Human Motion Reconstruction by Direct Control of Marker Trajectories

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Abstract. Understanding the basis of human movement and reproducing it in robotic environments is a compelling challenge that has engaged a multidisciplinary audience. In addressing this challenge, an important initial step involves reconstructing motion from experimental motion capture data. To this end we propose a new algorithm to reconstruct human motion from motion capture data through direct control of captured marker trajectories. This algorithm is based on a task/posture decomposition and prioritized control approach. This approach ensures smooth tracking of desired marker trajectories as well as the extraction of joint angles in real-time without the need for inverse kinematics. It also provides flexibility over traditional inverse kinematic approaches. Our algorithm was validated on a sequence of tai chi motions. The results demonstrate the efficacy of the direct marker control approach for motion reconstruction from experimental marker data.

Key words: human motion synthesis, operational space formulation, task/posture decomposition, prioritization, marker space.

1 Introduction

The central nervous system (CNS) is able to elegantly coordinate the complex structure of the human body to perform movements of great agility and sophistication. An effective way of understanding human movement involves mimicking motions which are optimal in performance. Such optimal movements include those exhibited by highly skilled practitioners in sports and the martial arts. Human motor performance depends on skilled motor coordination and posture control as well as physical strength and perception. Drawing inspiration from their biological counterparts humanoid robots are being imbued with skilled dynamic behaviors. Enhancing the authenticity of synthesized human motion in robotic systems has been a continuing challenge that draws together researchers from the fields of physiology, neuroscience, biomechanics, and robotics. This challenge has been addressed by researchers through retargetting methods [1, 10]. Additionally, adapting existing motion for a human character with a given set of constraints has been explored [4, 9]. However,

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these techniques, which map motion-capture data to different characters and scenes, require inverse kinematic computations.

We propose a new algorithm to reconstruct human movement through direct control of optical marker trajectory data. This approach directly projects marker points onto a simulated human model and tracks the trajectory in Cartesian space. Tracking the desired trajectories is accomplished using the operational space control framework [5]. With our algorithm we can drive a simulated model of the human body to experimental marker locations in real-time. This allows smooth tracking of the desired marker trajectories and extraction of joint angles within a reasonable error boundary. Further, the task/posture decomposition used in the operational space method constitutes a natural decomposition for dealing with marker data, thus avoiding the performance of inverse kinematics.

The algorithm presented here is validated through a sequence of slow tai chi motions. Tai chi motions are light, lively, and balanced, and they constitute a rich variety of motions useful for testing purposes. With our new algorithm we show that human movement can be controlled and reconstructed in real-time. This facilitates the investigation of other high performance dynamic skills.

2 Direct Marker Control Approach

Optical motion capture constitutes a common and effective method for capturing human motion. A series of markers attached to a subject's body are imaged by a set of cameras and the spatial positions of the markers are triangulated from the image data. A number of post processing steps need to be performed to convert the raw marker positions into useful kinematic data. The most significant step is to convert the marker trajectories into joint space trajectories. This has commonly been done using inverse kinematic techniques.

As an alternative to performing inverse kinematics on marker data we propose to dynamically track the markers using a task-level control approach. We will refer to this approach as direct marker control. For the purposes of our direct marker control application, we will define task space as the space of Cartesian coordinates for the motion capture markers. However, it must be noted that marker trajectories obtained through motion capture are not independent. For example, markers on the same body link are rigidly constrained to each other and the relative motion between markers on adjacent links is limited by the freedom in the connecting joints. To accommodate for motion dependencies the markers are grouped into independent subsets, $\{m_1, \ldots, m_n\}$. Each subset, m_i, is represented by a single task vector, x_{m_i}, that is formed by concatenating the Cartesian coordinates of the individual markers contained within that subset. Using a prioritized control approach a hierarchy of marker task vectors is formed where the tasks that are lower in the hierarchy are projected into the null space of the tasks that are higher in the hierarchy. At the end of this recursive process, independent subsets of marker tasks are obtained, ensuring the overall feasibility of the marker control. The operational space formulation [5] is then used to directly control the marker trajectories.

