Proceedings of the 2010 IEEE
International Conference on Robotics and Biomimetics
December 14-18, 2010, Tianjin, China

Upper Body Motion Tracking With Inertial Sensors

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***Abstract*— We introduce a motion tracking method of arbitrary human upper body motion. Low cost wearable inertial sensors are employed in our approach to track the upper body movement in 3D space and in real time. We first establish a kinematic chain of a human upper body consisting of a trunk and two limbs. Then joint variables are computed for given rotation matrices of body segments which are measured using 6 inertial measurement units. For this purpose, we solve a reduced form of inverse kinematics in the Lie group setting. To compare efficiency and accuracy of our system with the commercial marker based optical tracking system, *Hawk Digital Real Time System*, the upper body motion experiment was performed using the proposed algorithm.**

***Index Terms*—motion tracking, inertial sensors, joints, kinematics, motion capture.**

I. Introduction

In recent, the motion tracking for the human body has broadened its range of applications from sports training [1] to rehabilitation [2]. Several tracking solutions have been provided to analyze human movement based on different sensing technologies such as optical systems, audio systems, radar systems, magnetic systems, inertial systems and mechanical motion systems [3]. Motion tracking with inertial sensors has been an active research area due to its several advantages. With the advance of Micro Electro Mechanical Systems (MEMS) technology, inertial sensors became smaller and lighter. Thus they can be rigidly attached to a segment and independently determine the orientation of each segment relative to the global reference frame [11]. Another benefit is that they are source-free compared to audio or radar systems that include an emission source [10]. Due to these benefits, inertial systems became portable and wearable, which made motion tracking available outdoors [6].

The motion tracking has been extensively studied in recent years. El-Gohary *et al.* proposed the algorithm which estimates the joint angles from inertial sensors based on the robotic kinematic model using Denavit-Hartenberg representation [4]. Zhou *et al.* described upper limb motion tracking system. They developed a kinematic model of human arm and estimated position and orientation of the forearm based on inertial sensors. They also proposed the filtering method that eliminates the errors whose Euclidean distances is larger than a threshold [5]. Zhu *et al.* presented the motion tracking system which tracks orientations and positions of human segments applying axis-angle pairs consisting of a joint angle and a rotation axis rather than the Euler angles to avoid Euler angles' singularities [6]. They also implemented the linear Kalman filter to estimate sensing variables from inertial sensors.

Some researches employed both vision and inertial sensors in motion tracking systems. Tao *et al.* proposed the motion tracking system to track the arm movement [7]. They integrated visual-based color object tracking and inertial sensor tracking by fusing the data from the two different sensors using the geometry and structure information. Chen *et al.* proposed the method to estimate structure and motion by integrating visual and inertial sensor data via an Extended Kalman filter [8]. They use gyro data and acceleration and estimate structure in addition to motion. Marlins *et al.* integrated multisensory signals via a nonlinear Kalman filter based on a nonlinear quaternion model [9].

In this paper, we present the method to track the human upper body movement. The algorithm uses data from inertial sensors in the Lie group setting. The joint variables of the arms and the waist are estimated from the rotation matrices based on the robotic kinematic model. The estimated joint variables are used to control the 3D human upper body model.

The rest of the paper is organized as follows. Section 2 describes about the human upper body kinematic model and conduct tracking based on the collected rotation matrices. Section 3 introduces experimental results. Conclusion and future works are presented in Section 4.

II. Kinematic modeling

A. Forward Kinematics

Human upper body motion can be modeled by a kinematic chain [12].The proposed upper body model consists of three open kinematic chains, i.e. torso to left arm, torso to right arm, and torso to pelvis as shown in Fig. 1. Each upper arm is linked to the trunk by a spherical joint and each forearm is linked to each upper arm by a revolute joint. The trunk and the pelvis are linked by a spherical joint. The forearm and the hand are considered as one rigid segment. Therefore, the upper body model consists of eleven joint variables, i.e. three joints variables for each shoulder, one joint variable for each elbow, and three spherical joints variables for the waist. Each sensor is attached on each segment: the upper arms, the forearms, the torso, and the pelvis as shown in Fig. 1. The kinematics of the model is presented by multiples of matrices parameterized by joint variables in the product of exponentials formula and end-effector lies in the Euclidean motion group, $SE(3)$. Given a set of joint variables $q \in Q$,

This work was supported by the Sports Promotion Fund of Seoul Olympic Sports Promotion Foundation from Ministry of Culture, Sports and Tourism.

