

# An Unsupervised Approach to Detecting and Isolating Athletic Movements

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**Abstract**—To enable automatic analysis of athletic movement, the first task is to recognize the athletic movements to be analyzed from a continuous motion data stream. Automated detection of athletic movement and the isolation of the recruited body parts would enable the analysis of sporting movements for improving sports performance and preventing possible injuries. In this paper, an unsupervised method for detecting and isolating athletic movements is proposed. Given motion capture data, the method automatically identifies when athletic movements are being performed and the body parts involved using the concepts of the manipulability and kinematic dimensionality reduction. Experiments demonstrate the ability of the proposed approach to detect and isolate athletic movements from a variety of motion data.

## I. INTRODUCTION

Athletic training is increasingly taking advantage of advanced motion measurement and analysis techniques. For instance, tracking of athletic performance is increasingly reliant on data analysis and athletes are helped by the analysis of their training (e.g. [1]). Data-driven analysis of athletic movement has the potential to improve performance tracking, facilitate motion learning and prevent injury [2]. When an athlete is first learning to perform a skill, they primarily acquire knowledge about correct execution through demonstrations [3]. Understanding proper skill form from demonstration, including the appropriate timing and joint recruitment, is important not only for effective skill learning but also for preventing injuries during training.

A similar research problem is encountered in robotics, in the domain known as learning from demonstration (LfD). LfD is an affordable and effective way of learning motions not only for humans but also for robots [4]. A key challenge in LfD is the “*what to imitate*” problem, where the robot must automatically determine which part of the demonstration should be learned. A robot must extract meaningful segments (or remove meaningless segments) from demonstration [5] and understand them with the use of correct representation [6]. Without considering these two issues, LfD will be valid only in structured experiment settings.

In this paper, a method that automatically detects athletic movements of body parts is proposed. The proposed method is different from movement segmentation methods (e.g. [7]) in that it provides not only temporal segments of the movements, but also isolates the recruited body parts. It is also different from most human activity recognition

approaches in that it can detect various athletic movements without labeled training data while human activity recognition methods usually rely on the labelling information for exploiting supervised learning techniques [8].

The proposed method exploits the inherent properties of athletic movements and uses an unsupervised learning technique for detecting and isolating athletic movements without labels. The contributions of the paper are as follows: First, the concept of manipulability, a concept used for describing the dexterity of a manipulator in robotics, is applied for recognizing pre-athletic poses. Second, a novel dimensionality reduction technique called kinematic dimensionality reduction is proposed for representing the kinematic synergy of joint movements and observing the coherency in the movement. Finally, an index that indicates the probability that the current observation is an athletic movement is introduced by synthesizing the values of manipulability and coherency.

The remainder of the paper is organized as follows: In Section II, the athletic movement detection method is described including the use of manipulability and the novel kinematic dimensionality reduction technique. The ability of the proposed method is validated with various motion capture data provided by CMU [9] and the results are presented in section III. Finally, conclusions and future works are discussed in Section IV.

## II. ATHLETIC MOVEMENT DETECTION

One of the inherent properties of athletic movements is the use of the stretch-shortening cycle, also known as pre-stretch step [2]. In athletic movements, a limb often first moves in the opposite direction of the target movement for storing energy and is then rapidly released in the intended direction for making an explosive movement. In other words, athletic movements usually start from a flexed pose and are followed by quick and coherent motions which are differentiated from other movements.

For example, a movement starting from a flexed pose may not be an athletic movement if it moves slowly and with little coordination between joints. Also, a movement moving quickly and coherently may not be an athletic movement if it is, e.g., a hand-signal made with a stretched arm. On the other hand, numerous athletic movements such as throwing, kicking, jumping, etc. first start from a flexed arm/leg/body pose, followed by a coherent extension of the recruited limb.

Based on these observations, the proposed method captures a pre-athletic pose followed by a coherent movement to detect and isolate athletic movements of body parts.

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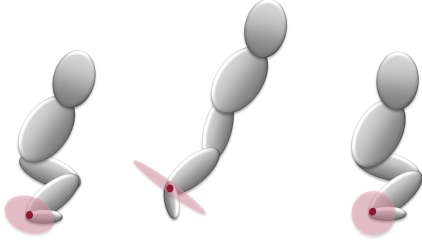


Fig. 1. The manipulability ellipsoid at the ankle is changing over a jumping motion. As the leg is stretched out, the manipulability ellipsoid become oblate and the magnitude of the manipulability, which is the ratio of the ellipsoid axes, decreases.

