006 0.0013
	ELM	Young Older	0.0037 0.0034	0.0078 0.0094	- -
Hip	BNN	Young Older	**0.0010** **0.0002**	**0.0021** **0.0030**	0.0029 0.0038
	ELM	Young Older	0.0394 0.0378	0.0330 0.0544	- -

The best test results for the dominant knee and hip networks are shown to be for BNN except for the results for the older group hip, where ELM performed slightly better. For non-dominant hip and knee BNN presented better results for every situation. Nevertheless, in both dominant and non-dominant cases, similar performances were obtained with the exception of the hip results for young subjects.

Table 5. BNN's and ELM topology for best test accuracies.

Limb	Age group	Dominant/Non-Dominant	Nº hidden neurons	
			BNN	ELM
Knee	Young	D	16	5
		ND	17	4
	Older	D	8	4
		ND	20	6
Hip	Young	D	20	4
		ND	11	4
	Older	D	9	4
		ND	15	4

Table 5 presents the number of hidden neurons that resulted in the best accuracies for the several BNN and ELM.

Two subjects outside of the training and validation set were used to test CI's capabilities of generating accurate and smooth subject adapted joint angle curves. Choice of the subjects for every net was based on the overall difference from his characteristics (age, height, weight, gait speed) to the mean characteristics of subjects used in the train. The test subject that showed to have lower differences between his characteristics and the train mean characteristics will be referred to as, the closest to the range test subject. On the contrary, the subject who showed greater difference will be identified as the furthest from range subject. Table 6 contains the MSE of the joint angle curves generated by the CI's to the real test subject joint angle curve for the subject closest to the range. Table 7 contains the MSE for the subject furthest from range.

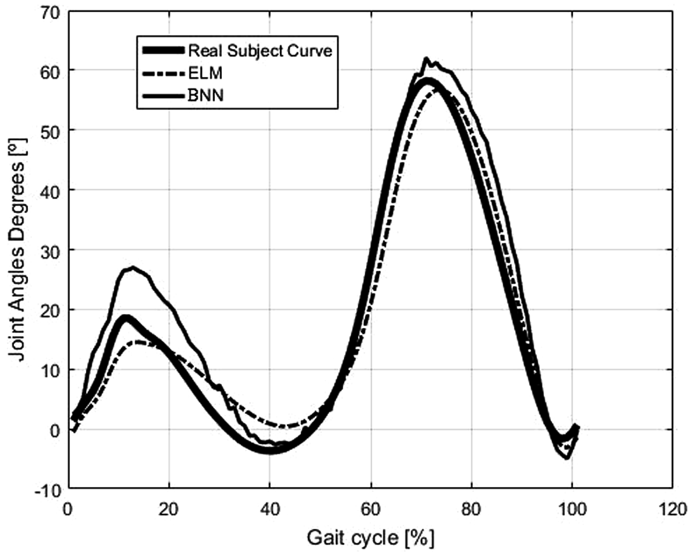

Fig. 3. Dominant joint angle knee curve generation for young subject and real subject joint angle knee curve.

Figures 3 and 4 show the real flexion/extension for dominant knee and hip of the test subject furthest from the range. Both figures also have the respective subject CI generated joint angle curve. Figures 4 and 5 present the same data for test subject furthest from the range.

For the case of the test subject furthest from mean characteristic, all knee results are better or very similar to the ELM. Hip results show better performance of the BNN. For the closest to the range test subject most results are favorable to the BNN. Nevertheless, in both dominant and non-dominant cases, BNN's weren't capable of generating smooth joint angle curves neither for knee nor the hip (see Figs. 3, 4, 5 and 6). ELM presents, in every case, smooth joint angle curves.

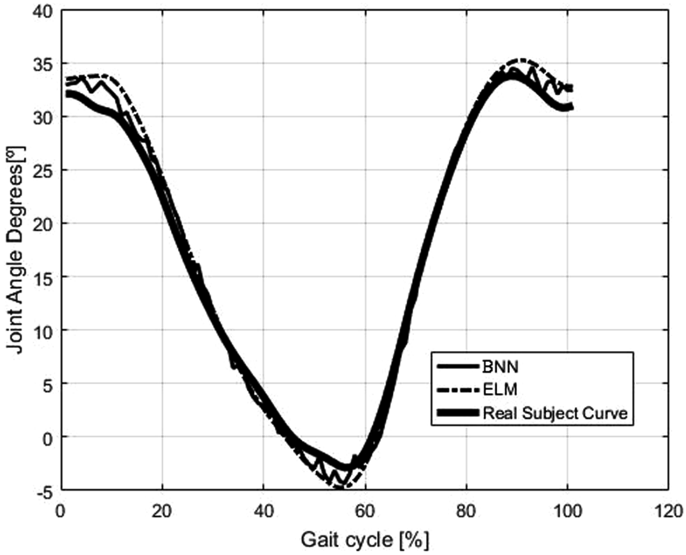

Fig. 4. Dominant joint angle hip curve generation for young subject and real subject joint angle hip curve.

