Hindawi Publishing Corporation
EURASIP Journal on Image and Video Processing
Volume 2008, Article ID 693427, 15 pages
doi:10.1155/2008/693427

Research Article

Compression of Human Motion Animation Using the Reduction of Interjoint Correlation

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Received 1 February 2007; Revised 14 July 2007; Accepted 23 October 2007

Recommended by Nikos Nikolaidis

We propose two compression methods for the human motion in 3D space, based on the forward and inverse kinematics. In a motion chain, a movement of each joint is represented by a series of vector signals in 3D space. In general, specific types of joints such as end effectors often require higher precision than other general types of joints in, for example, CG animation and robot manipulation. The first method, which combines wavelet transform and forward kinematics, enables users to reconstruct the end effectors more precisely. Moreover, progressive decoding can be realized. The distortion of parent joint coming from quantization affects its child joint in turn and is accumulated to the end effector. To address this problem and to control the movement of the whole body, we propose a prediction method further based on the inverse kinematics. This method achieves efficient compression with a higher compression ratio and higher quality of the motion data. By comparing with some conventional methods, we demonstrate the advantage of ours with typical motions.

1. INTRODUCTION

3D motion capture systems have been widely used in CG amusement and human motion analysis such as games and athlete training. To use these human motion capture data to produce compelling animation, the users need a motion library to store the existing motion data. Large motion databases do not accept the uncompressed forms, since the motion data are often huge. For example, the size of only a 3-second sample of the skeleton motion capture data with 200 frames, in a typical motion format, is about 200 KB. On the other hand, motion data transmission often requires compactly coded motion [1]. Studying these issues, we believe the motion compression is essential for all these tasks.

In this paper, we propose two compression methods for the human motion in 3D space, based on the forward and inverse kinematics. Analyzing the human motion signals, such as walking, dancing, and kicking, we find that these motions contain mainly low-frequency components and discarding some small wavelet coefficients will not bring great effects on the motion. Thus, in the first method, we propose a compression algorithm for motion data which combines wavelet transform and forward kinematics (FK) to achieve a progressive motion compression. Due to appearance of distortion caused by the quantization, the error is propagated from higher to lower levels in a motion chain hierarchy. To reduce this effect, we compensate the error by a forward kinematics fashion. The method also gives a hierarchical description of the motion by virtue of the wavelet transform so that the progressive encoding/decoding is possible, which is efficient for motion editing and key framing [2–5].

The second method uses a prediction, based on the inverse kinematics (IK). Although this is not a hierarchical coding, more efficient compression in a sense of accuracy can be given. This method exploits two redundancies, the correlation between frames and the correlation between joints. For motion compression, these two should be taken into account simultaneously. However, few techniques specially address them. In our method, the correlation between the joints is efficiently reduced by the inverse kinematics.

In the general motion formats, the motion of all joints in a frame is described by three rotation angles with respect to X, Y, and Z axes. In this paper, we apply a converted format, which includes two angles of transformation and one angle of orientation for each joint, to be compressed instead of the three rotation angles. This approach brings the advantages as the first, to control the *position* more precisely by assigning more bits than *orientation* that is less important than the *position* in many cases; secondly, to save computation time and improve the compression efficiency, two angles of transformation are utilized to get a closed form expression of the Jacobian matrix.

The remainder of the paper is organized as follows. After a review of previous work in Section 2, we present the introduction about the transformation from the general motion format to the converted format in Section 3 and give a brief description of wavelet-based compression algorithm and using forward kinematics for data optimization in Section 4. In Section 5, we explain the inverse kinematics-based compression algorithm in detail. The motion compression procedure with a predicting technique is also assigned in this section. Illustrative motion examples are given in Section 6 to show the advantage of our approach. In Section 7, we conclude the method.

2. BACKGROUND

Many works in computer graphics address the problem of huge motion data and present compact expression of the motion [1–3, 6]. These previous methods focus on the reduction of the number of motion samples. Liu et al. introduced a system for analyzing and indexing motion databases [7]. Their method reduces the size of the database by selecting the principal markers and constructing simple models to describe groups of similar poses. Furthermore, recently, the researchers in motion identification, extracting, analysis, and classification pay more attention to controlling the motion signals in low dimensionality [8–10]. Although the need for compressing the large motion database exists in many fields, their studies are only located in using key-poses to represent the action synopsis by a sequence of motions. For a monotone and periodic sample, the key-poses can synopsize the action well, while they are not sufficient to the complicated action. In this case, only the compressed representation of the whole motion fulfills the requirement of the users.

While the motion compression attempts to represent the whole motion by fewer amounts of data without subsampling, the conventional key framing methods subsample it and interpolate the key frames smoothly while rendering. The key framing realizes a compact representation as well. However, if one applies the key framing to the compression, some problems arise. First, essentially selected key frames should not be correlated. It is difficult to compress a lot even though the number of frames is smaller. Moreover, when the key frames are regularly sampled, it is difficult to compensate sudden changes by the interpolation and it often results in over- and under-shoots. When irregular key frame sampling is applied (which is much more common in CG), one needs to encode not only the data but also the time indexes, resulting in increase of data. Lim and Thalmann achieve motion compression by the key-posture extraction of motion data using the motion curve simplification in [6]. Based on the method in [6], Etou et al. proposed the use of only five joints as the important joints and applied the motion curve simplification method in these selected joints to reduce the dimensionality [2]. Ahmed et al. utilized the wavelet technique to compress each sample [11]. In [12] Arikan introduced a lossy compression algorithm. They approximated the short clips of motion using Bezier curves and clustered principal component analysis. To avoid solving the nonlinear problem of the orientations, they represent the motion by 3 times more storage (3 virtual marker positions for each frame instead of 3 joint angles). Obviously, this representation introduces a problem of space complexity. To reduce the high dimensionality, they group the similar looking clips into clusters and use PCA in each cluster. This processing brings another problem of time complexity. For motion compression, one should take into account (1) the correlation between joints and (2) the correlation in time domain. In other words, the level of accuracy should be accordingly changed, depending on frames and joints such as end effectors which often require higher precision than other general types of joints due to motion characters. Most of these conventional methods [2, 6, 11, 12] focus on the correlation only in time domain.

To solve those two problems, we proposed a compression algorithm for motion data which combines wavelet transform and forward kinematics. To reduce the distortion in hierarchy chain, we compensate the error by a forward kinematics fashion. The method also gives a hierarchical description of the motion by virtue of the wavelet so that progressive encoding/decoding is possible, which is efficient for motion editing and key-framing.

However, according to the forward kinematics, in a motion chain, the distortion of a joint that comes from the quantization introduces the warp of the position to its child joint. The distortion of this child joint affects its grand child joint in turn, and so on. The warp may be accumulated to the end effector which is usually treated as the most important joint for some motion feature. To reduce the propagation of the warp to the end effectors, we have to minimize the errors between the actual positions and the compressed results in the lower level of hierarchy. The forward kinematics cannot address this problem perfectly.

To control the movement of the whole body, it is common to use the inverse kinematics [13]. It is presumed that the specified joints, called the end effectors are assigned in target positions from preceding positions. By position changes of the end effectors one may get variations of the motion of the entire body using the inverse kinematics algorithm. Therefore, for most joints, when recovering motion in a decoder, we only require a series of small modifications to the corresponding values. The author of [12] realizes the importance of the end effectors and compresses them separately by DCT. Unfortunately, in his paper we cannot find a solution for exploiting correlation between joints.

A linear prediction has been widely used and successfully applied in compression of time series data. If we can predict every next frame, we only need to save the first frame and the difference between real value and its prediction. The better the predictions, the more common corrections we can get and the more bits we can save. The inverse kinematics based approach solves the above problems efficiently [14].

