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Feature Selection of Input Variables for Intelligence Joint Moment Prediction Based on Binary Particle Swarm Optimization

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ABSTRACT Joint moment is an important parameter for a quantitative assessment of human motor function. However, most existing joint moment prediction methods lacking feature selection of optimal inputs subset, which reduced the prediction accuracy and output comprehensibility, increased the complexity of the input sensor structure, making the portable prediction equipment impossible to achieve. To address this problem, this paper develops a novel method based on the binary particle swarm optimization (BPSO) with the variance accounted for (VAF) as fitness function to reduce the number of input variables while improves the accuracy in joint moment prediction. The proposed method is tested on the experimental data collected from ten healthy subjects who are running on a treadmill with four different speeds of 2, 3, 4 and 5m/s. The BPSO is used to select optimal inputs subset from ten electromyography (EMG) data and six joints angles, and then the selected optimal inputs subset be used to train and predict the joint moments via artificial neural network (ANN). Prediction accuracy is evaluated by the variance accounted for (VAF) test between the predicted joint moment and multi-body dynamics moment. Results show that the proposed method can reduce the number of input variables of five joint moment from 16 to less than 11. Furthermore, the proposed method can better predict joint moment (mean VAF: $94.40 \pm 0.84\%$) in comparison with the state-of-the-art methods, i.e. Elastic Net (mean VAF: $93.38 \pm 0.96\%$) and mutual information (mean VAF: $86.27 \pm 1.41\%$). In conclusion, the proposed method reduces the number of input variables and improves the prediction accuracy that may allow the future development of a portable, non-invasive system for joint moment prediction. As such, it may facilitate real-time assessment of human motor function.

INDEX TERMS Joint moment prediction, artificial neural network, binary particle swarm optimization, feature selection.

I. INTRODUCTION

Joint moment is an important parameter to quantitative evaluate human motor function [1]. These predictions can play a very important role in rehabilitation [2], athlete training evaluation [3], [4], and prosthesis and orthosis design [5]–[7]. However, due to the complexity of coordination of muscles in human motion, it is difficult to directly measure human joint moment in vivo at present [8].

It can be calculated in vivo by using computational models, such as inverse dynamic analysis [9], [10], and EMG-driven model [11], [12]. Nevertheless, the computational models

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face a challenge to represent the neuro-musculoskeletal system in a precisely way, because of individual difference in anatomic and functional characteristics [8]. Previous studies [13]–[17] indicate that Artificial Neural Network(ANN) is good at adapting to individual characteristics in biomechanics when the mathematical relationship between input and output is unknown. For example, Uchiyama *et al.* [18] used 7 EMG signals and 5 EMG signals with shoulder and elbow joint angles as the inputs of ANN to predict the elbow joint moment, respectively. Luh *et al.* [19] utilized 6 EMG data, elbow joint angle and angular velocity to investigate the elbow isokinetic moment. Song and Tong [20] utilized 3 EMG data, elbow joint angle and angular velocity to investigate the elbow dynamic moment. Hahn [21] included the inputs of age, gender, height, body mass and EMG signals to predict the isokinetic knee extensor and flexor moment.

As listed, all the above studies just give the input variables without feature selection of optimal inputs subset, which cannot effectively reduce the number of input sensor and therefore presents a key challenge to portable joint moment prediction. To address this problem, we used feature selection to select optimal input subsets, which are enough and necessary for joint moment prediction. Feature selection is an effective data analysis preprocessing technique that improves prediction accuracy by reducing the amount of data needed in the learning process and enhancing output comprehensibility [22]. For examples,, Ardestani *et al.* [1] utilized mutual information to select ground reaction force (GRFs) and EMG signals as input to reduce information redundancy in the prediction of lower extremity joint moment. Similarly, Xiong *et al.* [23] used the Elastic Net algorithm to reduce input variables for calculating lower extremity joint moment. However, mutual information has no theoretically justified stopping criterion in the feature selection procedure and does not consider the interrelationship between variables [24], while the Elastic Net involves the linear regression method, which may not be able to optimize the non-linear system [25]. The BPSO is a typical nonlinear optimization algorithm, which can be used to solve this problem.