In particular, the concepts of manipulability and kinematic dimensionality reduction technique are applied in order to capture a pre-athletic pose and a coherent movement, respectively.

#### A. Manipulability for pre-athletic pose detection

Manipulability [10] is a quantitative measure used for the analysis of robotics trajectories that describes the robot arm's ability to change the position or orientation of its endpoint in each direction. Applying this measure to human movement, the endpoint corresponds to the distal part of each limb, e.g. hand, foot, and head, and the manipulability of each distal body part describes its mobility in each direction at a given pose. Manipulability can be defined as follows.

$$J_0 = \frac{\rho}{\det JJ^T} \quad (1)$$

where  $J$  is the Jacobian of a robot arm or a human limb. Note that  $J$  is a function of joint variables, thus, the value of manipulability varies according to the joint configurations.

Since (1) is equivalent to the volume of the manipulability ellipsoid [11] which is constructed from the eigenvalues and eigenvectors of the Jacobian, it increases if the eigenvalues are similar and decreases if they are dissimilar. In other words, manipulability is a measure of the differences in eigenvalues of the Jacobian, thus, it can be also defined as the inverse of the condition number of the Jacobian.

$$= \frac{\min(J)}{\max(J)} \quad (2)$$

Regarding the various poses of a limb, the magnitude of the manipulability decreases when the limb is stretched out so that the pose is close to singularity. On the other hand, if the limb is flexed so that it has omni-directional mobility, the magnitude of the manipulability increases and becomes close to one (Fig. 1).

As a result, a flexed pose or pre-athletic pose can be detected by observing the magnitude of the manipulability; if the magnitude is low, the pose of the limb is likely to be a stretched pose, thus, it is not a pre-athletic pose. On the contrary, if the magnitude is high, it is likely to be a flexed pose and potentially can be a pre-athletic pose. Note that if the effective direction of the target movement is known,  $\max$  of the corresponding direction can be used as the manipulability instead of using (2).

#### B. A Lie group formulation for human body kinematics

The movement of a limb can be regarded as a rigid body motion of serial links which are connected by rotational joints. In this section, we will present the Lie group formulation for representing rigid body motions of serial links.

Rotational motion of a rigid body can be expressed with an element of the special orthogonal group,  $SO(3)$ .

$$SO(3) = \{R \in \mathbb{R}^{3 \times 3} | R^T R = I \text{ \& \; } \det(R) = +1\} \quad (3)$$

$\mathfrak{so}(3)$ , which is the Lie algebra of  $SO(3)$ , is the tangent space to  $SO(3)$  at the identity element.

$$\mathfrak{so}(3) = \left\{ \begin{bmatrix} 0 & \theta_3 & \theta_2 \\ \theta_3 & 0 & \theta_1 \\ \theta_2 & \theta_1 & 0 \end{bmatrix} \in \mathbb{R}^{3 \times 3} \right\} \quad (4)$$

Note that  $\mathfrak{so}(3)$  can also be expressed in a vector form,  $\theta = [\theta_1; \theta_2; \theta_3]^T \in \mathbb{R}^3$  since the degrees of freedom of  $\mathfrak{so}(3)$  are three.

The exponential mapping, which is defined as the usual matrix exponential, maps Lie algebra elements to corresponding Lie group elements. Conversely, the logarithm mapping maps Lie group elements to the Lie algebra elements.

$$\exp : \mathfrak{so}(3) \rightarrow SO(3) \quad (5)$$

$$\log : SO(3) \rightarrow \mathfrak{so}(3) \quad (6)$$

Finally, the result of serial joint motions can be expressed as products of exponentials (POE) [12] as described in the equation below:

$$f(q_1; q_2; \dots; q_n) = e^{[\theta_1] q_1} e^{[\theta_2] q_2} \dots e^{[\theta_n] q_n} R_{0;n} \quad (7)$$

where  $R_{0;n} \in SO(3)$  describes the coordinate change from the home frame to the frame at the endpoint at home position while  $[\theta_i] \in \mathfrak{so}(3)$  and  $q_i \in \mathbb{R}$  describes represents the rotational axis at home position and joint variable, respectively.

