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Trajectory Planning for Active Walking in Lower Limb Rehabilitation Exoskeletons Based on GRNN-DMPs

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Abstract. This paper presents a novel approach for active gait trajectory planning in lower limb rehabilitation exoskeletons, specifically targeting hemiplegic patients. The proposed method integrates dynamic motion primitives (DMPs) and generalized regression neural networks (GRNN) to accurately simulate lower limb joint motion trajectories. Experimental results demonstrate the superiority of the GRNN-DMPs method over the standalone DMPs approach, as it generates joint trajectories with reduced error and enhanced precision. This approach holds great promise for active rehabilitation training with exoskeleton robots for lower limb rehabilitation.

Keywords. Lower limb rehabilitation exoskeleton, trajectory planning, dynamic movement primitives, generalized regression network.

1. Introduction

In recent years, the population of individuals experiencing lower limb walking difficulties has significantly increased due to factors such as aging and conditions like brain injury, spinal cord injury, or accidents[1]. Consequently, there is a growing need for rational planning of walking gaits in lower limb rehabilitation exoskeleton robots to aid patients in regaining their locomotion[2].

Currently, two main types of walking trajectory planning methods are employed in lower limb rehabilitation exoskeletons: those based on standard human gait databases[3] and those utilizing intelligent algorithms[4]. For example, Ailegs[5], a wearable lower limb rehabilitation exoskeleton developed by Beijing Da Ai Robotics Technology Co. Ltd, is based on a human standard database for rehabilitation of human gait, aiming at restoring normal walking posture through various therapeutic activities.

On the other hand, the latter method, based on intelligent algorithms, has significantly improved the adaptability of exoskeleton robots to overcome and navigate

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obstacles[6]. Stefan Schaal and his team of researchers in proposed Dynamic Motion Primitives (DMP) algorithms, which model the motion control as nonlinear differential equations and generate trajectories by learning and adapting to the motion schematic data[7]. However, as with any method, they have limitations that need to be considered. For example, dynamic motion primitives are prone to overfitting.

To address these limitations, this paper presents an active gait trajectory planning method for lower limb rehabilitation exoskeletons. By combining dynamic movement primitives[8] and generalized regression neural networks[9], GRNN-DMPs enables more precise simulation and control of lower limb joint motion trajectories, resulting in reduced errors and improved fits compared to the standalone DMPs method. Thus, it helps patients with lower limbs to regain their ability to walk.

2. Trajectory generation based on dynamic motion primitives

Dynamic movement primitives (DMPs) can be categorized into two forms[10]: periodic DMPs based on limit cycles for representing periodic motion trajectories, and discrete DMPs based on point attractors for representing discrete motion, a periodic DMP based on limit cycles is adopted to model the gait of lower limb rehabilitation exoskeleton robots.

The limit cycle system used in trajectory planning for cyclic Dynamic Movement Primitives (DMPs) is similar to a spring-damper system. Its first-order dynamical system equation can be expressed as:

$$\begin{cases} \tau \dot{z} = \alpha_z \left(\beta_z (g-\theta) - z \right) + f(\phi, r) \\ \tau \dot{\theta} = z \end{cases} \tag{1}$$

By introducing the regularization system, it can make variable $f(\phi, r)$ independent of time, thereby adjusting the trajectory time by changing variable τ .

We select demonstration trajectories $\theta_{demo}(t)$, $\dot{\theta}_{demo}(t)$, and $\ddot{\theta}_{demo}(t)$ with a duration of $t \in [1, \cdots, P]$. We set the target trajectory as f_{target} and let the target trajectory simulate the demonstration trajectories. By substituting the variables into equation (1), we have:

$$f_{\text{target}} = \tau^2 \ddot{\theta}_{\text{demo}} - \alpha_z \left(\beta_z \left(g - \theta_{\text{demo}} \right) - z \right) \tag{2}$$

In the global regression setting, the criterion for minimizing the quadratic error is:

$$J_i = \sum_{t=1}^{P} \psi_i(t) \left(f_{target}(t) - \omega_i r \right)^2 \tag{3}$$

Further derivation yields:

$$\omega_i = \frac{S^T \Gamma_i f_{target}}{S^T \Gamma_i S} \tag{4}$$

The DMPs model can generate the motion trajectory θ_{gene} by integrating equation (1) with the initial system state $[\theta_{demo}(t), \dot{\theta}_{demo}(t), \ddot{\theta}_{demo}(t)]$ nd initial phase ϕ_0.

3. An active gait trajectory planning method based on GRNN-DMPs

3.1. GRNN modelling

GRNN (Generalized Regression Neural Network) is an improved version of the Radial Basis Function Neural Network (RBFNN) that exhibits enhanced learning speed and nonlinear mapping capability[11].