The BPSO was first introduced by Kennedy and Eberhart for discrete optimization problems in 1997 [26]. Recently, the BPSO has been successfully used to solve prediction problems in various areas, such as blasting environmental impacts [27], hydrological modeling [28], cancer classification [29] and other areas where BPSO can be applied. In this paper, a BPSO based feature selection approach for joint moment prediction is developed based the BPSO's fitness function and evaluated by the variance accounted for.

The method is tested on the data recorded from ten healthy subjects who are running on a treadmill at different speeds, i.e. 2, 3, 4 and 5 m/s. Based on the EMG driven musculoskeletal model taking EMG signals and joint angles data as inputs to predict the joint moments of human body [12], ten major EMG signals and six joint angles of the right leg are used as candidate signal sets in this study. The BPSO is then used to select the optimal input variables for the right lower limb's five joint moment prediction, i.e. hip flexion extension (Hip FE) moment, hip adduction abduction (Hip AA) moment, hip rotation (Hip R) moment, knee flexion extension (Knee FE) moment and ankle plantar dorsiflexion (Ankle PDF) moment. To evaluate the prediction ability of our method, a generic ANN is designed and trained with all four speeds data. The ANN predictions are validated by multi-body dynamics [9], [10], using variance accounted for (VAF) [30], and compare with Elastic Net [23] and mutual information [1].

II. MATERIALS AND METHODS

A. EXPERIMENTAL DATA

Experimental data for biomechanical model calibration and dynamic moment prediction of lower limb was acquired from a publicly available database (https://simtk.org/projects/nmbl_running; accessed on, 2 April 2019), which was obtained from ten healthy male subjects (age 29±5 years, height 1.77±0.04 m, mass 70.9±7.0 kg). The data include EMG signals of gastrocnemius medialis, gastrocnemius lateralis, tibialis anterior, vastus medialis, biceps femoris long head, gluteus maximus, rectus femoris, vastus lateralis, soleus and gluteus medius. In the experiment, the subjects run on a treadmill at different speeds, i.e. 2, 3, 4 and 5 m/s. The corresponding data over 6 gait cycles per speed were recorded of each subject. The right leg moment of hip-flexion- extension (Hip FE), hip-adduction-abduction (Hip AA), knee-flexion-extension (Knee FE), and ankle-plantar-dorsiflexion (Ankle PDF) are calculated by using the multi-body dynamic method [9], [10] with opensim software according to the experimental data of the open-access database. In order to analyze every gait cycle without the influence of speed, the EMG signals, motion data and ground reaction force were filtered and resampled to obtain 101 time points of each gait. For a complete description of this publicly available database, see [31].

B. FEATURE SELECTION

A large number of input variables do not necessarily translate into high prediction accuracy. In some cases, irrelevant and misleading features may reduce the accuracy and speed of the prediction algorithm [22]. For joint moment prediction, the number of input variables not only affects the efficiency of the algorithm, but also increases the complexity of the input sensor structure, which makes the portable prediction equipment impossible to achieve. Therefore, reducing the number of input variables through feature selection is an effective means to realize the portability of joint moment prediction, while improve the efficiency of prediction algorithm [32], [33]. Considering the nonlinearity of joint moment prediction model and the problems of feature selection methods such as mutual information [24],and Elastic Net [25], we used BPSO to get the optimal inputs subset for joint moment prediction. The BPSO is an effective method for solving discrete optimization problems based on