#### C. Kinematic dimensionality reduction

Dimensionality reduction techniques, e.g. principal component analysis (PCA), provide various benefits such as discovering the latent space of data, improving the computational efficiency, reducing the effects of data noise, etc. However, if the dimensionality of the data is reduced in improper way, the data may lose critical information. Thus, it is important to be aware of what information is lost through the dimensionality reduction technique and apply the technique with careful consideration of the intrinsic structure of the data.

In this section, a novel dimensionality reduction technique based on the kinematic structure of the movement data is proposed. By using the novel technique called kinematic dimensionality reduction (KDR), the dimensionality of a limb's motion data is reduced to three, focusing on the kinematic synergy of the recruited joints at the endpoint of each limb. The reduced dimensional data will be used for detecting athletic movements in the following section.

In short, KDR is a way of estimating joint synergies using approximated POE formula for a limb's serial joint motions. To approximate the POE formula in (7), *Baker-Campbell-Hausdorff* (BCH) formula [13] is introduced, which gives the solution of the product of two exponentials in Lie algebra.

$$\begin{aligned} \mathbf{C} &= \log(e^{\mathbf{A}}e^{\mathbf{B}}) \\ &= \mathbf{A} + \mathbf{B} + \frac{1}{2}[\mathbf{A};\mathbf{B}] + \\ &\quad \frac{1}{12}([\mathbf{A};[\mathbf{A};\mathbf{B}]] + [\mathbf{B};[\mathbf{B};\mathbf{A}]]) + \dots \end{aligned} \quad (8)$$

where  $\mathbf{A};\mathbf{B} \in \mathfrak{so}(3)$  and the Lie bracket  $[\mathbf{A};\mathbf{B}]$  represents  $\mathbf{AB} - \mathbf{BA} \in \mathfrak{so}(3)$ . Note that if  $\mathbf{A}$  and  $\mathbf{B}$  are sufficiently small, i.e., the rotations caused by  $\mathbf{A}$  and  $\mathbf{B}$  are near the identity, the high-order terms of (8) can be ignored.

As a result, the product of the two Lie group elements  $e^{\mathbf{A}}e^{\mathbf{B}}$  can be approximated with another Lie group element,  $e^{\mathbf{C}}$ , if  $\mathbf{A}$  and  $\mathbf{B}$  are sufficiently small. By cascading this consolidating process for all exponentials in (7), the POE formula can be abstracted into the product of two  $\text{SO}(3)$  matrices.

$$\begin{aligned} \mathbf{f} &= e^{[t+1]q_1} e^{[t+2]q_2} \dots e^{[t+n]q_n} \mathbf{R}_{0:n} \\ &= e^{[t+1]q_1} e^{[t+2]q_2} \dots e^{[t+n]q_n} \mathbf{R}_{0:n} \end{aligned} \quad (9)$$

Note that  $\mathbf{R}_{0:n}$  is a constant  $\text{SO}(3)$  matrix.

In this research, we set  $q_i$  as the instantaneous angle change of joint  $i$  between time  $t$  and  $t+1$  to make the magnitude of  $[t+1]q_i$  small, thus, the approximation in (9) is reasonable. In that case, (9) describes the instantaneous kinematic synergy caused by joint actuation at time  $t$  and can be parameterized by  $[t+1]q_i \in \mathfrak{so}(3)$  which has only three variables. In other words, the dimensionality of the original movement data is reduced from  $3n$  to 3 through (9).

#### D. Index for athletic movement detection

Athletic movements are characterized by a flexed pose followed by a coherent movement. The flexed pose detection was described in Section II-A; if the manipulability of a limb is high, the limb can be considered as being far from a stretched pose, thus, it is in a flexed pose. However, since all flexed poses are not necessarily transformed into athletic movements, coherent movements after a flexed pose must also be detected.

Let us think about the features of coherent movements. If serial joints of a limb are coherently actuated with a certain purpose, the direction of the kinematic synergy of the joints in (9) would not be arbitrarily changing, but be indicating a certain constant direction. In other words, the trajectory of the reduced KDR data may not span the whole 3D space but live in a low-dimensional subspace, e.g. a line or a plane, due to the coherency of the movement.

