Title: Uncertainty Management in the Dynamics of Biological Systems: A Key to Goal-Oriented Rehabilitation

Running Title: Managing Uncertainty in Rehabilitation

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Abstract

Purpose of the study— Clean, noise-free data is an ideal, but often unattainable, circumstance in biological control systems. Filters are usually employed to remove noise, but this process also leads to the loss or alteration of information. A considerable challenge is managing the uncertain knowledge using a proper and realistic mathematical representation and staying consistent with the actual biological patterns and behaviors. The purpose of this study is to explore the potential of fuzzy logic as a computational paradigm to manage uncertainties in the nonlinear dynamics of human walking, a field that has paid little attention to this aspect despite its considerable nonlinear and uncertain behavior due to adaptability, muscle fatigue, environmental noise, and external disturbances.

Method— We employed a fuzzy logic-based controller, integrated with Functional Electrical Stimulation (FES) and the concept of a gait basin of attraction, to enhance gait performance. Our controller focused on accommodating imprecision in shank angle deviation and angular velocity, rather than relying on predetermined trajectories.

Results— Our findings indicate that more fuzzy rules and partitions improve the similarity of the gait dynamics to those of a healthy human. Moreover, higher membership function overlaps lead to more robust gait control.

Conclusion— The study demonstrates that fuzzy logic can effectively manage uncertainties in the nonlinear dynamics of human walking, improving gait performance and robustness. This approach offers a promising direction for goal-oriented rehabilitation strategies by mimicking the human mind's ability to handle challenging and unknown environments.

Keywords— Rehabilitation; Gait performance; Fuzzy control; Knowledge management; Imprecision tolerance; Functional Electrical Stimulation.

Highlights

- Managing uncertainty improves gait without exoskeletons or set paths.
- The proposed fuzzy-based approach enhances gait control by managing uncertainties.
- Increasing fuzzy rules and partitions improves gait dynamics.
- More membership function overlap leads to more robust gait control.
- Effective management of uncertainty can revolutionize rehabilitation.

Plain Language Summary

Walking and maintaining balance simultaneously is a complex process influenced by factors such as muscle fatigue, environmental noise, and various disturbances, leading to inherently complex dynamics. The way a person walks is generally referred to as a movement pattern, and in rehabilitation, the main goal is to create a movement pattern similar to that of a healthy person in individuals with movement disorders. Achieving this goal depends significantly on our approach to designing treatment and control strategies. To effectively control such behavior, we need a control strategy that interacts with the nonlinear nature of the system, rather than simply tracking a predetermined path, while always maintaining a holistic view. This strategy must manage existing uncertainties and imprecise knowledge in system dynamics while aligning with the desired goal. Among various control strategies, fuzzy logic stands out because it mimics the human mind's ability to manage fuzzy and imprecise knowledge, making it particularly suitable for handling the complexities of biological systems such as walking. In this study, we investigate the potential of fuzzy logic to address this challenge by creating a synergy between a fuzzy controller and the identified mapping related to the shank dynamics, which serves as the input for this controller.

1. Introduction

The modern dormant lifestyle, injuries, and strokes have led to increasingly many incidents of walking disorders. However, the brain can reorganize itself and make adaptive changes, known as neural plasticity (Ding, Kastin, & Pan, 2005; Johansson, 2007). Hence, there is a possibility for walking healthily again with an effective rehabilitative and muscle-strengthening program. To this end, functional electrical stimulation (FES) is often considered a viable neurorehabilitation technology. However, devising an effective FES-based control strategy could be highly complex and uncertain due to human gait rehabilitation's unknown and time-varying dynamics. Robotic devices used concurrently with FES are also suggested to assist with diverse sensory and motor functions (Díaz et al., 2011; Shi et al., 2019; Zhou et al., 2021; Viteckova et al., 2013). For instance, Andrews et al. used a hybrid FES orthosis for patients with spinal cord damage paraplegic in cases where the quadriceps muscles (Andrews, 1988) were electrically excitable. But the common concern in such rehabilitation programs remains to find a suited control strategy (Marchal-Crespo & Reinkensmeyer, 2009; Meng et al., 2015; Foroutannia et al., 2022), with the added complexity of choosing the proper combination of electrical stimulation and robotic devices (Brunetti et al., 2011; Del-Ama et al., 2014; Kimura et al., 2018).

So far, diverse control methods have been designed to restore movement and gait correction in patients with movement disorders. These studies suggest that using the traditional trapezoidal stimulation intensity approach is inappropriate due to its incompatibility with the muscle activity patterns in healthy walking. In contrast, a stimulation strategy based on the natural muscle activation patterns could improve walking in disorders such as foot drop. FES performance could also improve while reducing muscle fatigue and energy consumption (Lyons et al., 2000; O'Keeffe et al., 2003). Furthermore, to correct foot drop, we can use an algorithm to predict step frequency for applying excitation close to natural walking by simulating natural patterns from the EMG dataset of the anterior tibialis muscle (Chen et al., 2013). A sliding-mode controller (SMC), in which an adaptive fuzzy controller compensates for approximation errors, is suggested for paraplegic patients. In this case, the control strategy guarantees accurate tracking, leading to muscle excitation patterns similar to normal gait and fast convergence (Nekoukar & Erfanian, 2011). Furthermore, a decoupled controller structure, i.e., separately for each joint-muscle dynamics, is suggested in (Nekoukar & Erfanian, 2012) that consists of an adaptive fuzzy terminal sliding mode controller to adjust the pulse width of the stimulation signal and a fuzzy controller to adjust the pulse amplitude of the excitation signal.

Partial and decoupled handling of joints and using predetermined trajectories are not the appropriate framework for a biological system's real-world uncertainties and complex dynamics. Instead, a suitable control strategy should carry a holistic view by operating around a stable walking phase space manifold (Fu et al., 2014). This objective, however, is non-trivial due to biological systems' time-varying and complex and uncertain dynamical behavior. In other words, an ill-defined problem is posed here since the exact equations of the system and its saddle cycle in the gait phase space and its manifolds are not known.

