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Characterization of Motor Skill Based on Musculoskeletal Model

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Abstract— **In this paper, we propose two methods to quantitatively analyze the motor skill in sports. The first method is the dimensionality reduction using the principal component analysis (PCA). The motion data, e.g. the joint angles (143-dimensional vector) or the muscle tensions (989-dimensional vector), are projected to a lower dimensional space that well represents the characteristics of original data. The similarities and differences become clear by observing the data in the low-dimensional space. The second method utilizes the joint stiffness obtained from joint kinematics and a biological muscle model. Though muscle tension data contain richer information than joint angle data, the dimension is so high that simply applying PCA does not give useful insights. Here we calculate the joint stiffness using the muscle tension data and a biological muscle model. This information represents the muscle usage skill which can not be observed only from motion data, and reflects the redundancy of the muscle tensions. We demonstrate the two methods by analyzing skilled performers' motions.**

Keywords: Musculoskeletal Model, Skill of Sports, Principal Component Analysis, Biological Muscle Model.

I. INTRODUCTION

Compact representation of high-dimensional human motion is crucial for intuitively and quantitatively evaluating motion patterns in sports. Ohtsuki et al. developed quantitative measures for evaluating sports motion such as skillfulness [1]. Sakurai et al. investigated the characteristics of muscle function and performance accuracy of skilled and unskilled players in badminton smash stroke [2]. They measured the EMG of arm, forearm, and shoulder muscles, and concluded that the difference of EMG pattern is the reason for the accuracy in skilled players' motions. Hirashima et al. used a three-dimensional analysis technique to characterize overarm throws by focusing on how each joint angular acceleration is produced by the muscle torques, gravity torques, and velocity-dependent torques [3]. The throwing motion of a skilled baseball player was measured at three different speeds, and their dynamics was analyzed by "nonorthogonal torque decomposition" that can clarify how angular acceleration about a joint coordinate axis is generated by the muscle, gravity, and interaction torques. They showed that skilled ball throwers adopt a hierarchical control in which the proximal muscle torques create a dynamic foundation for the entire limb motion and resulting interaction torques contribute to distal joint rotation. The techniques mentioned above assume the knowledge about the characteristics of each movement to be evaluated. For most people, however, it is difficult to know how to improve their movements only by looking at those of skilled players.

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There are mainly two parameters that can be measured or computed from motion patterns of sports using musculoskeletal models [4], [5]: joint angles and muscle tensions. Here we propose two methods to analyze these data. The first method is principal component analysis (PCA), which is often used to reduce the dimension of high-dimensional data and extract its characteristics. Joint angle and muscle tension data are projected to a lower dimensional space that well represents the characteristics of original data. Similarities and differences of motions become clear by observing the data in such low-dimensional space.

Although dimensionality reduction based on PCA turned out to be effective for analyzing joint angle data, the dimension of muscle tension data is high and its singular values do not decrease dramatically unlike joint angle data. Therefore simply applying PCA does not give useful insights for the analysis of muscle tension data. The optimization using quadratic programming and EMG data can estimate the muscle tension pattern including the redundant antagonistic muscle that can be important for skilled sports performances. The stiffness of joint is considered as the low-dimensional representation of muscle tensions. This represents the redundant information of muscle usage in the dimension equal to the skeleton model's degrees of freedom (DOF). This parameter is computed based on a biological muscle model [6], [7] and the musculoskeletal model geometry.

This paper is organized as follows. In Section II, we characterize the motor skill using PCA. The skilled boxers performances are analyzed by the proposed method, and the similarity and difference are clarified. The method to analyze the muscle tensions by joint stiffness estimated using the musculoskeletal model and a biological muscle model is shown in Section III, followed by the concluding remarks.

II. PCA CHARACTERIZATION OF MOTOR SKILL

There are mainly two parameters that can be measured or computed from motion patterns of sports using musculoskeletal models [4], [5]: joint angles and muscle tensions. In this section, these data are analyzed using principal component analysis (PCA), which is often used to reduce the dimension of high-dimensional data and extract its characteristics. We use two skilled boxers' punch motions (Fig. 1) as an example.

