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GPR and SPSO-CG based gait pattern generation for subject-specific training

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Dear editor,

Gait training has been proved effective for recovery of walking ability for nerve injury patients caused by stroke, spinal cord injury (SCI), traumatic brain injury (TBI), etc. The traditional gait training methods, usually carried out by hands, are laborious and time-consuming, and hence, the training intensity is difficult to be maintained and the rehabilitation results are not satisfactory. To overcome the limitation, lower limb rehabilitation robots (LLRRs) have been developed for clinical gait training, the typical ones of which including Lokomat, ReoAmbulator, and Rewalk.

In order to apply LLRRs in clinical practice, the gait training trajectory should be designed according to patients' physiological conditions. However, due to the complicated relationships between human gaits and the gait associated factors, e.g., age, height, and gender, how to select the exact factors which are closely related to human gait patterns and how to model the relationships are still open questions. The later one is researched in this study.

Present methods for modeling subject-specific gait trajectories are mainly for prediction and can be classified into two categories, namely linear modeling methods, such as multiple linear regression [1], and nonlinear ones, such as multi-layer perceptron neural networks (MPNNs) [2], generalized regression neural networks (GRNNs) [3], and Gaussian process regression (GPR) [4]. However, all of these methods have limitations for the clinical application. On one hand, the highly nonlinear relationships between human gait patterns and the associated factors are difficult to be represented by linear models. On the other hand, MPNNs are difficult to be designed and have little generalization capabilities in nature. As for the GRNN method, the network size will become huge when the number of training samples is large, which makes it computationally expensive; meanwhile, the effect of each anthropometric factor on gait pattern has not been shown in the GRNN model [3]. These deficiencies can be overcome to some extent by Yun's method [4], where the human gait trajectories were modeled based on GPR by using 14 anthropometric features that significantly affect gait patterns. One of the limitations is that, the gait pattern was represented by 77 points of the gait trajectory [4], which makes the computation relatively complicated and the model difficult to be applied on the LLRRs. Meanwhile, the conjugate gradient (CG) method is used to optimize the hyperparameters [4], which however is sensitive to the initial position and makes the global optima difficult to be obtained.

Therefore, a novel GPR model for subject-specific gait patterns is designed in this study, where the gait patterns are represented by the coefficients and periods of the finite Fourier series (FFS). Then, a modified stochastic particle swarm optimization (SPSO) algorithm based on CG method (SPSO-CG) is proposed for optimizing the hyperparameters. The performance of the proposed method is demonstrated by the comparison experiment.

Subject-specific gait modeling based on FFS and GPR. Human gaits can be represented by the hip, knee, and ankle joint trajectories. In order to simplify the computation, these trajectories are parameterized by using the FFS method, as follows:

$$\theta_i(t) = \sum_{l=1}^{5} \left(\frac{a_{i,l}}{lw_{i,f}} \cos(lw_{i,f}t) + \frac{b_{i,l}}{lw_{i,f}} \sin(lw_{i,f}t) \right) + c_i, \quad \forall i = 1, 2, 3, \tag{1}$$

where hip, knee, and ankle joint angles are respectively represented by θ_1, θ_2 and θ_3; $w_{i,f} = 2\pi/t_{i,f}$; $t_{i,f}$ is the trajectory period. The motion period for each joint is estimated respectively to improve the accuracy. The gait trajectories are normalized by the method of [4], and gait patterns can be

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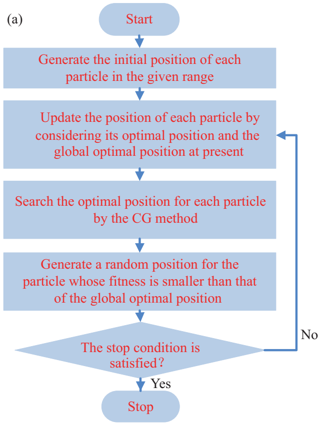
(a)



The reconstructed errors for the GPR models basedon CG and SPSO-CG, and the RF model

Model		Hip	Knee	Ankle
RF	RMSE (deg)	2.51	6.54	2.63
	MVE (deg)	14.23	21.05	11.05
GPR (CG)	RMSE (deg)	2.14	9.53	1.32
	MVE (deg)	11.85	93.49	4.77
GPR (SPSO-CG)	RMSE (deg)	0.86	0.78	0.53
	MVE (deg)	4.79	4.57	2.98

(b)

Figure 1 (Color online) (a) The flow chart of SPSO-CG algorithm; (b) the reconstructed errors for the GPR models based on CG and SPSO-CG, and the RF model.

given by

$$\boldsymbol{\Phi} = \begin{pmatrix} w_{1,f}, a_{1,1}, \ldots, a_{1,5}, b_{1,1}, \ldots, b_{1,5}, c_1 \\ w_{2,f}, a_{2,1}, \ldots, a_{2,5}, b_{2,1}, \ldots, b_{2,5}, c_2 \\ w_{3,f}, a_{3,1}, \ldots, a_{3,5}, b_{3,1}, \ldots, b_{3,5}, c_3 \end{pmatrix}. \tag{2}$$

