Human Motion Capture Based on Incremental Dimension Reduction and Projection Position Optimization

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Three-dimensional (3D) human motion capture is a hot researching topic at present. The network becomes advanced nowadays, the appearance of 3D human motion is indispensable in the multimedia works, such as image, video, and game. 3D human motion plays an important role in the publication and expression of all kinds of medium. How to capture the 3D human motion is the key technology of multimedia product. Therefore, a new algorithm called incremental dimension reduction and projection position optimization (IDRPPO) is proposed in this paper. This algorithm can help to learn sparse 3D human motion samples and generate the new ones. Thus, it can provide the technique for making 3D character animation. By taking advantage of the Gaussian incremental dimension reduction model (GIDRM) and projection position optimization, the proposed algorithm can learn the existing samples and establish the relevant mapping between the low dimensional (LD) data and the high dimensional (HD) data. Finally, the missing frames of input 3D human motion and the other type of 3D human motion can be generated by the IDRPPO.

1. Introduction

Three-dimensional (3D) human motion capture is applied for many fields, such as medical diagnosis, animation making, and 3D video game development [1–3]. How to generate the human motion in 3D becomes curial to these works. Human motion in 3D is depicted by high-dimensional (HD) data, and the motion sequence consists of poses. Each pose can be exhibited by a human motion model. One complete motion cycle is called a gait.

3D human motion capture has been developed into a hot researching topic. How to generate the human motion in 3D has various techniques. One of the hot techniques is the reconstruction of 3D human motion from the image sequence, which needs some complex preprocessing methods to extract the image feature and analyze feature sample, such as video event analysis [4] and video feature analysis [5]. Another one is 3D human motion estimation of self-supervised learning (GIDRM) and projection position optimization, the proposed algorithm can learn the existing samples and establish the relevant mapping between the low dimensional (LD) data and the high dimensional (HD) data. Finally, the missing frames of input 3D human motion and the other type of 3D human motion can be generated by the IDRPPO.
2. Generation of Human Motion through IDRPO

2.1. Gaussian Incremental Dimension Reduction Model

According to the references above, the models can be given as follows [7, 12]:

1. Address the problem of filling the missing frames in the incomplete motion cycle and make the motion cycle complete and smooth

2. Address the problem of generating the other type motion cycle from the origin incomplete motion cycle by the help of the IDRPO

The performance of the IDRPO will be tested from the experiments, and the results will indicate the IDRPO can help to achieve the promising visual effect and low estimating error for human motion capture. The technique framework of IDRPO can be seen in Figure 1. Then, the details of IDRPO will be discussed in the following sections.
where $\Phi \in \mathbb{R}^{N_{K} \times N}$ is radial basis function, $\Phi_{h, k_{2}} = \phi(y_{k}, c_{k}) = \exp (\frac{1}{2} ||y_{k} - c_{k}||^2)$. $W_{D} \in \mathbb{R}^{N_{k} \times q}$ is the weight matrix, $N_{k} \leq N$. $W_{D}$ is least squares estimator, $\hat{W}_{D} = (\Phi^{T} \Phi)^{-1} \Phi^{T} X$. Then, $y^{*} \in \mathbb{R}^{D}$ denotes the new HD data sample, $x^{*} \in \mathbb{R}^{D}$ denotes the LD data of $y^{*} \in \mathbb{R}^{D}$. If $b$ is known, the mapping from $y^{*}$ to $x^{*}$ can be given as follows:

$$x^{*} = g(y^{*}) = (\Phi(y^{*}) W_{D})^{T} = W_{D}^{T} (\Phi(y^{*}))^{T},$$ (6)

where $\Phi(y^{*}) = [\phi(y^{*}, c_{1}), \phi(y^{*}, c_{2}), \ldots, \phi(y^{*}, c_{N})]$, then we can get the equation as follows:

$$X = \Phi \hat{W}_{D} + e.$$ (7)

In Equation (7), $e \in \mathbb{R}^{N_{k} \times N}$ is the error matrix, let $e = [e_{1}, \ldots, e_{N_{k}}, \ldots, e_{N}]^{T} = [e_{1}, \ldots, e_{N_{k}}, \ldots, e_{N}]^{T}$. Then, $X = [x_{1}, \ldots, x_{N_{k}}, \ldots, x_{N}]^{T} = [x_{1}, \ldots, x_{N_{k}}, \ldots, x_{N}]^{T} \in \mathbb{R}^{N_{k} \times q}$, $\hat{W}_{D} = [w_{1}, \ldots, w_{N_{k}}, \ldots, w_{N}]^{T} = [w_{1}, \ldots, w_{N_{k}}, \ldots, w_{N}]^{T} \in \mathbb{R}^{N_{k} \times q}$, and $\Phi = [\varphi_{1}, \ldots, \varphi_{N_{k}}, \ldots, \varphi_{N}] \in \mathbb{R}^{N_{k} \times N}$. Let $\Phi = \Phi W_{A}$, and $\hat{W} = [\hat{w}_{1}, \ldots, \hat{w}_{N_{k}}, \ldots, \hat{w}_{N}] \in \mathbb{R}^{N_{k} \times N}$ is a diagonal matrix $\hat{A}_{i,j} = a_{i,j}$. $A_{i,j} = 0$, otherwise.