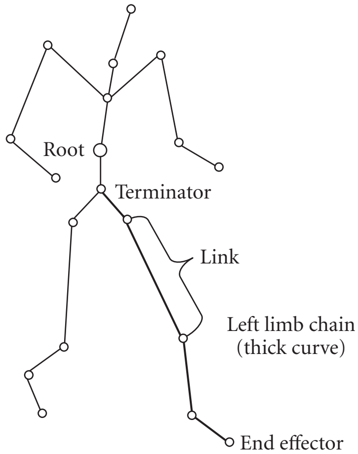


Figure 1: Human figure.

We further present an inverse kinematics based compression method in this paper. In our work, we improve the calculation for the prediction of next frame by adding the constraint of minimizing the acceleration of the motion instead of minimizing the velocity which is described in [14]. Because the constraint of minimizing the velocity, which deduces the Moore-Penrose pseudoinverse, relates a series of smallest changes of the rotation angles to a small displacement in the end effector, it is not adapted to the motion compression.

3. PRELIMINARY

3.1. General format

In CG application, a human figure is modeled by a hierarchical chain, in which connections between two neighboring joints are rigid, for example, the joints of a shoulder and an elbow move, but the distance between them is not changed. In this framework, the motion data is expressed by a series of rotations instead of x, y, z coordinates. A motion chain, which is hierarchically constructed by some linked joints, has one end that is free to move, which is called an end effector. The other end of the chain is fixed and called a terminator (see Figure 1). In Figure 1, a joint defined as an origin of coordinates is called a root. The root may have multiple trees and the several end effectors. Kinematics based motion data processing is to handle the motion chains, such as trunk, upper limbs and lower limbs.

The motion capture data format, such as BVH format which is employed in our experiment, typically includes the position of the root and orientation of other joints [15]. For the orientation of the joints, the three Euler rotation angles are adopted rather than the quaternion.

In the motion chain, to calculate the position of a joint we need to create a rigid transformation matrix by local translation and rotation information. A rotation matrix $\mathbf{R}$ is composed of three Euler rotation matrices with respect to X, Y, Z axes [16]. Suppose a rotation order is YXZ, by concatenating the Euler rotation matrices, we can get $\mathbf{R} = \mathbf{R}_Z \cdot \mathbf{R}_X \cdot \mathbf{R}_Y$. By applying a matrix $\mathbf{T}$ which is a homogeneous matrix to represent both the translation and the rotation by one common equation, the position of a joint in global coordinate p_G can be described by

$$p_G = \mathbf{T} \cdot p_L, \tag{1}$$

where $p_G = [1\, P_X\, P_Y\, P_Z]^T$, p_L is the position of this joint in local coordinate, and $p_L = [1\, P_x\, P_y\, P_z]^T$,

$$\mathbf{T} = \begin{bmatrix} 1 & \vdots & 0 \\ \cdots & & \cdots \\ l & \vdots & \mathbf{R} \end{bmatrix}, \tag{2}$$

and l is a translation vector $[1\, l_x\, l_y\, l_z]^T$. Once the local transformation of a joint is created, it will be concatenated with the transformation of its parent, then its grand parent, and so on. The position of this joint in world coordinate can be obtained by

$$p_{\text{world}} = \mathbf{T}_{\text{root}} \cdot \mathbf{T}_{\text{grandparent}} \cdot \mathbf{T}_{\text{parent}} \cdot \mathbf{T}_{\text{child}} \cdot p_{\text{child}}. \tag{3}$$

3.2. Converted angle format

We assume the motion chains are expressed by the rigid transform except for the root joint with the position, x, y, z, in the world coordinate. We first convert the three Euler rotation angles to two rotations and one orientation. The two rotations perfectly specify the position in 3D space, and the rest represents its orientation. Since in most applications the position is more important than the orientation, by assigning more bits during the compression one can have a degree of freedom to reconstruct the position more precisely than the orientation. This format also realizes the scalability of data. That is, if motions are described only by the positions (i.e., orientation is not included) like data captured from most of the motion capture equipments or a user in the decoder needs only the positions (i.e., orientation is not required), it is possible to transmit the two ϕ and φ of the three angles, which saves much more information to send. Moreover, as we will explain later, this converted format gives a closed form expression of Jacobian matrix in the inverse kinematics algorithm which is the partial derivative of the function about the position and the rotation angles of the joint with respect to a set of angles and saves computation time.

Suppose the length of a link connecting a child joint and a parent joint is r, and the two positions are related by a rotation $\mathbf{R}_{ZXY}$:

$$p_{\text{parent}} = \mathbf{R}_{ZXY} \cdot p_{\text{child}}, \tag{4}$$

$p_{\text{parent}} = [p_{X\text{parent}}\, p_{Y\text{parent}}\, p_{Z\text{parent}}]^T$ is represented by two angles:

$$\begin{aligned} p_{X\text{parent}} &= r \cdot \sin\phi \cdot \cos\varphi, \\ p_{Y\text{parent}} &= r \cdot \sin\phi \cdot \sin\varphi, \\ p_{Z\text{parent}} &= r \cdot \cos\phi, \end{aligned} \tag{5}$$

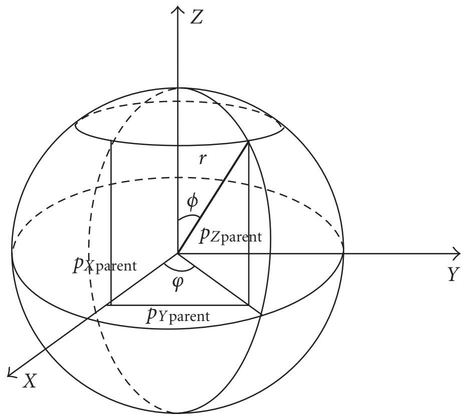


Figure 2: Direction of the spherical angles in a 3D coordinate system.

where ϕ and φ can substitute for three Euler angles to be compressed in the IK algorithm in Section 3. The Figure 2 shows the direction of these spherical angles of a 3D coordination system.

To represent the motion, the positions of the joints in world coordinate can be represented by two angles ϕ and φ sufficiently in (5), and these positions can represent the skeleton motion instead of the orientation of the joints. However, to apply our compression algorithm to more general CG animations, we further need a parameter, the orientation angle ψ, to retrieve the three Euler angle since a joint may present different orientation in a same position in the world coordinate. We can calculate the orientation angle ψ by a standard matrix of rotation around an arbitrary axis [17]. Suppose A is the matrix that rotates by angle ψ about the axis u is

$$A = \begin{bmatrix} tx_r^2 + c & tx_r y_r + sz_r & tx_r z_r - sy_r & 0 \\ tx_r y_r - sz_r & ty_r^2 + c & ty_r z_r + sx_r & 0 \\ tx_r z_r + sy_r & ty_r z_r - sx_r & tz_r^2 + c & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad (6)$$

where $c = \cos(\psi)$, $s = \sin(\psi)$, $t = 1 - \cos(\psi)$ and x_r, y_r and z_r are the components of a unit vector on the axis u though the origin and p_{parent}. In our case, $u = [p_{X\text{parent}}, p_{Y\text{parent}}, p_{Z\text{parent}}]$ holds. Suppose R_{cross} is the rotation matrix which is built by current position p_{child} and target position p_{parent}. Combine (4), (5), and (6), then we can easily get

$$R_{ZXY} = A \cdot R_{\text{cross}}. \quad (7)$$

Note that ϕ, φ, and ψ at each frame are data to be encoded. Since the variance of ψ is usually small, this angle format often improves compression efficiency in practice.

The three Euler angles may exhibit discontinuity when the angles are limited in $[0, 2^*\pi]$. This is easily addressed by the conventional phase unwrapping technique. We actually use "unwrap" in the MATLAB library. In the decoder, after reconstructing the rotation matrix $Rzxy$, the orientation angle can be retrieved by limiting three Euler angles in a quadrant and the absolute value of them between $[0, 2^*\pi]$.

4. WAVELET CODING ALGORITHM

4.1. General wavelet coding for motion

Analyzing the human motion signal, such as walking, dancing and kicking, we find these motions contain mainly low frequency components and discarding some small wavelet coefficients will not introduce the large effects on the motion. In [11], the author also gives a report about it. However, using a constant quantization for all motion signals may introduce visible error such that motion appears dithering or other unnatural manner. Thus, variable stepsizes in quantization are required to encode motion signals of different joints.