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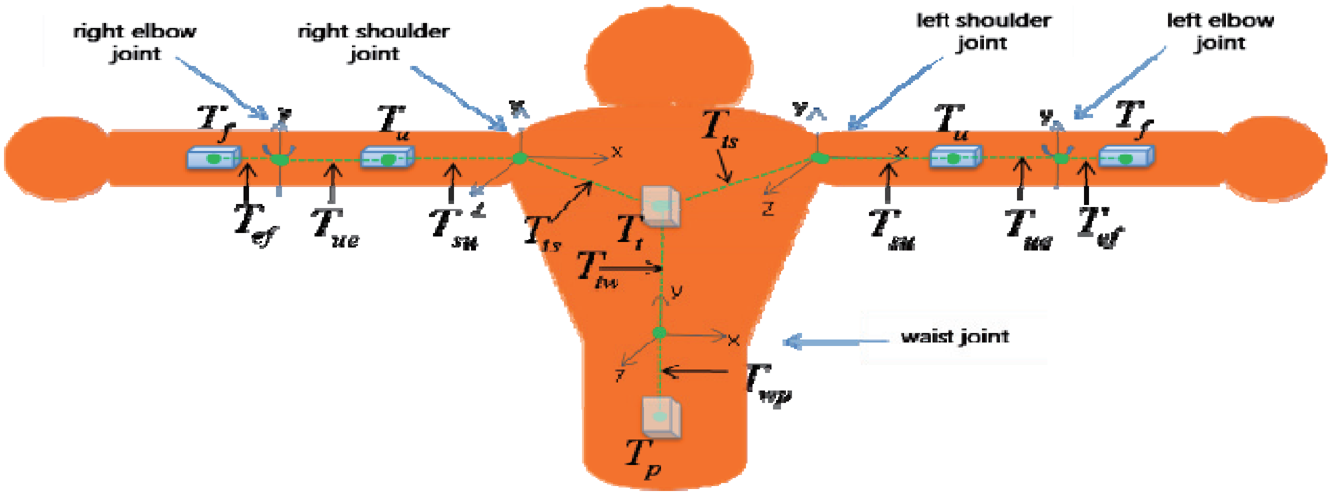


Fig. 1. Articulated Upper Body Model

the forward kinematics is represented by mapping $T: Q \rightarrow SE(3)$, where the joint space Q is the Cartesian product between each individual joint space [13].

If we define T_{tf} as the transformation from the coordinate frame of the torso to the coordinate frame of the left forearm, the overall kinematics are given by

$$T_{tf} = T_t T_{ts} e^{\mathbf{q}_s} T_{su} T_u T_{ue} e^{q_e} T_{ef} , \tag{1}$$

where $\mathbf{q}_s \in \mathbb{R}^3$ and $q_e \in \mathbb{R}$ are the joint variables of the shoulder joint and the elbow joint.

T_t : measured transformation (torso)
T_{ts} : translation from torso to shoulder joint
$e^{\mathbf{q}_s}$: rotation of shoulder joint
T_{su} : translation from shoulder joint to upper arm
T_u : measured transformation (upper arm)
T_{ue} : translation from upper arm to elbow joint
e^{q_e} : rotation of elbow joint
T_{ef} : translation from elbow joint to forearm

The same method can also be applied to the right arm. The transformation from the coordinate frame of the torso to the coordinate frame of the pelvis is given by

$$T_{tp} = T_t T_{tw} e^{\mathbf{q}_w} T_{wp} T_p , \tag{2}$$

where $\mathbf{q}_w \in \mathbb{R}^3$ is the joint variable of the waist joint.

T_t : measured rotation (torso)
T_{tw} : translation from torso to waist joint
$e^{\mathbf{q}_w}$: rotation of waist joint
T_{wp} : translation from waist joint to pelvis
T_p : measured transformation (pelvis)

The distance between the sensors and the joints are assumed to be known a priori. Each point on the forearms and the pelvis where each sensor is mounted is considered as the end-effector.