We have $W_{D} = (\Phi^{T} \Phi)^{-1} \Phi^{T} X$, then let $g = (W^{T} W)^{-1} W^{T} X$ and $\hat{g} = [\hat{g}_{1}, \ldots, \hat{g}_{N_{k}}, \ldots, \hat{g}_{N}]^{T} = [\hat{g}_{1}, \ldots, \hat{g}_{N_{k}}, \ldots, \hat{g}_{N}]^{T} \in \mathbb{R}^{N_{k} \times q}$. The equation can be got as follows:

$$\Phi \hat{W}_{D} = \Phi (\Phi^{T} \Phi)^{-1} \Phi^{T} X = \hat{W} \hat{A} (\hat{A}^{T} \hat{W}^{T} \hat{W} \hat{A})^{-1} \hat{A}^{T} \hat{W}^{T} X = W \hat{W}^{T} X = W \hat{g}.$$ (8)

Thus, Equation (8) can be written as:

$$X = \hat{W} \hat{g} + e.$$ (9)

According to the properties of least squares, $\hat{W}^{T} e = 0, e^{T} \hat{W} = 0$, we have:

$$X^{T} X = (\hat{W} \hat{g} + e)^{T} (\hat{W} \hat{g} + e)$$

$$= g^{T} W^{T} W \hat{g} + g^{T} W^{T} e \hat{g} + e^{T} \hat{g} + e^{T} e$$

$$= g^{T} W^{T} W g + e^{T} e,$$

where $\mu$ is the bias and $\sigma^{2}$ is the variance of Gaussian distribution $y \sim N(\mu, \sigma^{2})$, $y \in \mathbb{R}^{D}$, $x \in \mathbb{R}^{q}$, the mapping from HD space to LD space can be built as follows:

$$y = f(x) = \mu(x) = Y^{T} K_{Y}^{-1} [k_{Y}(x, x), k_{Y}(x, x), \ldots, k_{Y}(x, x)]^{T}$$

$$= Y^{T} K_{Y}^{-1} K_{Y}(x).$$ (4)

If two or more mappings from LD space to HD space need to be built, Equation (3) can be retrained according to the needs. After building the first mapping, the LD data from the first mapping can be fixed, which can be seen as the initial LD data of the second mapping training.

Then, the mapping of the incremental dimension reduction is built as follows:

$$X = \Phi \hat{W}_{D},$$ (5)
where $e^T e = X^T X - g^T W^T W g$. When training, the $N_k$ orthogonal vectors can be replaced; the equation can be got as follows:

$$
\min \left( \frac{1}{(N \times q)} \right) = \min \left( \frac{1}{(N \times q)} \right)
$$

Equation (11) is equivalent to the equation as follows:

$$S_w = \arg \max \left( \frac{1}{(N \times q)} \right) = \min \left( \frac{1}{(N \times q)} \right)
$$

In the above equation, $S_w = \{\tilde{w}_1, \cdots, \tilde{w}_{k_1}, \cdots, \tilde{w}_{N_k}\}$ and $S_w' = \{\tilde{w}_1', \cdots, \tilde{w}_{k_1}, \cdots, \tilde{w}_{N_k}\}$ both contain the set of orthogonal vectors. $S_w$ is the subset of $S_w'$, $S_w'$ is the set containing $\Phi^k_{k_1}$ which is the vector from $\Phi' = [\tilde{q}_1', \cdots, \tilde{q}_{k_1}', \cdots, \tilde{q}_{N_k}'] \in R^{N_\text{ld} \times N}$, then $\Phi^k_{k_1} = \phi(y_{k_1}) \in R^{N_\text{ld} \times N}$.

The training requires $\frac{1}{(N \times q)} < \epsilon_1, \epsilon_2 > 0$ is satisfied, the training can be finished. It means that the vector $\Phi_{k_1}^k$ is selected as few as possible to minimize the variable $NK$ for the satisfaction of the tolerance, so that the mapping training can be finished.