It is important to note that the objective of rehabilitation extends beyond merely generating movement in a disabled limb. Sometimes, purely mimicking movement without considering the dynamics of the system and the inherent synergy between muscles and joints can be detrimental. Moreover, human knowledge regarding various aspects of the surrounding world is limited, leading to simplification and modeling of phenomena like walking. However, this simplification and modeling process can increase uncertainty, potentially diverting us from the ultimate goal. This is precisely where the significance of employing the correct approach to address uncertainties in the dynamics of biological systems becomes apparent, particularly in the context of goal-oriented rehabilitation. By understanding and effectively dealing with these uncertainties, we can direct our efforts toward the creation of rehabilitation methods that are purposeful and aimed at achieving the desired outcomes.

This study aims to exploit this (tolerance for) uncertainty and imprecision to enhance the quality of gait rehabilitation. Specifically, we employ a fuzzy controller using a gait basin of attraction (Rezaee & Kobravi, 2020) and study how its uncertainty representation influences gait performance. The controller's inputs are the commonly measurable shank angle and shank angular velocity's deviation from a detected sine-circular map, and its output is the excitation signal.

The remainder of this report is organized as follows. The materials and methods in Section 2 include the human walking model, the data acquisition process, the control strategy, and simulations and analysis. Finally, the overall results and conclusions are presented in Sections 3 and 4, respectively.

2. Materials and Methods

2.1. Human walking model

A bipedal musculoskeletal model was used for this study (Fig. 1). In the musculoskeletal model used for simulation, the ankle and phalangeal joints are not explicitly considered, assuming the subject uses an ankle-foot orthosis while walking. By stabilizing the lower limb and correcting alignment, the orthosis allows the focus to remain on the dynamics of the knee and hip joints, thereby approximating a gait pattern that resembles normal walking. The integration of FES and orthosis effectively compensates for the simplified joint model. The orthosis stabilizes the lower limb and supports a natural walking pattern, while FES ensures that the knee and hip muscles are properly engaged. This combination enables the study to approximate healthy gait patterns despite modeling only two joints.

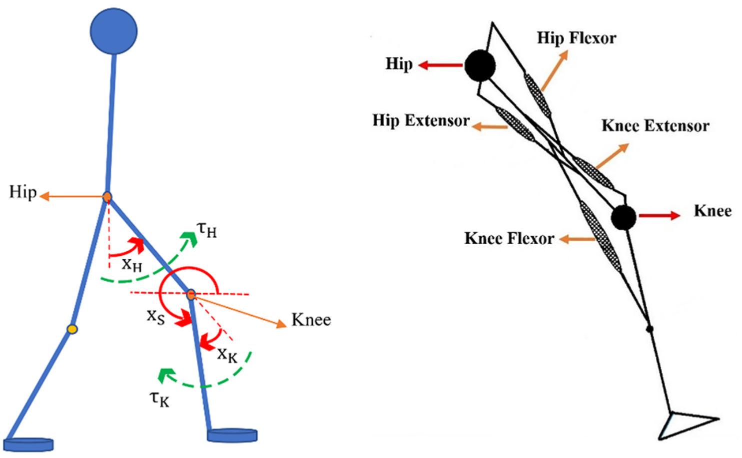

Fig 1. The bipedal model shows the definition of angles, joints, and muscles considered.

Eq. 1 describes the model dynamics:

$$M\ \ddot{x}(t)\ +\ C\dot{x}\ (t)\ +\ G\ +\tau_{fd}\ =\ \tau(t)\ +V(t), \tag{1}$$

where $X(t)= [x_K\ \ x_H]^T$ represents the angles vector (i.e., x_K and x_H are the knee and hip joint angles, respectively). $\dot{X}(t)$ = $[\dot{x}_K\ \ \dot{x}_H]^T$ *also* indicates the angular velocity of the knee and hip joints. *M* is the inertia matrix, C is the Coriolis torque matrix, *G* is the gravity force vector, τ_{fd} is a vector of ground reaction torque, and $V(t)$ is the white noise, which expresses the uncertainty process.

$T(t)= [\tau_S\ \tau_T]^T$ is the torque vector produced in the shank and thigh that is determined as follows:

$$\tau_i(t)= \tau_i^f(t)-\tau_i^e(t)-\tau_i^r(t),\ \ i = k, H,$$
$$\tau_S(t) = -\tau_K(t), \tag{2}$$
$$\tau_T(t) = \tau_K(t)+\tau_H(t),$$

where the parameters T_i^f , T_i^e , and T_i^r are flexor, extensor, and resistance torques, respectively, described as:

$$\tau_i^j(t) = (c_{i2}^j x_i^2 + c_{i1}^j x_i + c_{i0}^j\ )\cdot g_i^j(\dot{x}_i)\cdot a_i^j, \tag{3}$$
$$i \in \{k, H\} \qquad j \in \{f, e\}$$

$$\tau_K^r(t) = d_{11}\,(x_K - x_{K0}\,) + d_{12}\dot{x}_K + d_{13}e^{d_{14}x_K} - d_{15}e^{d_{16}x_K}, \tag{4}$$

$$\tau_H^r(t) = d_{21}\,(x_H - x_{H0}) + d_{22}\dot{x}_H + d_{23}e^{d_{24}x_H} - d_{25}e^{d_{26}x_K}, \tag{5}$$

