doi:10.3772/j.issn.1006-6748.2019.01.012

# Similarity comprehensive evaluation of humanoid robot arm motion<sup>®</sup>

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#### **Abstract**

A suitable comprehensive evaluation method for similarity comprehensive evaluation of humanoid motion (mainly to robotic arm) is proposed. For different robotic arms, a static comprehensive
evaluation model is established by projection pursuit evaluation based on indexes of humanoid robot
arm motion in robotics and ergonomics field. Based on projection pursuit evaluation with timing information entropy and time degrees, a dynamic comprehensive evaluation method is proposed by linear weighting to each time's static model's indexes weight according to timing weighted vectors.

Through comparing similarity comprehensive evaluation result based on static and dynamic comprehensive evaluation model, the results show that similarity based on dynamic comprehensive evaluation model is high. By comparing reliability, similarity and dispersion of static and dynamic comprehensive evaluation models, the results show that dynamic comprehensive evaluation result has better
accuracy, stability and lower dispersion, and the result is more reasonable and real. Therefore, the
dynamic comprehensive evaluation method proposed in this paper is more suitable for similarity comprehensive evaluation of humanoid robot arm motion.

**Key words:** humanoid robot arm motion, similarity comprehensive evaluation, projection pursuit evaluation method, dynamic comprehensive evaluation method, relative efficiency

#### 0 Introduction

Humanoid motion is the foundation of humanoid robot arm motion, and its technical maturity is directly related to whether humanoid robot can complete the specific tasks. When a new control algorithm is proposed, how to correctly evaluate whether the new algorithm can drive robot's attitude to obtain high similarity with human's attitude or not, has been one of important topics in humanoid robot study. A number of scholars have proposed many indexes to evaluate similarity of humanoid robot motion at home and abroad. In robotics field, the common indexes are joint angle<sup>[1]</sup> and joint position<sup>[2]</sup>. In ergonomics field, Jung et al. [3] propose a psychophysics index for describing joint discomfort. Almasri et al. [4] proposed an energy index.

There are many studies on similarity of humanoid robot arm motion based on single index in the two fields mentioned above at home and abroad, especially the quantization method, to promote optimization design for robotic motion based on single index<sup>[5-7]</sup>. However,

putting the information of various single index together as the basis of attitude similarity evaluation is a relatively effective method<sup>[8,9]</sup>. Therefore, how to comprehensively evaluate similarity of humanoid robot motion based on various single indexes is a problem that needs to be solved.

The comprehensive evaluation of humanoid robot motion similarity is an objective weighting evaluation problem. In quantitative calculation, projection pursuit evaluation is applied to research the relationships between multiple variables for comprehensive evaluation, and it is also an essential objective weighting method<sup>[10]</sup>, which is not introduced into robot comprehensive evaluation yet. Projection pursuit evaluation is a kind of exploratory data analysis method driven by sample data. And the method finds the optimum projection direction based on sample personal data characteristics to judge each index contribution on comprehensive evaluation index. And the projection value can be obtained by the optimum projection direction and the linear projection of evaluation index. Based on the projection value, similarity of humanoid robot arm motion can be comprehensively evaluated [11]. However, projection

① Supported by the National Natural Science Foundation of China (51415016).

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pursuit evaluation can just build static evaluation model for static evaluation, which is only suitable for single moment evaluation. In the static evaluation model with different time sections, index weight vectors are different from each other. So it is an urgent problem that is how to integrate each time's index weight information and establish an evaluation model suitable for multiple moments.

This paper intruduces timing information entropy and time degrees into projection pursuit evaluation, proposing a new dynamic comprehensive evaluation method. The dynamic comprehensive evaluation model is established by linear weighting to each time's static model's indexes weight according to timing weighted vectors. Through comparing similarity comprehensive evaluation's result of humanoid robot arm motion and the reliability, similarity and dispersion based on static and dynamic comprehensive evaluation model, the proposed dynamic comprehensive evaluation method is more suitable for similarity comprehensive evaluation of humanoid robot motion.