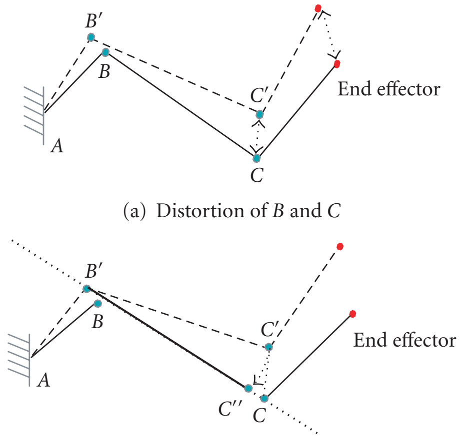
As applied in image compression and other computer graphics applications [18, 19], the general wavelet-based compression steps are given as follows. In an encoder phase, we decompose a signal into a sequence of wavelet coefficients W, then quantize them with multiple stepsizes to convert W to a sequence Q in quantization, finally apply entropy coding to compress Q into a sequence E. In decoder phase, the contrary operations are performed. Therefore, the motion data are quantized adaptively, so that the decoder receives a compressed data without visible artifacts.

In our compression algorithm, we perform the 9/7 tap wavelet transform, and our aim is to compress curves of all the joints represented by series of rotations in all frames.

4.2. ROI coding of motion

In motion compression, to keep some special characteristics, we have to consider two constraints which are also specified in motion editing [4, 5]. The one is used to describe an articulated figure [13], such as the elbow and knee joints should not bend backward, that is, the rotation angles about these types of joints should be in some ranges. The second constraint is used to guarantee that the end effector is placed at a particular position in some frames. For example, considering a motion in which a human puts a box on a desk, in last some frames, the box should be precisely put on the desk. In this paper, we call these frames "constraint frames." The constraint frames are derived automatically from the interaction between the figure and environment or specified by user. In the encoding steps, it is useful that the user can adaptively compress the joints. For example, smaller quantization stepsize is used for important joints. The important joints, which are located more precisely than others, are called "constraint joints" in this paper. This can be done by region-of-interest (ROI) coding.

To make this ROI coding possible, we apply the max shift method [18]. The max shift method is used in image compression for defining the ROI which is encoded and transmitted with better quality than the rest of the image and decoded first before any background information [20]. Before the quantization, the constraint frames are scaled up. Thus, the frames are quantized by a different stepsize to implement different compression ratio as motion behavior. In motion reconstruction, the signals are scaled down after dequantization. The decoder can distinguish these scaled signals from



(a) Distortion of B and C

(b) Rotate $B'C'$ to find optimal C''

FIGURE 3

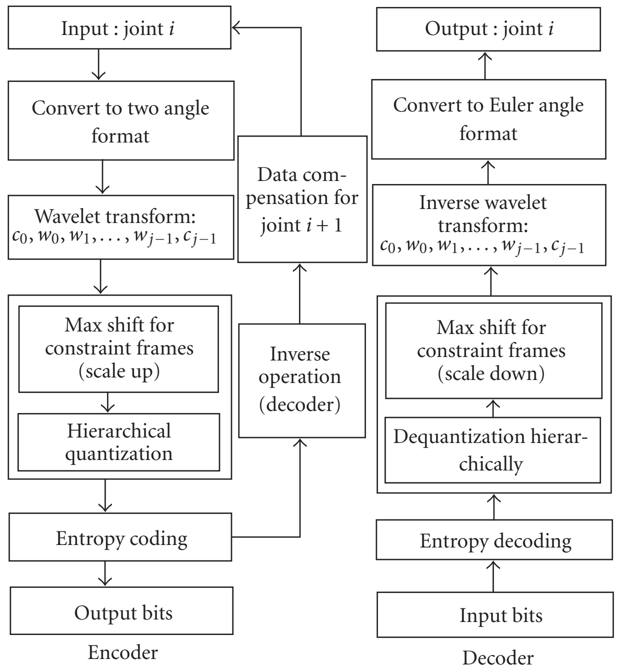


FIGURE 4: Adaptive algorithm for optimization-based motion data compression.

general signals. More accurate frames will be gained and hence the motion feature can be preserved.

4.3. *Forward kinematics for data optimization*

ROI-based approach preserves a large amount of features of the motion. However, the lossy compression for rotation angles produces some quantization error. In Figure 3(a), the position of B is warped to B' and in turn C is warped to C'. Finally, the warp is accumulated to the end effector.

To reduce the propagation of the warp, we have to minimize the error of position between C and C'. Utilizing the quantized position of the root joint and a correct position of the child joint, we can obtain an optimal position of the child joint instead of its warped one (Figure 3(b)).

Since the length between B' and C' is fixed, suppose this link is l, rotate the link $B'C'$ with respect to B' to meet the line $B'C$, we get an intersection C''. In triangle $\Delta B'C'C$ of Figure 3(b), $\overline{B'C'} + \overline{C'C} > \overline{B'C}$, we can easily educe $\overline{C'C} > \overline{C''C}$. That means C'' is closer to C than C', that is, $E_{C''} < E_{C'}$, where $E_{C''}$ denotes the error of distance between C'' and C, while $E_{C'}$ denotes the error of distance between C' and C. C'' is clearly the optimal position. Calculate $\mathbf{R}_{\text{new}}$ corresponding to C''. $\mathbf{R}_{\text{new}}$ indicates the rotation of C'' about B' and can be calculated by p_C and $p_{C''}$. p_C is original position of C in its parent coordinate with origin B and $p_{C''}$ is optimal position of C'' in its parent coordinate with origin B'.

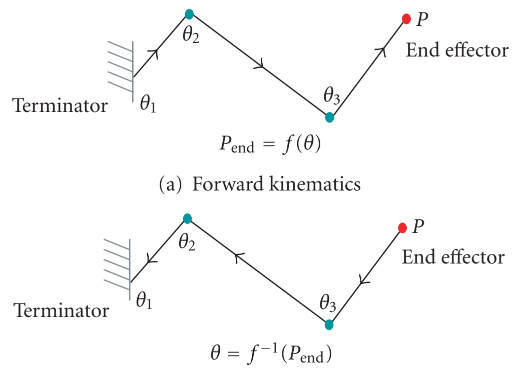
Then in each motion chain, the optimal rotation angles of a child joint can be gotten by warped position of its parent sequentially and encoded instead of the original data [21].

A motion data compression algorithm is shown in Figure 4.

5. INVERSE KINEMATICS BASED ALGORITHM

5.1. *Inverse kinematics*

According to the forward kinematics, in a motion chain, the transformation of a parent joint causes a change of its child



(a) Forward kinematics

(b) Inverse kinematics

FIGURE 5

joint position. The change of this child joint in turn affects its grand child joint, and so on. Finally the changes are accumulated to the end effector. Motion is inherited down the hierarchy from the parents to the children (Figure 5(a)). For simplicity, we discuss two-dimensional case. In the frame n, the position of the end effector P_n in two dimensional can be determined:

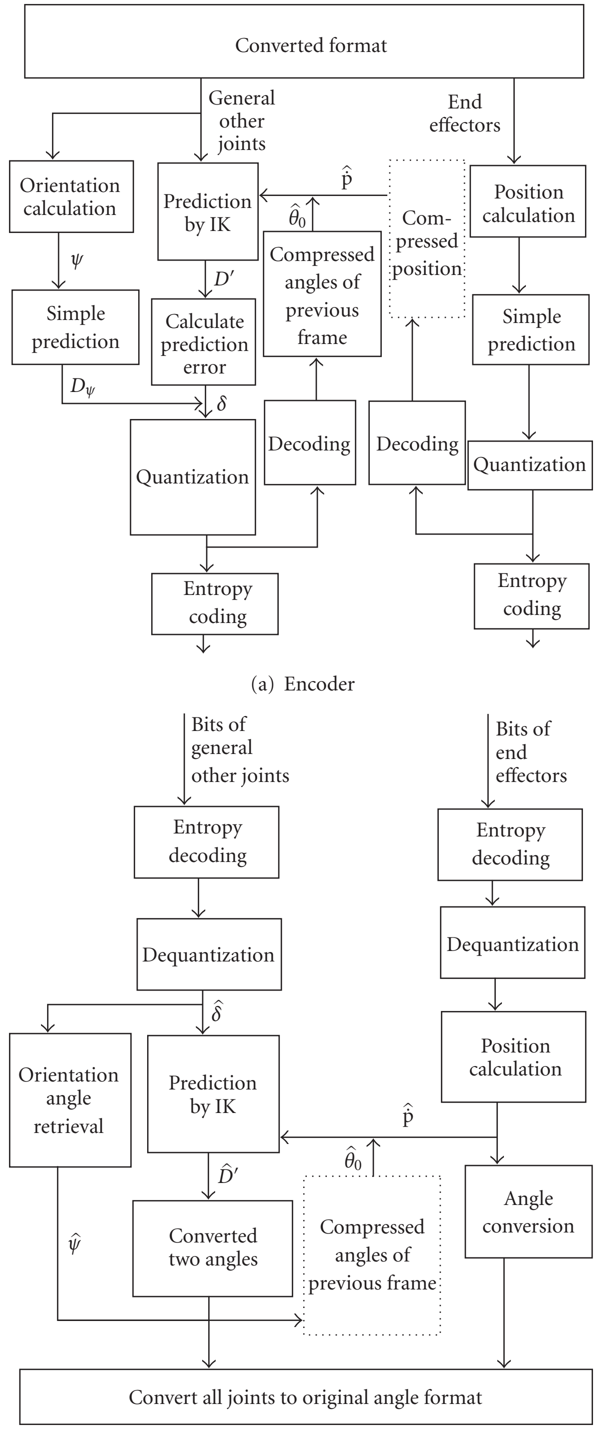
$$P_n = f(\boldsymbol{\theta}_{\mathbf{n}}), \tag{8}$$

where $\boldsymbol{\theta}_{\mathbf{n}}$ is composed of all angles $(\theta_1, \theta_2, \theta_3, \ldots, \theta_{Nj})$ for each joint in frame n.

In the inverse kinematics, motion is inherited up the hierarchy, from the extremities to the root (Figure 5(b)). The role of the IK algorithm is to automatically work out how each joint in a chain should be transformed so that the end

(1) The 3 Euler angles $\boldsymbol{\theta}_x, \boldsymbol{\theta}_y, \boldsymbol{\theta}_z$ of each joint in each frame are inputted
(2) Convert $\boldsymbol{\theta}_x, \boldsymbol{\theta}_y, \boldsymbol{\theta}_z$ into ϕ and φ by (4) and (5) calculate the ψ using (6)
(3) Calculate the increment Δp of the position of the end effector by (16)
(4) Calculate the Jacobian marix J using the angles ϕ and φ of last frame by (19)
(5) Get the pseudoinverse J^* of J by (14)
(6) Obtain the angle change of ϕ and φ by (15)
(7) Calculate the angle change of the ψ by simply finding the difference of the two connective frames
(8) Apply quantization in the data obtained in the step 3, 6 and 7 respectively using different stepsize
(9) Perform entropy coding for the data obtained in step 8
(10) Send the compressed data to the decoder

Algorithm 1: IK Algorithm.



(a) Encoder

(b) Decoder

Figure 6: IK algorithm-based compression flow chart.

effector can reach the goal. To find the set of the changes of the angles which satisfy a given displacement of the positions of the end effectors, we need to solve

$$\boldsymbol{\theta}_{\mathbf{n}} = f^{-1}(P_n). \tag{9}$$

However, this inverse is, in most cases, difficult to solve. Instead of this, Jacobian-based method is utilized [22–24]. Equation (8) is written in differential form:

$$\dot{P}_n = J\dot{\boldsymbol{\theta}}_n, \tag{10}$$

J is the Jacobian matrix of the displacement of the position of the end effector $\dot{P}_n$ with respect to the changes of the joint angles $\dot{\boldsymbol{\theta}}_n$ and

$$J \equiv \frac{\partial P_n}{\partial \boldsymbol{\theta}_n}. \tag{11}$$

To get the desire $\dot{\boldsymbol{\theta}}_n$, one has to solve

$$\dot{\boldsymbol{\theta}}_n = J^{-1}\dot{P}_n. \tag{12}$$

Since the natural human body motion typically is represented over 30 degrees of freedom (DOF) which is larger than rank of J, the set of (12) are underdetermined. To solve this, some constraints are needed. Meanwhile for motion compression, the constraint used to make adjustments of the joint angles must be considered to match the motion characters. Traditionally, one minimizes the norm of the velocity of the joint angl $\|\dot{\boldsymbol{\theta}}_n\|$ under the constraint $J\dot{\boldsymbol{\theta}}_n - \dot{P}_n = 0$. Then, (12) is written by

$$\dot{\boldsymbol{\theta}}_n = J^*\dot{P}_n, \tag{13}$$

where

$$J^* = J^T\left(JJ^T\right)^{-1} \tag{14}$$

and it is called Moore-Penrose pseudoinverse. Equation (13) linearly relates the displacement of the end effectors to the change of joint angles. However, it relates a series of smallest change of the rotation angles to a small displacement in the end effectors. Obviously it is not desirable for motion compression. It is possible to consider another solution than this constraint. In this paper, we employ the constraint of minimizing the norm of the differential acceleration $\|\dot{\boldsymbol{\theta}}_n - \dot{\boldsymbol{\theta}}_{n-1}\|^2$ and get the solution in our prediction algorithm:

$$\dot{\boldsymbol{\theta}}_n = \boldsymbol{\theta}_0 + J^*(\dot{P}_n - J\boldsymbol{\theta}_0), \tag{15}$$

where $\boldsymbol{\theta}_0 = k\dot{\boldsymbol{\theta}}_{n-1}$, k is the parameter that determines the weighting between the solution and the error. It is clear that this method leads to satisfying the natural motion character better than traditional minimizing the velocities of the joint angles. When ΔP_n, which is a displacement of end effector from previous position to current position, is given, the change of each joint can be determined by (13).

Our IK algorithm consists of the following steps.

(1) Calculate the increment Δp of the position of the end effector from the frame $i-1$, p_{i-1} to the frame i, p_i:

$$\Delta p = p_i - p_{i-1}. \tag{16}$$

(2) Calculate Jacobian matrix $J(\phi_1, \varphi_1, \phi_2, \varphi_2, \phi_3, \varphi_3, \dots, \phi_{Nj}, \varphi_{Nj})$ using the angles of last frame $(\phi_1, \varphi_1, \phi_2, \varphi_2, \phi_3, \varphi_3, \dots, \phi_{Nj}, \varphi_{Nj})$, where ϕ_j and φ_j are the two angles in (5). Since

$$p_i(x, y, z) = \begin{bmatrix} f_1(\phi, \varphi) \\ f_2(\phi, \varphi) \\ f_3(\phi) \end{bmatrix}, \tag{17}$$

where,

$$\begin{aligned} f_1(\phi, \varphi) &= \sum_{j=1}^{n} L_j \cdot \sin(\phi_j)\cos(\varphi_j), \\ f_2(\phi, \varphi) &= \sum_{j=1}^{n} L_j \cdot \sin(\phi_j)\sin(\varphi_j), \\ f_3(\phi) &= \sum_{j=1}^{n} L_j \cdot \cos(\phi_j) \end{aligned} \tag{18}$$

by (5) and L_j is the length of link j, then by (10), $\Delta p = J[\dot{\phi}_j \dot{\varphi}_j]$ and

$$\mathbf{J} = \left[\frac{\partial f_1(\phi,\varphi)}{\partial \phi_j} \; \frac{\partial f_1(\phi,\varphi)}{\partial \varphi_j}, \frac{\partial f_2(\phi,\varphi)}{\partial \phi_j} \; \frac{\partial f_2(\phi,\varphi)}{\partial \varphi_j}, \frac{\partial f_3(\phi)}{\partial \phi_j} \; 0\right], \tag{19}$$

where

$$\begin{aligned} \frac{\partial f_1(\phi,\varphi)}{\partial \phi_j} &= L_j \cos(\phi_j)\cos(\varphi_j), \\ \frac{\partial f_1(\phi,\varphi)}{\partial \varphi_j} &= -L_j \sin(\phi_j)\sin(\varphi_j), \\ \frac{\partial f_2(\phi,\varphi)}{\partial \phi_j} &= L_j \cos(\phi_j)\sin(\varphi_j), \\ \frac{\partial f_2(\phi,\varphi)}{\partial \varphi_j} &= L_j \sin(\phi_j)\cos(\varphi_j), \\ \frac{\partial f_3(\phi)}{\partial \phi_j} &= -L_j \sin(\phi_j). \end{aligned} \tag{20}$$

(3) Get the pseudoinverse of J by (14).

