Networked Human Motion Capture System Based on Quaternion Navigation *

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ABSTRACT

In this paper, from the perspective of human ergonomics, we analyze the movement of the joints in the process of human body movements, and we establish a dynamic model according to the human skeleton structure. On this basis, from the rigid body dynamics point of view, combined with the principle of inertial navigation, a body sensor network based on MEMS inertial sensors is built to capture human body motion in real time. On the basis of space trajectory of human body movement and traditional human motion solution strategy, a human motion solution strategy based on particle filter fusion solution is proposed to realize the prediction of human motion analysis. Therefore, we evaluate the performance of the designed system by comparing with the real motion. Finally, in order to verify the human motion data, the motion capture data verification platforms are established. Experimental results show that the proposed joint attitude solution algorithm can achieve a relatively smooth tracking effect and provides a certain reference value.

Keywords

motion capture; inertial navigation; particle filter; body sensor network

1. INTRODUCTION

The behavior of all kinds of human actions are the embodiment of their physiological reaction mechanism and thinking consciousness. If it is possible to capture the process of human motion and physiological signals without the constraints of time and space, then according to captured results of human action, we can record, simulate and scale the human action process to analyze the details of the behavior of action process, simulate or reconstruct human action process, and evaluate the physiological function of target object. Therefore, according to captured results, we can make real-time identification for various types of behavior, understand the intention of the behavior about objects, get their behavior habits, and realize natural interaction between human and machine [1]. Throughout the applicability of human motion capture, it has a wide range of practical applications, such as human-computer interaction [2], film and television

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production [3], interactive game [4], sports training [5], and medical rehabilitation [6].

At present, human motion capture is mainly realized by optical principle. The history of motion capture began in the Chinese Warring States period with the traditional "shadow" theatre which represents the earliest optical motion capture technology. It uses light projection to project the motion of model onto a translucent screen, thus forming a lifelike character image [7]. State-of-the-art optical motion capture method has high precision and real-time performance, but its cost is too high and it is inconvenient to carry. Furthermore, it is easily influenced by light conditions, perspective, shadow, occlusion, scene and other factors [8].

With the development of micro-electromechanical systems, wireless communication and sensor network technology, wireless body sensor network (BSN) [9] [10] - a kind of wireless sensor network (WSN) - are becoming more and more popular. A BSN is composed of multiple sensor nodes (each capable of data acquisition, processing and communication) placed on different parts of human body. BSNs are being gradually applied in the human body motion capture field and inertial motion capture has become a new research hotspot [11]. The inertial motion capture technology is not affected by occlusions and illumination effects, and can be used both indoors and outdoors, so it is easier to achieve all-weather, unlimited motion capture [12]. However, it also has disadvantages; for example, number of sensors, layout and performance, and attitude solution algorithm can affect the accuracy, dynamic characteristics and stability of motion capture [13]. To overcome the limitations of current inertial motion capture, many domestic and foreign scholars have proposed different methods to solve these problems. For instance, Roetenberg et al. [14] proposed a compensation Kalman filter algorithm; Bachmann [15] proposed a Kalman filter algorithm based on quaternion, et al. But at present, the algorithms still have some limitations.

This paper aims at improving current state of the art methods. First, a microprocessor network intelligent motion capture node combined with an inertial sensor is designed. Furthermore, a motion sensing network composed of sensor nodes distributed on the human body is established to collect sensor data from different parts of the body. A particle filter fusion method is also proposed based on strap-down inertial navigation system by considering the complexity of the algorithm and interference effects. By using the parallel solution of each node, real-time performance of the attitude solving process is improved. With the aid of the high-speed wireless data channel, a kind of real-time wireless attitude data transmission protocol is established. Finally, according to the theory of computer graphics, we completed the real-time capture of human body motion attitude by using the captured attitude data to drive the human body model in host computer, and we built the MATLAB and Visual Studio attitude capture data verification platform to validate the motion captured data, which further improved the performance of our system.