2.1 Prioritized Control in Marker Space

In this section, we develop the proposed framework for direct control of marker trajectories. The need to address high performance dynamic behaviors and the need for flexibility over traditional inverse kinematic approaches constitute the motivation for our approach.

A behavioral task generally involves descriptions of various parts of the multi-body mechanism, each represented by an operational point $x_{t(i)}$. The full task is represented as an $m \times 1$ vector, x_t, formed by vertically concatenating the coordinates of all operational points. The Jacobian associated with this task is denoted as J_t. The derivation of the operational space formulation begins with the joint space dynamics of the robot [8]

$$A\ddot{q} + b + g = \Gamma \tag{1}$$

where q is the the vector of n generalized coordinates of the articulated system, A is the $n \times n$ kinetic energy matrix, b is the vector of centrifugal and Coriolis generalized forces, g is the vector of gravity forces, and Γ is the vector of generalized control forces.

Task dynamic behavior is obtained by projecting (1) into the space associated with the task, which can be done with the following operation

$$\overline{J}_t^T [A\ddot{q} + b + g = \Gamma] \Longrightarrow \Lambda_t \ddot{x}_t + \mu_t + p_t = \overline{J}_t^T \Gamma \tag{2}$$

Here, $\overline{J}_t^T$ is the dynamically-consistent generalized inverse of J_t [8], Λ_t is the $m \times m$ kinetic energy matrix associated with the task and μ_t and p_t are the associated centrifugal/Coriolis and gravity force vectors.

The operational space framework [5] is used as the basis for our direct marker control algorithm. In this formulation, the task behavior is divided into a set of independent task points and the torque component for the task is determined in a manner that compensates for the dynamics in task space. For a task behavior, x_t, with decoupled dynamics and unit inertial properties $\ddot{x}_t = F_t^*$, this torque is given by the force transformation

$$\Gamma_{\text{task}} = J_t^T F_t \tag{3}$$

where J_t is the Jacobian of the task and F_t is the operational space force. This operational space force is given by

$$F_t = \Lambda_t F_t^* + \mu_t + p_t \tag{4}$$

A task/posture decomposition allows us to represent the dynamics of a simulated human subject in a relevant task space that is complemented by a posture space. The total control torque is decomposed into two dynamically decoupled torque vectors: the torque corresponding to the commanded task behavior and the torque that only affects posture behavior in the null space of the task

$$\Gamma = \Gamma_{\text{task}} + \Gamma_{\text{posture}} = J_t^T F_t + N_t^T \Gamma_p \tag{5}$$

In this expression N_t^T is the null space projection matrix, and Γ_p is the torque projected into the null space.

The prioritized control framework [7, 11] is used to control the collection of marker task vectors. In this framework the torque decomposition is:

$$\Gamma = J_t^T F_t + N_t^T (J_p^T F_p) \tag{6}$$

where the posture torque can be rewritten as

$$\Gamma_{\text{posture}} = (J_p N_t)^T F_p = J_{p|t}^T F_{p|t} \tag{7}$$

Consequently, Equation (5) can be represented as:

$$\Gamma = J_t^T F_t + J_{p|t}^T F_{p|t} \tag{8}$$

Alternately, if an additional task is projected into the posture we express this as

$$\Gamma = J_{t_1}^T F_{t_1} + J_{t_2|t_1}^T F_{t_2|t_1} \tag{9}$$

This is generalized for an arbitrary number of additional tasks

$$\Gamma = J_{t_1}^T F_{t_1} + J_{t_2|t_1}^T F_{t_2|t_1} + \cdots + J_{t_n|t_{n-1}|\cdots|t_1}^T F_{t_n|t_{n-1}|\cdots|t_1} \tag{10}$$

2.2 Direct Marker Control Formulation

For the application to marker space we will use m_i to denote the task for a particular marker subset. Equation (10) then becomes:

$$\Gamma = J_{m_1}^T F_{m_1} + J_{m_2|m_1}^T F_{m_2|m_1} + \cdots + J_{m_n|m_{n-1}|\cdots|m_1}^T F_{m_n|m_{n-1}|\cdots|m_1} \tag{11}$$