GRNN offers several advantages, including one-shot training without the need for iterative processes, automatic determination of the number of neurons in the hidden layer based on training samples, automatic determination of connection weights between network layers, and eliminating the need for manual weight adjustments.

In this paper, a GRNN-DMPs algorithm is proposed and applied to the task of gait trajectory planning for active rehabilitation training in order to reduce fitting errors. The structure of the GRNN is illustrated in Figure 1.

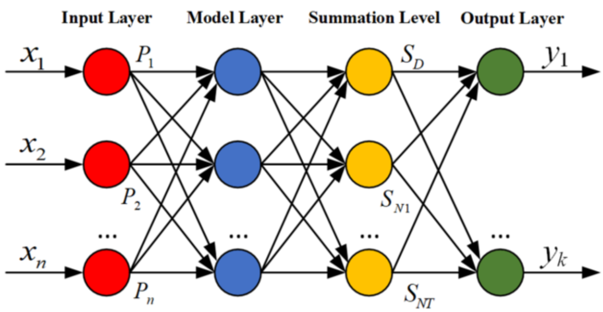


Fig 1. The structure of GRNN.

3.2. GRNN-DMPs Active Walking Trajectory Planning

Figure 2 illustrates the flow chart of the trajectory simulation for the GRNN-DMPs model, which is based on the GRNN-DMPs approach for active gait trajectory planning in lower limb rehabilitation exoskeletons.

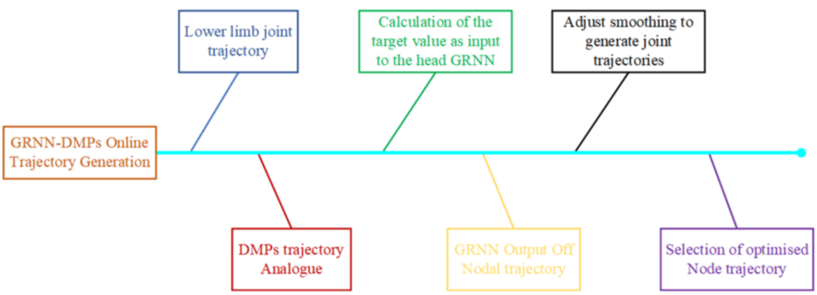


Fig 2. GRNN-DMPs flow chart.

The specific process of GRNN-DMPs trajectory simulation is as follows:

The parameters are first initialised according to the parameter values in Table 1, and then the dynamical system is established based on the initial parameters. The distribution of each Gaussian kernel function is deduced and the corresponding weights of the Gaussian kernel functions are determined according to Equation (4). Then input the angular trajectories of the hip and knee joints, calculate their velocities and accelerations, determine the forcing term according to Eq. (2), and calculate the forcing term function f, take f as the input vector of the GRNN input layer, and then output the joint trajectories modulated by the GRNN.

The simulation parameters of the combined model are shown in Table 1.

Table 1. Combining model parameter selection.

Parameter name	Numerical	Parameter name	Numerical
Gain factor α_z	25	Gain factor β_z	6.25
Number of kernel functions N	10	Time constant τ	0.5
Target state g	1	Wideband h	15
Focal point c	1	Smoothness σ	0.005

4. Simulation experiments

Based on research, we set the duration to 1.2m/s[12] and chose three different sets of values. To demonstrate the effectiveness of GRNN-DMPs, we will use the left leg joint for example. Figure 3 shows the output of the GRNN-DMPs specifically for the left leg joint.