(4) In each motion chain, obtain the changes in frame i for $\phi_1, \varphi_1, \phi_2, \varphi_2, \dots, \phi_{Nj}, \varphi_{Nj}$ by (15). $\dot{\boldsymbol{\theta}}_i$ is the change of the angles in frame i and is given by $\dot{\boldsymbol{\theta}}_i = k\dot{\boldsymbol{\theta}}_{i-1} + J^*(\Delta p - J^* k\dot{\boldsymbol{\theta}}_{i-1})$. We obtain the good results with $k = 2$.

In step (2), if the general format, which is composed of rotation angles about X, Y, Z axes, is applied to calculate the Jacobian matrix, each element of the Jacobian matrix almost involves all the related trigonometric functions of the corresponding angles in the motion chain. While in our converted format, since ϕ and φ are calculated by the product of all the related rotation matrices from current joint to root joint, using converted format, the Jacobian J is given in a closed form. Although two angles format is sufficient to represent the position of the joints in the world coordinate, the constraints on the joints generally controlled by the orientation of the joints. To apply our compression algorithm to more general CG animations, we further using the parameter ψ that is the orientation angle and calculated by the standard matrix of rotation around an arbitrary axis introduced in Section 3.2. Therefore, initial orientation of the three Euler angles of the joint is retrieved perfectly.

Finally, the algorithm is stated in Algorithm 1.

5.2. *Compression with prediction technique*

Considering motion characters, we have to assign more bits to some special joints such as the end effectors than other general types of joints. An adaptive quantization approach preserves features of the motion greatly. To achieve this, the hierarchical stepsize for different joints can be implemented in quantization step.

Meanwhile, since the amount of motion data is considerable, high compression rate is needed. Prediction based techniques have been widely and successfully applied in compression of series of data. If we can predict every next frame, we only have to save the first frame and the difference between real value and predicting result. The better the predictions, the more common corrections we can get and the more bits we can save.

The aforementioned two points characterize our IK compression approach properly when comparing with previous works. Actually, there are no conventional algorithms that specialize the constraints in joints, that is, precise reconstruction of the end effectors, and achieve efficient compression rate simultaneously.

To predict every next frame, an intuitive method is to utilize the last frame directly. Taking the difference D_i between the current frame i and last frames $i-1$ may be one of the simplest methods. By this method, we can decode current value θ_i in decoder using the equation

$$\theta_i = \theta_{i-1} + D_i. \tag{21}$$

Generally, compression rate improvement only depends on stepsizes. We have to explore a better prediction method that can provide the data closer to θ_i.

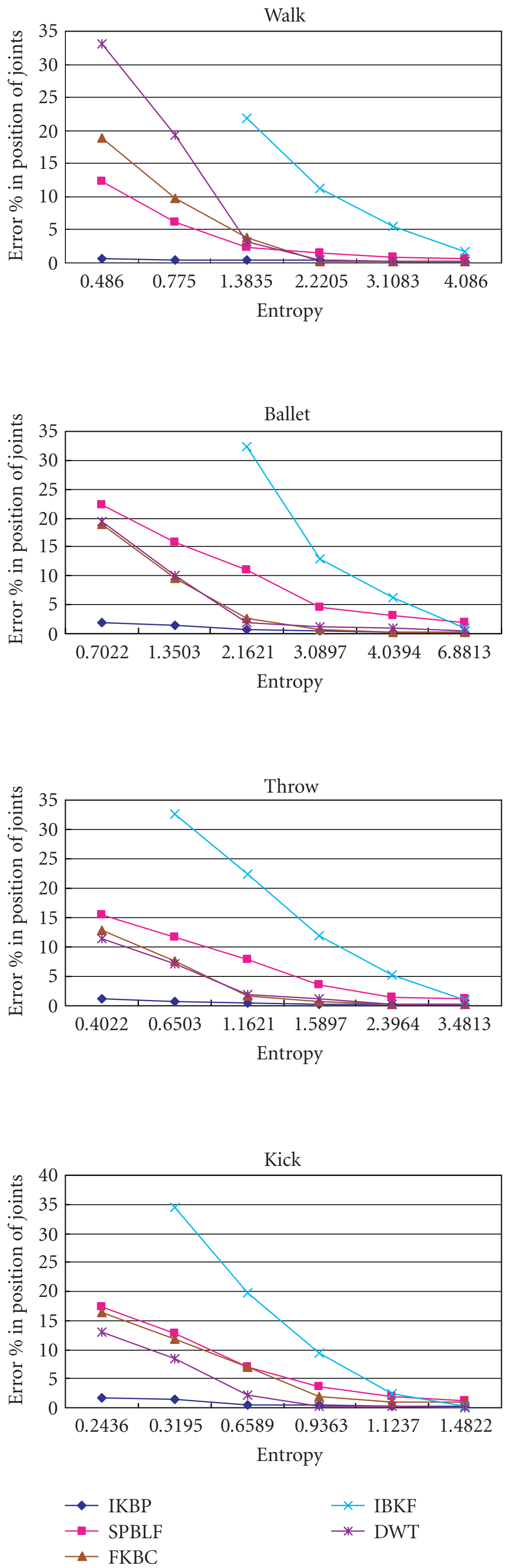


Figure 7: RD curve of the position of the walk, ballet, throw, and kick motions; IKBP—IK-based prediction method, FKBC—FK-based compression, SPBLF—simple prediction by last frame, IBKF—interpolation between the key frames, DWT—discrete wavelet transform.

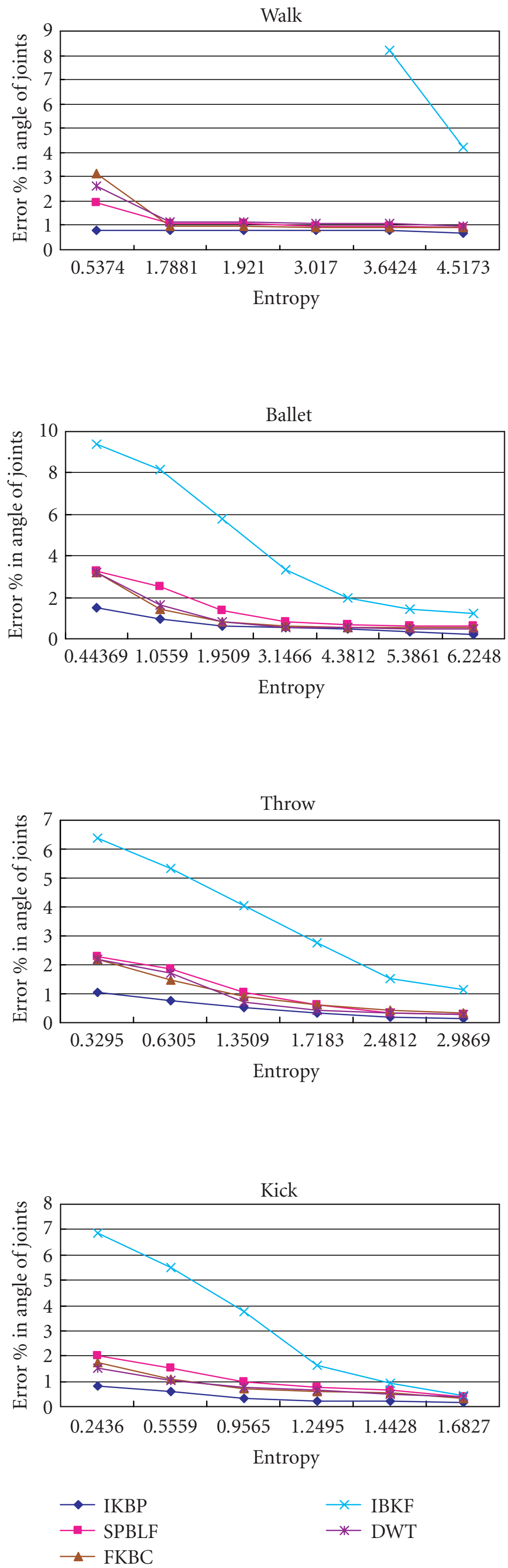
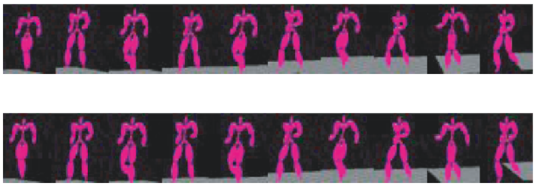