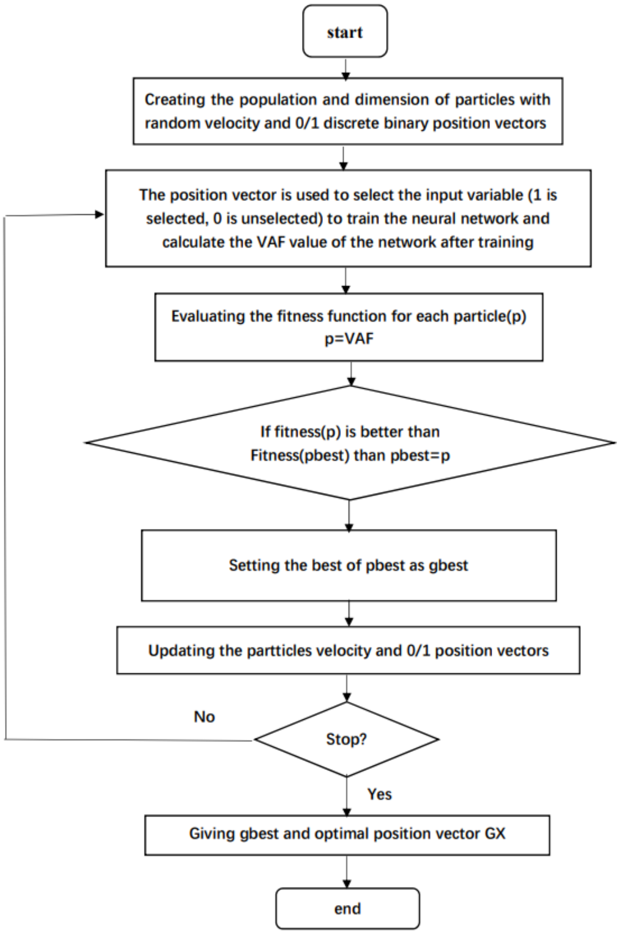

FIGURE 1. Flow chart of particle swarm optimization.

population which was first introduced by Kennedy and Eberhart for discrete optimization problems in 1997 [26]. Since BPSO is a robust global search algorithm [34], it can be used to determine optimal inputs subset. The fitness function of the BPSO is evaluated by the variance accounted for (VAF) [30]

$$\mathrm{VAF} = [1 - \frac{var(\widehat{y} - y)}{var(y)}] * 100\% \tag{1}$$

where $\widehat{y}$ represents predicted joint moment and y represents the multi-body dynamics moment.

From EMG-driven model [12], we know that EMG signals and joint angles as inputs can be used to predict joint moments. Therefore, subjects' ten EMG signals and six joint angles (hip flexion extension angle (Hip FE angle), hip adduction abduction angle (Hip AA angle), hip rotation angle (Hip R angle), knee flexion extension angle (Knee FE angle), ankle plantar dorsiflexion angle (Ankle PDF angle) and subtalar eversion inversion angle (Subtalar EI angle)) are selected as candidate input signals to predict lower limb joint moments (A total of 16 variables as candidate sets). The BPSO is designed to select the optimal set of input variables in the candidate sets. Its processing flow chart is shown in Fig. 1.

TABLE 1. The sum of ten subjects' selected input variables about the output joint moment.

Input variable	Hip FE	Hip AA	Hip R	Knee FE	Ankle PDF
Hip FE angle	10	9	9	10	10
Hip AA angle	8	10	10	8	8
Hip A angle	4	8	7	4	5
Knee FE angle	10	10	10	10	7
Ankle PDF angle	6	8	9	8	10
Subtalar EI angle	2	2	3	4	5
Biceps femoris long head EMG	6	6	4	5	6
gastrocnemius lateralis EMG	4	7	7	4	7
gastrocnemius medialis EMG	9	8	5	7	10
Gluteus maximus EMG	6	5	3	5	6
Gluteus medius EMG	2	2	3	3	5
rectus femoris EMG	5	4	1	3	4
Soleus EMG	7	3	8	5	4
tibialis anterior EMG	5	6	5	6	7
vastus lateralis EMG	7	8	8	5	5
vastus medialis EMG	7	6	5	4	4

Hip flexion extension=Hip FE, hip adduction abduction =Hip AA, hip rotation=Hip R, knee flexion extension=Knee FE, ankle plantar dorsiflexion=Ankle PDF and subtalar eversion inversion =Subtalar EI.