2. METHODOLOGY

2.1 Human Body Model

Human body model is a kind of graphical description of human form by abstracting out the structure of the human body in the field of motion capture. Using the captured data

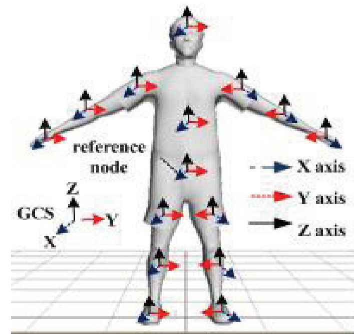

Figure 1: Definition of the human body coordinate system

obtained by tracking equipments, it is possible to simulate the movement of the human body mode.

In this paper, on the basis of human body biomechanics structure, referring to the idea of the surface model [16], the human body is divided into 15 major bone segments: pelvis, left thigh, right thigh, left calf, right calf, left foot, right foot, lumbar spine, the head, right arm, left arm, right elbow, left elbow, right hand, left hand respectively. The bones are connected through joints. Then, we set the pelvis as the reference node and traverse the skeleton structure by inverse kinematics principle. Finally, we define the human body coordinate system based on three-dimensional kinematic theory, as shown in Fig. 1. For convenience, we define Global Coordinate System GCS, Body Coordinate System BCS, and Sensor Coordinate System SCS.

Through the definition of the human body motion structure, in this paper, 3D human skeleton files based on the triangular mesh by 3Dmax are established, as shown in Fig. 2.

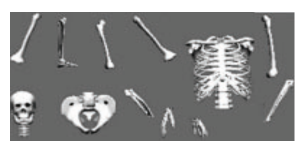

Figure 2: Scattered human skeleton model

In order to build a complete human model, we combine the Visual Studio integrated development environment with the OPENGL graphical program interface to load the skeleton files, so the scattered bones are finally assembled into a complete model of the human body by matrix operation. Fig. 3 depicts the 3D human body motion tracking platform constructed in this paper.

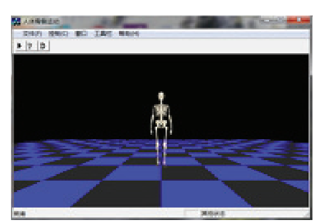

Figure 3: 3D human motion tracking platform

2.2 Design of the BSN-based motion capture system

In this paper, the network is composed of a sink node and multi-sensor nodes. Sensor nodes collect, deal with the attitude information in the process of human movement, and communicate with the sink node through high CAN bus. The sink node packages the whole data from the sensor nodes and passes them to the host computer through WiFi. The sensor network structure is shown in Fig. 4.

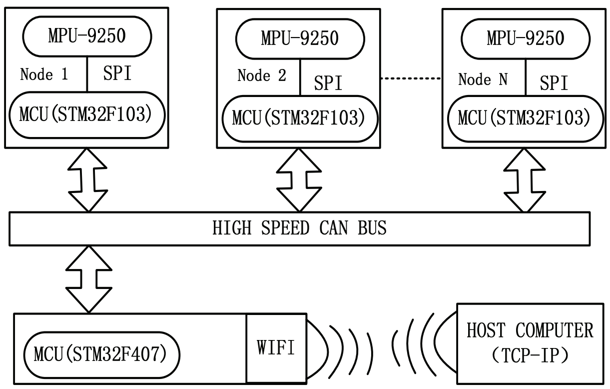

Figure 4: Structure of the BSN motion capture system

The sensor node, shown in Fig. 5, which is composed of a nine-axis inertial sensor (MPU9250) and a microprocessor (STM32F103T8U6). The inertial sensor integrates a three-axis accelerometer with a range of ±16 g, a three-axis gyroscope with a range of ±2000 dps, and a three-axis magnetometer with a range of ±12 gauss. SPI interface allows high-speed sampling rate up to ±18 MHZ. The main frequency of the microprocessor is up to 72 MHZ, which can achieve high-speed sensor data processing. Such design can reduce the physical dimension of the node and increase the processing speed. The sink node, shown in Fig. 5, is composed of 32 bit microcontroller (STM32F407) and MIX-CHIP EMW3162 WiFi module. The sink node can receive the attitude data from sensor nodes in real time through high speed CAN bus and it forwards the packed data to the host computer by WiFi wireless data channel (TCP-IP).