The variables g_i^j are determined as:

$$g_i^f(\dot{x}_i) = \begin{cases} b_{i1} & \dot{x}_i < \dfrac{1-b_{i1}}{b_{i2}^f}, \\ 0 & \dfrac{1}{b_{i2}} \le \dot{x}_i, \\ 1 - b_{i2}\dot{x}_i & \dfrac{1-b_{i1}}{b_{i2}} \le \dot{x}_i < \dfrac{1}{b_{i2}}, \end{cases}$$

$$g_i^e(\dot{x}_i) = \begin{cases} b_{i4} & \dfrac{b_{i4-1}}{b_{i3}} \le \dot{x}_i, \\ 0 & \dot{x}_i \le \dfrac{-1}{b_{i3}}, \\ 1 + b_{i3}\dot{x}_i & \dfrac{-1}{b_{i3}} \le \dot{x}_i < \dfrac{b_{i4-1}}{b_{i3}}, \end{cases} \tag{6}$$

The variables a_i^j in Eq. 3 indicate the activity of flexor and extensor muscles that are determined as below**:**

$$\dot{a}_j^i = \begin{cases} [u_i/\tau_{act} + (1-u_i)/\tau_{deact}](u_i - a_i) & u_i \ge a_i, \\ (u_i - a_i)/\tau_{deact} \qquad u_i < a_i, & i = 1,2,3,4, \end{cases} \tag{7}$$

where the variables u_i are the normalized output signals of the controller, which are applied to the four muscles involved in gait in this model (i.e., flexor and extensor muscles of the hip and knee joints). The values of the parameters τ_{act} and τ_{deact}, which are time constants of activation and deactivation, respectively, 20 and 60 ms are adjusted.

Further details and adjustments of the values of the parameters are described in (Nekoukar & Erfanian, 2011; Dosen & Popovic, 1999; Kimura et al., 2009).

Table 1. Characteristics of participants (Rezaee & Kobravi, 2020).

	Gender	Age (y)	Height(m)
Sub1	Female	24	1.68
Sub2	Female	24	1.65
Sub3	Female	26	1.75
Sub4	Female	29	1.68
Sub5	Male	23	1.78

Note: The subjects were asked to walk at their normal walking speed. Datasets are acquired by the motion analyzer system (Qualisys product) with a recording frequency of 100 Hz.

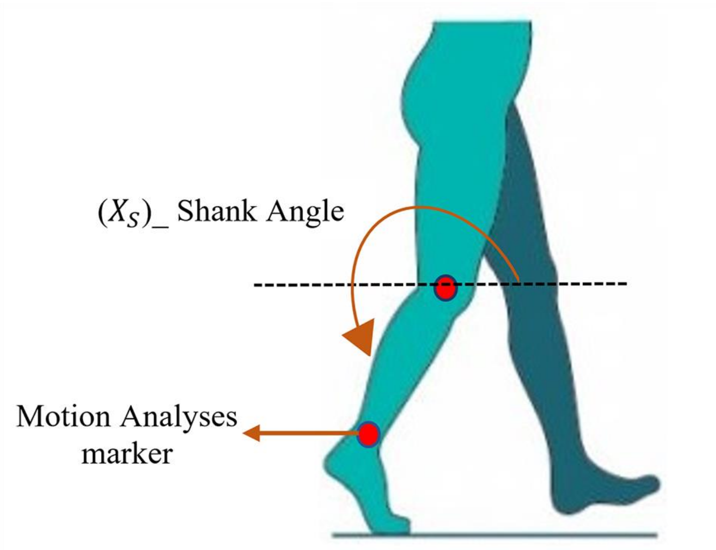

Fig 2. The location of the markers for tracking the shank movement by the motion analysis system.

2.2. Data acquisition

In this study, we used the data from (Rezaee & Kobravi, 2020). The present analysis uses shank angle data of 5 healthy volunteers during three uninterrupted gait cycles. Specifications of volunteers are given in Table 1. Also, Fig. 2 presents the markers' position for tracking the shank movement during gait and data acquisition.

2.3. Control strategy

In this study, four main steps are taken to design the controller. The first step is to plot and reconstruct the phase space of the system based on drawing the shank angle, the shank angular velocity, and the shank angular acceleration relative to each other (Fig. 3).

The second step is to apply the Poincaré section in the gait phase space to collect points that contain essential information about gait dynamics (Fig. 4). In this research, the method of computing the normal vector is used to get the Poincaré section equation (Rezaee & Kobravi, 2020).

The third step is to select a proper map describing the relative variations of the collected points by the Poincaré section. The walking process has a cyclical behavior, and its basin of attraction can have periodic, quasi-periodic, or chaotic characteristics.

Hence, we use the sine-circle map because it can describe these features. Eq. 8 defines the sine-circle map where θ is the desired parameter, Ω represents the frequency rate, and K determines the degree of nonlinearity in (Jensen et al., 1960; DeGuzman & Kelso, 1991; Hilborn, 2000). Ω and K are estimated using the least square error method (Rezaee & Kobravi, 2020).

$$\theta_{n+1} = \theta_n + \Omega - \frac{K}{2\pi} \sin(2\pi\theta_n), \tag{8}$$

In this study, to simplify the structure of the controller, only the two maps identified in the study (Rezaee & Kobravi, 2020), which are related to the shank angle and shank angular velocity, have been used.

Table 2. The computed parameters of the identified mean sine-circle maps (Rezaee & Kobravi, 2020).

		Mean ± SD		
Sine-circle map1 (Shank Angle)	K_1	0.78±0.12	Ω1	0.61±0.05
Sine-circle map2 (Shank Angular Velocity)	K_2	6.49e-008±1.40e-007	Ω2	0.02±0.03

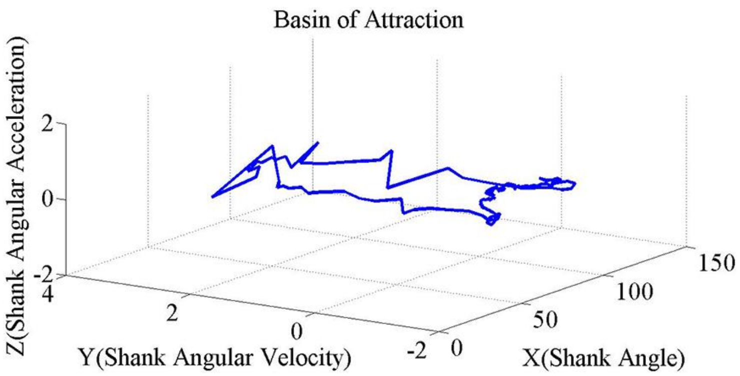

Fig 3. Phase space related to one gait cycle data.

