Yoga: kinematic and kinetic diversity

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ABSTRACT

Yoga is widely practiced for improving physical and mental health, yet the biomechanical demands of individual yoga poses remain poorly characterized. Existing experimental studies typically examine only a small number of poses or muscles, limiting their ability to guide pose selection for rehabilitation or exercise prescription. Here we present a computational framework for estimating whole-body biomechanics from two-dimensional images of yoga poses. The framework combines manual pose digitization, a sagittal-plane MuJoCo human model, and constrained optimization based on static equilibrium and minimization of metabolic energy to predict joint torques, reaction forces, and ground contact forces. We applied the framework to 55 sagittally symmetric yoga poses from Light on Yoga, generating a dataset of joint kinematics, kinetics, and contact locations. The results show that these poses collectively span nearly the full physiological range of motion of the major joints while imposing highly diverse joint torque requirements, with the greatest average demands on the lower extremities and lumbar region. Principal component analysis revealed a striking contrast between kinematics and kinetics: the joint-angle data required nearly all ten degrees of freedom to represent the pose repertoire, whereas over 90% of the variance in joint torques was captured by only three principal components, suggesting substantial diversity in body configurations despite a much lower-dimensional space of mechanical loading. Predicted torque distributions were also robust to uncertainty in the relative weighting of joint metabolic costs for many poses. This framework enables large-scale biomechanical analysis of yoga poses and provides a foundation for designing evidence-based yoga interventions and future personalized rehabilitation strategies.

Introduction

Yoga, an ancient Indian exercise tradition, has gained global popularity since the mid-20th century[1]. The classical form of yoga, termed Hatha yoga, involves holding static (isometric) poses against gravity. Extensive literature has highlighted its benefits for cardiometabolic, mental, and physical health[2,3]: studies have shown improvements in physical well-being, pain relief, and reduced pain medication use in people with musculoskeletal disorders[4]. For individuals with movement disorders such as Parkinson's disease, stroke, and cerebral palsy, yoga has also been shown to improve joint mobility, balance, flexibility, and lower limb strength[5–8]. These findings suggest that yoga has potential as a therapeutic tool for physical and mental disorders. However, yoga-based therapies are not routinely prescribed in clinical practice because we lack a quantitative understanding of the biomechanical demands of individual poses, which is essential for making patient-specific recommendations on the type, intensity, and frequency of practice.

Previous studies of the effects of yoga poses on muscles and joints are not comprehensive[9–27]. First, collectively they examine only a small fraction of the roughly 200 poses currently known[28]. Second, individual studies focus on specific body regions (lower extremity, core, or shoulder) or selected muscle groups. This is partly because they rely on experimental techniques such as surface EMG, which are typically limited to surface muscles and a relatively small number of muscles due to device limitations.

A promising alternative is to use computer simulations to study many yoga poses and their effects on the whole body. Omkar et al.[29] proposed a computational model to predict upper and lower extremity joint torques for nine two-point contact poses. However, they assumed negligible horizontal ground contact forces, which is unrealistic, and did not validate their predictions experimentally. Here, we propose a computational framework to predict the joint torques of individual yoga poses from 2D images (figure 1). The framework is based on the hypothesis that humans minimize metabolic energy while holding a pose. We demonstrate its use by predicting the joint torques of 55 yoga poses that are symmetric about the sagittal plane.