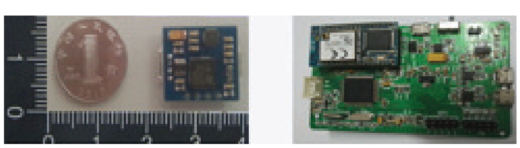

Figure 5: Sensor node and Sink node

2.3 Body orientation estimation

According to the theory of spatial kinematics, the motion of human body can be expressed as a combined rotation from bone to space. In the present study of human navigation, we always use Euler angle, rotation matrix or quaternion to express the space movement of body. However, there is a singularity in the Euler angle during the rotation, which leads to the gimbal lock [17]; relatively speaking, the rotation matrix requires complex trigonometric function calculation, which takes a longer period of time. In order to improve the calculation efficiency, we use quaternion to express the space movement of body.

A quaternion is usually composed of a four-dimensional vector, which is in turn composed of an imaginary part $q_v = [q_x, q_y, q_z]^T$. and a real (scalar) part $q_w \in R$.

$$q = [q_w, q_v]^T = [q_w, q_x, q_y, q_z]^T \tag{1}$$

with $q_w^2 + q_x^2 + q_y^2 + q_z^2 = 1$. Any 3D rotation can be represented by a unit quaternion q. For example, given a point $p[x, y, z]$, we can build a quaternion $P[0, p]^T$. Given a unit vectorη , which is the desired axis, andθ , the desired angle of rotation, we build the quaternion $q = [q_w, q_v]$, where $q_w = \cos(\theta/2)$ and $q_v = \eta \sin(\theta/2)$. Then the process of this point revolves around the rotation axis of θ angle can be expressed as:

$$P_{rotate} = q * P * q^{-1} \tag{2}$$

Where $*$ represents quaternion multiplication and q^{-1} is the inverse quaternion of q. In order to smooth the motion between two frames, we need to interpolate the quaternions of frame t and t-1 using the Slerp function [18] by an amount $\lambda \in [0, 1]$.

$$Slerp(q_t, q_{t-1}, \lambda) = q_t \frac{\sin(1-\lambda)\varphi}{\sin\varphi} + q_{t-1} \frac{\sin(\lambda)\varphi}{\sin\varphi} \tag{3}$$

Where q_t and q_{t-1} are concatenated frames, furthermore, $\varphi = \cos^{-1}(q_t, q_{t-1})$. In order to express the segment kinematics of motion reconstruction, the relationship between the sensor attached to the segment and the corresponding joint of the segment needs to be established. Let us set the lower limbs as an example (see Fig. 6). Then, thigh and leg are expressed by F_i and F_{i-1} respectively, BCS r_{i-1}, r_i, r_{i+1} are calibrated on the 3 joints of the lower limbs. Sensor node are distributed on the surface of thigh, and calibrate SCS. For initialization, performers are required to perform a special gesture: the T-pose [19]. For frame t, we could estimate the sensors global orientation by fusing the sensor data with the fusion algorithm. However, q_t^{gs} cannot directly represent segment orientation as SCS and BCS are not exactly matched. We have to determine the global orientation of each bone segment q_t^{gr} by matching the orientation of the sensor q_t^{gs} with the transformation from SCS to BCS q_t^{rs} . As the relative relationship between SCS to BCS keeps constant during the movement, so q_t^{rs} is a fixed constant, and, so

$$q_t^{gr} = q_t^{gs} * (q_0^{rs})' \tag{4}$$

2.4 Motion Estimation by the Fusion of Sensor Data

In this paper, based on heterogeneous multi-sensor data fusion,such as complementary filter and kalman filter [17], [20], we design a quaternion attitude solution strategy based on particle filter. Algorithm execution flow chart is shown in Fig. 7. First, in the process of human motion, for each bone segment, we define a state variable x, the state variable contains two parameters: 1) the vector part of quaternion q^T 2) the gyro drift β^T, then the state vector x can be expressed as