The emergence of a low-dimensional submanifold can be simply detected by checking the singular values of the data within a fixed size window (e.g. 0.1sec). If the data in the window live in a submanifold, the summation of  $n-1$  or fewer number of the highest eigenvalues will take up a high ratio of all eigenvalues. Thus, we can conclude that

movement coherency is proportional to the rates of the  $n-1$  highest eigenvalues in the reduced KDR space.

$$= \frac{\sum_{j=1}^{n-1} \lambda_j}{\sum_{i=1}^n \lambda_i} \in [0;1] \quad (10)$$

where  $\lambda_i$  represents the  $i$ 'th biggest singular value of the data in the window. If  $\lambda_i$  is close to one, it means that  $n-1$  dimensional space can cover most data, implying the existence of a low-dimensional subspace.

The required conditions for athletic movements is not only the coherency but also the explosiveness of the movement. The data which travel a greater distance in a submanifold are preferable to the data which travel a short distance. For taking this point into account, a scaling factor which emphasizes explosive movements is introduced as follows:

$$= \frac{\text{max. distance of two pts in the window}}{\text{max. distance of two pts in the whole data}} \in [0;1] \quad (11)$$

Finally, the index for detecting athletic movements is a combination of the manipulability  $\in [0;1]$  in (2) and the scaled coherency  $\in [0;1]$  in (11). An additional hyperparameter  $\in [0;1]$  is introduced to combine the two factors.

$$= (\text{manulability})^{(1-\alpha)} (\text{scaled coherency})^{\alpha} \in [0;1] \quad (12)$$

Note that a flexed pose and a coherent movement do not happen at the same time. Large values of the scaled coherency can be observed after large values of the manipulability in athletic movements. Thus, it is reasonable to combine the two values with a time delay. If the size of the fixed window is  $2m+1$  samples and  $\lambda_i$  represents the coherency from  $i-m$  to  $i+m$ , the index for detecting athletic movements is

$$\lambda_i = (\lambda_{i-m})^{(1-\alpha)} (\lambda_{i+m})^{\alpha} \in [0;1] \quad (13)$$

The hyperparameters to be manually chosen are the size of the window  $m$ , the combining ratio  $\alpha$ , and the threshold  $\lambda$  to determine athletic movements. Once those hyperparameters are set, the proposed method automatically detects athletic movements given motion capture data.

### III. EXPERIMENTS

The proposed method is evaluated on the CMU motion capture dataset [9]. The CMU dataset includes a large variety of motions, from activities of daily living to uncommon activities, e.g. mimicking animal behaviors. Among various motions, we chose four kinds of sports motions - *jumping*, *soccer kicking*, *baseball pitching* and *golf* - and a long stream of nonsports motions - *window washing*, *painting*, *hand waving*, etc. By using the sports and nonsports motions, the ability of the proposed method to detect and isolate athletic movements is tested. Additional results and implementation code are available as supplementary material [14].

The skeleton model in the CMU dataset consists of five serial chains, that is, torso, right/left arms, and right/left legs. The proposed method is applied to the arms and legs (not torso), and the endpoints of the arms and legs are regarded