It can be seen from Fig.1 that the BPSO based method is performed as follows: Firstly, the positions X and the velocities V of N particles are randomly generated. Since there are 16 variables in the candidate set, the position of each particle is a 16-dimensional 0/1 discrete binary vector. The selected input variables are determined by the 0/1 value of the particle's position, where 1 represents the selected and 0 represents the unselected. Then the selected input variables are used to train the neural network, and the VAF of the test set after training is calculated, and the fitness function is updated by the VAF value. Finally, the values of locally optimal "pbest" and globally optimal "gbest" are updated, and the d-th dimension of the i-th particle' s velocity V_{id} and position X_{id} are updated with the following formulas:

$$\begin{aligned} V_{id} &= \omega V_{id} + C_1 random(0,1)(P_{id} - X_{id}) \\ &\quad + C_2 random(0,1)(P_{gd} - X_{id}) \end{aligned} \tag{2}$$

$$X_{id} = \begin{cases} 1 & \dfrac{1}{1+\exp(-V_{id})} > \dfrac{6 * random(0,1)}{3+\exp(-0.2796 * T)} \\ 0 & \dfrac{1}{1+\exp(-V_{id})} <= \dfrac{6 * random(0,1)}{3+\exp(-0.2796 * T)} \end{cases} \tag{3}$$

where ω is the inertia factor, C_1 and C_2 are the acceleration constant, $C_1 = C_2 \in [0, 4]$. Random (0,1) represents random numbers on [0,1]. P_{id} represents the extreme value of the d-th dimension of the i-th particle. P_{gd} represents the d-th dimension of the global optimal solution, T is the total number of iterations.

Using the BPSO described above, statistical data of the ten subjects' selected input variables of hip-flexion- extension (Hip FE) moment, hip-adduction-abduction (Hip AA) moment, hip rotation(Hip R) moment, knee-flexion-extension (Knee FE) moment and ankle-plantar-dorsiflexion (Ankle PDF) moment are shown in Table 1.

As TABLE 1 shows, the optimal input variables for each subject's joint moment prediction are different for the gap of

TABLE 2. The globally optimal position of the input variable about the output joint moments.

Input variable	Hip FE	Hip AA	Hip R	Knee FE	Ankle PDF
Hip FE angle	1	1	1	1	1
Hip AA angle	1	1	1	1	1
Hip A angle	0	1	1	0	0
Knee FE angle	1	1	1	1	1
Ankle PDF angle	1	1	1	1	1
Subtalar EI angle	0	0	0	0	0
Biceps femoris long head EMG	1	1	0	0	1
gastrocnemius lateralis EMG	0	1	1	0	1
gastrocnemius medialis EMG	1	1	0	1	1
Gluteus maximus EMG	1	0	0	0	1
Gluteus medius EMG	0	0	0	0	0
rectus femoris EMG	0	0	0	0	0
Soleus EMG	1	0	1	0	0
tibialis anterior EMG	0	1	0	1	1
vastus lateralis EMG	1	1	1	0	0
vastus medialis EMG	1	1	0	0	0

Hip flexion extension=Hip FE, hip adduction abduction =Hip AA, hip rotation=Hip R, knee flexion extension=Knee FE, ankle plantar dorsiflexion=Ankle PDF and subtalar eversion inversion =Subtalar EI.