$$x = [q^T \beta^T]^T \tag{5}$$

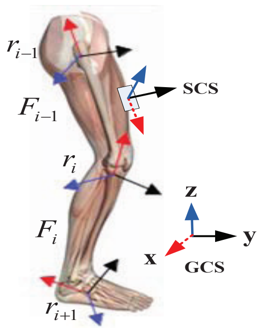

Figure 6: Definition of lower limb coordinates

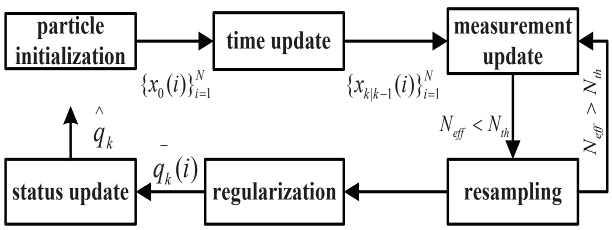

Figure 7: Algorithm execution flow chart

The quaternion q^T represents the quaternion vector from the GCS conversion to BCS, which can be calculated by combining the data of accelerometer and magnetometer on the basis of inertial navigation. Subsequently, we make filtering for quaternion, which can be mainly divided into the following six steps:

Step1 - particle initialization: when k = 0, we produce N particle points $x_0(i)_{i=1}^N$ from the vector x, which obeys the initial probability density $p(x_0)$, then we split these particles into quaternion part and gyro drift part, which can be expressed as:

$$x_0(i) = \begin{bmatrix} q_0(i) \\ \beta_0(i) \end{bmatrix} \tag{6}$$

Step2 - time update: at time K, we make sampling from the importance density function $x_k(i) \sim q(x_k|x_{0:k-1,z_{1:k}})$ to obtain the updated particle points $x_{k|k-1}(i)_{i=1}^N$,where $q(x_k|x_{0:k-1}, z_{1:k}) = p(x_k|x_{k-1})$,these particles can be divided into two parts which are called quaternion part and gyro drift part. The two parts can be expressed as:

$$x_{k|k-1}(i) = \begin{bmatrix} q_{k|k-1}(i) \\ \beta_{k|k-1}(i) \end{bmatrix} \tag{7}$$

Step3 - measurement update: when we get the measured values of $q_{s,k}$ at time K, the particle weight $\omega_k^*(i)$ can be updated through the likelihood probability density function$p(z_k|x_k)$:

$$\omega_k^*(i) = p_{z_k|q_k}(z_k|q_k(i))\omega_{k-1}^*(i) \tag{8}$$

Then, we normalize the weight of the particles, where:

$$\omega_k(i) = \frac{\omega_k^*(i)}{\sum_{i=1}^{N} \omega_k^*(i)} \tag{9}$$

At this point, we make state estimation for the quaternion [21]. State estimation and empirical covariance calculation can be expressed as

$$\hat{x_k} = \sum_{i=1}^{N} \omega_k(i) x_k(i) \tag{10}$$

$$S_k = \sum_{i=1}^{N} \omega_k(i)(x_k^i - \hat{x_k})(x_k^i - \hat{x_k^i})^T \tag{11}$$

Step4 - resampling: Before resampling, we need to judge the degradation of particles. The relationship can be evaluated as follows:

$$N_{eff} = \frac{N}{E_q[\omega_k^2]} < N \tag{12}$$

Where, the effective number of particles is defined as:

$$N_{eff} = \frac{N}{1/N \sum_{i=1}^{N} [\omega_k(i)]^2} \tag{13}$$

WhenN_{eff} is less than the predetermined threshold N_{th} , we make resampling.

Step5 - regularization: although the sampling process avoids the particle degeneracy phenomenon in a certain extent, it introduces the problem of particle dilution. To this end, we need to introduce a regularized resampling procedure [22]. After regularization, the regularized sampling quaternion is:

$$\bar{q_k}(i) = \delta q_k(i) \otimes q_k(i) \qquad i = 1, 2, \cdots, N \tag{14}$$

Where$\delta q_k(i) = [\delta\xi^T(i)1]^T$. $\delta\xi^T(i)$ is the vector of quaternion perturbation particle points [23].