# 1 Dynamic comprehensive evaluation method

Projection pursuit evaluation method is used for static comprehensive evaluation [12]. When the projection pursuit evaluation method is introduced into time information entropy and time degree to determine timing weight vectors [13], a dynamic comprehensive evaluation method is proposed. The multi-moments dynamic comprehensive evaluation model can be established by linearly weighting each time's static evaluation model's indexes weights according to the timing weighted vectors. The modeling process by the dynamic comprehensive evaluation is expressed as follows.

# 1.1 Normalization of index data set

When m is the number of evaluated objects and n is the number of evaluation index, the original data is expressed as  $\{x_{ij}^0 \mid i=1,2,\cdots,m; j=1,2,\cdots,n\}$ , and the normalized data is expressed as  $\{x_{ij} \mid i=1,2,\cdots,n\}$ ,  $\cdots,m; j=1,2,\cdots,n\}$ .

#### 1.2 Projection pursuit evaluation

When the projection direction (the index weight) is expressed as  $\boldsymbol{\omega} = (\omega_1, \omega_2, \dots, \omega_n)$ , the projection value (the comprehensive evaluation value) of the evaluated object i can be expressed as

$$y_i = \sum_{j=1}^n \omega_j x_{ij} \tag{1}$$

The calculation to optimal projection direction is achieved by solving the problem of projection index

function's maximization which is expressed as follows:

max 
$$Q = S(y)D(y)$$
  
s. t.  $\sum_{j=1}^{n} \omega_j = 1 \quad \omega_j \in [0,1]$  (2)

where S(y) is the projection value's standard deviation, D(y) is the local density, and Q = S(y)D(y) is the projection index function<sup>[14]</sup>.

# 1.3 Calculation of timing information entropy

Let the number of total time participating in evaluation be T. The timing weighted vectors are expressed as  $\boldsymbol{\rho}=(\rho_1,\,\rho_2,\cdots,\,\rho_T)$ , which reflects the contribution difference of each time's information to dynamic comprehensive evaluation. Among them,  $\rho_t\in[0,1]$ 

and  $\sum_{i=1}^{I} \rho_i = 1$ . The definition of timing information entropy with measurement  $\rho$  is shown as

$$I = -\sum_{t=1}^{T} \rho_t \ln \rho_t \tag{3}$$

The timing information entropy I is higher, the uncertainty reflected by  $\rho$  is higher.

### 1.4 Calculation of time degree

The time degree reflects the decision maker's attention to long-term data and short-term data. The definition of the time degree is defined as

$$\lambda = \sum_{i=1}^{T} \frac{T-t}{T-1} \rho_t \tag{4}$$

The time degree  $\lambda$  is lower, while the attention degree to short-term data is higher.

#### 1.5 Dynamic comprehensive evaluation model

The decision-maker gives the time degree  $\lambda$  in advance, and the timing weighted vectors can integrate each time's static evaluation model's information and consider the timing difference. The mathematical model can be expressed as

max I

s. t. 
$$\lambda = \sum_{t=1}^{T} \frac{T-t}{T-1} \rho_t$$
 (5)

 $\sum_{t=1}^{t} \rho_t = 1 \quad \rho_t \in [0,1]$ 

Eq. (5) is a common nonlinear constrained optimization problem. By linear weighting to each time's static model's indexes weight according to timing weighted vectors, the dynamic comprehensive evaluation model is established as follows:

$$\hat{y}_i = \sum_{j=1}^n W_j x_{ij} \tag{6}$$

where  $W_j = \sum_{t=1}^{r} \rho_t \omega_j(t)$ ,  $\omega_j(t)$  is the projection direc-

tion (the index weight) of evaluation index j in time section t,  $\hat{y}_i$  is the dynamic evaluation value of evaluated object i, and it is the ith experimenter's evaluation value.

evaluation method is used to comprehensively evaluate the similarity of humanoid robot arm motion, and its calculation flowchart is shown in Fig. 1.