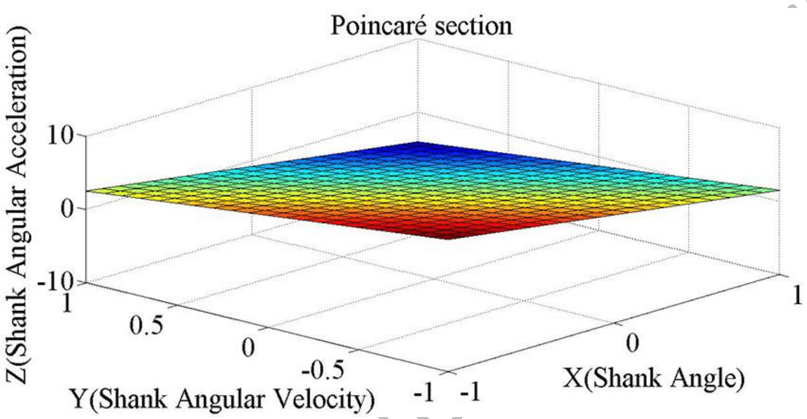

Fig 4. A poincaré section in the phase space.

Eq. 9 shows two identified maps where X_S is the shank angle, and $\dot{X}_S$ is the shank angular velocity.

$$X_{S(n)} = X_{S(n\text{-}1)} + \Omega_1 - \frac{K_1}{2\pi}\sin\,(2\pi X_{S(n\text{-}1)}),$$
$$\dot{X}_{S(n)} = \dot{X}_{S(n\text{-}1)} + \Omega_2 - \frac{K_2}{2\pi}\sin\,(2\pi \dot{X}_{S(n\text{-}1)}), \tag{9}$$

Table 2 shows the values of the computed parameters of the recognized mean maps. Further details on these three steps are described in (Rezaee & Kobravi, 2020).

The fourth step is designing a fuzzy controller that consists of two inputs. For this purpose, we apply the Mamdani fuzzy inference system and centroid of area method for defuzzification.

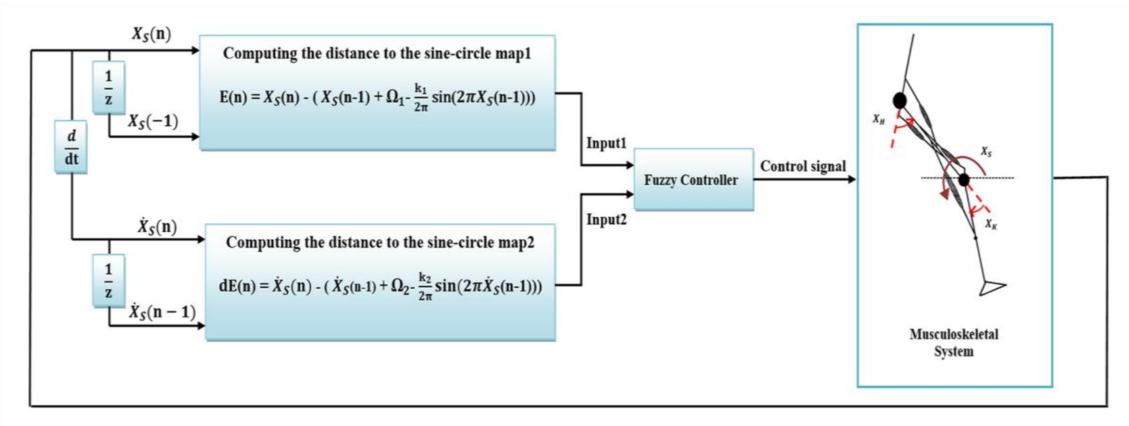

Fig 5. Block diagram related to the control strategy.

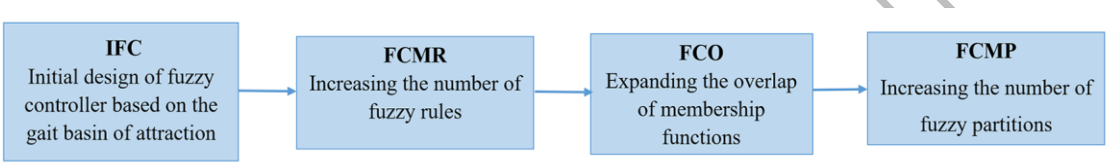

Fig 6. The overview of the analysis done in this research.

The inputs of this fuzzy controller include the values of the system trajectory distance from the detected sine-circle maps related to the shank angle and the shank angular velocity, respectively. Its output regulates the excitation signal applied to the four muscles involved in walking. Fig. 5 shows the block diagram of the applied control strategy.

2.4. Simulation and analysis

In this section, we examine the effects of handling existing uncertainties and imprecisions in the gait dynamics on the control quality by increasing the number of fuzzy rules, expanding the overlap of membership functions, and increasing the number of fuzzy partitions. The research process is shown in Fig. 6.

2.4.1. The initial design of the fuzzy controller

In the first step, we initially designed a fuzzy controller with five membership functions in each input and output, without any overlap, and five fuzzy rules. As you can see in Fig. 7, the angles obtained in the hip and knee joints are abnormal due to the crisp behavior of the controller, and the model output has distortion.