The Jacobian and the force associated with marker space are deduced from the above equation as follows:

$$J_{\otimes} \triangleq \begin{bmatrix} J_{m_1} \\ J_{m_2|m_1} \\ \vdots \\ J_{m_n|m_{n-1}|\cdots|m_1} \end{bmatrix} \quad \text{and} \quad F_{\otimes} \triangleq \begin{bmatrix} F_{m_1} \\ F_{m_2|m_1} \\ \vdots \\ F_{m_n|m_{n-1}|\cdots|m_1} \end{bmatrix} \tag{12}$$

The overall control torque is then

$$\Gamma = J_{\otimes}^T F_{\otimes} \tag{13}$$

An analysis on the bounds of the joint space errors can be performed using the Jacobian associated with the marker space. We note

$$\Delta x_{\otimes} = J_{\otimes} \Delta q \tag{14}$$

The inverse of this relationship is

$$\Delta q = \bar{J}_{\otimes} \Delta x_{\otimes} \tag{15}$$

where $\bar{J}_{\otimes}$ is the dynamically-consistent generalized inverse of $J_{\otimes}$. Joint angles obtained through prioritized control in marker space deviate from the actual values but are bounded by:

$$|\Delta q| \leq |\bar{J}_{\otimes}||\Delta x_{\otimes}| \tag{16}$$

This allows us to tune the prioritized marker controller to accommodate the desired accuracy, for given configurations.

3 Simulation and Validation

A series of real-time movements performed by a tai chi master were recently captured using an optical marker system to provide validation for our new algorithm. The subject was a fifty-five year old male of average build. An eight-camera retro-reflective motion capture system was used to capture his movements at a rate of 60 Hz.

Among the motions performed, a sequence of slow movements were chosen for validation and real-time simulation. Marker data of the recorded motion were then segmented and smoothed using the EvART software (Motion Analysis Corporation).

Marker trajectories were imported into the SAI environment [6] which allows dynamic 3D simulations. Our existing human model which consists of 25 joints, was scaled to match the anthropometry of the tai chi master. The data used in this model have been derived from SIMM models [2]. The skeleton has been modeled as a multibody system within SAI and scaled based on body segment mass-center locations [3]. Figure 1 depicts the scaled human model simulated in the SAI environment.

The human motion reconstruction described in Section 2 was executed using crucial upper body joint marker trajectories (e.g. shoulder, elbow and wrist of both right and left arms). Sets of two decoupled markers were grouped into distinct marker subsets. The first subset consisted of the right shoulder and the left wrist markers and the second set consisted of the left elbow and the right wrist markers. The markers were then directly tracked through the entire movement sequence using prioritization.

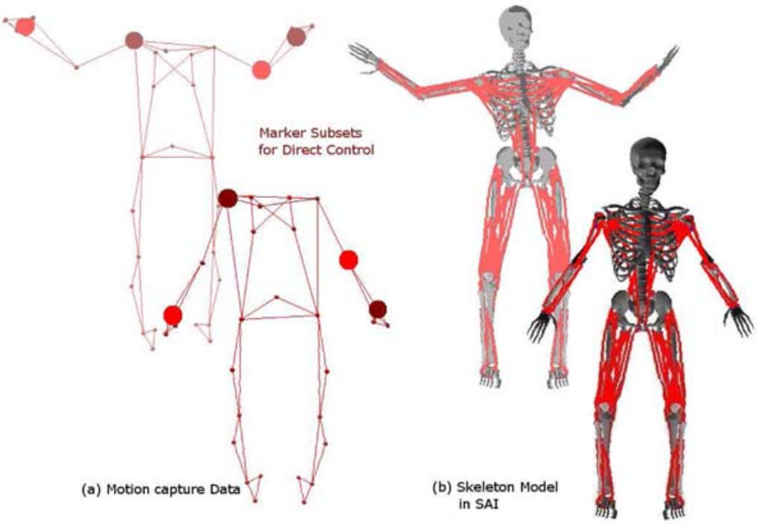

Fig. 1 The scaled human model of the tai chi master simulated in the SAI environment. Markers of the right shoulder and the left wrist are selected to form the first marker set to be controlled (dark spheres). The second subset is formed by the left elbow and the right wrist markers (light spheres).