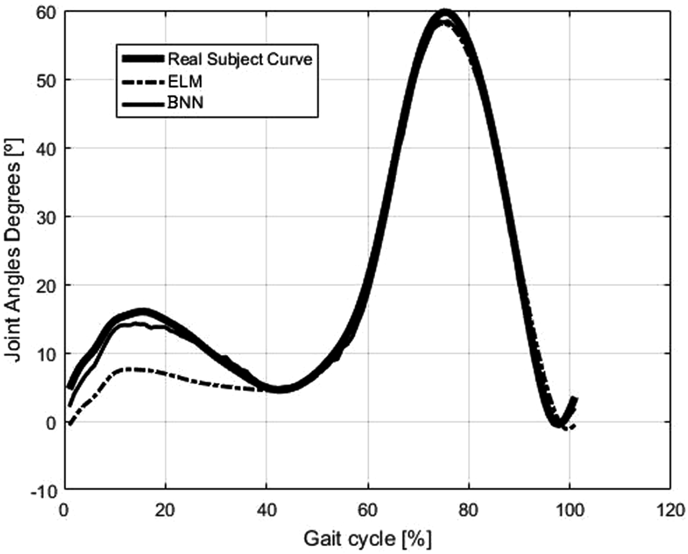

Fig. 5. Dominant joint angle knee curve generation for young subject and real subject joint angle knee curve.

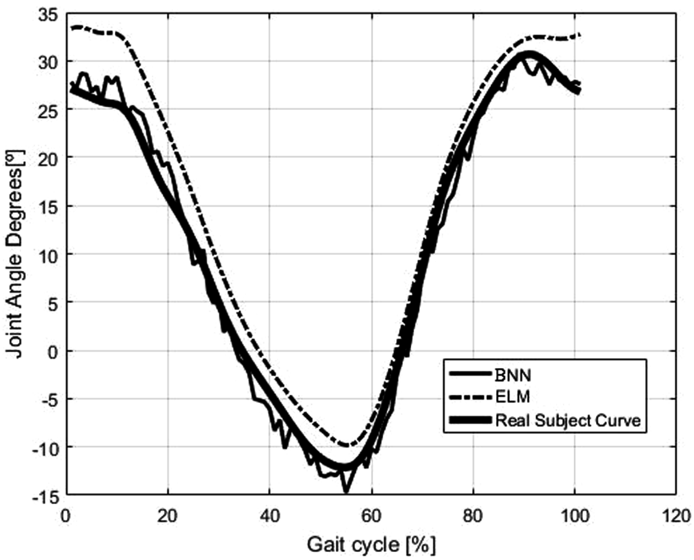

Fig. 6. Dominant joint angle hip curve generation for young subject and real subject joint angle hip curve.

Figures 7, 8, 9 and 10 show the joint angles prediction for test subjects (age 33, height 179 cm, weight 75 kg in the case of the knee and age 25, height 174 cm, weight 83 kg for hip) at the 3 distinct speeds (slow, comfortable, fast) together with literature reference joint angles curve. CIs predictions and the literature joint angle curve were both compared to the real subject joint curves and Table 8 contains the MSE results as well as the trial concrete speeds.

Table 6. Error for test subject furthest from subject's mean characteristics.

Network information			Subject input information				CI's MSE	
Limb	Age Group	D/ND	Age	Height (cm)	Weight (kg)	Gait Speed (m/s)	BNN	ELM
Knee	Young	D	30	171.0	95.4	1.27	0.0053	**0.0028**
		ND	24	184.0	61.1	1.65	**0.0004**	0.0028
	Older	D	55	165.6	79.1	0.89	0.0044	**0.0006**
		ND	84	155.5	66.4	1.00	0.0009	**0.0008**
Hip	Young	D	36	182.5	64.0	1.34	0.027	**0.0021**
		ND	37	155.0	69.6	0.69	**0.001**	0.031
	Older	D	84	155.5	66.4	1.00	**0.0009**	0.043
		ND	84	155.5	66.4	1.00	**0.002**	0.003

Table 7. Error for test subject closest from subject's mean characteristics.