Step6 - status update: After obtaining progeny particles by regularized sampling, in order to make the estimated particles more accurately, we re-compute the likelihood of posterior particles, which can be written as:

$$\hat{\omega}(i) = \frac{1}{N} p_{y_k|x_k}(z_k|\bar{q}(i)) \tag{15}$$

Finally, we can get the final estimated value of quaternion $\hat{q_k}$.

$$N\hat{q}_k = \lambda\hat{q}_k \tag{16}$$

Where the estimated quaternion $\hat{q_k}$ is the corresponding minimum characteristic vector of matrix N when cost function J is the smallest. The cost function J is discussed in detail in [23].

3. EXPERIMENTAL RESULTS

In view of the proposed algorithm model, three experiments are designed to verify its feasibility. Fig. 8 shows the sensor location on the body during the experiments. In experiment 1, we verify the superiority of quaternion relative to the Euler angle in the rotation by controlling the rotation of the rectangular. Experiment 2 shows the effect of the actual motion capture. In order to further verify the algorithm model, in experiment 3, we compared the real motion with the reductive motion.

Experiment 1 - The contrast of rotating effect between quaternion and the Euler angle: at first, in order to demonstrate the superiority of quaternion comparing to the Euler angle when represent rotation. We design an experiment with MATLAB. During the experiment, the calculated

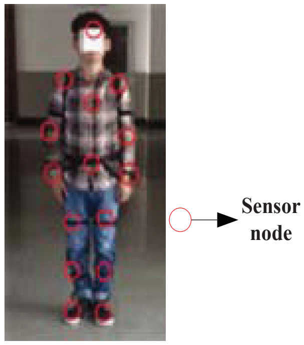

Figure 8: Sensor location on the body

quaternion and Euler angle by our algorithm are mapped to the center of a three-dimensional cuboid, which will be used to drive the cuboid rotation around the rotation center point. Fig. 9 shows the raw data, and Fig. 10, Fig. 11, Fig. 12 depict the comparison results.

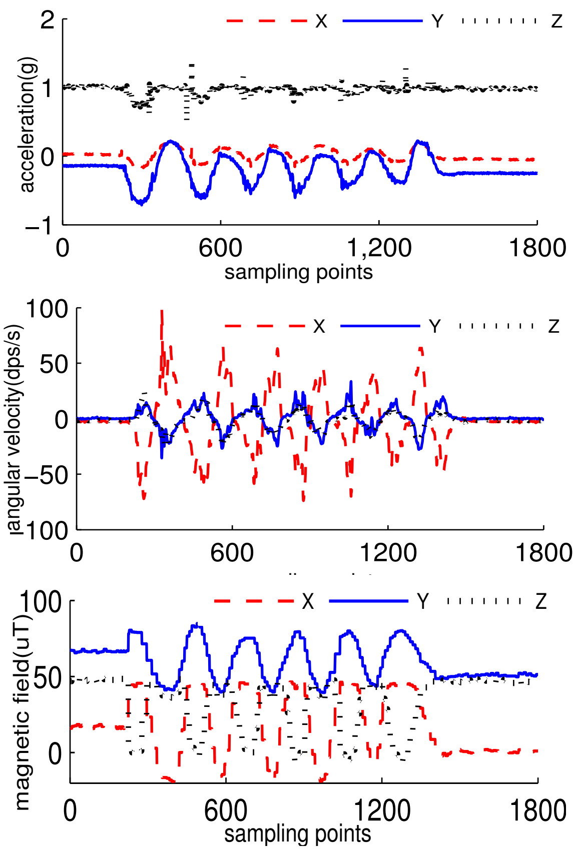

Figure 9: The RAW data of sensors

According to the results of experiment 1, when we use the quaternion and Euler angle to represent rotation, if the cuboid does not reach the rotation singularity, the two kinds of rotations can equally keep pace with each other. But when the cuboid reaches the rotation singularity, if we use Euler angle to represent the rotation, at this time, according to the scatter diagram, the particles will occur scattered