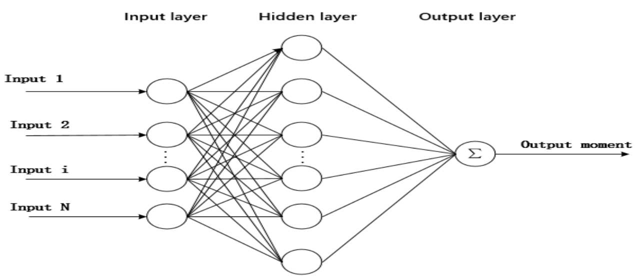

FIGURE 2. Structure of the designed ANN.

subject living habits and muscular synergy in the process of human movement. Therefore, we use the statistical sum of ten subjects to determine whether the input variable is selected about the output. The expressions are as follows:

$$\begin{cases} GX^{jm} = 1 \sum_{i=1}^{10} GX_i^{jm} > 5 \\ GX^{jm} = 0 \sum_{i=1}^{10} GX_i^{jm} <= 5 \end{cases}$$
$$(m = 1, 2, 3, \ldots, 16, j = 1, 2, 3, 4, 5) \tag{4}$$

where GX_i^{jm} is the optimal position of the m-th input variable about the j-th joint of the i-th subject, GX^{jm} is the optimal position of the m-th input variable about the j-th joint. From Eq. 4, the optimal inputs subset respect to the joint moments are obtained, which are shown in TABLE 2.

C. ARTIFICIAL NEURAL NETWORK (ANN)

After obtaining optimal inputs subset by BPSO, we designed an ANN model to train and predict joint moment. Considering the successful application of ANN in joint moments prediction [18]–[20], [1], [35]–[38], a three layers ANN model (Fig.2) is utilized to construct a model describing the relation between joint moment and inputs. Since the optimal input subset are obtained by the BPSO, the unit number of input layer are determined by TABLE 2. The neurons number of output layer and hidden layer are 1 and 20. The ANN model is run by using the neural network toolbox of MATLAB (v. 2016a, The Math Works, Inc., Natick, MA).

TABLE 3. Performances of joint moment prediction, evaluated by variance accounted for (VAF) in percentage (%).

participants	Hip FE	Hip AA	Hip R	Knee FE	Ankle PDF
subject 1	95.89	87.12	88.12	97.14	96.42
subject 2	92.19	92.67	84.16	93.90	96.92
subject 3	93.77	86.48	62.53	87.31	78.26
subject 4	95.04	93.46	95.46	98.59	98.28
subject 5	94.94	87.46	60.84	96.72	94.69
subject 6	93.00	90.31	88.40	95.25	93.55
subject 7	96.35	92.38	92.39	92.21	96.95
subject 8	97.31	92.80	91.37	98.92	97.97
subject 9	97.46	94.49	93.49	98.25	98.22
subject 10	97.36	87.61	88.54	98.43	97.05
mean	95.33	90.48	84.53	95.67	94.83
Std	1.88	3.04	12.46	3.67	6.01

D. PREDICTION EVALUATION

We design a generic ANN model (three layers, 20 hidden neurons) and train it with four speeds (i.e. 2, 3, 4 and 5 m/s). In the test, we randomly select 4 gait cycles ($4 * 101 = 404$ time points) data from each speed for training, the rest 2 gait cycle (101 time points) for testing. The accuracy of the ANN is evaluated by VAF between predicted joint moment and multi-body dynamics moment.

III. RESULTS

The prediction results of joint moment at each speed are shown in Fig. 3 for a typical subject. Multi-body dynamics moments are compared. As shown in Fig. 3, the general pattern of lower extremity joint moments can be well predicted at all speeds. Compared with the reference joint moments (multi-body dynamics moment), the predicted waveforms only have some difference in maximum and minimum values (cross-correlation coefficient > 0.957). TABLE 3 show the mean VAF ($\pm$ standard deviation) of joint moment prediction for Hip FE, Hip AA, Hip R, Knee FE, and Ankle PDF are $95.33\pm1.88\%$, $90.48\pm3.04\%$$84.53\pm12.46\%$, $95.67\pm3.67\%$ and $94.83 \pm 6.01\%$.