Joint angles over the entire trajectory were directly obtained as a natural consequence of the direct marker control approach, thus avoiding any need for computing inverse kinematics. Figure 2 illustrates the joint angles obtained through direct marker tracking.

The commanded and tracked positions of the controlled markers, as well as the joint angles, were recorded during real-time simulation. Figure 3 shows the comparison between tracked and commanded positions of each tracked marker. The consistency between the two curves in each plot suggests the efficacy of the human motion reconstruction algorithm proposed.

Bounds on the joint angle errors can be addressed using Equation (15). We can compute the maximum and minimum joint angle error bounds among all the joints. Thus

$$\Delta q_{\max} = \max(\Delta q) \quad \text{and} \quad \Delta q_{\min} = \min(\Delta q) \tag{17}$$

where $\Delta q = \bar{J}_{\otimes} \Delta x_{\otimes}$. Figure 4 shows the margin of marker position errors and the margin of joint angle errors respectively. Maximum and minimum joint angle error magnitudes vary stably over the trajectory, suggesting well bounded errors on the joint angles.

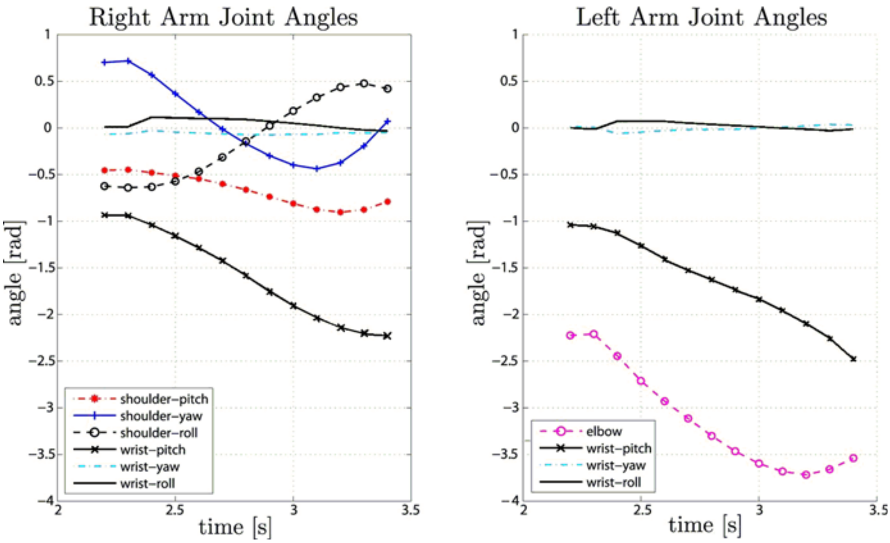

Fig. 2 Joint angles obtained through direct control of marker data. The joint angles for the shoulder, elbow and wrist segments are shown for the corresponding arm. Smooth joint space trajectories are generated without inverse kinematics.

4 Conclusions

In this paper, we presented a new algorithm to control marker trajectories based on the operational space method of Khatib [5], and task/posture decomposition using prioritization. The algorithm reconstructs human motion in real-time through smooth tracking of marker trajectories. This facilitates the extraction of joint angles without the need for inverse kinematic calculations. The algorithm also easily accommodates anthropometric scaling of the simulation model to the human subject.

We validated our new algorithm through a set of tai chi movement data. The results illustrate smooth tracking of the marker trajectories in marker space. Smooth joint angles trajectories were obtained as a natural output of the marker tracking methodology. A bound on the joint space error was obtained and the results of this analysis indicated stable error bounds over the trajectory. The errors can further be decreased with a more precise camera calibration during motion capture experiment and a more accurate model scaling of the simulation.