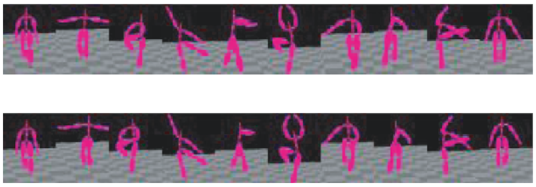
Figure 8: RD curve of the rotation angle of the walk, ballet, throw, and kick motions; IKBP—IK-based prediction method, FKBC—FK-based compression, SPBLF—simple prediction by last frame, IBKF—interpolation between the key frames, DWT—discrete wavelet transform.

Walk motion



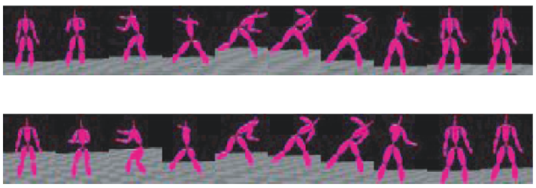
Top: original motion frames
Bottom: compressed motion frames when entropy = 0.6679
The index of the frames is
1 55 142 184 268 307 392 441 500 600

Ballet motion



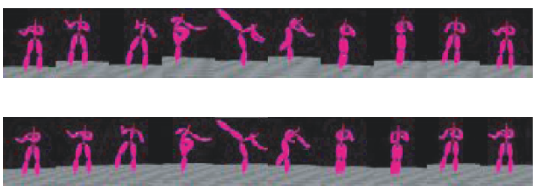
Top: original motion frames
Bottom: compressed motion frames when entropy = 1.4227
The index of the frames is
1 121 139 166 220 238 254 313 332 388

Throw motion



Top: original motion frames
Bottom: compressed motion frames when entropy = 0.5891
The index of the frames is
1 20 25 33 39 44 48 62 76 179

Kick motion



Top: original motion frames
Bottom: compressed motion frames when entropy = 0.5256
The index of the frames is
1 30 37 51 67 80 96 107 127 147

Figure 9: Series of samplings of the motions.

The inverse kinematics gives a solution exactly. In our compression method, an encoder calculates the differences of position of end effectors between two sequential frames. More bits are assigned to them to keep the precision of the end effectors in quantization. Then these differences will be sent to decoder. Next, both in encoder and decoder, using these differences and the angles in previous frame we can calculate the change of the rotation angle in each joint by IK algorithm approximately. Suppose the difference between the value predicted by IK and the value in the last frame is $D_i{}'$ and

$$\theta_{i\text{predict}} = \theta_{i-1} + D_i{}', \tag{22}$$

$D_i{}'$ can be calculated by (14) as the $\dot{\boldsymbol{\theta}}_n$. We need transfer $\delta = D_i - D_i{}'$ to the decoder which may reconstruct current value θ_i by

$$\theta_i = \theta_{i\text{predict}} + \delta. \tag{23}$$

We adopt a prediction for orientation angles of each joint. Our prediction method is simply done by subtracting the current frame by the last frame. The IK based compression procedure with the prediction technique is shown in Figure 6. In the encoder, the data of the rotation angles of the end effectors and the other general joints are processed separately.

Firstly, for the general joints, the change of the rotation angle in each frame $D_i{}'$ can be predicted by the compressed angles $\hat{\theta}_0$ of previous frames and the change of the position $\hat{\text{p}}$ of the end effectors. Here we use the quantized version $\hat{\theta}_0$ instead of θ_0 and $\hat{\text{p}}$ instead of $\hat{\text{p}}$ to get the same result in the decoder. After calculating the prediction error δ, we adopt general quantization and entropy coding to the prediction error. Meanwhile, we adopt the simple prediction method by every last frame for the orientation angle ψ of each joint to get $D\,\psi$.

For the end effectors, after the position calculation, we also adopt the simple prediction method by every last frame. The quantization and entropy coding are applied into the simple predicted sequence of the end effectors.

The bits of the end effectors and the other general joints are sent to the decoder, respectively.

For the bits of the general other joints, the entropy decoding and dequantization are implemented as the opposite processing in the encoder. Using the IK algorithm, we predict the rotation angles of a current frame by the last decoded frame $\hat{\theta}_0$, then add the compressed prediction error $\hat{\delta}$ and the change of the position of the end effectors $\hat{\text{p}}$ using

$$\hat{\theta}_i = \hat{\theta}_{i-1} + \hat{D}' + \hat{\delta}. \tag{24}$$

This process is the same as the prediction in the encoder.

For the end effectors, after the entropy decoding and dequantization of the bits, we retrieve the position of the end effector of each frame. Finally, the angle conversion of the end effectors is added to convert the position of the end effectors to the rotation angles following the original data format.

6. EXPERIMENTAL RESULTS

In our experiment, we adopted one of the most well-known format of the human motion, the BVH file format [15, 25]. The BVH file has two parts, a header section which describes any number of skeleton hierarchies and the initial pose of the skeleton by translational offsets of children segments from their parent, and a data section which contains the position of the root joint and the rotation information of motion of

Table 1: Error of position of each joint in a limb chain for walking motion. This table records almost the same entropy of different methods for compression ratio and the error of the positions of several joints for the quality of the compressed motion correspondingly. In the walking motion, the left shoulder chain includes 4 joints (left shoulder, left humerus, left radius, and left hand).

Method	Entropy	Compression ratio%	Error of the position			
			Root joint left shoulder	Child joint left humerus	Grand child joint left radius	End effector left hand
IKBP	0.7144	4.81381	0.4985	0.6238	0.9506	2.1912
SPBLF	0.7269	4.89805	1.6457	2.7175	6.4688	6.3385
FKBC	0.7350	4.95263	3.2423	7.6778	16.009	12.066
IBKF	0.7233	4.87379	>100	>100	>100	>100
DWT	0.7296	4.91625	13.709	28.270	40.623	37.992
IKBP	1.3821	9.31297	0.3576	0.5779	0.7809	1.1068
SPBLF	1.3673	9.21325	0.8872	1.5062	4.8276	4.6992
FKBC	1.3834	9.32173	0.8286	1.3859	1.7912	3.2002
IBKF	1.4056	9.47132	24.459	20.725	26.814	31.092
DWT	1.3850	9.33251	1.1968	1.6492	2.8112	3.4743
IKBP	2.1971	14.8046	0.0613	0.1005	0.1048	0.1616
SPBLF	2.2147	14.9232	1.2701	1.8213	1.0853	1.4703
FKBC	2.2205	14.9623	0.1057	0.1396	0.1376	0.1808
IBKF	2.3724	15.9858	13.021	16.758	14.668	13.227
DWT	2.2181	14.9461	0.1658	0.2417	0.2814	0.3500
IKBP	3.0171	20.3300	0.0521	0.054	0.0649	0.0831
SPBLF	3.1294	21.0867	0.5823	0.8639	0.8143	0.9136
FKBC	3.1083	20.9446	0.0622	0.0653	0.0697	0.0851
IBKF	3.1114	20.9654	4.8487	6.3667	6.8840	7.1055
DWT	3.0573	20.6009	0.0654	0.0714	0.0698	0.0856
IKBP	4.0977	27.6114	0.0237	0.0441	0.0648	0.0726
SPBLF	4.0860	27.5326	0.5423	0.6663	0.6373	0.6093
FKBC	4.0860	27.5326	0.0612	0.0628	0.0662	0.0736
IBKF	4.4625	30.0695	1.5934	2.0052	2.1053	2.4268
DWT	4.1962	28.2751	0.0634	0.0697	0.0677	0.0741