We also compared our method (mean VAF: $\overline{\text{VAF}} = 94.40\pm0.84\%$) with Elastic Net(mean VAF: $\overline{\text{VAF}} = 93.38\pm 0.96\%$) [23] and mutual information(mean VAF: $\overline{\text{VAF}} = 86.27 \pm 1.41\%$) [1]. Considering that there is no theoretically reasonable stopping criterion for mutual information in the process of feature selection, we select as many input variables as BPSO according to reference [1]. So, the number of selected input variables and the number of selected EMG signals of the three methods are shown in TABLE 4.

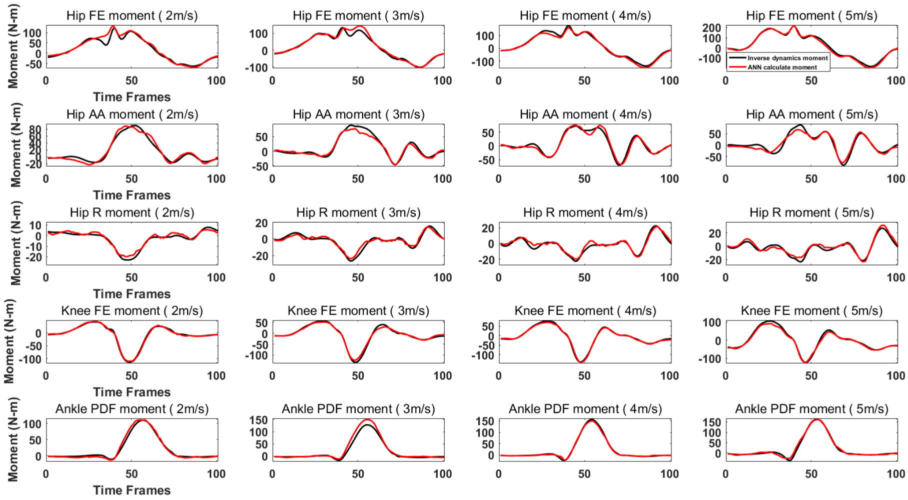

FIGURE 3. A typical subject's joint moment prediction at each speed.

TABLE 4. The number of selected input variables/the number of selected EMG signals of the three methods.

method	Hip FE	Hip AA	Hip R	Knee FE	Ankle PDF
BPSO	10/6	11/6	8/3	6/2	9/5
mutual information	10/7	11/7	8/4	6/4	9/6
Elastic Net	11/6	8/4	8/5	10/6	8/5

Take BPSO($\overline{\text{VAF}} = 94.40\%$) as a reference and compare with Elastic Net($\overline{\text{VAF}} = 93.38\%$) and mutual information ($\overline{\text{VAF}} = 86.27\%$), it is found that the $\overline{\text{VAF}}$ of the moment predicted by the Elastic Net($\overline{\text{VAF}} = 93.38\%$) and mutual information($\overline{\text{VAF}} = 86.27\%$) are almost reduced by 1.08% and 8.61% as show in TABLE 5. In order to further analyze the differences between BPSO and Elastic Net, the VAF of each joint moment prediction value with optimal inputs subset as input obtained by BPSO and Elastic Net are calculated in TABLE 6.

TABLE 5. Comparison performances of BPSO, mutual information and Elastic Net, evaluated by variance accounted for in percentage (%).

participants	BPSO	mutual information	Elastic Net
subject 1	95.78	83.24	95.03
subject 2	95.11	86.54	93.58
subject 3	92.66	84.72	91.34
subject 4	93.96	87.36	92.87
subject 5	94.08	85.90	93.16
subject 6	93.97	86.06	92.97
subject 7	94.19	86.36	93.17
subject 8	94.15	87.03	93.59
subject 9	94.80	87.55	93.93
subject 10	94.95	87.97	94.16
mean	94.40	86.27	93.38
Std	0.84	1.41	0.96