# 2 Application of dynamic comprehensive evaluation method

In following sections, the dynamic comprehensive

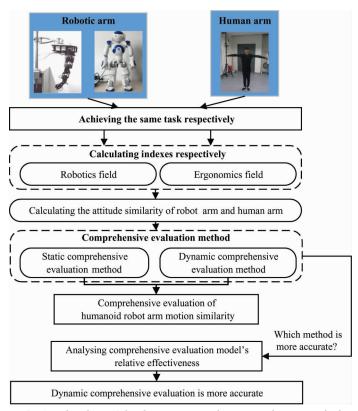


Fig. 1 Flowchart of the dynamic comprehensive evaluation method

#### 2.1 Indexes of humanoid robot arm motion

For two points in the same multi dimensional space, similarity of the variables represented by the two points can be usually evaluated by the distance between the two points. The shorter the distance is, the greater the similarity is. Based on this idea, the distance between two attitudes can be used to measure the similarity of attitudes. For a robot attitude and a human attitude, the distance between them is expressed as the  $dist({\bf R}, {\bf H})$ , and the similarity between the two attitudes is defined as

$$S(\mathbf{R}, \mathbf{H}) = \frac{1}{1 + dist(\mathbf{R}, \mathbf{H})}$$
 (7)

The value of  $S(\mathbf{R}, \mathbf{H})$  is between (0,1]. When  $dist(\mathbf{R}, \mathbf{H}) = 0$ , the similarity is the largest, and  $S(\mathbf{R}, \mathbf{H}) = 1$ .

2.1.1 Attitude similarity based on joint angle

Robot attitude and human attitude are expressed as  $\theta_r$  and  $\theta_h$  with the same N joint angles. The range of angle for the ith degree of freedom is  $[\theta_{ri\_max}, \theta_{ri\_min}]$ . The distance between robot attitude r and human attitude  $h^{[15]}$  is expressed as follows.

$$dist(\boldsymbol{\theta}_r, \boldsymbol{\theta}_h) = \left(\sum_{i=1}^{N} \| \frac{\boldsymbol{\theta}_{ri} - \boldsymbol{\theta}_{hi}}{\boldsymbol{\theta}_{ri, max} - \boldsymbol{\theta}_{ri, min}} \|^2 \right)^{\frac{1}{2}} (8)$$

2.1.2 Attitude similarity based on linkage's direction vector

It is different from the size and the proportion of skeleton's length between robot and human so that evaluating the attitude similarity by joint position is unreasonable. Based on linkage direction vector, the method of measurement to the attitude distance is designed. The distance between robot and human attitude [16], which are expressed as  $V_r$  and  $V_h$ , is expressed as follows:

$$dist(V_r, V_h) = \left(\sum_{i=1}^{N} \| \frac{1}{\|V_{ri}\|} V_{ri} - \frac{1}{\|V_{hi}\|} V_{hi} \|^2\right)^{\frac{1}{2}}$$
(9)

where, N is the number of the linkages,  $V_{ri}$  and  $V_{hi}$  are the robot and human ith linkage direction vector.

Attitude similarity based on minimum potential energy index

Potential energy includes gravitational potential energy  $f_{GPE}$  and elastic potential energy  $f_{EPE}$ . Therefore, the minimum potential energy index[17] is expressed as

$$f_{TPE} = f_{GPE} + f_{EPE}$$

$$= m_u g h_u + m_l g h_l + \frac{1}{2} k (\pi - \phi)^2 \qquad (10)$$

where,  $m_u = (0.088m_b - 1.8)/2$  is the mass of main arm,  $m_l = (0.044 m_b - 0.5)/2$  is the mass of fore $arm^{[18]}$ , g is acceleration of gravity,  $h_u$  is the height of main arm center of mass,  $h_l$  is the height of forearm center of mass,  $\phi$  is the rotation angle of elbow, k is the stiffness coefficient of torsion spring, and  $m_b$  is the mass of human.