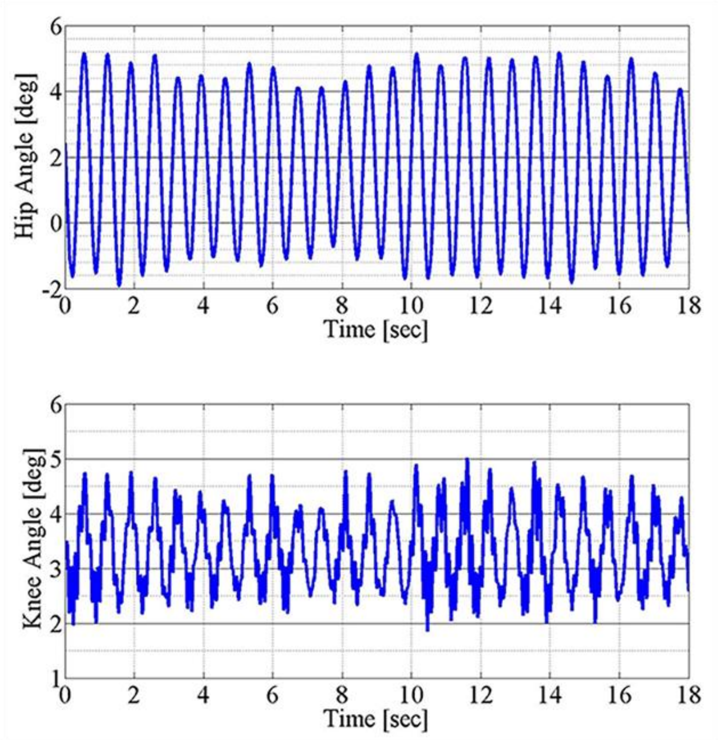

Fig 7. The range of angles in hip and knee joints in the initial fuzzy controller (IFC).

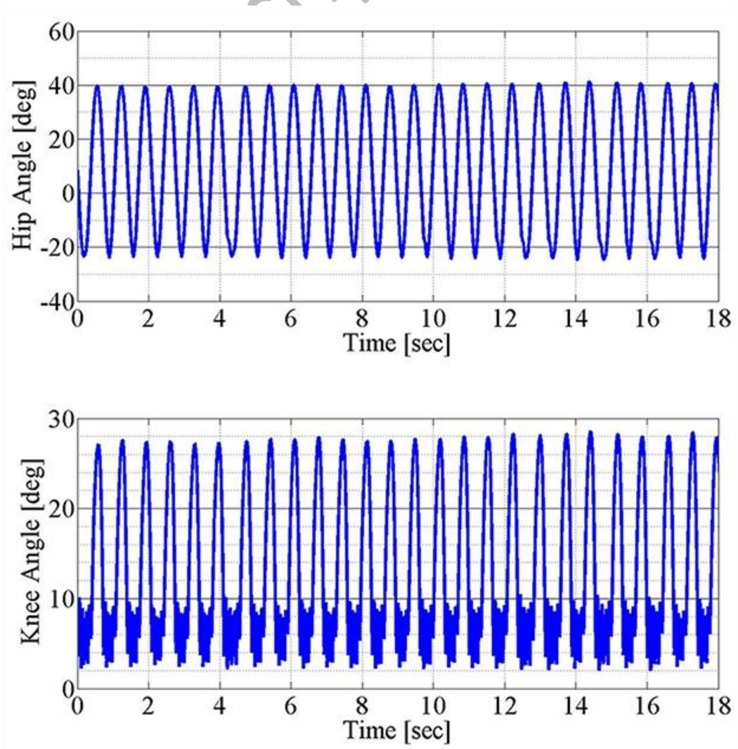

Fig 8. The range of angles in hip and knee joints in fuzzy controller with more rules (FCMR).

2.4.2. Increasing the number of fuzzy rules

In the second step, we increase the number of fuzzy rules from 5 to 25 while keeping the number of fuzzy partitions and rate of overlapping unchanged. During this phase, the angles obtained in the hip and knee joints remain within the normal range (Fig. 8).

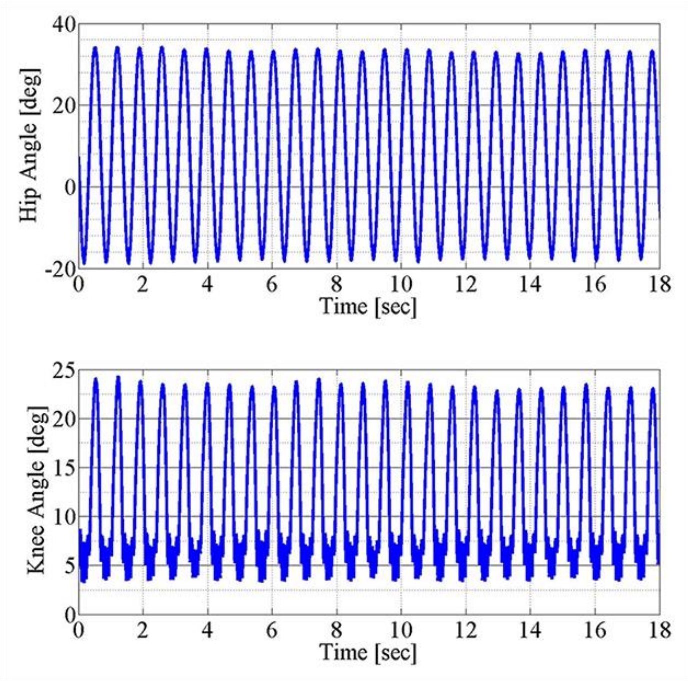

Fig 9. The range of angles in hip and knee joints in fuzzy controller with overlap (FCO).