A whole-body motion with T frames is measured using an optical motion capture system with 35 markers, and the

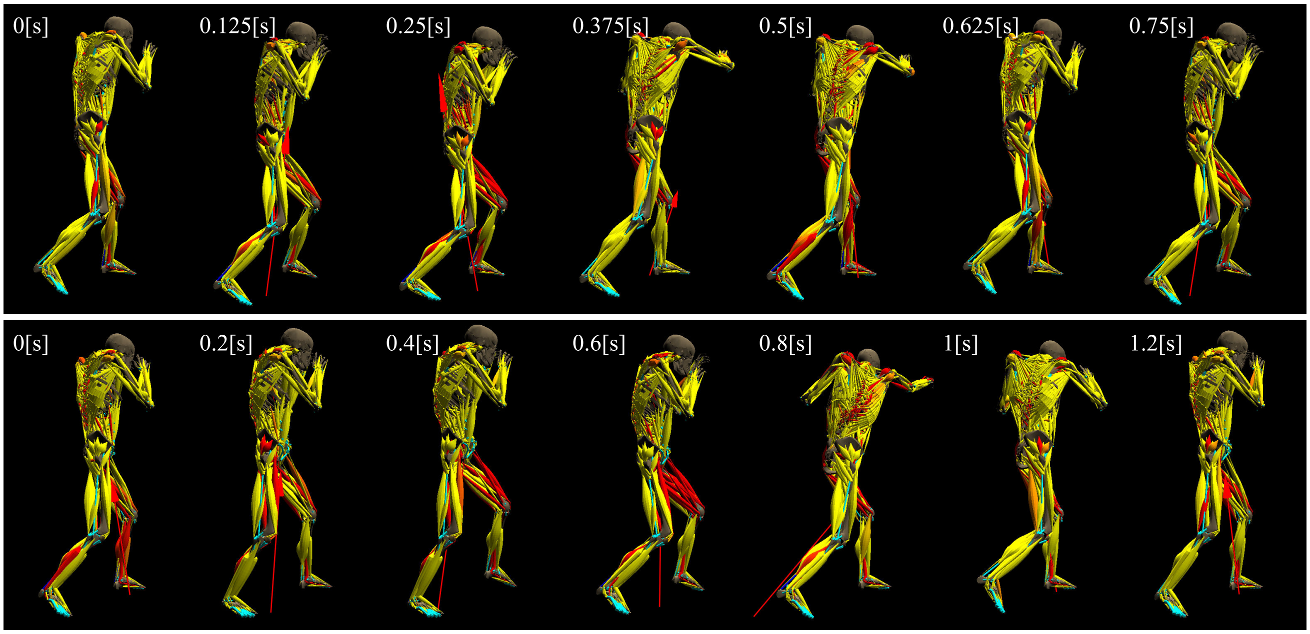

Fig. 1. The snapshots of punch motion. Top: Subject A, bottom: Subject B.

inverse kinematics computation based on a $n_{DOF}(=143)$-DOF skeleton model calculates the joint angle data $\boldsymbol{\theta}(\in \mathcal{R}^{n_{\mathrm{DOF}} \times T})$. In this paper, the joint angle is represented using the ZYX-Euler angles. Then the inverse dynamics is carried out to calculate the generalized force data $\boldsymbol{\tau}_G(\in \mathcal{R}^{n_{\mathrm{DOF}} \times T})$, and we estimate the tensions of $n_{muscle}(=989)$ muscles $\boldsymbol{f}(\in \mathcal{R}^{n_{\mathrm{muscle}} \times T})$ using a biological muscle model and optimization.

Figure 2 represents the singular values of $\boldsymbol{\theta}$ and $\boldsymbol{f}$ of each subject sorted in the descending order. The horizontal axis represents the index normalized by the dimension of data (n_{DOF} or n_{muscle}), and the vertical axis represents the singular values. The red line represents Subject A, the blue line represents Subject B, and the dashed line represents the singular value of joint angles, the solid line represents the singular value of muscle tensions. Though the singular values of joint angles decease dramatically at 34 % of the total DOF (= 49-th singular value), those of muscle tensions decrease slowly. The third singular value of joint angles is about 10^{-4}, so the first three principal components are enough to represent the characteristics of joint angle data. For muscle tension data, on the other hand, their singular values do not decrease dramatically, and simply applying PCA does not give useful insights.