If robot and human attitudes are respectively expressed as  $f_{\mathit{TPEr}}$  and  $f_{\mathit{TPEh}}$  , the distance between them is expressed as follows.

$$dist(\mathbf{f}_{TPEr}, \mathbf{f}_{TPEh}) = \|f_{TPEr} - f_{TPEh}\|$$
 (11)  
2.1.4 Attitude similarity based on comfort index

Psychophysics index<sup>[19]</sup> is for describing the dis-

comfort of joint. The specific equations are shown as follows:

$$\begin{cases} Psychophysical \_ cost \_function = \sum_{i=1}^{n} w_i \left( \frac{(\theta_i - \theta_{ci})^2}{\Delta \theta_i} \right) \\ \theta_{ci} = \frac{\theta_{i\min} + \theta_{i\max}}{2} \\ \Delta \theta_i = \frac{\theta_{i\min} + \theta_{i\max}}{2} - \theta_{i\min} \end{cases}$$

where,  $w_i$  is weight index,  $\theta_i$  is joint angle,  $\theta_{i\min}$  and  $heta_{i_{ ext{max}}}$  are joint rotation range, and  $heta_{ci}$  is the middle angle of each joint rotation range.

If robot and human attitudes are respectively expressed as Pcfr and Pcfh, the distance between them is

$$dist(\mathbf{P}cfr, \mathbf{P}cfh) = \left(\sum_{i=1}^{N} \|\mathbf{P}cfr - \mathbf{P}cfh\|^{2}\right)^{\frac{1}{2}}$$
(13)

#### Comprehensive evaluation model relative ef-2.2 fectiveness

At present, for solving the problem of comparing comprehensive evaluation non-uniformity and evaluation model effectiveness of the result, three relative effectiveness indexes of reliability, similarity, and dispersion<sup>[20]</sup> are often used. The higher the value of reliability and similarity is, the higher the accuracy of comprehensive evaluation result is, the lower the value of dispersion is, the higher the accuracy of comprehensive evaluation result is.

# Relative effectiveness based on reliability

The reliability<sup>[21]</sup> of comprehensive evaluation model means evaluation accuracy or reliability of result. The reliability coefficient indicates the reliability, which is expressed as

$$r = \sum_{j} \sum_{k} l_{jk} / \sum_{j} \sum_{k} \frac{(l_{jj} + l_{kk})}{2} (k > j)$$
 (14)

where  $X_i$  means the score of evaluated object in jth comprehensive evaluation model, and  $l_{ij} = (X_j - \bar{X})^2$  is the sum of squares of deviation from mean of  $X_i$  which expresses the square of the difference between the evaluated object score made by the jth expert and evaluated object average score, and  $l_{ik} = (X_i - \bar{X}_i)(X_k - \bar{X}_i)$ means the product of the difference between the evaluated object score made by the *j*th expert and the project average score, and the difference between the evaluated object score made by the kth expert and the object average score.

### 2.2.2 Relative effectiveness based on similarity

The similarity<sup>[22]</sup> is for measuring each evaluation results' similarity. The value of similarity can measure each comprehensive evaluation model relative effective-

The evaluated object has m evaluation models, and  $X_i$  ( $j = 1, 2, \dots, m$ ) expresses the order of evaluated object in the *j*th evaluation model, and the correlation coefficient can be calculated as

$$r_{jk} = 1 - 6 \sum_{i} d_i^2 / n(n^2 - 1) \quad (k = 1, 2, \dots, m)$$
(15)

where  $d_i$  is the *i*th evaluated object rank in the *j*th evaluation model,  $d_i = X_i - X_k$  is order difference value between the ith evaluated object rank in the jth evaluation model and its rank in the kth evaluation model. Then the average rank correlation coefficient of the jth evaluation model can be calculated as

$$R_{j} = \frac{1}{m-1} \sum_{j} R_{jk}(k = 1, 2, \dots, m)$$
 (16)

## 2.2.3 Relative effectiveness based on dispersion

The dispersion<sup>[23]</sup> is the measure index that expresses the difference of cognition to the evaluated object between one comprehensive evaluation model and other models. Comprehensive evaluation model dispersion can be measured by the average of the difference between one evaluation model result and other model results.