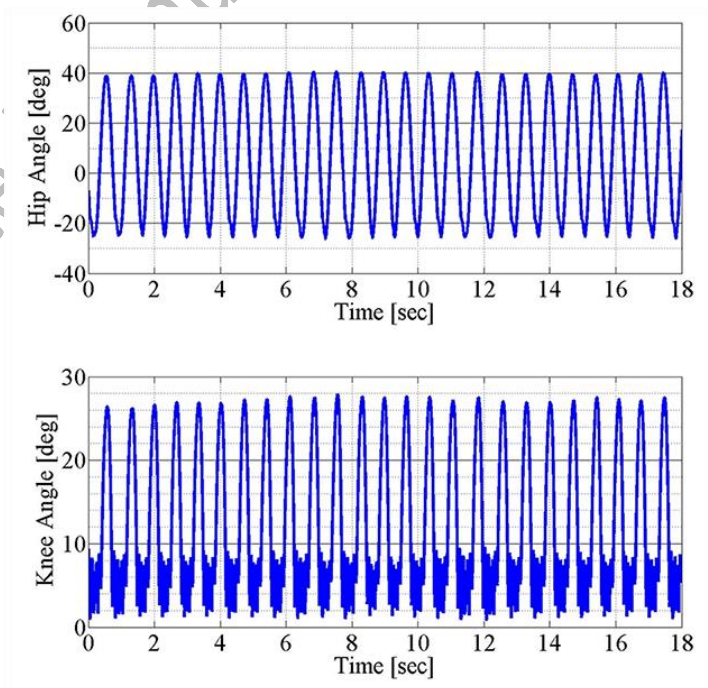

Fig 10. The range of angles in hip and knee joints in fuzzy controller with more partitions (FCMP).

2.4.3. Expanding the overlap of membership functions

In the third step, we expand the overlap. The angles obtained in the hip and knee joints are in the normal range (Fig. 9).

2.4.4. Increasing the number of fuzzy partitions

In the fourth step, while the number of fuzzy rules remains constant at 25, we increase the number of fuzzy membership functions. The obtained angles in the hip and knee joints fall within the normal range (Fig. 10).

The fuzzy rules database is provided in Table 3, and Fig. 11 depicts the membership functions of input/output variables related to the mentioned fuzzy controllers. Also, Fig. 12 shows the control surface of the mentioned fuzzy controllers.

Table 3. Fuzzy rules database of the mentioned fuzzy controllers.

IFC					
dE	**E**				
	NB	**NS**	**ZERO**	**PS**	**PB**
NB	-	NB	-	NS	-
NS	-	-	-	-	-
ZERO	-	-	ZERO	-	-
PS	-	ZERO	-	PS	-
PB	-	-	-	-	-

FCMR & FCO					
dE	**E**				
	NB	**NS**	**ZERO**	**PS**	**PB**
NB	NB	NB	NS	NS	ZERO
NS	NB	NS	NS	ZERO	PS
ZERO	NS	NS	ZERO	PS	PS
PS	NS	ZERO	PS	PS	PB
PB	ZERO	PS	PS	PB	PB

FCMP							
dE	**E**						
	NB	**NM**	**NS**	**ZERO**	**PS**	**PM**	**PB**
NB	NB	-	NB	NB	NM	-	ZERO
NM	-	-	-	-	-	-	-
NS	NB	-	NM	NS	ZERO	-	PM
ZERO	NB	-	NS	ZERO	PS	-	PB
PS	NM	-	ZERO	PS	PM	-	PB
PM	-	-	-	-	-	-	-
PB	ZERO	-	PM	PB	PB	-	PB

Note: "E" refers to the difference between the shank angle and the sine-circle map1, and "dE" represents the difference between the shank angular velocity and the sine-circle map2.

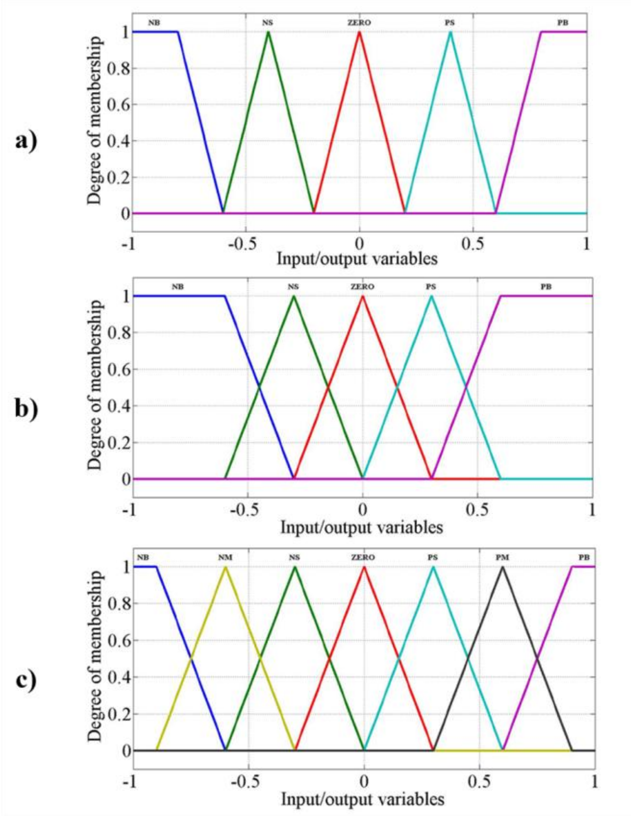

Fig 11. The input/output variables membership functions in fuzzy controllers: a) IFC & FCMR, b) FCO, c) FCMP. Inputs are "E" and "dE". Output is excitation signal.