B. *Inverse Kinematics*

In this paper, the joint variables are estimated by using the rotation matrices. The inverse kinematics problem is to find the joint variables when the position and the orientation of the end-effector are given [13]. The problem of inverse kinematics for the open kinematic chain, from torso to left arm, is expressed as follows. Given a 4×4 homogenous transformation

$$H = \begin{bmatrix} R & d \\ 0 & 1 \end{bmatrix} \in SE(3) , \tag{3}$$

with $R \in SO(3)$, find solutions of the forward kinematic equation

$$T(q_1, q_2, q_3, q_4) = H , \tag{4}$$

for the joint variables q_1, q_2, q_3, q_4. Equation (4) results in 12 nonlinear equations in 4 unknown variables.

The inverse kinematics problem can be decoupled into two simpler problems, known as inverse position kinematics and inverse orientation kinematics [12]. Equation (4) can be expressed as two sets of equation representing the rotational and positional equations

$$f(q_1, q_2, q_3, q_4) = R \tag{5}$$

$$g(q_1, q_2, q_3, q_4) = p , \tag{6}$$

where p and R are the given position and orientation of the tool frame.

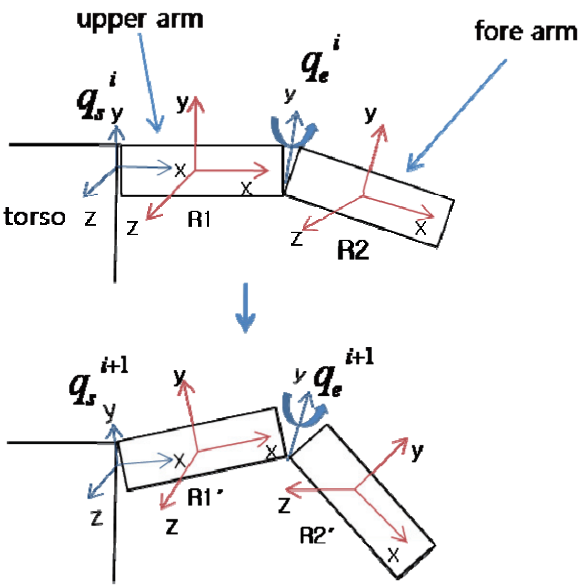


Fig. 2. Physical segment model and the definition of its orthogonal frame.

Since only the orientations are of our concern, the equation representing the rotational equations is used. The rotational equations for the two sensors on the arm are given as

$$R_n = f_n(q), n = 1, 2\,, \qquad (7)$$

where $q = (\mathbf{q}_s, q_e)^T = (q_1, q_2, q_3, q_4)^T$ and R_n represents the rotation matrix of the body frame of *inertial sensor n*, which rotates a vector in the sensor co-ordinate system to the global reference system. We define $f_n(q)$ as the rotational equation of *inertial sensor n*.

The Newton-Raphson method is used to find solutions of nonlinear equations [14]. The first order approximation of $f_n(q)$ around $q^i \in \mathbb{R}^4$ is

$$R_n^{i+1} \approx R_n^i + \sum_{j=1}^{4} \left.\frac{\partial f_n}{\partial q_j}\right|_{q=q^i} (q_j^{\,i+1} - q_j^{\,i}), n = 1, 2\,, \qquad (8)$$

where we assume a rotation matrices as a general 3 by 3 matrix.

It can be re-expressed using body Jacobian as follows:

$$R_n^{i-1} R_n^{i+1} - I = \sum_{j=1}^{4} f_n^{-1} \left.\frac{\partial f_n}{\partial q_j}\right|_{q=q^i} (q_j^{i+1} - q_j^{i})\,, n = 1, 2\,. \qquad (9)$$

Note that $f_n^{-1} \left.\frac{\partial f_n}{\partial q_j}\right|_{q=q^i}$ represents body Jacobian with respect to the jth joint variable and represented as a 3 by 3 skew-symmetric matrix and can therefore be represented as a 3dimensional vector.

Since R_n^i and R_n^{i+1} represent estimates of a rotation matrix at the ith and i+1th iteration, it is reasonable to assume that R_n^i and R_n^{i+1} are close to each other when the iteration converges. In this case $R_n^{i-1} R_n^{i+1}$ converges to identity as well and its first order approximation in an exponential sense can be given as $R_n^{i-1} R_n^{i+1} \approx I + [\omega]$ because $R_n^{i-1} R_n^{i+1} = e^{[\omega]} = I + [\omega] + \frac{1}{2}[\omega]^2 + \cdots$.