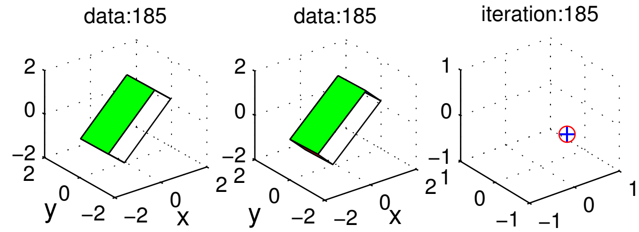

Figure 10: The object has not rotated to the singularity

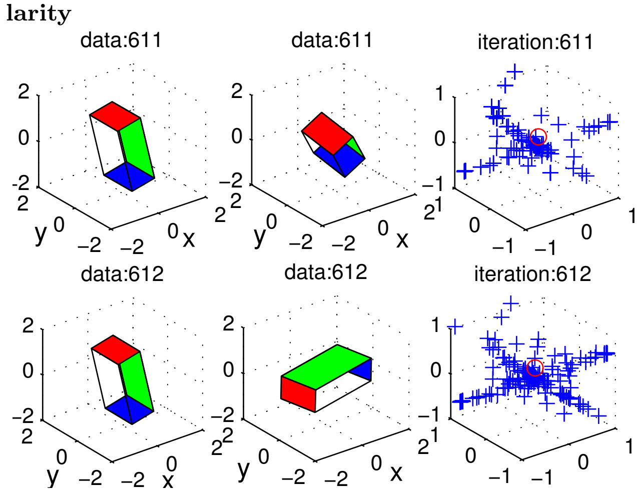

Figure 11: The object has rotated to the singularity

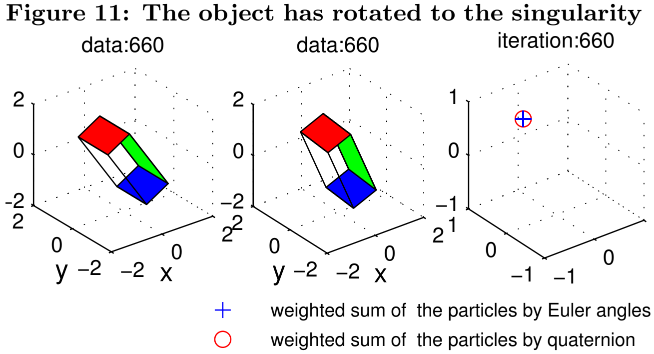

Figure 12: The object has returned from singularity

phenomenon, which will cause the disorder of rotation. The use of the quaternion can effectively avoid this issue. Thus, in the rotation process, quaternion is indeed better than the Euler angle. Fig. 13 shows the calculated quaternion by our method.

Experiment 2 - The evaluation of captured effect: this experiment has been carried out to evaluate the overall effect of the designed motion capture system. Taking the motion capture of full body as an example, Fig. 14 describes the whole motion capture effect of the system. By comparing the tracking effect of the 3D human model to the real human person, we can find that our designed system can effectively realize the task of human motion capture.

Experiment 3 - Validation of the data of motion: through the motion capture interface, we can get the corresponding Biovision Hierarchical Data (BVH) motion capture data in real time. The BVH data preserves the data of attitude

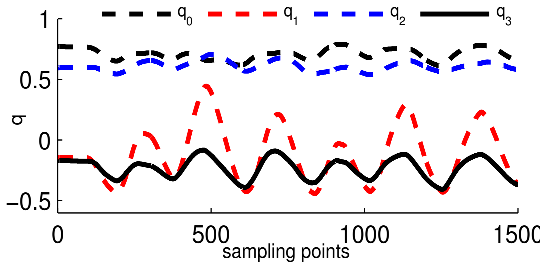

Figure 13: The calculated quaternion with our method

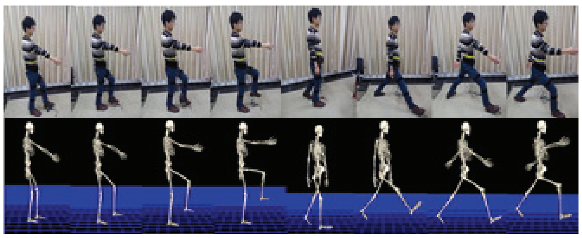

Figure 14: The effect of motion capture

corresponding to each node by frame format in the process of motion capture.