### 2.2 Projection Position Optimization

The learning of the incomplete gait of human motion needs projection position optimization in the LD space. Let us give some definitions: $\text{Prj}_{AB}$ denotes the projected operation of vector $AB$, $AB$ is the first known LD data before the missing human motion sequence, $B$ is the last known LD data after the missing human motion sequence, and $C_i, i = 1, 2, \cdots, N_{\text{miss}}$ denotes the LD data of the missing frames. According to Figure 2, we have:

$$\text{Prj}_{AB} \frac{AB}{N_{\text{miss}} + 1} = 0, \tag{13}$$

$$\text{Prj}_{AB} \frac{AB}{N_{\text{miss}} + 1} = 0. \tag{14}$$

After dimension reduction, $c$ in Equation (14) is a preset parameter which denotes the distance between the missing dot and projection dot in Figure 2. The position of missing frames should satisfy Equation (13) and Equation (14); thus, Equation (3) can be trained optimally during the second training. Then, according to Equation (13) and Equation (14), the objective function and gradient function can be got respectively, as follows:

$$\min F(X_{\text{miss}}) = \frac{N_{\text{miss}}}{i=1} \left( \frac{\text{Prj}_{AB}(x_i - A) - \frac{1}{(N_{\text{miss}} + 1)} \frac{AB}{N_{\text{miss}} + 1}}{AB} \right)^2 \tag{15}$$

$$\frac{dF(X_{\text{miss}})}{dx_i} = 2 \left( \frac{\text{Prj}_{AB}(x_i - A) - \frac{1}{(N_{\text{miss}} + 1)} \frac{AB}{N_{\text{miss}} + 1}}{AB} \right) \frac{AB}{AB} + \frac{2 \left( \frac{||x_i - \text{Prj}_{AB}(x_i - A)||}{AB} \right) \frac{AB}{AB} - c(\frac{1}{(N_{\text{miss}} + 1))}}{AB} \tag{16}$$

From Equation (16), $AB = \frac{AB}{AB} \frac{AB}{AB} \frac{AB}{AB} \frac{AB}{AB} \frac{AB}{AB} \frac{AB}{AB} \frac{AB}{AB}$, “*” denotes product of the entry of matrix. The solution of Equation (15) will not be a unique solution, but any of the solutions can keep the relative position of each missing frame in the LD space during training. Thus, the second training can
obtain the LD data samples of missing frames. The solution of Equation (15) can be got by some traditional gradient optimization methods [23].

2.3. The Procedure of Generating the Human Motion. Some definitions are listed as follows: $Y_I$ and $Y_{II}$ are denoted as HD data sample sequences of type I and II human motions, respectively; $Y_I$ contains the missing frames; $X_1$ and $X_2$ are denoted as the LD data sequences of $Y_I$ and $Y_{II}$, respectively; $y_I'$ and $y_{II}'$ are denoted as the new HD samples of type I and II human motions, respectively. Then, the procedure of generating the human motion is summarized as follows:

Figure 3: The visual comparison of generating the human running motion between IDRPOPO and IDRNPPO.
Equation (3) can be used to process the $Y_I$ which is containing missing frames for dimension reduction; then, $X_1$ and corresponding training parameters can be obtained (the external and internal iteration numbers of this step are set to $S_{11}$ and $S_{12}$, respectively).

Adopt the projection position optimization to process $X_1$. It is equivalent to minimize Equation (15) by the help of Equation (16) (the iteration number of this step is set to $S_{21}$). 

The training parameters in step 1 and $X_1$ processed in step 2 can be took into Equation (3) for the second training, then the training parameters, the updated $X_1$ and mapping $f_1$ from $X_1$ to $Y_I$ can be obtained. The missing frames in the $Y_I$ can be generated from $X_1$ processed in step 2. Build the mapping $g$ from $Y_I$ to $X_1$ through Equation (5) next (the external and internal iteration numbers of building $f_1$ are set to $S_{31}$ and $S_{32}$, respectively, the iteration numbers of building $g$ is set to $N_k$ ($N_k \leq N$)).

Build the mapping $f_2$ from $X_1$ to $Y_{II}$ through Equation (3), $X_1$ is obtained from step 3, and $X_1$ is fixed during this training. After finishing the training of Equation (3), the mapping $f_2$ can be obtained (the external and internal iteration numbers of building $f_2$ are set to $S_{41}$ and $S_{42}$, respectively).

When there comes $y_{II}^{\prime}$, $y_{II}^{\prime\prime}$ can be generated by the equation $y_{II}^{\prime\prime} = f_2(g(y_{II}^{\prime}))$.

The computational complexity of the whole algorithm is depending on the iteration number of each step usually. The computational complexity is denoted by $O(\cdot)$, which is mainly described by the time frequency. If the data preprocessing and matrix calculation are without consideration, as the result of which are not the core steps of proposed algorithm, we can get the computational complexity is $O(S_{11}S_{12} + S_{21} + S_{31}S_{32} + N_k + S_{41}S_{42})$. Thus, the computational complexity is depending on each iteration number which can reach the max iterative magnitude.