In this context, we define a linearization function for a given rotation matrix R near the identity as follow:

$$lin(R - I) = \begin{bmatrix} \frac{r_{13} - r_{31}}{2} & \frac{r_{12} - r_{21}}{2} & \frac{r_{23} - r_{32}}{2} \end{bmatrix}^T, \qquad (10)$$

where $R = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix}$. Note that a linearization function is similar to log mapping which maps SO(3) to so(3) near the identity but can be implemented far more efficiently.

Using the linearization function, we build a matrix equation from the equation (9) as follows:

$$\begin{bmatrix} lin(R_1^{i^{-1}} R_1^{i+1} - I) \\ lin(R_2^{i^{-1}} R_2^{i+1} - I) \end{bmatrix} = \begin{bmatrix} J_1 \\ J_2 \end{bmatrix} (q^{i+1} - q^i),$$

where J_i is a 3 by 4 body Jacobian matrix composed with vectorized $f_n^{-1} \left.\frac{\partial f_n}{\partial q_j}\right|_{q=q^i}$, $j = 1, \cdots 4$.

Finally q^{i+1}, estimates to joint variable at the ith iteration can be found by solving least squares problem as

$$q^{i+1} = q^i + \begin{bmatrix} J_1 \\ J_2 \end{bmatrix}^{\dagger} \begin{bmatrix} lin(R_1^{i^{-1}} R_1^{i+1} - I) \\ lin(R_2^{i^{-1}} R_2^{i+1} - I) \end{bmatrix}, \qquad (11)$$

where † indicates pseudo inverse of the matrix. We iterate this process until the convergence.

The same method is applied for the open kinematic chain, from torso to right arm. The inverse kinematics problem for the open kinematic chain, from torso to pelvis, is determined by solving (2) for q_w Thus we have

$$\mathbf{q}_w = \log((T_p T_{wp})^{-1} T_t T_{tw}^{-1}) \qquad (12)$$

where $\mathbf{q}_w \in \mathbb{R}^3$.

Thus the eleven joint variables of the upper body model can be estimated from (11) and (12).

III. Experimental Results

A. System Configuration

Each inertial measurement unit (IMU) is consisted of a tri-axis accelerometer ADXL345 with high resolution measurement at up to ±16g, a tri-axis gyroscope

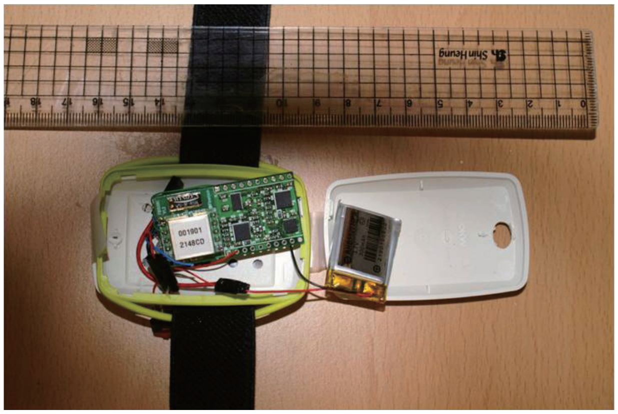


Fig. 3. Photograph of inertial measurement unit

LPY5150AL with a full scale of ± 1500 , a tri-axis magnetometer HMC5843 with ± 4 gaussmeasurement range, a microcontroller (Cortex M3), and a Bluetooth module (FB155BC). The sampled data from all sensors were transmitted to a microcontroller. The microcontroller processed the received sensor data and determined the rotation matrix of the IMU. The rotation matrix was transmitted to a personal computer through a Bluetooth module.