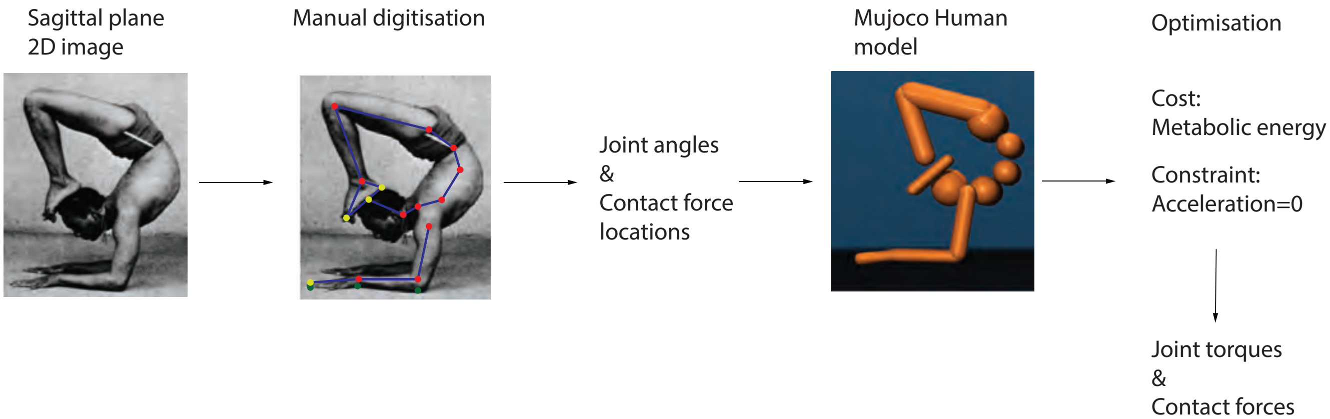

Figure 1. Yoga simulation framework. Images of yoga poses symmetric about the sagittal plane are digitized to extract joint angles and contact locations. These are used to initialize a 2D human model in the MuJoCo physics engine; constrained optimization predicts joint torques, joint reactions, and contact forces.

Methods

The simulation framework consists of five parts (figure 1): (1) collecting sagittal-plane images of the poses, (2) a user-centred program to digitize the images and extract body positions and contacts, (3) extracting joint angles and contact locations from the digitized points, (4) a sagittal-plane human model in MuJoCo, and (5) performing constrained optimization with a metabolic energy cost function and zero-acceleration constraints to predict joint torques, joint reactions, and contact forces.

We analyzed 55 sagittal-plane poses from the book *Light on Yoga*[28] (figure 2), a modern foundational classic of yoga practice. We considered only poses symmetric about the sagittal plane so that they could be modeled in 2D using one arm and one leg. Although other image datasets of yoga poses are available[30], they contain inconsistencies in pose names. We therefore used *Light on Yoga*[28], which contains an extensive collection of roughly 200 poses with images and descriptions. From each pose image, we recorded the number of body segments in contact with the ground, the names of the contacting segment pairs, and the locations of joints, the toe, heel, hand tip, and crown of the head. The contact information, absent from previous datasets, is essential for modeling each pose. We represented the spine, including the neck, with five joints (lumbar lower, lumbar mid, lumbar upper, neck lower, neck upper) to account for spinal curvature during the poses, and modeled three joints each in the lower extremity (ankle, knee, and hip) and the upper extremity (wrist, elbow, and shoulder).

We performed static simulations in MuJoCo[31]. We used a 2D human model with 10 joints and 11 rigid segments, obtained by modifying the humanoid model[32] provided as part of the MuJoCo inventory (figure 3B). We removed joint stiffness, added a hand segment and a torso joint, and constrained all segments and joints to move in the 2D sagittal plane. The model had three joints in the upper extremity (wrist, elbow, and shoulder), three in the lower extremity (ankle, knee, and hip), and four in the spine (lumbar lower, lumbar mid, lumbar upper, and neck). We used a custom contact formulation instead of MuJoCo's native formulation, treating each segment-ground contact as a two-point contact. Contact locations were obtained from the digitized data, with one horizontal and two vertical contact force components defined for each contacting segment.

We hypothesize that humans minimize metabolic energy while holding a pose. This is formulated as a constrained optimization problem, with metabolic energy as the cost and static posture as the constraint. In earlier work[33], we found that metabolic energy scales nonlinearly with joint torque τ, specifically scaling like τ^{γ}, with $\gamma \approx 1.64$. This implies metabolic energy $= \sum_{\mathrm{i}=1}^{\text{all joints}} \alpha_{\mathrm{i}} \tau_{\mathrm{i}}^{1.64}$, where α_{i} is a joint-specific proportionality constant. As a simple default, we assumed equal coefficients for all joints, $\alpha_{\mathrm{i}} = 1$ but repeated the optimization fifty times with randomly generated α values to assess their effect on the predictions. The initial pose was specified from the joint angles estimated by image digitization. We imposed static equilibrium by constraining the accelerations of all joints and body segments to zero, and solved the optimization using the trust-constrained algorithm in the SciPy Python library. The optimization predicted joint torques, joint reactions, and horizontal and vertical contact forces.

Results

Optimizations converged for all poses, and the resulting simulations are shown in figure 4. The acceleration constraint and optimality violation were below 10^{-4} for every pose. Each optimization required only a few seconds because the problem is static and does not require dynamic trajectory integration.