For the BVH format data, this paper establishes the motion capture data verification platform based on MATLAB and Visual Studio, which can realize analysis and reduction for the BVH motion capture data. Through comparison and verification, we can achieve a more accurate analysis of motion capture data flow.

In this paper, taking the walking and jumping movement as examples, the BVH data, which are exported by motion capture system, contain 713 frames walking data and 2980 frames jumping data, respectively. Fig. 15 and Fig. 16 show the comparison of the real action and the reductive action by BVH.

We find that the BVH data can basically rebuild the real motion through the reduction effect of motion, and the restored motion is very smooth. Thus, the preliminary results are promising and worth further investigation and quantitative evaluation.

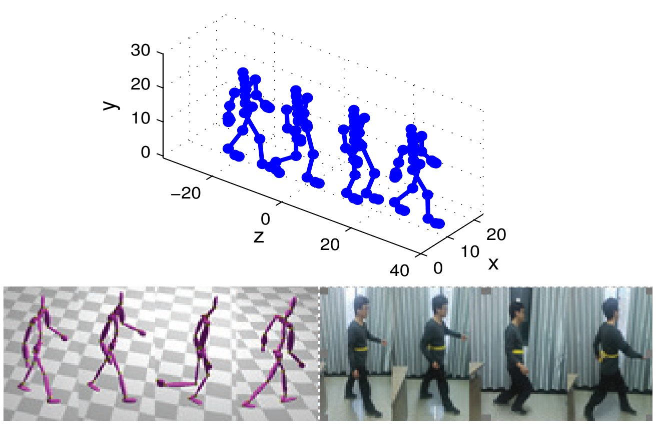

Figure 15: The reduction effect of walking

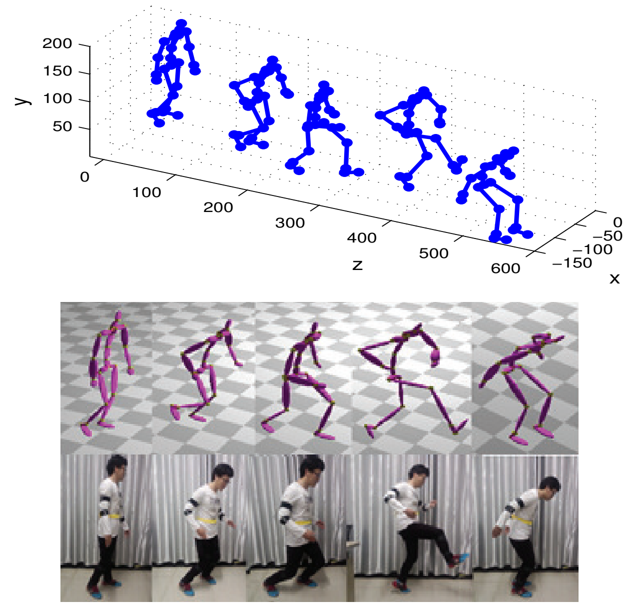

Figure 16: The reduction effect of jumping

4. CONCLUSIONS AND FUTURE WORKS

On the basis of distributed sensor motion capture system, the human motion capture based on quaternion navigation strategy has been designed. The paper then discussed the fusion optimization for the attitude quaternion by combining with the particle swarm filtering fusion algorithm. A geometric constraint model based on quaternion has been also established. All these make the human motion reconstruction more precise and smooth. Finally, we have compared the rotation effect between Euler angle and quaternion by empirical experimentation. In order to evaluate the performance of the system, we have also compared the capture effect of our system with real motion. At last, we validated the algorithm with MATLAB and Visual Studio motion capture platform. Ongoing works are devoted to improve the proposed method; for example we are improving its robustness against environmental noise, such as magnetic interference, which can currently degrade the acquired signal. The motion capture model also need further optimization, such as skinned mesh production.

Acknowledgments

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