B. Results

The accuracy is evaluated by comparing the performance of the proposed algorithm with that of the commercial motion capture system, *Hawk Digital Real Time System.* The subject wears both the suit of the Hawk system with markers and our inertial sensors. The initial posture of the 3D model for this experiment is to stretch out the right arm and fix it to the trunk. Then repeat to move the forearm upward and downward, back to the initial posture, maintaining the right upper arm fixed to the trunk. Fig. 4 shows measurements of this arm movement. The Hawk system provides the wrist position represented in the world coordinate systems. The wrist position is also calculated by using the proposed human upper body kinematic model. Dashed lines represent data from the Hawk system, and solid lines from our system. Three coordinates x, y, z of the position trajectories of the wrist joint are plotted.

As can be seen in Fig. 4, the data from the Hawk system and that from our system match well. The data of the x was less accurate than the other coordinates, but the difference between the two systems for the y and z coordinates is less than 5cm. The results are quite promising and show that the proposed system is reasonably accurate.

The wrist position is calculated by substituting the joint variables which are computed for given rotation matrices of body segments into the proposed kinematic model. In this experiment, the posture is to stretch out the right arm vertically and remain still. Fig. 5. shows the position data of the right wrist in a stationary condition. Three coordinates x, y, z of the position trajectories of the wrist joint are plotted. As shown in Fig. 5., The position continues to remain stable.

Fig. 6 shows the human upper body motion capture results of the three different movements. The first movement is to raise both arms above the head. The initial posture of the 3D

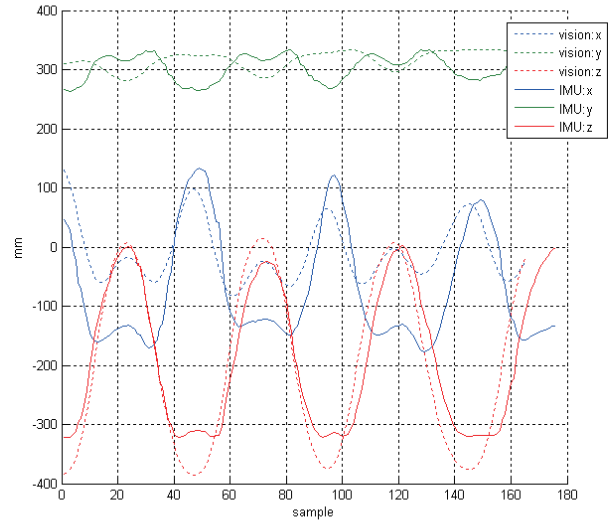


Fig. 4. Measurements of human arm movement (solid lines measured by the proposed kinematic models and dashed lines measured by Hawk Real Time System)

model is to spread both arms out horizontally as shown in Fig. 6(a). Fig. 6(b) shows that the movement of the 3D human upper body model matches that of the subject. As shown in Fig. 6(c) and 6(d), the second movement is to attach the upper arms to the body and bend the arms to make the forearms face upward. Then stretch out the arm one by one. The third movement is to bend the waist side to side as shown in 6(e) and 6(f). Since the pelvis is fixed, the whole upper body above the waist moves side to side.

By comparing the movement of the 3D human upper body model and that of the subject, we can see that the 3D model simultaneously makes the same movements as the subject. Various movements of the upper body have been tested extensively.

The proposed algorithm has shown a stable and accurate performance in the test, which means that the joint variables estimated from the rotation matrices of the sensors have reasonable accuracy. However, since the kinematics of the 3D model and that of the subject does not match perfectly, a slight difference between the movements exists. The length of the segments was measured with errors. Thus the computed positions of joints cannot be perfectly accurate.

IV. CONCLUSION AND FUTURE WORKS

We have presented a kinematic model and motion tracking algorithm to track human upper body motion using low cost inertial sensors. Our inertial sensor can measure a rotation matrix of a body segment accurately. Given these rotation matrices of the coordinate frames attached to a torso, a pelvis, upper and forearms, we estimate joint variables corresponding to a current posture by solving inverse rotation kinematics in a Lie group setting. The 3D human upper body model is controlled with the estimated joint variables. The position of each joint is calculated by substituting joints variables into the proposed kinematic model. Our approach showed comparable results to the commercial optical tracking