all joints in each frame. In the BVH format, the motion is described by a series of the three orientation matrices with respect to y, x, z axes. We convert them to the two angles ϕ and φ by (5) to represent the position and the orientation ψ, and then compress them using prediction method.

To evaluate the efficiency, we calculate the error of the position of joint i of the compressed motion comparing with the original one by

$$E_{\text{position}}(i) = \frac{1}{N_f}\sum_{j=1}^{N_f}\sqrt{\|P_{oj}^i - P_{cj}^i\|^2} \tag{25}$$

and the error of all joints in all frames by

$$E_{\text{position}} = \frac{1}{N_j}\sum_{i=1}^{N_j}E_{\text{position}}(i), \tag{26}$$

where P_{oj}^i and P_{cj}^i are the 3D positions of joint i in frame j of original and compressed motions, respectively in world coordinate. And N_f is the number of frames, while N_j is the number of total joints.

We also calculate the error of three orientation angles of joint i of the compressed motion comparing with the original one by

$$E_{\text{angle}}(i) = \frac{1}{N_f}\sum_{j=1}^{N_f}\sqrt{\|O_{oj}^i - O_{cj}^i\|^2} \tag{27}$$

and the error of all joints in all frames by:

$$E_{\text{angle}} = \frac{1}{N_j}\sum_{i=1}^{N_j}E_{\text{angle}}\ (i), \tag{28}$$

where O_{oj}^i and O_{cj}^i are orientation angles of joint i in frame j of original and compressed motions, respectively, and N_f is the number of frames, while N_j is the number of total joints. Note that the three orientation angles of our method are ϕ, φ and ψ, while the original format consists of three angles with respect to X, Y, Z axes.

We compare the proposed FK-based compression (FKBC) and IK based prediction (IKBP) method with other

Table 2: Error of angle of each joint in a limb chain for walking motion. This table records almost the same entropy of different methods for compression ratio and the error of the orientation angles of several joints for the quality of the compressed motion correspondingly. In the walking motion, the left shoulder chain includes 4 joints (left shoulder, left humerus, left radius, and left hand).

Method	Entropy	Compression ratio%	Error of the angle Root joint left shoulder	Child joint left humerus	Grand child joint left radius	End effector left hand
IKBP	0.5374	3.62115	0.9531	1.1785	0.4022	1.3495
SPBLF	0.5421	3.65282	0.9572	1.1932	0.8255	2.0165
FKBC	0.5539	3.73233	0.9585	1.1967	1.4382	2.9845
IBKF	0.4862	3.27615	34.530	53.226	>100	>100
DWT	0.5336	3.59554	0.9550	1.1717	1.4839	2.2946
IKBP	1.7881	12.0487	0.9530	1.1780	0.4015	1.3490
SPBLF	1.7938	12.0871	0.9568	1.1931	0.5984	2.0154
FKBC	1.7653	11.8950	0.9539	1.1826	0.4606	2.0059
IBKF	1.7804	11.9968	9.557	10.620	19.830	30.80
DWT	1.7671	11.9072	0.9542	1.1792	0.4093	2.0041
IKBP	1.9210	12.9442	0.9530	1.1757	0.4015	1.3483
SPBLF	2.0423	13.7615	0.9557	1.1878	0.5832	2.0151
FKBC	1.9756	13.3121	0.9537	1.1785	0.4534	2.0012
IBKF	2.1027	14.1685	2.2900	10.211	7.8120	30.410
DWT	2.0167	13.5891	0.9539	1.1789	0.4049	1.9998
IKBP	3.6424	24.5435	0.9529	1.1679	0.4009	1.3480
SPBLF	3.6982	24.9195	0.9537	1.1821	0.4439	2.0085
FKBC	3.6733	24.7517	0.9532	1.1781	0.4217	2.0002
IBKF	3.6081	24.3123	1.9200	3.2180	2.0250	7.2390
DWT	3.6729	24.7490	0.9529	1.1778	0.4015	1.9902
IKBP	4.5173	30.4388	0.9528	1.1650	0.3145	1.3483
SPBLF	4.5628	30.7454	0.9529	1.1776	0.4013	1.9961
FKBC	4.6805	31.5385	0.9529	1.1779	0.4014	1.9839
IBKF	4.4625	30.0696	0.8800	1.4900	0.9800	4.2000
DWT	4.5819	30.8741	0.9529	1.1772	0.3978	1.9837

three methods, the simple prediction by last frame (SPBLF) based on (21) in Section 5, the interpolation between the key frames (IBKF) and the motion compression technique using the discrete wavelet transform (DWT) appearing in [11]. (The wavelet transform and interpolations are implemented by Matlab software which is trustworthy implementation.) In IBKF based compression method we apply the Piecewise Cubic Hermite (PCH) interpolation into the key frames which are obtained by curve simplification in [6], while in DWT method we adopt the 9/7 wavelet transform to compression the motion data. We give the RD curves of four motions in Figure 7. The x-axis represents the summation of the entropies of the three angles obtained by those five methods, respectively.

The entropy coding is widely used to estimate the bit rate of the coded stream, which gives theoretically minimal bit rate. The entropy of a random variable X, which is defined as $H(X) = -\sum_{x\in Ax} f_X(x) \log_2 f_X(x)$ can be interpreted as the average amount of information conveyed by the outcome of the random variable X. A_x is known as the alphabet elements. $f_X(x)$ is the probability of the outcome $X = x$. In our experiment, since we use the same Arithmetic coding in all methods, the entropy values the compression ratio of each method.

In Figure 7, the results of the five methods including the proposed methods are shown. The proposed algorithm IKBP can get the more common corrections and save more bits than the general algorithm. The variance of the error of the joint position calculated by IKBP method is smaller than the results by FKBC, SPBLF, and IBKF methods. It demonstrates that our proposed algorithm IKBP can get the more common corrections and save more bits than the general algorithm.

For the curves generated by the IBKF method, we change the number of the key frames which are obtained by the IBKF method introduced in [2] to get the different compressed form of the motion data. Since the error of the position of the walking motion by IBKF is more than 100 when the entropy is smaller than 1.0 and the position of the ballet motion by the IBKF is more than 50 when entropy is smaller than 1.5, we abridge these large values of the error to give an observable comparison in the range from 0 to 35. Same processing is used in other two motions.

Table 3: Error of position of each joint in a limb chain for ballet motion. This table records almost the same entropy of different methods for compression ratio and the error of the position of the joints for the quality of the compressed motion correspondingly. In the ballet motion, the left shoulder chain includes 3 joints (left shoulder, left elbow, and left wrist).