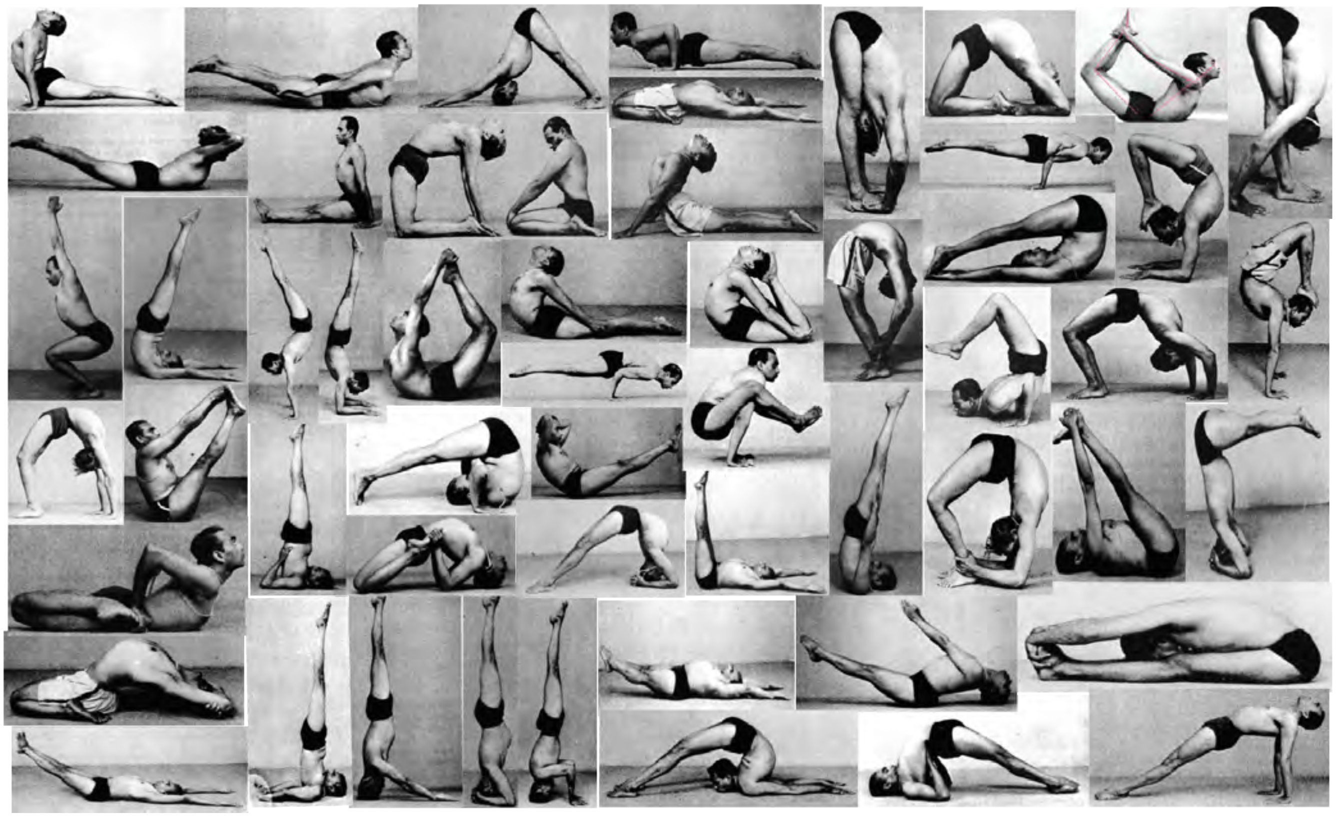

Figure 2. Sagittal plane images of 55 yoga poses taken from light on yoga book[28].