When the order of the *j*th evaluation model is the standard, if  $X_j = X_k$ ,  $D_{jk} = 1$ , else  $D_{jk} = 0$ , and j = 1,  $2, \dots, m$ . Therefore, the dispersion of the *j*th evaluation model can be expressed as

$$D_{j} = \frac{1}{m-1} \sum_{k=1}^{m-1} D_{jk} (j = 1, 2, \dots, m)$$
 (17)

# 3 Similarity comprehensive evaluation of humanoid robot arm motion

### 3.1 Experiments

Nao robot and Robairobotic arm are the objects for the simulation and experimental verification of the above static and dynamic comprehensive method. In the experiment, both Nao robot arm and human arm achieve the same drawing circle task, and both Robairobotic arm and human arm achieve the same going through the hole task. Both Nao robot and Robairobotic arm are controlled by using the RRT algorithm. Sixty volunteers averaged 23.2 years old participated in experiment. For the unified comparison, volunteer arms size data are transformed to the motion data in Nao robot joint configuration and Robairobotic arm joint configuration by BVH data, then humanoid motion similarity between the robot arm and human arm can be solved.

Experiment a is the drawing circle task. The circle position is relatively same for volunteers and the robot. Volunteers and the robot ratios of circle diameter

to arm length are the same. Both volunteers and the robot use same time and motion to draw a circle at constant speed. The movement is recorded every 0.1 s so that the process has totally 50 moments. Four moments of the process are shown in Fig. 2.

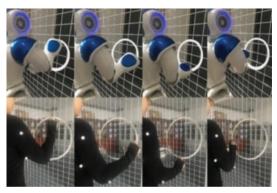


Fig. 2 The drawing circle task

Experiment b is the going through the hole task. The object position is relatively same for volunteers and Robairobotic arm. Both volunteers and Robairobotic arm begin at the same position, use same time and motion to go through the hole and pick up the eraser and then return to their initial position at constant speed. The movement is recorded every 0.14 s so that the process has totally 50 moments. Six moments of the process are shown in Fig. 3

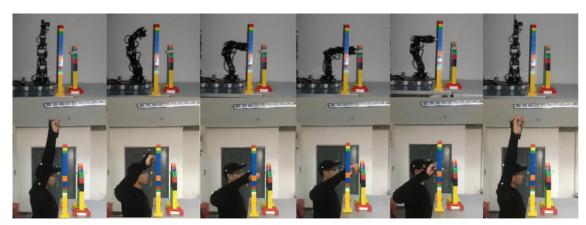


Fig. 3 The going through the hole task

# 3. 2 Static comprehensive evaluation based on projection pursuit evaluation method

When 60 volunteer arms and the robot arms do the drawing circle task and the going through the hole task, every task has been recorded in 50 moments, the value of each joint angle at each moment can be obtained. When establishing an evaluation sample, the

number of evaluated objects is 60 which is the ordinate of the evaluation sample matrix, the number of indexes is 4, and each index value  $x_1$ ,  $x_2$ ,  $x_3$ ,  $x_4$  is the average value of fifty moments' indexes, which is the abscissa of the evaluation sample matrix.

Standardizing the original evaluation sample matrix data, and optimizing the standardized data by particle swarm optimization according to Eq. (2), each

task optimum projection direction (the optimum index weight) can be solved. The drawing circle task optimum projection direction (the optimum index weight) is  $\omega = (0.3178, 0.2598, 0.1991, 0.2233)$  and the going through the hole task optimum projection direction (the optimum index weight) is  $\omega = (0.3054, 0.2981, 0.2014, 0.1951)$ . Based on the optimum projection direction, the static comprehensive evaluation model with two tasks, which is similarity comprehensive evaluation function of humanoid robot arm motion, is solved.