Fig. 3 represents the projection of $\boldsymbol{\theta}_A$ and $\boldsymbol{\theta}_B$, the joint angle data of Subject A and Subject B in the motion shown in Fig. 1, to the first three principal axes of $[\boldsymbol{\theta}_A \boldsymbol{\theta}_B]$. This parameter is computed via singular value decomposition as follows:

$$[\boldsymbol{\theta}_A \boldsymbol{\theta}_B] = \boldsymbol{U}\boldsymbol{\Sigma} \left[\begin{array}{c} \boldsymbol{V}_A^T \\ \boldsymbol{V}_B^T \end{array} \right] \tag{1}$$

where the matrices $\boldsymbol{U}$, $\boldsymbol{\Sigma}$, and $\boldsymbol{V}^T$ have the following

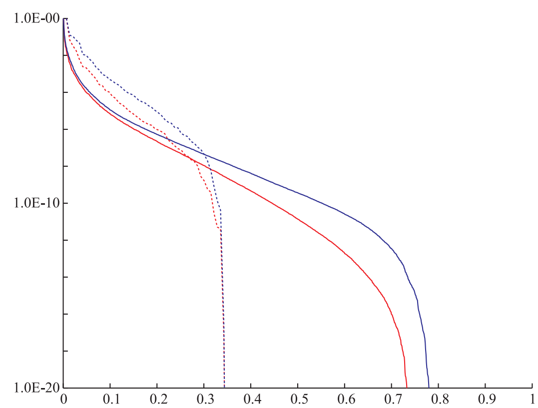

Fig. 2. The singular values of the whole-body joint angles and muscle tensions. Red line: subject A, blue line: Subject B. Dashed line: singular value of joint angles, solid line: singular values of muscle tensions.

properties:

1) the (i,j) element of $\boldsymbol{U}$ represents the contributing rate of the j-th principal component to the i-th DOF.
2) $\boldsymbol{\Sigma}$ is a diagonal matrix and its (i,i) element represents the i-th singular value. This value represents how the i-th principal component is dominant in the motion.
3) the i-th row of $\boldsymbol{V}^T$ represents the i-th principal component that is the i-th dominant wave pattern in the motion.

The top and bottom graphs of Fig. 3 represent the projection onto the first and second and the first and third principal axes respectively. The red line represents Subject A, and the blue line represents Subject B. The circle mark represents 0 sec, and the cross marks are placed every 0.05 sec. These graphs show that the second principal component represents

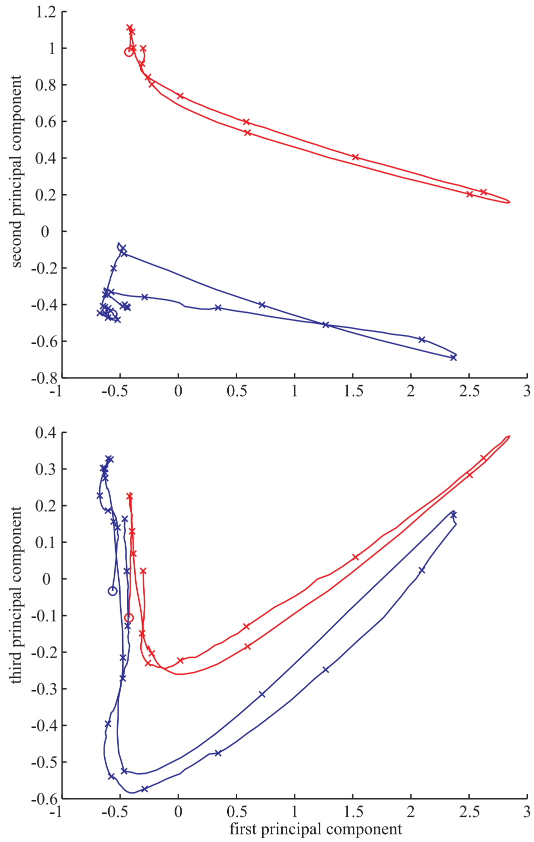

Fig. 3. The principal components of the whole-body joint angles. Both subjects' data are projected to the same low-dimensional space. Red line: Subject A, blue line: Subject B. Top: 1st and 2nd principal components, bottom: 1st and 3rd principal components. Circle marks: 0 sec, cross marks: every 0.05 sec.