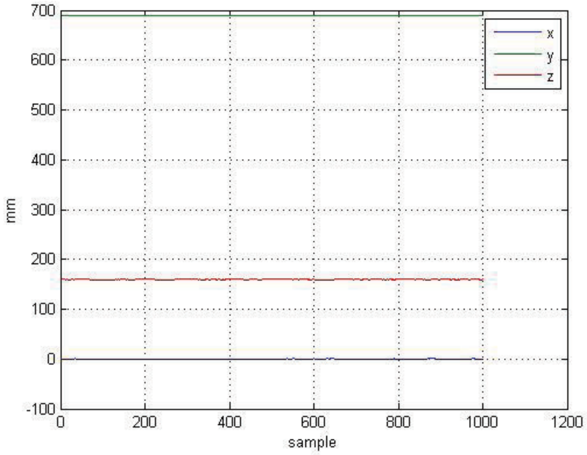
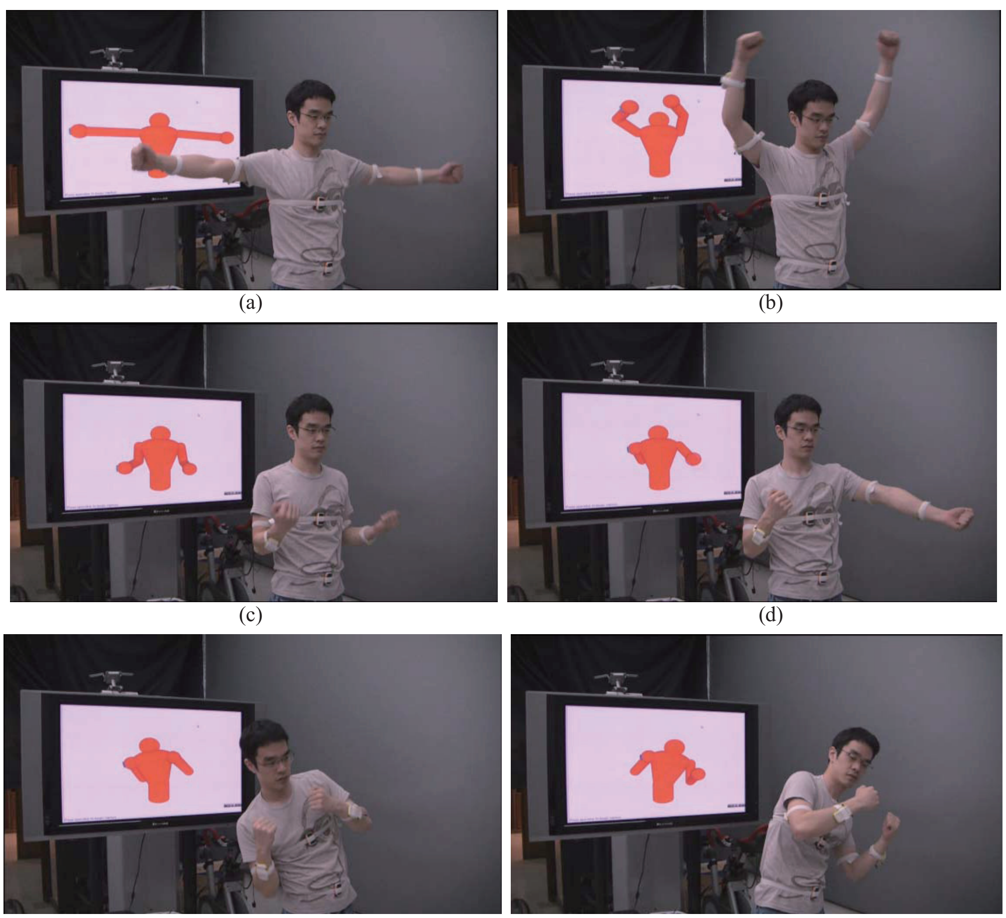


Fig. 5.Wrist position (solid lines measured by the proposed kinematic models) in a stationary condition.

system.

However we noticed that overall accuracy of our system heavily depends on kinematic parameters of the model such as lengths of body segments, locations of IMU sensors, etc. These factors cause errors in a performance. Hence our future work includes automatic and accurate estimate methods to obtain more accurate kinematic parameters.

Extending the proposed method to track the whole body movement will also be interesting. However a basic assumption of our work is that we have at least one grounded body segment which defines an absolute global reference frame. Hence free flying full body motion such as a jumping motion requires additional techniques to track with respect to a global coordinate frame.



(a) (b) (c) (d) (e) (f)

Fig. 6. The upper body motion capture results

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