There are plans to extend our algorithm to address task/posture decomposition in the camera space of the optical motion capture system. This may exploit further advantages of our approach by accommodating arbitrary operational spaces. Additionally, where precise knowledge of the subject anthropometry is not known a priori, our approach can be adapted so that limb lengths can be adjusted until they optimally track the marker data. This provides a way of inferring more precise anthropometry through direct tracking of marker data. By extending our new algorithm

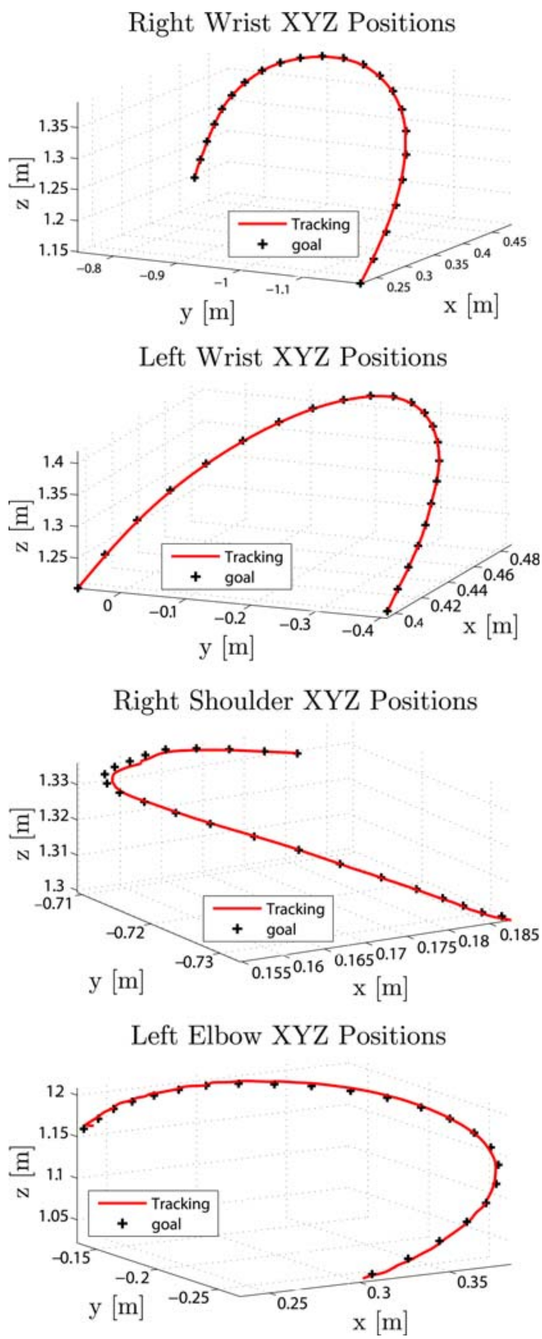

Fig. 3 Tracked and goal trajectories of markers. The tracked trajectories (solid lines) are shown for markers attached to the wrist, shoulder, and elbow segments. It can be seen that the generated trajectories closely track the corresponding goal trajectories (dotted lines).

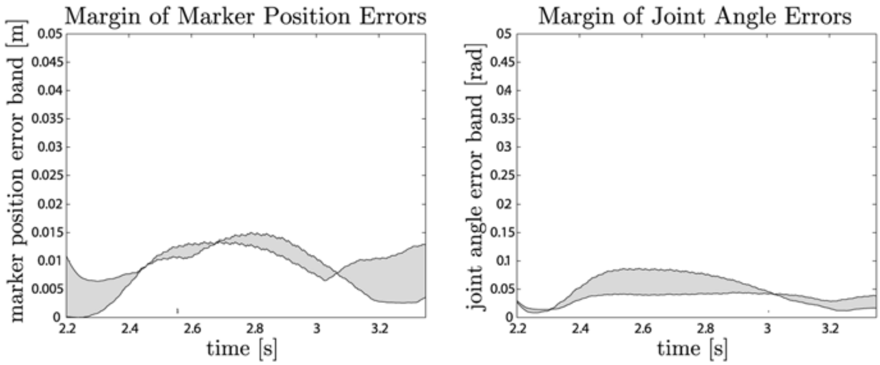

Fig. 4 Margin of marker position errors and margin of joint angle errors over the trajectory. Joint angle error magnitudes show a stable variation over the trajectory, thus ensuring well bounded errors on the joint angles.

to incorporate other operational spaces, we hope to synthesize and investigate motor control models for skilled human movement using a task-level framework.

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