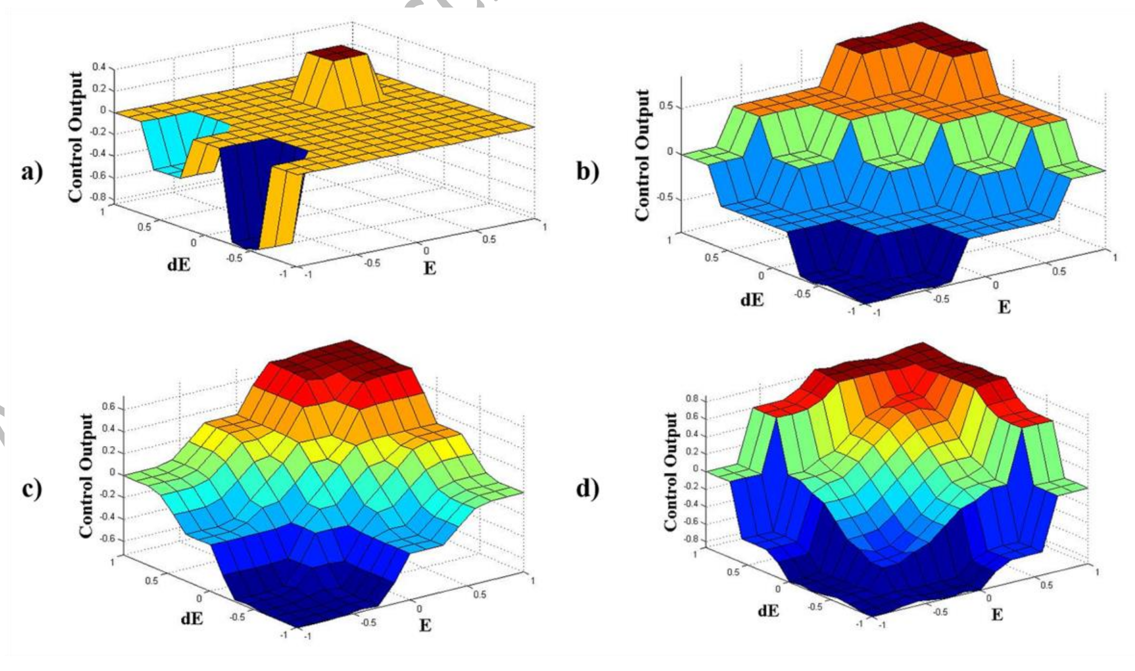

Fig 12. The control surface of the fuzzy controllers: a) IFC, b) FCMR, c) FCO, d) FCMP. "E" refers to the difference between the shank angle and the sine-circle map1, while "dE" represents the difference between the shank angular velocity and the sine-circle map2. The term "Control Output" refers to the excitation signal that is applied to the four muscles involved in gait.

Table 4. The mathematical equation of the applied quantitative criteria (Hilborn, 2000).

Quantitative Criteria	Mathematical Mode	Parameter
Correlation Dimension	$\begin{cases} D_c = \lim\limits_{R\to 0} \dfrac{\log C(R)}{\log(R)} \\ C(R) = \dfrac{1}{N}\sum\limits_{i=1}^{N} p_i(R) \\ p_i(R) = N_i/N - 1 \end{cases}$	N = number of trajectory points; $p_i(R)$ = the relative number of points within the distance R of the ith point
Lyapunov exponent	$\begin{cases} \lambda = \dfrac{1}{n} \ln \dfrac{d_n}{d_0} \\ d_n = \lvert x_{j+n} - x_{i+n} \rvert \end{cases}$	n = number of trajectory points; x_i and x_j = two nearby trajectory points in state space

Table 5. Comparison of quantitative criteria values in the mentioned fuzzy controllers.

Quantitative Criteria	Fuzzy Controllers: IFC	FCMR		FCO		FCMP		The study by (Rezaee & Kobravi, 2020)	
Max Tolerated Noise Amplitude	–	0.29		**0.34**		0.28		Not	
Max Tolerated Step Disturbance Amplitude	–	0.74		**0.94**		0.69		Not	
		Difference	Value	Difference	Value	Difference	Value	Difference	Value
***D_c* _Shank (Normal level 1.85±0.01)**	–	0.17	1.68	0.19	1.66	0.18	1.67	0.22	1.63
***D_c* _Thigh (Normal level 1.78±0.02)**	–	**0.02**	**1.76**	0.03	1.75	0.03	1.75	**0.02**	**1.76**
***λ* _Shank (Normal level 2.10±0.12)**	–	**0.12**	**2.22**	0.23	2.33	0.19	2.29	0.28	2.38
***λ* _Thigh (Normal level 2.64±0.17)**	–	**0.09**	**2.55**	0.27	2.91	0.16	2.48	0.44	2.20
Features: Number of fuzzy rules	5	25		25		25		Not	
Features: Number of fuzzy partitions	5	5		5		7		Not	
Features: Overlapping membership functions	×	×		✓		✓		Not	

Note: D_c _Shank, D_c _Thigh, λ _Shank, and λ _Thigh represent the correlation dimension and Lyapunov exponent for the shank and thigh angles, respectively. The difference indicates the absolute value of the difference between the mentioned criteria related to the model output and their normal values in the presence of each controller. "Not" indicates that the test was not conducted in the mentioned study. Best results, which indicate that our criterion falls within the normal range of a healthy person, are shown in bold. Due to the invalid output of controller 1, the specified criteria have not been calculated, and a "-" mark has been assigned to the respective sections.

3. Results

In this study, we evaluate the performance of the designed fuzzy controllers using a series of quantitative criteria. These criteria include the maximum amplitude of noise and step disturbances that the controller can handle while remaining stable. Additionally, we employ four used quantitative criteria in the study by (Rezaee & Kobravi, 2020) for comparison and evaluate our controller performance, including the correlation dimension and Lyapunov exponent for the shank and thigh angles (D_c _Shank, D_c _Thigh, λ _Shank, λ _Thigh), as detailed in Table 4. We introduce explicit disturbances, such as noise and step disturbances, directly into the model to assess the robustness of our fuzzy controller. This approach differs from the study conducted by (Rezaee & Kobravi, 2020), where the uncertainty is implied but not explicitly addressed, and no specific disturbance tests are performed. In contrast, our study focuses on investigating uncertainty, and to assess the performance of the fuzzy controller under such uncertain conditions, we include disturbance tests. By applying disturbances with varying amplitudes, we simulate real-world conditions and demonstrate that our simplified fuzzy controller, which uses only two inputs, how manages these challenges.