For the reaching point task, the grasping object task and the drawing circle task, the similarity comprehensive evaluation function of humanoid robot arm motion based on static evaluation model is shown as Eq. (18) and Eq. (19) respectively.

$$y_1 = 0.3178x_1 + 0.2598x_2 + 0.1991x_3 + 0.2233x_4$$

$$y_2 = 0.3054x_1 + 0.2981x_2 + 0.2014x_3 + 0.1951x_4$$
(19)

Substituting the drawing circle task and the going through the hole task sample data standardized into Eq. (18) and Eq. (19), the comprehensive evaluation results of humanoid robot arm motion similarity based on the static evaluation method can be solved (Fig. 4 and Fig. 5). The higher the value of evaluation result, the higher the similarity of humanoid robot arm motion. The realization of similarity comprehensive evaluation of humanoid robot arm motion proves the static evaluation method based on projection pursuit evaluation effectiveness to the similarity comprehensive evaluation of humanoid robot arm motion.

#### 3.3 Dynamic comprehensive evaluation

To the drawing circle task, the time degree is

0.7, which means that the recognition degree of short-term data is basically equal to long-term data. And to the going through the hole task, the time degree is 0.6, which means the recognition degree of short-term data is a little bit higher than that of long-term data.

Solving model in Eq. (5)'s by interior point method, timing weighted vector  $\boldsymbol{\rho} = (\rho_1, \rho_2, \dots, \rho_{50})$  in the drawing circle task and going through the hole task is solved in Table 1 and Table 2 respectively.

When 60 volunteers and the robot do the drawing circle task and the going through the hole task, every task has been recorded in fifty moments, the value of each joint angle at each moment can be obtained. Dynamic evaluation does linear weighting to each single index weight according to timing weighted vectors in Table 1 and Table 2, when establishing an evaluation sample, the number of evaluated objects is 60 which is the ordinate of the evaluation sample matrix, the number of indexes is 4, and each index value  $x_1$ ,  $x_2$ ,  $x_3$ ,  $x_4$  is the average value of fifty moment indexes, which is the abscissa of the evaluation sample matrix. For the dynamic comprehensive evaluation method, the weights of the  $x_1$ ,  $x_2$ ,  $x_3$ ,  $x_4$  indexes are the sum of each single index weight multiplied by the timing weighted vector, which is the difference between static comprehensive evaluation and dynamic comprehensive evaluation.

Based on Eq. (6), Eq. (18) and Eq. (19), the drawing circle task index weight is  $\omega = (0.3342, 0.2413, 0.2037, 0.2208)$ , and the going through the hole task index weight is  $\omega = (0.2379, 0.3165, 0.2388, 0.2077)$ . Therefore, the dynamic comprehensive evaluation model with two tasks, which is the similarity comprehensive evaluation function of humanoid robot arm motion, is solved.

	Table 1 Timing weighted vector in the drawing circle task									
$\rho_1$	0.0180	$oldsymbol{ ho}_{11}$	0.0189	$ ho_{21}$	0.0197	$ ho_{31}$	0.0205	$oldsymbol{ ho}_{41}$	0.0212	
$oldsymbol{ ho}_2$	0.0181	$oldsymbol{ ho}_{12}$	0.0190	$oldsymbol{ ho}_{22}$	0.0198	$oldsymbol{ ho}_{32}$	0.0206	$oldsymbol{ ho}_{42}$	0.0212	
$\rho_3$	0.0181	$oldsymbol{ ho}_{13}$	0.0191	$oldsymbol{ ho}_{23}$	0.0199	$ ho_{33}$	0.0206	$oldsymbol{ ho}_{43}$	0.0213	
$oldsymbol{ ho}_4$	0.0182	$oldsymbol{ ho}_{14}$	0.0192	$ ho_{24}$	0.0200	$ ho_{34}$	0.0207	$ ho_{ ext{44}}$	0.0213	
$ ho_5$	0.0183	$oldsymbol{ ho}_{15}$	0.0193	$ ho_{25}$	0.0201	$ ho_{35}$	0.0208	$ ho_{\scriptscriptstyle 45}$	0.0214	
$oldsymbol{ ho}_6$	0.0184	$oldsymbol{ ho}_{16}$	0.0194	$ ho_{26}$	0.0201	$ ho_{36}$	0.0209	$ ho_{ ext{46}}$	0.0214	
$oldsymbol{ ho}_7$	0.0185	$oldsymbol{ ho}_{17}$	0.0195	$oldsymbol{ ho}_{27}$	0.0202	$oldsymbol{ ho}_{37}$	0.0209	$oldsymbol{ ho}_{47}$	0.0215	
$oldsymbol{ ho}_8$	0.0186	$oldsymbol{ ho}_{18}$	0.0196	$ ho_{28}$	0.0202	$ ho_{38}$	0.0210	$oldsymbol{ ho}_{48}$	0.0215	
$ ho_9$	0.0187	$oldsymbol{ ho}_{19}$	0.0196	$ ho_{29}$	0.0203	$ ho_{39}$	0.0211	$ ho_{49}$	0.0216	
$ ho_{10}$	0.0188	$oldsymbol{ ho}_{20}$	0.0197	$ ho_{30}$	0.0204	$ ho_{\scriptscriptstyle 40}$	0.0211	$ ho_{50}$	0.0217	