IV. DISCUSSION

This study demonstrated that ANN with the input variables determined by BPSO could be used to predict joint moments under different gait speeds. This method effectively reduces the input variables, reduces the complexity of the input sensors, and makes it possible for portable online joint moment prediction equipment. Different from the previous studies [1], [18]–[21], [35], [39]–[46] on joint moment prediction using ANN model, this research obtains the optimal input variables from the non-linear system by the BPSO algorithm, which can be measured online; It reduces the input of EMG signals and makes it possible to predict joint moment using EMG signals of large muscle groups as input; It also avoids the use of ground reaction force and marker trajectories which need special equipment and can be time-consuming. Our novel method yields a high accuracy of prediction with $\overline{\text{VAF}} = 94.40 \pm 0.84\%$. Thus, the proposed method is suitable for exoskeleton robot control and quantitative online analysis of gait that requires the detection device to be portable.

Unlike the inverse dynamic analysis [9], [10], and EMG-driven model [11], [12], our method can predict joint moments and release the necessity of 3D motion capture which makes it possible to predict joint moments in hospitals, research laboratories and in free state. It also can be adapted to the individual differences in the training process, which does not need a musculoskeletal model or a subject-specific scaling, and therefore reduces the error caused by individual differences.

Comparing the BPSO ($\overline{\text{VAF}} = 94.40\%$) with mutual information ($\overline{\text{VAF}} = 86.27\%$), the latter's VAF reduced by 8.61%. We can see that the prediction accuracy decreases considerably when the same input variables, especially the EMG signals increase, because the correlation between variables is not considered. Therefore, when using mutual

TABLE 6. Comparison performances of BPSO and Elastic Net in each joint moment, evaluated by variance accounted for in percentage (%).

method	Hip FE	Hip AA	Hip R	Knee FE	Ankle PDF
BPSO	95.33	90.48	84.53	95.67	94.83
Elastic Net	94.99	90.58	77.22	93.22	94.14

information, we should consider the relationship between variables to effectively reduce the information redundancy of input variables. Comparing BPSO ($\overline{\text{VAF}} = 94.40\%$) with Elastic Net ($\overline{\text{VAF}} = 93.38\%$), the latter's VAF only reduced by 1.08%. We can see that the prediction accuracy does not change much. But from TABLE 4, we know that the number of BPSO's optimal inputs subset are less than that of Elastic Net exception of Hip AA and Ankle PDF. we further analyze TABLE 6 and find that the BPSO's Ankle PDF moment prediction more accurate, but BPSO's Hip AA moment prediction worse than Elastic Net. Therefore, it can be inferred that the optimal inputs subset of Hip AA obtained by BPSO is the local optimal solution. We need to improve this algorithm in the future.

It is worth mentioning that there are few limitations of the current study at present. Firstly, we developed our method based on BPSO which may obtain suboptimal solution for the limitation of BPSO algorithm. Secondly, we developed our method based on the EMG data recorded from only 10 muscles of the right leg, which cannot represent all the muscles associated with the joints. In the future, we will test the proposed method in a larger dataset. In addition, the gait patterns of the experimental data are very limited and only include the gait patterns of running. More gait patterns data will be collected in our future study, such as cutting, squatting and so on. Finally, the joint moments were estimated by using multi-body dynamics, where the error between predicted moment and the real moment may not be assessable.

V. CONCLUSION

The method proposed in this paper can be developed as an artificial intelligence algorithm, which can be used to estimate human joint moment with fewer input variables and may allow the future development of a portable, non-invasive system for joint moment prediction. As such, it may facilitate real-time assessment of human motor function.

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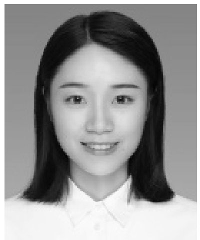

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