Method	Entropy	Compression ratio%	Error of the position		
			Root joint left shoulder	Parent joint left elbow	Child joint left wrist
IKBP	0.5054	6.2786	0.5621	1.1875	1.2351
SPBLF	0.5016	6.2314	1.0252	11.6327	17.4201
FKBC	0.5321	6.6103	2.6686	8.9683	13.7177
IBKF	0.5000	6.2115	>100	>100	>100
DWT	0.5391	6.6973	3.1183	8.7364	13.9129
IKBP	1.0624	13.198	0.2159	0.4591	0.5628
SPBLF	1.0545	13.100	1.0191	11.5586	15.9806
FKBC	1.0298	12.793	1.9960	4.6145	6.8852
IBKF	1.0264	12.751	21.1268	21.8202	23.1181
DWT	1.0297	12.792	2.0151	4.7956	7.2744
IKBP	2.1256	26.406	0.1376	0.3624	0.3563
SPBLF	2.0841	25.891	1.0025	4.8103	5.2754
FKBC	2.0821	25.866	0.2623	0.5816	0.9040
IBKF	2.0064	24.925	9.1289	9.7715	10.5541
DWT	2.1014	26.106	0.4755	0.8853	1.2702
IKBP	4.2955	53.363	0.0633	0.0606	0.0649
SPBLF	4.3064	53.499	0.6863	1.4141	1.7705
FKBC	4.3674	54.256	0.0600	0.0691	0.0785
IBKF	4.3231	53.706	1.4282	1.5323	1.7680
DWT	4.3067	53.502	0.1267	0.2102	0.2908
IKBP	6.9143	85.897	0.0575	0.0541	0.0583
SPBLF	6.9749	86.650	0.5604	1.1152	1.5466
FKBC	6.9160	85.918	0.0551	0.0561	0.0573
IBKF	6.9896	86.832	0.2412	0.2856	0.3554
DWT	6.9365	86.173	0.0932	0.1046	0.1519

At low bit rates, FKBC is inferior to SPBLF, FKBC gains better compression in low compression rate. Note that FKBC is a hierarchical coding scheme and a progressive decoding is possible by virtue of the wavelet, while IKBP and SPBLF do not have this property.

Figure 8 shows the RD curves about the error of the three orientation angles. The x-axis represents the summation of the entropies of three angles. For the curve generated by the IBKF method, since the error of the rotation angle of the walking motion by the IBKF is more than 100 when the entropy is smaller than 3, we also abridge the data of the large error by IBKF to give a comparison in the error range from 0 to 9.

We also present the error of positions and the orientations of each joint in a limb chain corresponding to the different entropy value of the walk motion in Tables 1 and 2 and the ballet motion in Tables 3 and 4, respectively, to demonstrate the advantage of our approach. Since different motion has different hierarchy skeleton, in the walk motion the left shoulder chain includes 4 joints (left shoulder, left humerus, left radius, and left hand), while in the ballet motion, the same motion chain has 3 joints (left shoulder, left elbow and left wrist). When the entropy is smaller than 1, the error of the positions of some joints by IBKF is larger than 100 and the recovered motion is totally distorted. In the same compressing ratio, the proposed algorithm IKBP produces small error of the positions in these joints than the general algorithms.

Figure 9 shows series of samples of the original motions and the decoded one by IKBP method correspondingly. These series of samplings present a period of the motion. In walk motion, when entropy is larger than 1.1206 it is difficult to discovery the difference between the original motion and the decoded one. We also show the results of other three motions, "ballet," "throw" and "kick." Table 5 gives the description of these four motions.

Finally, we compare the compression and decompression times in Table 6. The specification of the hardware of PC is that CPU is Pentium(R) 4 3.00 GHz and Memory is 0.99 GB. We record the encoding and decoding times of one frame of the walk motion with 580 frames. Although our proposed method appears about 0.3 milliseconds lower than SPBLF method and about 0.18 milliseconds lower than IBKF method in compressing a frame, considering the compression ratio and quality of the recovered motion our algorithm is much better than IBKF and better than other methods.

Table 4: Error of angle of each joint in a limb chain for ballet motion. This table records almost the same entropy of different methods for compression ratio and the error of the orientation angle of the joints for the quality of the compressed motion correspondingly. In the ballet motion, the left shoulder chain includes 3 joints (left shoulder, left elbow and left wrist).

Method	Entropy	Compression ratio%	Error of the position		
			Root joint left shoulder	Parent joint left elbow	Child joint left wrist
IKBP	0.5054	6.2786	0.2648	0.6546	2.5389
SPBLF	0.5016	6.2314	1.4050	1.5067	6.4131
FKBC	0.5321	6.6103	0.6517	1.0528	2.3071
IBKF	0.5000	6.2115	45.4032	63.6985	66.9011
DWT	0.5391	6.6973	1.4340	1.7459	2.8383
IKBP	1.0624	13.198	0.2319	0.5896	1.5122
SPBLF	1.0545	13.100	1.3362	1.4687	5.5020
FKBC	1.0298	12.793	0.2685	0.6239	1.7313
IBKF	1.0264	12.751	30.2023	49.6792	66.2010
DWT	1.0297	12.792	0.2723	0.6732	1.9386
IKBP	2.1256	26.406	0.2302	0.5428	0.6538
SPBLF	2.0841	25.891	0.2816	0.9719	1.5518
FKBC	2.0821	25.866	0.2307	0.5430	0.6586
IBKF	2.0064	24.925	10.8476	33.8133	49.7030
DWT	2.1014	26.106	0.2391	0.5847	0.7053
IKBP	4.2955	53.363	0.2259	0.5378	0.3868
SPBLF	4.3064	53.499	0.2296	0.5620	0.4168
FKBC	4.3674	54.256	0.2267	0.5371	0.3483
IBKF	4.3231	53.706	3.4238	8.8972	20.4645
DWT	4.3067	53.502	0.2271	0.5384	0.3831
IKBP	6.9143	85.897	0.2257	0.5372	0.3504
SPBLF	6.9749	86.650	0.2257	0.5405	0.3483
FKBC	6.9160	85.918	0.2267	0.5371	0.3476
IBKF	6.9896	86.832	2.9320	4.1791	8.5528
DWT	6.9365	86.173	0.2265	0.5371	0.3479

Table 5: Four original motion data.

	Data size	Number of joints	Sampling rate	Number of frames
Walk	324 k	23	0.00833 (s)	580
Ballet	183 k	20	0.0400 (s)	388
Throw	70 k	17	0.033333 (s)	179
Kick	56 k	19	0.033333 (s)	147

Table 6: Compression and decompression times for one frame.

	Encoding	Decoding
IKBP	1.26 (ms)	1.32 (ms)
SPBLF	0.96 (ms)	1.09 (ms)
FKBC	1.12 (ms)	1.20 (ms)
IBKF	1.08 (ms)	1.20 (ms)
DWT	1.12 (ms)	1.15 (ms)

7. CONCLUSION

The compression of captured motion data is an important issue in motion storing, retrieval, editting and transmitting. For the motion compression, some specific types of joints such as end effectors often require higher precision than other general types of joints in, for example, CG animation and robot manipulation. There are no conventional algorithms specialize the constraints in joints and achieve efficient compression rate simultaneously. Using forward kinematics, we implemented a constraint based compression algorithm for motion data with special characteristics which can be indicated by motion behavior or specified by user. However, to solve the problem that the distortion of parent joint coming from quantization in turn affects its child joint and is accumulated to the end effector, the forward kinematics cannot work perfectly.

Inverse kinematics is a common approach to control the movement of the whole body. The position of end effector can be specified in a target position from preceding position. By the changes of the position of the end effectors we may get variations of the motion of the entire body. The inverse kinematics, on the other hand, supports a prediction-based compression. To predict motion in decoder, we only save the first frame and a series of small differences between real value and prediction gotten by the variations of the positions of the end effectors. Therefore, it can solve the problems of specific joints and achieve efficient compression of the motion data.

We applied the FK based compression and IK based compression in our reduced two-angle format. Some experimental results of example motions demonstrate the advantage of our methods compared with conventional methods.

ACKNOWLEDGMENTS

This work was partly supported by a Grant-in-Aid for Young Sciences (no. 14750305) of Japan Society for the Promotion of Science, fund from MEXT via Kitakyushu innovative cluster project, and Kitakyushu IT Open Laboratory of National Institute of Information and Communications Technology (NiCT).

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