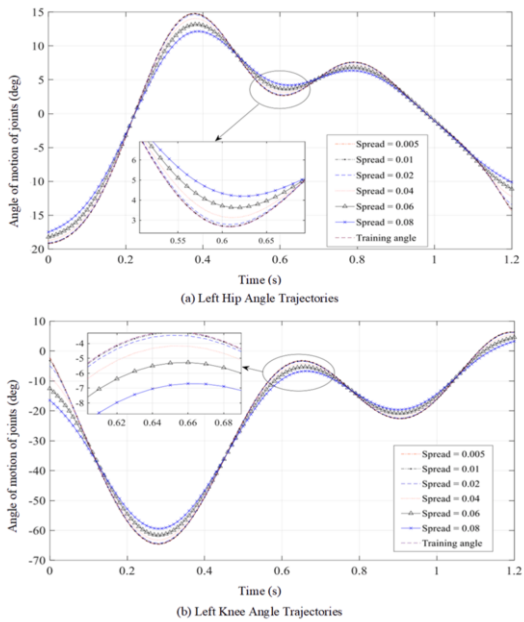
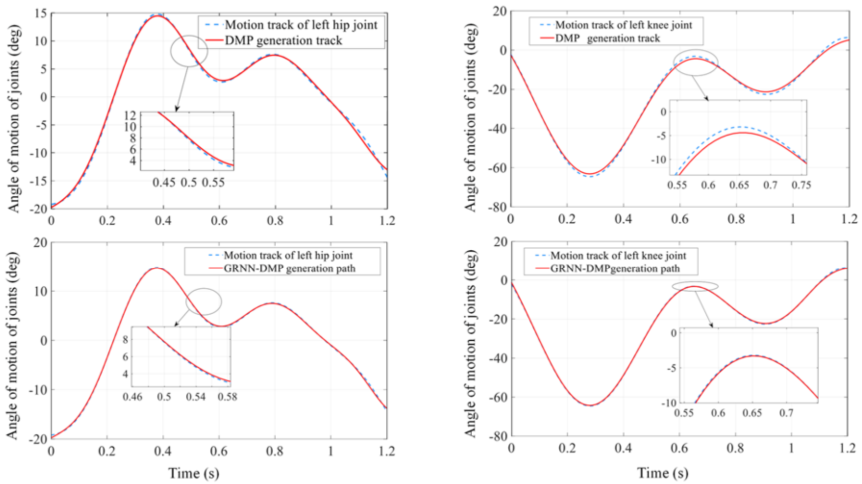


Fig 3. GRNN-DMPs planning track of each joint.

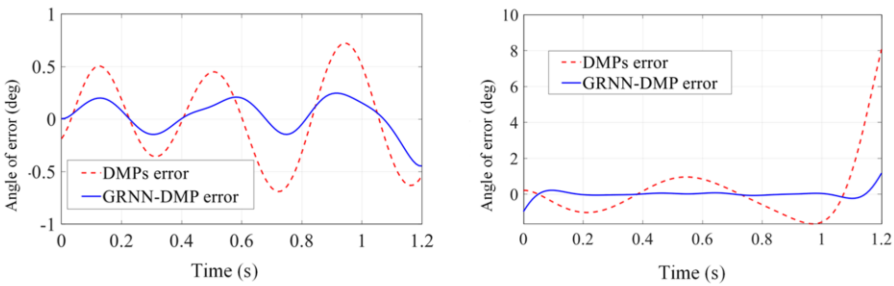
Figure 3 demonstrates that the motion trajectory planning of the hip joint and knee joint using GRNN-DMPs shows positive effects. When the smoothness is set to 0.005, the error between the joint motion curve and the actual motion trajectory curve generated by the combined model is minimized, and the motion trajectory closely aligns with the design requirements.

To assess the accuracy and precision of the proposed GRNN-DMPs model, trajectory generation graphs of both DMP and GRNN-DMPs are provided. Additionally, a trajectory generation error diagram is included for comparison. These diagrams can be found in Figure 4 and Figure 5.



(a) Comparison of trajectories generated for the left Hip (b) Comparison of trajectories generated for the left knee

Fig 4. DMPs and GRNN-DMPs trajectory generation graphs.



(a) Left Hip Error Comparison (b) Left Knee Error Comparison

Fig 5. trajectory generation error diagram.

In Figure 5, it is evident that the joint trajectories generated using the DMPs method exhibit larger errors during the flexion and extension of the joints in a walking gait cycle. Specifically, the knee trajectory shows a maximum error exceeding 8°. In contrast, the combined GRNN-DMPs method produces smaller trajectory generation errors. The maximum error for online generation of the hip trajectory does not exceed 0.5°, while for the knee joint, it does not exceed 2°. These findings highlight the superior trajectory planning ability of the GRNN-DMPs method.

5. Conclusion

This paper introduces a combined GRNN-DMPs method for trajectory simulation in the active rehabilitation training stage of patients. The method aims to establish online joint trajectories based on patients' active rehabilitation training. The results illustrate that the combined model achieves a maximum error in generating joint trajectories that does not exceed 2°, which is smaller compared to using DMPs alone. Additionally, the generated trajectory curves closely resemble the actual joint trajectories of the lower limbs. These joint trajectories generated by the GRNN-DMPs method can be used as inputs for subsequent rehabilitation control strategies.

Indeed, while the current paper focuses primarily on level walking training in the active-passive rehabilitation of lower limb exoskeletons, it is crucial to consider a wider range of activities that patients may encounter in their daily lives. Activities like stair climbing and squatting require different movement patterns and may pose additional challenges for patients in rehabilitation.

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