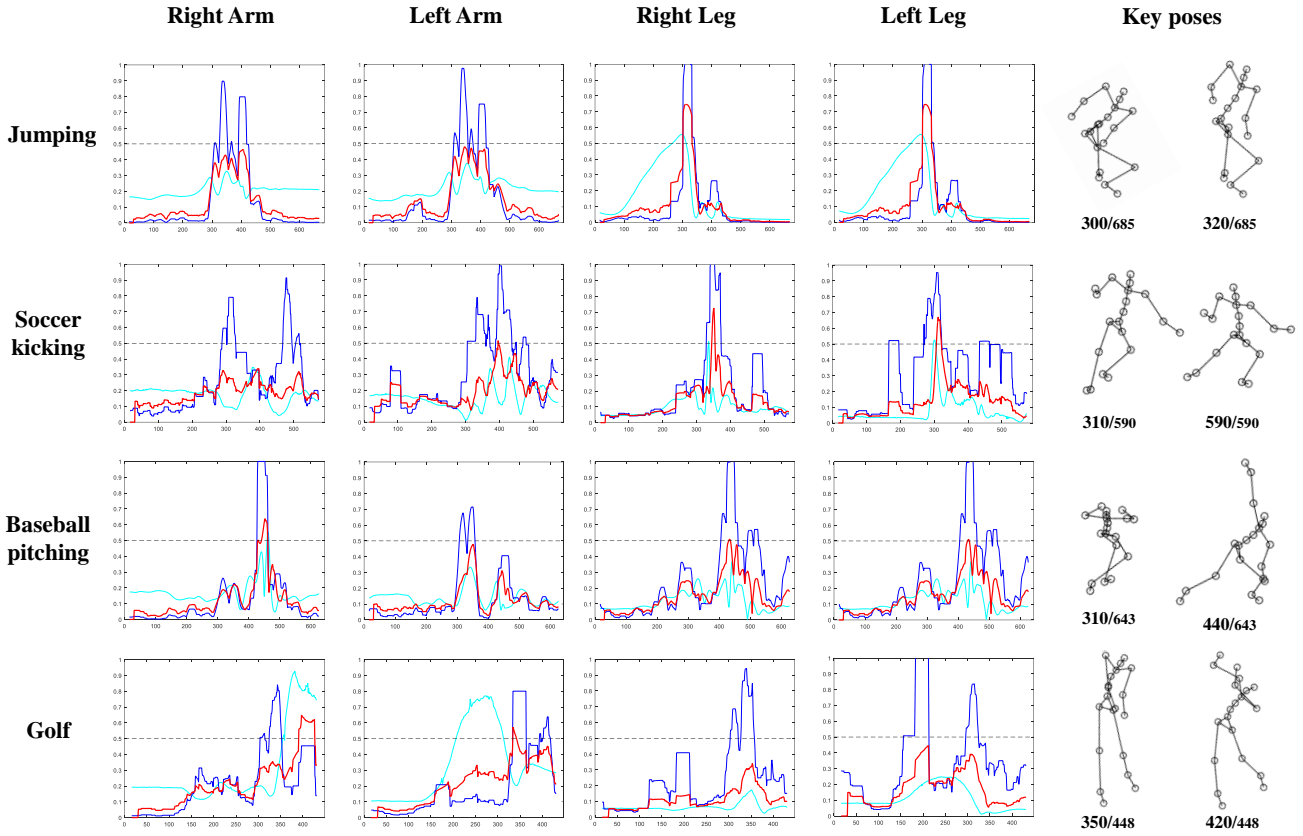


Fig. 2. The figure presents the manipulability (cyan), scaled coherency (blue) and index for detecting athletic movement (red) with the threshold value  $\nu_T = 0.5$  (dots). Also, key poses at the moments beyond the threshold are presented on the right with the frame numbers. The proposed method detects rapid changes of human poses from flexed to stretched poses and recognize them as athletic movements.

as wrists and ankles, respectively. That is, manipulability and scaled coherency values are computed based on the wrists and ankles, and their involved joints.

Since there is no prior knowledge to determine the hyperparameters, we chose these values by intuition. In the following experiments, the size of the window  $2m + 1$  is set to be 31 samples (0.25sec), the combining ratio be 0.5, and the threshold of  $\tau$  be 0.5. If labeled training data are available, these parameters can be adjusted by using, e.g., maximum likelihood approach.

Fig. 2. presents the changes of the manipulability (cyan), scaled coherency (blue) and index for detecting athletic movements (red) for various sports motions. In addition, key poses detected by the indexes and threshold values (dots) are presented next to the graphs. High values of the scaled coherency follow high values of the manipulability in most athletic movements. Also, by matching the key poses with the highest index values, we can observe that key poses of athletic movements are correctly extracted based on the proposed method.

In the jumping motion, only one athletic movement is detected in each limb motion. The indexes of the two legs are activated at the same time when they are stretched from the flexed pose and the indexes of the two arms are lightly activated right before activating the two legs. For the soccer

kicking motion, the right leg is activated with the highest value, and the left leg is activated before the right leg activation due to the approaching motion before kicking.

The graph of baseball pitching shows more complex behaviors. Although baseball pitching is relatively complicated compared to jumping or soccer motions, the method correctly captures the moments when the right leg pushes the body forward and the right arm throws the ball. Golf motion is different from the other athletic motions in that it stores energy by twisting the body while others do by flexing the body. Despite the different pre-athletic poses, the proposed method successfully captures the moment when the two arms stretch out in order to hit the ball.