	Table 2 Timing weighted vector in the going through the hole task									
$\rho_1$	0.0151	$ ho_{11}$	0.0169	$ ho_{21}$	0.0193	$ ho_{31}$	0.0214	$oldsymbol{ ho}_{41}$	0.0229	
$ ho_2$	0.0153	$oldsymbol{ ho}_{12}$	0.0172	$oldsymbol{ ho}_{22}$	0.0194	$oldsymbol{ ho}_{32}$	0.0216	$oldsymbol{ ho}_{42}$	0.0231	
$\rho_3$	0.0155	$ ho_{13}$	0.0174	$oldsymbol{ ho}_{23}$	0.0196	$oldsymbol{ ho}_{33}$	0.0218	$oldsymbol{ ho}_{43}$	0.0232	
$ ho_4$	0.0156	$oldsymbol{ ho}_{14}$	0.0176	$oldsymbol{ ho}_{24}$	0.0199	$oldsymbol{ ho}_{34}$	0.0219	$ ho_{ ext{44}}$	0.0234	
$ ho_5$	0.0157	$ ho_{15}$	0.0179	$oldsymbol{ ho}_{25}$	0.0201	$ ho_{35}$	0.0221	$ ho_{45}$	0.0237	
$ ho_6$	0.0159	$ ho_{16}$	0.0183	$ ho_{26}$	0.0204	$ ho_{36}$	0.0222	$oldsymbol{ ho}_{46}$	0.0238	
$ ho_7$	0.0161	$ ho_{17}$	0.0185	$oldsymbol{ ho}_{27}$	0.0206	$oldsymbol{ ho}_{37}$	0.0223	$oldsymbol{ ho}_{47}$	0.0240	
$ ho_8$	0.0163	$ ho_{18}$	0.0187	$oldsymbol{ ho}_{28}$	0.0209	$ ho_{38}$	0.0224	$ ho_{48}$	0.0242	
$ ho_9$	0.0165	$ ho_{19}$	0.0189	$ ho_{29}$	0.0210	$ ho_{39}$	0.0226	$ ho_{49}$	0.0244	
$oldsymbol{ ho}_{10}$	0.0167	$oldsymbol{ ho}_{20}$	0.0191	$ ho_{30}$	0.0213	$oldsymbol{ ho}_{40}$	0.0227	$ ho_{50}$	0.0246	

For the drawing circle task and the going through the hole task, the similarity comprehensive evaluation function of humanoid robot arm motion based on dynamic evaluation model is shown as Eq. (20) and Eq. (21) respectively.

$$\hat{y}_1 = 0.3342x_1 + 0.2413x_2 + 0.2037x_3 + 0.2208x_4$$

$$\hat{y}_2 = 0.2379x_1 + 0.3165x_2 + 0.2388x_3 + 0.2077x_4$$
(21)