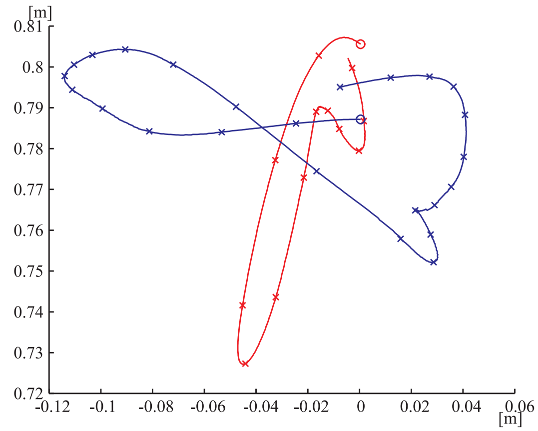

Fig. 4. The COM trajectory during the punch motion. Red line: Subject A, blue line: Subject B. Circle marks: 0 sec, cross marks: every 0.05 sec.

the difference between the subjects well. Then we check the column of $\boldsymbol{U}$ that represents the relationship between each principal component and joint. The second principal component has a high correlation with the left articulatio coxae angle and the twisting angle of body trunk. The analysis of motion data (raw video data) indicates that Subject A punches only with the upper arm and forearm using the vertical center-of-mass (COM) movement, while Subject B punches with the anteroposterior COM movement by the articulation coxae movement and the twist of upper body. Figure 4 represents the trajectory of COM during the punch motion. The horizontal axis represents the anteroposterior and the vertical axis represents the vertical position of COM. The red line is Subject A, and the blue line is Subject B. The movement of COM corresponds to what is observed in the raw video. This result indicates that PCA of joint angle data can represent the difference of skilled performance.

The good number of PCA is three for an easy analysis because we can intuitively figure out three dimensional trajectory. And derived difference of performance can be presented as follows. If Subject A is a professional and B is a beginner, and j-th principle component represents the difference significantly, the difference between subject A and B projected to the j-th principle component is:

$$\delta\boldsymbol{\theta}_{A-B} = \boldsymbol{U}\boldsymbol{\Sigma}_j(\boldsymbol{V}_A^T - \boldsymbol{V}_B^T) \tag{2}$$

where $\delta\boldsymbol{\theta}_{A-B}$ represents the difference, and $\boldsymbol{\Sigma}_j$ is the matrix whose (j, j) element represents the j-th singular value. By showing the motions whose joint angle data are $\boldsymbol{\theta}_B$ and $\boldsymbol{\theta}_B + \delta\boldsymbol{\theta}_{A-B}$, Subject B can grasp the difference between a professional player and himself.

III. Joint Stiffness Analysis

In this section, we show a method to analyze the muscle tension using a musculoskeletal model that represents the geometry and dynamics of human body, and a biological muscle model that represents the dynamics property of muscle. This data contains much richer information than what we would obtain only from motion data. Especially, the activity of antagonistic muscle can not be estimated only from motion data, but it is important for the performance because it determines the fleetness and fineness.

As shown in the previous section, however, PCA of muscle tension data cannot effectively reduce the dimension. We therefore propose an alternative where we convert muscle tensions to joint stiffness based on a musculoskeletal model and a biological muscle model. This method can reduce the dimension to the number of joints in the skeleton model, while preserving the antagonistic muscle activity information.

The joint stiffness is represented as the relationship between the small variations of joint torque and joint angle. First, the relationship between joint torque and muscle tension is written as follows:

$$\boldsymbol{\tau} = \boldsymbol{J}^T(\boldsymbol{\theta})\boldsymbol{f} \tag{3}$$

where $\boldsymbol{J} = \partial\boldsymbol{l}/\partial\boldsymbol{\theta}$ is the posture-dependent Jacobian matrix of muscle lengths with respect to joint angles. $\boldsymbol{l}(\in \mathcal{R}^{n_{\text{muscle}}})$ is the muscle lengths and $\boldsymbol{\tau}(\in \mathcal{R}^{n_{\text{DOF}}})$ is the joint torques. We also consider a biological muscle model [6], [7] that represents the muscle tension as a function of muscle length, its velocity and activity. The k-th muscle tension is represented as follows:

$$f_k = -a_k F_l(l_k) F_v(\dot{l}_k) F_{\max k} \tag{4}$$

where a_k, l_k, $\dot{l}_k$ and $F_{\max k}$ are the activity, length, its velocity, and maximum isometric force of muscle k respectively, and $F_l(*)$ and $F_v(*)$ are the functions that represent the tension-length and tension-velocity relationships. The relationship between the joint torque variation and the angle velocity can be written in the following equation:

$$\begin{aligned} \frac{\partial \boldsymbol{\tau}}{\partial \boldsymbol{\theta}} &= \frac{\partial \boldsymbol{J}^T}{\partial \boldsymbol{\theta}} \boldsymbol{f} + \boldsymbol{J}^T \frac{\partial \boldsymbol{f}}{\partial \boldsymbol{\theta}} \\ &= \frac{\partial \boldsymbol{J}^T}{\partial \boldsymbol{\theta}} \boldsymbol{f} + \boldsymbol{J}^T \frac{\partial \boldsymbol{f}}{\partial \boldsymbol{l}} \boldsymbol{J} \end{aligned} \tag{5}$$

where the first term of the right side represents the change of joint torque caused by the posture change with the constant muscle tension, and the second term represents the change of joint torque caused by the muscle dynamics properties. Here we consider the joint stiffness caused by the elasticity of muscle represented by the second term, and assume that a_k, $F_v(*)$, and $F_{\max k}$ are constant. $F_l(*)$ is represented as follows [6], [7]:

$$F_l(l_k) = \exp\{-\left(\frac{l_k - l_{0k}}{K_l}\right)^2\} \tag{6}$$

where l_{0k} is the original length of the k-th muscle, and K_l is a constant whose value is shown in [7]. We can then compute $\partial f_k / \partial l_k$ as follows:

$$\frac{\partial f_k}{\partial l_k} = -2 \frac{l_k - l_{0k}}{K_l^2} f_k \tag{7}$$

The top and bottom graphs of Fig. 5 represent the stiffness of right elbow and the speed of right hand during a punch motion respectively. In both graphs, the horizontal axis represents the time [sec]. The vertical axis represents the joint stiffness [Nm/rad] and the speed of right hand [m/sec] in the bottom graph. The solid line represents Subject A, the dashed line represents Subject B, the red line represents the joint stiffness around the flexion / extension axis, the green line represents around the abduction / adduction axis, and the blue line represents around the external / internal rotation axis. Note that lower value indicates stronger stiffness. This result shows that Subject B's right elbow is stiffer than that of Subject A during the punch motion. The characteristics of punch motions are: Subject A uses the flexibility of body, and Subject B rigidizes his own body and moves linearly. These characteristics agree with this joint stiffness parameter. The stiffness of joint increases the robustness against sudden external forces, but reduces the rapidity of punch motion. Stiffness and rapidity are trade-off and we do not know which is important, but this result of joint stiffness correspond to the observed punch speed.

IV. Conclusion

In this paper, we proposed two methods using PCA and joint stiffness to quantitatively analyze the motor skill, and showed the following points.

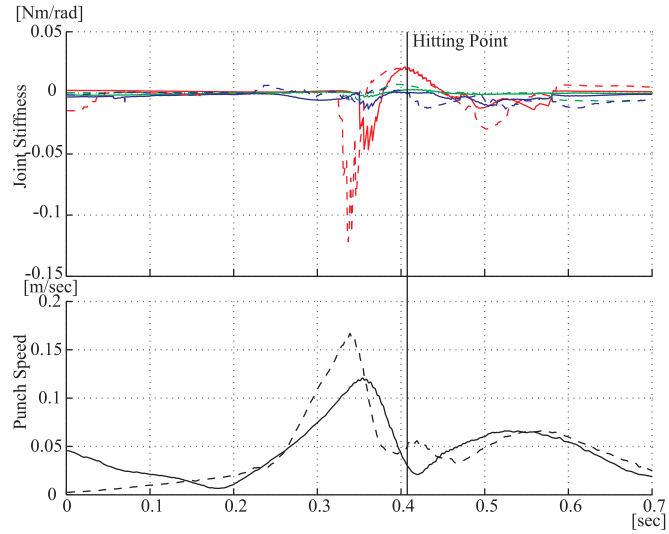

Fig. 5. Joint stiffness around right elbow during punch motion. Solid line: Subject A, dashed line: Subject B. Top: joint stiffness, bottom: right hand speed. Red line: stiffness around flexion/extension axis, green line: around abduction/adduction axis, blue line: external/internal rotation axis.

1) The dimensionality reduction based on PCA is effective for characterizing joint angle data.
2) Simply applying PCA did not give insights for analyzing muscle tension data because of its high-dimensionality.
3) Joint stiffness can be used as an alternative to PCA because its dimension is the same as the number of joints of the skeleton model, while it also preserves the antagonistic muscle activity information.
4) The proposed method can be used to evaluate and improve the sports performance automatically if the other techniques, e.g. clustering or recognition using HMM, are implemented.

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