The proposed method is also tested with the nonathletic (Fig. 3(a)) and mixed (Fig. 3(b)) motion data. In Fig. 3(a), only spraying paint motions are detected as athletic movements, because the movements are similar to a disc throwing motion which first retracts the arm and stretches it in a whipping motion. For other motions, none of them are detected as athletic movements, although the movements include a wide variety of speeds and poses. In Fig. 3(b), punching motions are detected as athletic movements in arm movements, and squat, running and jumping motions are lightly activated in leg movements. The result of leg movements indicates the need of modifying the threshold

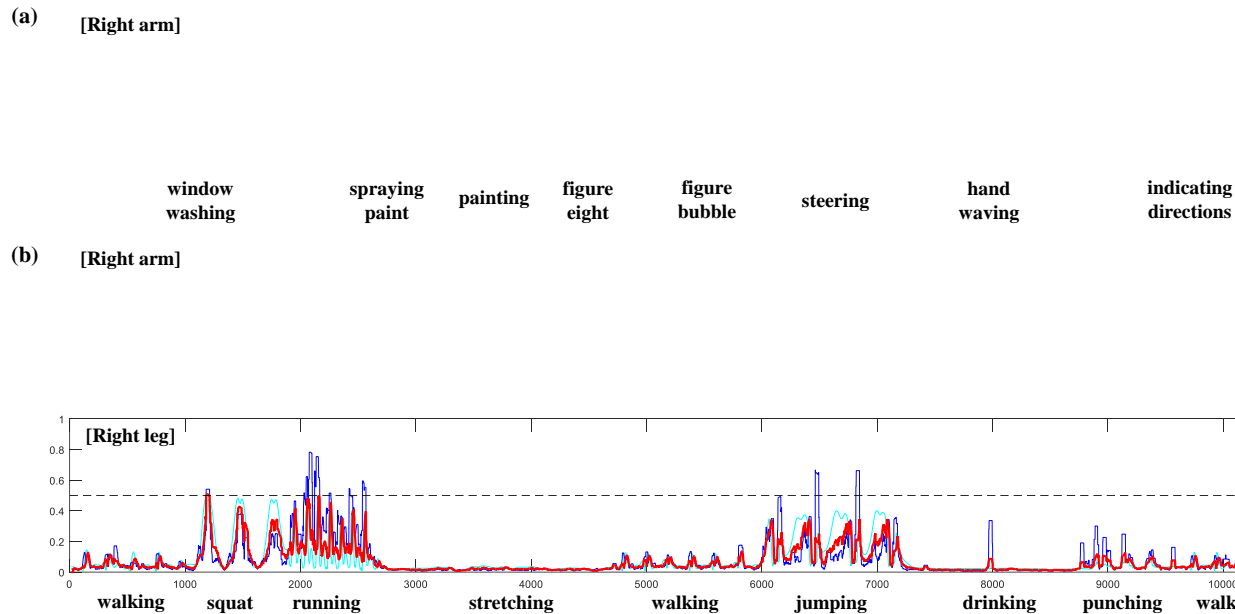


Fig. 3. The proposed method is applied to (a) nonathletic right-arm movements, which include window washing, painting, hand waving, etc., and (b) mixed movements, which include walking, running, punching, etc. The proposed method is not activated by nonathletic motions despite they have a wide variety of speeds and poses.

value for correctly detecting different levels of athletic movements. Nevertheless, the experiment results illustrate that the proposed method does not make false positive results for nonathletic movements and is only activated by athletic movements.

#### IV. CONCLUSIONS

In this paper, an unsupervised approach for detecting and isolating athletic movements is proposed. Athletic movements are characterized by a flexed pose followed by coherently stretching a limb with a kinematic synergy of the involved joints. To detect the flexed pose and coherent movement, manipulability and scaled coherency are introduced, based on the novel dimensionality reduction method called kinematic dimensionality reduction (KDR) technique. Based on the index that combines the manipulability and scaled coherency, athletic movements are successfully detected in various athletic and nonathletic motions.

The proposed approach does not require data-based training, can be used to automatically extract athletic motions from a long stream of motion data. Moreover, since the measure is based on the inherent geometry of human motions, it can be combined with machine learning to improve, e.g., athletic motion recognition tasks in the future.

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