The results of the simulation and analysis are given in Table 5. Regarding the quantitative criteria related to the correlation dimension and Lyapunov exponent, in addition to the output value of the model, the absolute value of its difference from the normal level (Rezaee & Kobravi, 2020) is also included in the table for a better comparison.

According to Table 5, FCMR demonstrates increased accuracy and improved similarity to a healthy human gait compared to other fuzzy controllers. Also, FCMR controller results in three of the four criteria ($\boldsymbol{Dc}$_Thigh, $\boldsymbol{\lambda}$_Shank, $\boldsymbol{\lambda}$_Thigh) falling within the normal range, aligning more closely with healthy gait dynamics. This is despite the fact that in the study by (Rezaee & Kobravi, 2020), although there was an effort to approximate healthy walking dynamics, only one of the criteria ($\boldsymbol{Dc}$_Thigh) fell within the normal range. This is attributed to the increased number of fuzzy rules and the absence of overlap in membership functions, as indicated by the correlation dimension and Lyapunov exponent values in the shank and thigh.

In contrast, FCO exhibits an expanded overlap of membership functions, leading to increased tolerance for noise and step disturbance compared to other fuzzy controllers. However, this comes at the cost of reduced accuracy and a larger deviation from the walking dynamics of a healthy person, as indicated by the correlation dimension and Lyapunov exponent values.

Lastly, FCMP suffers from incomplete coverage of the decision space due to an increased number of fuzzy partitions and insufficient rules. Consequently, it exhibits reduced tolerance for noise and step disturbance compared to other fuzzy controllers. However, the increased number of fuzzy partitions results in improved accuracy compared to FCO and closer dynamic with normal gait dynamics, as indicated by the values of D_c_Shank, λ_Shank, and λ_Thigh.

4. Discussion

4.1. Advantages and conclusions of the proposed work

The primary objective of rehabilitation is to establish a movement pattern that closely resembles the dynamics of a healthy individual. Regrettably, some studies overlook this crucial aspect and focus solely on generating movement in the paralyzed limb without considering the potential harm it can inflict on the neuromuscular system. However, the creation of effective and goal-oriented rehabilitation, capable of generating and controlling a natural and healthy dynamic, encounters various challenges. On one hand, the employed simplifications and linearizations for modeling purposes, and on the other hand, the uncertainties inherent in the dynamics of biological systems, stemming from their chaotic nature, impede the attainment of a comprehensive understanding and accurate modeling of biological phenomena. Consequently, the only viable approach to tackle this challenge is to embrace the true uncertainties present in the surrounding world. Rather than disregarding reality and resorting to unnecessary simplifications, the intricate behavior of biological systems arising from their inherent uncertainty should be duly acknowledged when designing the desired control strategy. Effective knowledge management in this uncertain and imprecise world necessitates the use of appropriate tools. In this research, our primary focus was to develop a fuzzy controller based on the concept of the gait basin of attraction, leveraging the methodology outlined in the previous study (Rezaee & Kobravi, 2020). We strived to streamline the design of the controller, aiming to create a simplified structure that incorporates only two inputs. However, our main objective is to emphasize the significant role of proper management of uncertainty and imprecision knowledge in gait dynamics.

The fuzzy rules used in this study are developed through a comprehensive process that integrates simulation experiments and expert knowledge. This approach ensures that the final rules are accurately tuned to meet system requirements and enhance controller performance. Our findings highlight the potential of fuzzy logic in managing the nonlinear dynamics of walking and enhancing gait performance, with implications for rehabilitation. By effectively addressing uncertainties, the employed fuzzy logic-based controller offers a transparent structure and robust solution. This study underscores the importance of addressing these challenges and sheds light on the role of fuzzy logic in gait rehabilitation.

Although this study explicitly models and controls only two joints, the use of FES and ankle-foot orthoses is crucial in approximating healthy walking patterns. FES stimulates the knee and hip muscles, while the orthosis supports and stabilizes the ankle and foot, allowing the study to achieve gait patterns similar to those of a healthy subject. As shown in the results section, our investigation reveals that increasing the number of fuzzy rules and partitions enhances the output accuracy and gait dynamics' similarity to a healthy human, while incomplete coverage of the decision space due to an increased number of fuzzy partitions and insufficient rules reduces the controller's robustness. On the other hand, expanding the overlap of membership functions reduces the output accuracy but improves the robustness of the control strategy. This study demonstrates the effective management of uncertainties and imprecisions in system dynamics by adjusting the number of fuzzy rules, partitions, and membership function overlaps. Despite the simplicity of the designed controller structure with only two inputs, it outperforms the study (Rezaee & Kobravi, 2020) due to its proper handling of the existing uncertainties and imprecisions in walking dynamics. In other words, these results indicate that a well-designed fuzzy controller, even with a simplified structure, can maintain stability and accuracy under challenging conditions. This improvement is due to the careful design of fuzzy rules, appropriate partitioning, and proper overlap of membership functions, which together provide a more resilient control strategy.

4.2. Limitations of the proposed work

Whereas the study dataset was acquired from five volunteers during three uninterrupted gait cycles, more participants with different ages and genders and more gait cycles were needed to conclude the process accurately.

4.3. Future works

The employed control strategy can be used not only for people who are completely paralyzed but also for people who have muscle weakness. We hope to integrate the proposed strategy with an exoskeleton robot at the next step of this research. Also, we intend to consider the controller output as multi-variable in the future so that a separate control signal applies to each of the agonist and antagonist muscles of the knee and hip joints.

Data and code availability

The data and software code during this study are available from the corresponding author upon reasonable request.

Compliance with ethical guidelines

A waiver of ethical approval. As this study used the data from (Rezaee & Kobravi, 2020), ethical approval is not required.

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Author Contributions

Zohre Rezaee: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Validation, Software, Writing - original draft. **Mohammad-R Akbarzadeh-T:** Conceptualization, Methodology, Visualization, Validation, Supervision, Writing - review & editing.

Conflict of interest

The authors declared no conflicts of interest.

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