Network information			Subject input information				CI's MSE	
Limb	Age group	D/ND	Age	Height (cm)	Weight (kg)	Gait speed (m/s)	BNN	ELM
Knee	Young	D	33	179.3	75.9	0.96	**0.0003**	0.003
		ND	33	179.3	75.9	0.96	**0.0007**	0.002
	Older	D	68	167.0	70.3	1.30	0.029	**0.005**
		ND	68	167.0	70.3	1.30	**0.0001**	0.0016
Hip	Young	D	31	172.9	77.9	1.48	**0.001**	0.014
		ND	33	179.3	75.9	0.68	**0.005**	0.024
	Older	D	68	167.0	70.3	1.58	**0.001**	0.023
		ND	62	164.5	70.5	0.78	**0.005**	0.094

For the test subject used BNN and ELM presented significant improvements when compared with the literature curve. The literature MSE increased for faster gait speeds. BNN shown lowest error results specifically for the knee, and MSE decreased for faster gait speed. Nevertheless, joint angle curves originated were not smooth. ELM presented better or similar results as the BNN for knee, as seen in [29], and slightly worse results for the hip.

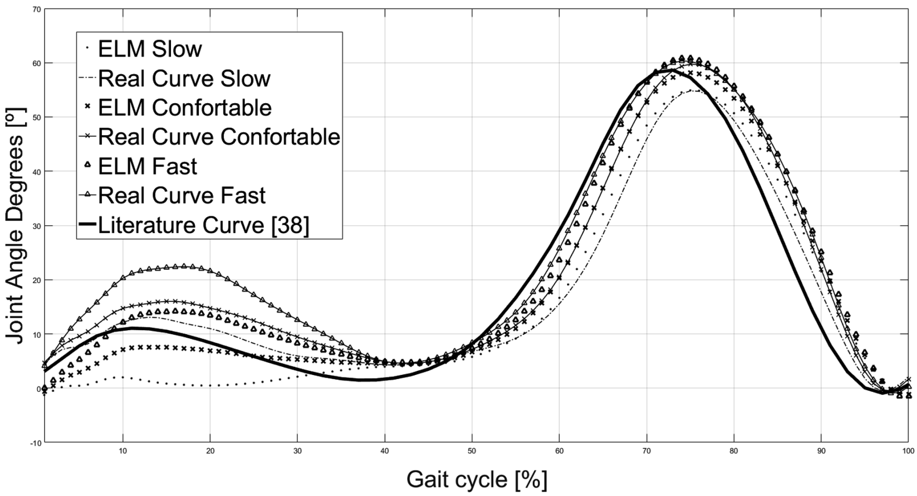

Fig. 7. Dominant joint angle knee curve generation for young subject at several speeds and literature reference curve.

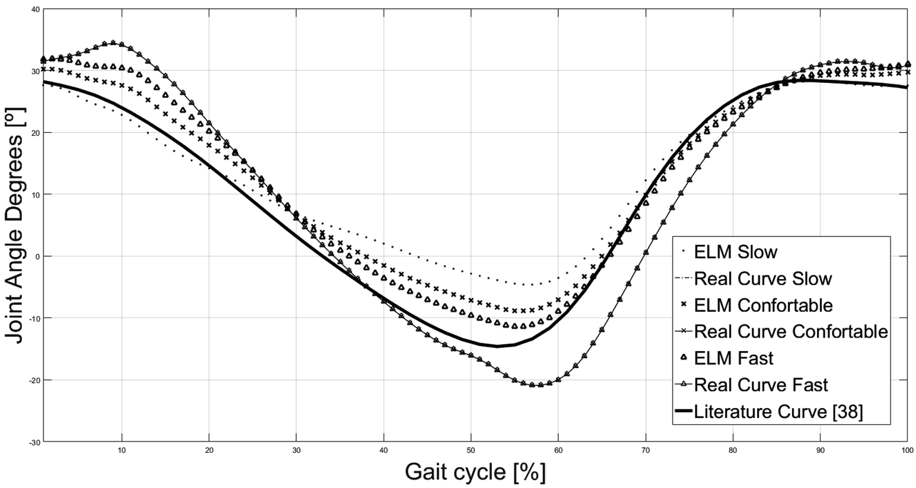

Fig. 8. Dominant joint angle hip curve generation for young subject at several speeds and literature reference curve.