Fourteen human body parameters are used to estimate gait patterns, which are same to those of [4] and can be given by $\boldsymbol{x} = (x_1, x_2, \ldots, x_{14})$, where $x_1, x_2, \ldots, x_{14}$ represent age, height, mass, gender, thigh length, calf length, bi-trochanteric width, bi-iliac width, anterior superior iliac spine breadth, knee diameter, foot length, malleolus height, malleolus width, and foot breath, respectively. In order to construct a gait model as accurate as possible, each element of (2) is modeled based on human body parameters and by using the GPR method [5]. The mean function and the covariance function are determined by

$$m(\boldsymbol{x}) = 0, \tag{3}$$

$$k(\boldsymbol{x}, \boldsymbol{x}') = \nu_1 \exp\left(\frac{-\Delta\boldsymbol{x}\Lambda\Delta\boldsymbol{x}^{\mathrm{T}}}{2}\right) + \nu_2\delta_{i,j}, \tag{4}$$

where $\Delta\boldsymbol{x}$ is defined by $\boldsymbol{x} - \boldsymbol{x}'$; the elements of the diagonal matrix Λ are $\lambda_1, \ldots, \lambda_{14}$; $\delta_{i,j}$ is the Kronecker delta function. The gait pattern $\boldsymbol{\Phi}$ can be estimated based on the training samples and the body parameters of the test sample $\boldsymbol{x}^*$, as $\phi_i^* = \boldsymbol{k}_*^{\mathrm{T}}\boldsymbol{K}^{-1}\boldsymbol{\phi}$, where ϕ_i^* represents the element of $\boldsymbol{\Phi}$ to be estimated; $\boldsymbol{K}$ is a matrix whose elements $k_{i,j}$ is the value of a covariance function $k(\boldsymbol{x}_i, \boldsymbol{x}_j)$; $\boldsymbol{\phi}$ is the output vector of the training set; $\boldsymbol{k}_*$ is given by $\boldsymbol{k}_* = [k(\boldsymbol{x}^*, \boldsymbol{x}_1), \ldots, k(\boldsymbol{x}^*, \boldsymbol{x}_n)]$.

SPSO-CG based hyperparameter optimization. In order to estimate the gait pattern of a test sample, the hyperparameters, $\lambda_1, \ldots, \lambda_{14}$, ν_1, and ν_2 should be determined first, which is carried out by using the maximizing likelihood estimation method. The objective function to be maximized is given by

$$\log p(\boldsymbol{\phi}|\boldsymbol{X}, \Omega) = -\frac{1}{2}\boldsymbol{\phi}^{\mathrm{T}}\boldsymbol{K}^{-1}\boldsymbol{\phi} - \frac{1}{2}\log|\boldsymbol{K}| - \frac{n}{2}\log 2\pi. \tag{5}$$

It can be seen that the optimization problem of this study is highly nonlinear and nonconvex. The SPSO algorithm, whose global convergence performance has been proven can be used for this problem. However, it is found in the experiment that, the searching speed is very slow and the global optima is difficult to be achieved. Meanwhile, the CG algorithm has fast convergence speed, and however, the global convergence performance cannot be guaranteed because of its sensitivity to the initial positions.

Therefore, an SPSO-CG algorithm is proposed to utilize both the advantages of the SPSO and CG algorithms. In the proposed SPSO-CG algorothm, the initial positions of the particles are generated randomly in the given ranges, and the new positions are generated by using the particles' present optimal positions and the global optimal position. When a particle's present position, its best location, and the best global location, are equal to each other, the particle's position will be regenerated to maintain the global convergence performance. After updating the position of a particle, the CG searching method is used to find the optimal position, and the global optimal position is to be substituted by the particle's optimal position when its fitness is samller than that of the global optimal position. The flow chart of the SPSO-CG algorithm is given in Figure 1(a).

Experiment. As the GPR model based on CG method shows the relatively good performance at present, a comparison experiment between two GPR models, respectively based on the SPSO-CG and CG methods, was carried out. Meanwhile, the random forest (RF) algorithm has also been used to model the relationship between the gait patterns and the anthropometric features recently, which shows good efficiency [6]. Therefore, the comparison between the GPR model based on SPSO-CG method and the RF model was also carried out. The data set used in this study is from [4]. In the experiment, human gait patterns were described by (2). The GPR and RF method were respectively used to model the subject-specific gait trajectories. The proposed SPSO-CG method and the CG method were used to optimize the hyperparameters of the GPR model, respectively. The particle population of the SPSO-CG is 600, and the maximum number of iteration times is 20. The initial position of the CG method was set to zero.

The results are given in Figure 1(b), where RMSE and MVE are respectively the root-mean-square and maximal values of the reconstructed errors. It can be seen that the reconstructed errors for the GPR model based on SPSO-CG are smallest. Due to that the CG method is sensitive to the initial position and there is no effective method for finding the best initial position at present, the CG method is difficult to be used in the practical application. Meanwhile, although the parameters of the RF model, the tree number and the feature number for each node, are optimized, the reconstruction errors for the RF model are relatively big. Therefore, the GPR method based on the SPSO-CG algorithm is more efficient for the subject-specific gait modeling.

Conclusion and future work. This study proposed a method for modeling and optimizing the subject-specific gait patterns. In this method, human gait trajectories are parameterized by using the FFS method and gait patterns are represented by the coefficients and periods. Then, a GPR model is designed to describe the relationships between the anthropometric features and personalized gait patterns, and an SPSO-CG algorithm is proposed to optimize the hyperparameters, which can utilize both the global convergence performance of the SPSO algorithm and the fast convergence performance of the CG algorithm. It is shown by the comparison experiment that the proposed method can achieve better performance than the usually used methods in the literature. Meanwhile, it should be noted that, the proposed method can be used to accurately fit the training samples, and however, the prediction performance has not been validated. When the test sample is the same as one of the training samples, it can be reconstructed accurately. Otherwise, methods for measuring the similarity between the test and training samples can be used to make a judgement whether the designed model can be applied or it should be retrained by including the new sample, which is to be researched in the future work.

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