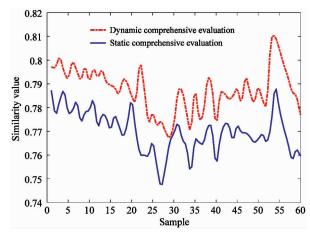
Substituting the drawing circle task and the going through the hole task sample data standardized into Eq. (20) and Eq. (21), the similarity comprehensive evaluation results of humanoid robot arm motion based on dynamic evaluation method can be solved in Fig. 4 and Fig. 5 respectively. The higher the value of evaluation result, the higher the humanoid robot arm motion similarity. The realization of similarity comprehensive evaluation of humanoid robot arm motion, proves the effectiveness of dynamic evaluation method proposed to the similarity comprehensive evaluation of humanoid robot arm motion.

# Comparison of static and dynamic comprehensive evaluations

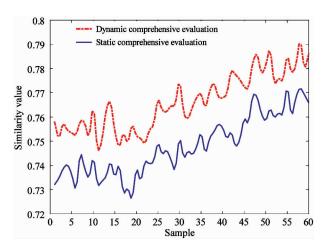
### Comparison of results

For the drawing circle task and the going through the hole task, comparison of similarity comprehensive evaluation results of humanoid robot arm motion between static evaluation model and dynamic evaluation model are illustrated in Fig. 4 and Fig. 5 respectively.

Both results based on static evaluation model and dynamic evaluation model in Fig. 4, and Fig. 5 have basically the same tendency which are also in high level, proving the effectiveness of static evaluation method and dynamic evaluation method applied to similarity comprehensive evaluation of humanoid robot arm motion. However, the similarity based on dynamic evaluation model has higher value, which means its humanoid robot arm motion similarity is in higher level. Because dynamic evaluation model includes the dimension of time, doing linear weighting to each humanoid motion index weight according to timing weighted vectors, and shows the relationship between indexes importance and time more clearly.



Comparison results of drawing circle task



Comparison results of going through the hole task

#### Comparison of relative efficiency

Based on Eq. (14), Eq. (16) and Eq. (17), the reliability, similarity, and dispersion of static evaluation model and dynamic evaluation model can be calculated.

For the drawing circle task and the going through the hole task, comparison of reliability, similarity, and dispersion between static evaluation model and dynamic evaluation model can be illustrated in Fig. 6 and Fig. 7 respectively.

It shows that, the reliability and similarity of dynamic evaluation method is higher than those of static evaluation method, and the dispersion of dynamic evaluation method is lower than static evaluation method, so the dynamic comprehensive evaluation result has better accuracy and stability and lower dispersion, and the result is more reasonable and real. Compared with the static evaluation method, dynamic comprehensive evaluation method is more suitable for similarity comprehensive evaluation of humanoid robot arm motion, and it is meaningful for humanoid robot motion design to be highly similar to human action and will help to promote the development of humanoid robot research.

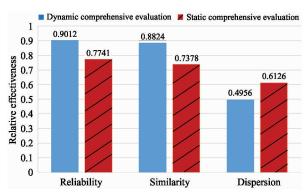


Fig. 6 Comparison of relative efficiency of the drawing circle task

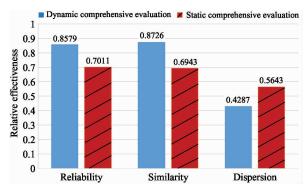


Fig. 7 Comparison of relative efficiency of going through the hole task

#### 5 Conclusion

For different robotic arms, based on indexes of humanoid robot arm motion in robotics and ergonomics field, based on the projection pursuit evaluation with timing information entropy and time degrees, a dynamic

comprehensive evaluation method of similarity of humanoid robot motion is proposed. Through comparing the humanoid robot arm motion similarity comprehensive evaluation result and the reliability, similarity, and dispersion of static evaluation model and dynamic evaluation model, the consequence shows that the dynamic comprehensive evaluation result has better accuracy and stability and lower dispersion, and the result is more reasonable and real.

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