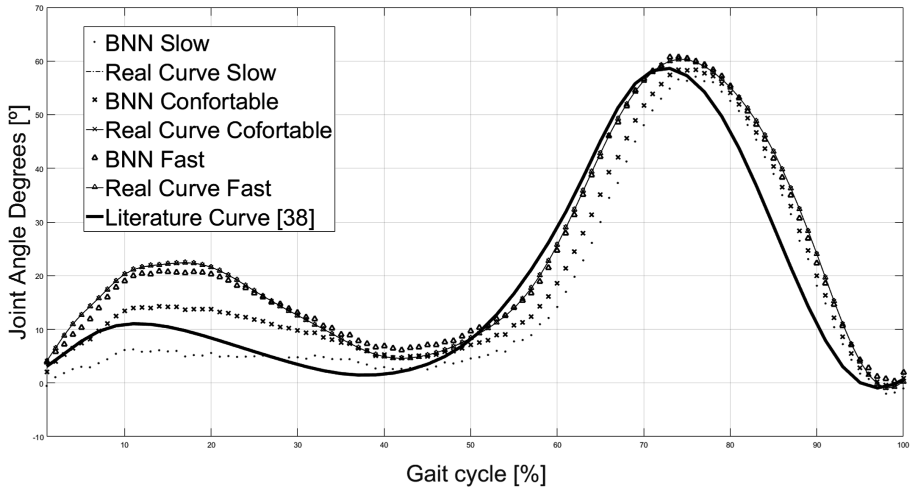

Fig. 9. Dominant joint angle knee curve generation for young subject at several speeds and literature reference curve.

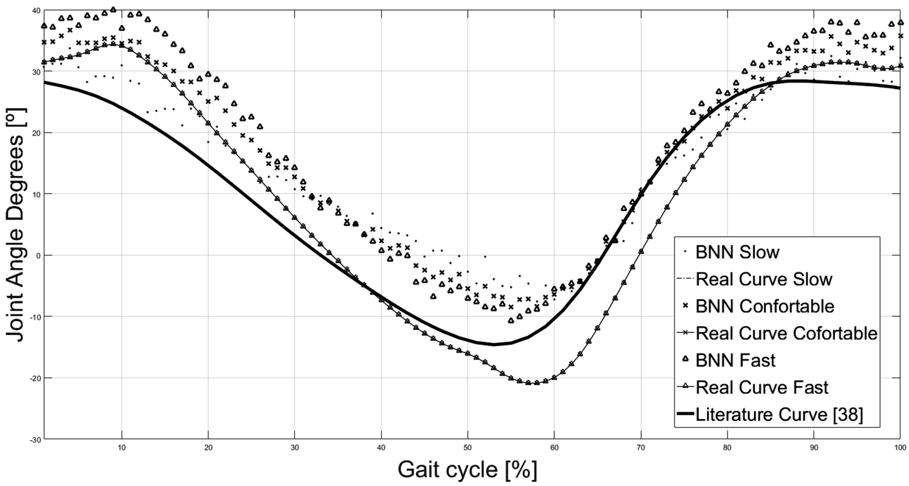

Fig. 10. Dominant joint angle hip curve generation for young subject at several speeds and literature reference curve.

Table 8. CI's and literature MSE at different gait speeds for young subjects.

Limb	Gait speed (m/s)	Literature [38] MSE	CI's MSE	
			BNN	ELM
Knee	0.68	0.017	0.014	**0.005**
	0.96	0.016	0.004	**0.003**
	1.29	0.021	**0.0002**	0.003
Hip	0.92	0.16	0.024	**0.011**
	1.32	0.12	**0.004**	0.022
	1.56	0.11	**0.004**	0.026

5 Conclusions

Both CIs generated reference curves closer to real curves than literature standard curve. The capability of generation of this healthy profile for subject characteristics and gait speed permit the use of this methodology in gait assessment in a broad range of impairments. Such results were reinforced for increasing gait speeds.

For the BNN, the lack of smoothness of the curves for subjects at the edge of the train data set was a recurrent issue, although accuracies were higher than with ELM for most cases. For the knee, ELM presented similar or better accuracy than BNN and showed better generalization capacity. Curves generated with ELM were always smooth, and the results of the furthest from mean subjects were better than with BNN, suggesting that this CI has better generalization and is the indicated CI to generate knee, subject-specific, healthy joint angle curves for both dominant and non-dominant limbs. BNN was better suited for subjects closest from mean of the data set, although generated curves need to be smoothed.

For future work, subject-specific reference joint angle curves and knee-hip graphs will be generated for patients with gait pathologies. It is expected that this methodology will allow an easier gait pathology diagnosis.

Compliance with Ethical Standards

Conflict of Interest. All authors declare that they have no conflict of interest.

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