### 3. Experiment and Evaluation

Some heuristic algorithms and dimension reduction models cannot generate one type human motion from the other type mostly. How to optimize the projection position is the key to the generation of human motion. Thus, the algorithm using incremental dimension reduction with no projection position optimization can be called IDRNPPO. IDRNPPO and IDRPPO will be used to generate the human motion for the experimental tests. In the experiments, the visual effect and error from the missing frames and generated poses will be the evaluation criterion of the performance. The missing frames can adopt the walking motion, and the generated motion can adopt running motion which will be generated by the walking motion. Our test environment is listed as follows:

- CPU: i7-9750H
- RAM: 16GB
- GPU: Nvidia GTX 1660Ti 6GB
- HD: 1.5TB solid state disk
- Software: MATLAB R2009b

#### 3.1. The Visual Comparison

IDRPPO and IDRNPPO are used to generate the human running motion, respectively, when the input incomplete motion is walking. The results can be seen in Figures 3 and 4.

From Figure 3, the human running poses from IDRPPO are better than the ones from IDRNPPO in the visual effect. The 30th, 35th, 40th, 45th, 48th, 52nd, and 58th frames from the IDRNPPO are the same, which cannot constitute the smooth motion sequence to show the running process. Furthermore, from Figure 4, the missing frames in the input motion from IDRNPPO are the same, which cannot display the missing smooth walking sequence. However, the running motion and the missing walking motion from the
IDRPPO are very smooth, which are constituting the ideal sequences of running motion and the missing walking motion, respectively. The running time testing results are reported in Table 1. From Table 1, when generating the running motion, the IDRNPPO consumes 7.83 seconds, and the IDRPOPO consumes 7.96 seconds; thus, the running times of both are close. Then, when generating the missing walking motion, the running times of both are also close, the IDRNPPO is 2.15

| Test type    | Test content                                      | IDRNPPO | IDRPOPO |
|--------------|---------------------------------------------------|---------|---------|
| Visual test  | Generating running motion                         | 7.83    | 7.96    |
|              | Generating missing walking motion                  | 2.15    | 2.13    |
| Error test   | Generating running motion and missing walking motion| 8.28    | 9.51    |

Table 1: The running time test (seconds).

![Figure 5: The LD data of the missing frames in LD space.](image)

(a) The LD data of the missing frames from IDRNPPO (green ones)  
(b) The LD data of the missing frames from IDRPOPO (green ones)

![Figure 6: The error comparison of IDRPOPO and IDRNPPO.](image)

(a) The error of generating running motion  
(b) The error of generating the missing walking motion

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seconds, and the IDRPPO is 2.13 seconds. From the running time test, it can be found that the IDRPPO will not be time-consuming relatively. In Figure 5, the LD data of missing frames from IDRNNPPO and IDRNPPO are obviously different, which are denoted by the green ones in Figure 5(a) and Figure 5(b), respectively. The ones of IDRNNPPO are without projection position optimization. They are becoming a mess curve, which are difficult to be distinguished. On the contrary, the ones of IDRPPO are very neat and smooth, which can constitute the missing part from the whole curve. The results of Figure 5 can also explain why the missing frames of IDRPPO will be the smooth motion sequence in another aspect. On the whole, Figures 3, 4, and 5 can indicate IDRPPO has better performance than IDRNNPPO.

3.2. The Error of the Generation. The IDRPPO and IDRNPPO can be seen in Figure 6, respectively. How to calculate error can be seen in [24]. From Figure 6, the errors of the human running motion and the missing walking motion from IDRPPO are lower than IDRNPPO on the whole. It is the normal phenomenon that some frames of both have the close error in Figure 6(a), because some frames of IDRNPPO can display the running motion correctly. However, the tendency of errors can be evaluated by mean error. The mean error from IDRPPO is lower than IDRNPPO as depicted in Figure 6(b). From Table 1, it can be found that the runtime testing results are 8.28 seconds (IDRNNPPO) and 9.51 seconds (IDRNPPO), respectively. The small gap of the required running times for both will also be indicated. Finally, the results of Figure 6 can illustrate the IDRPPO performance of generating the motion is better than the IDRNNPPO again.

4. Conclusion

The IDRPPO is proposed to obtain the 3D human motion. IDRPPO with the GIDRM can help to learn the incomplete gait, and generate the other gait, which makes up the defects of some self-supervised or unsupervised algorithms. From the experiments, the projection position is crucial to the performance of IDRPPO. The experimental results can reveal IDRPPO is efficacious in making 3D human character animation, which can do great help to generating the motion cycle fast. IDRPPO can promote the small-scale self-supervised or unsupervised learning undoubtedly. However, IDRPPO cannot process the complex and irregular human motion samples, which will be improved in the future research. The human motion model can be replaced by a more advantaged model [25], so that the high-level multimedia product can be made by this technique.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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