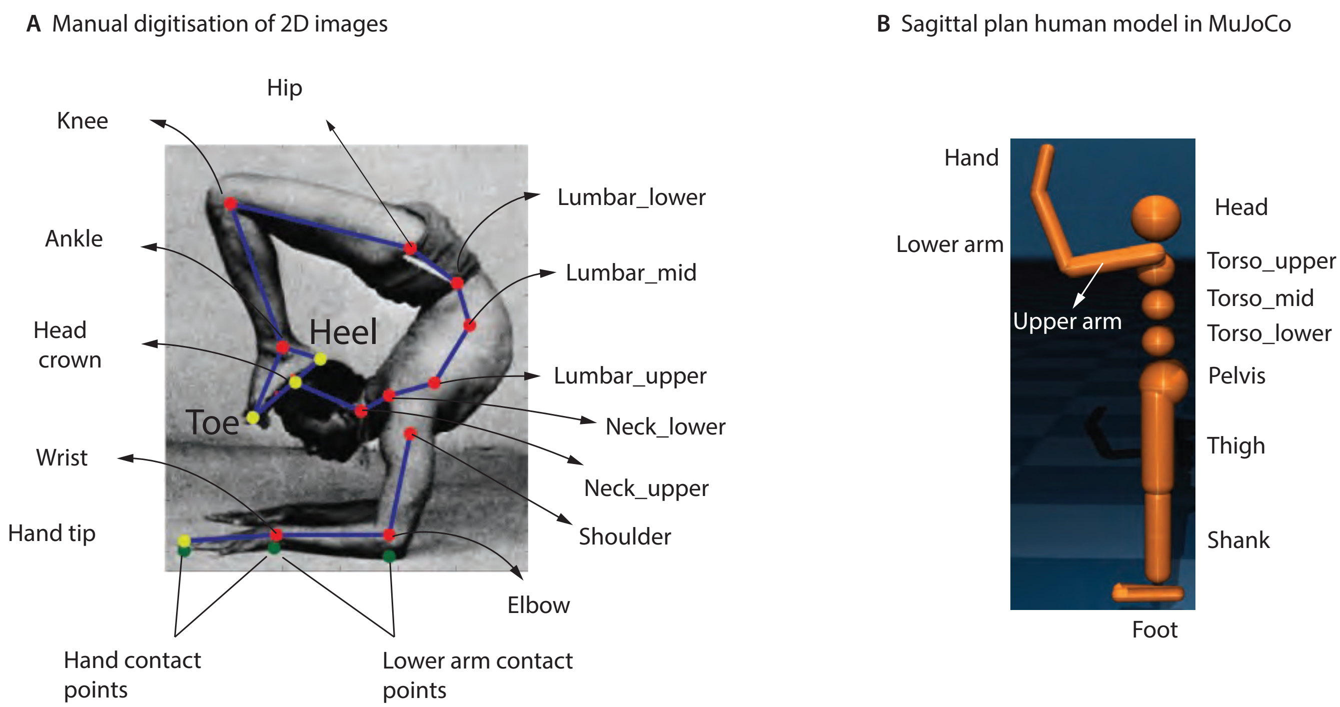

Figure 3. Manual digitization and Mujoco human model. A) Digitized image of a pose showing the coordinates of joint centers, body extremities (toe, heel, hand tip, and crown of the head), and contact points (two each on the hand and lower arm). **B)** Sagittal-plane human model in MuJoCo with 11 rigid segments and 10 joints.

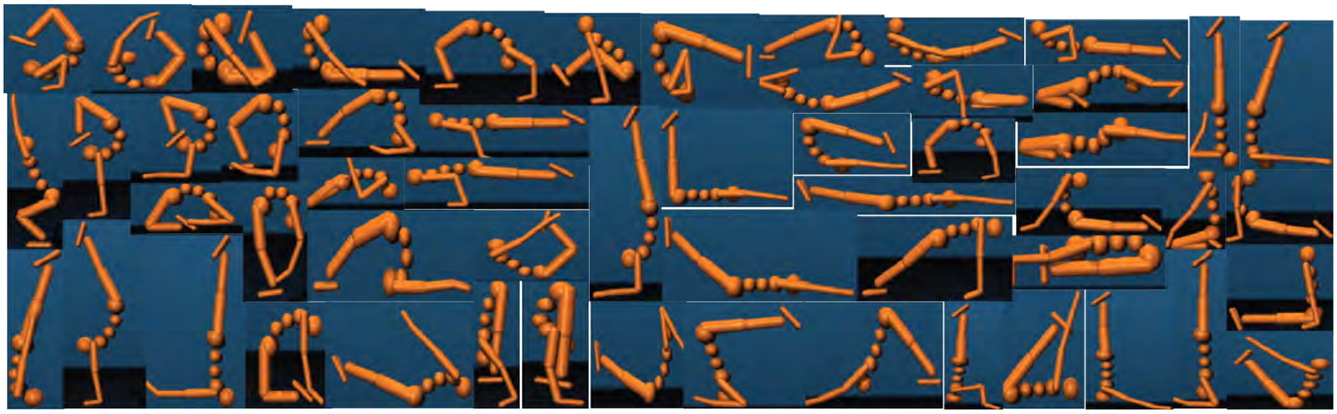

Figure 4. Static simulation in mujoco: images of converged kinematic state.

Joint angles across the 55 poses spanned nearly the full physiological range of motion of all joints (figure 5A). We performed principal component analysis (PCA) of the joint angles to assess the dimensionality of the pose repertoire in kinematic space. PCA of the joint angles showed that nearly all ten dimensions were required to represent the 55 poses (figure 5D): the first principal component explained 30% of the variance, whereas each subsequent component explained an additional 5–10%. Thus, the poses exhibit substantial kinematic diversity with little redundancy.

Model-predicted joint torques showed that the hip required the greatest torques on average, followed by the lumbar spine and knee, whereas the wrist required the least (figure 5B). Grouping joints by body region showed that the lower extremities experienced the greatest average torques, followed by the torso and head, and then the upper extremities (figure 5C). As with the joint angles, we performed We performed principal component analysis (PCA) of the joint torques to assess the dimensionality of the pose repertoire in kinetic space. In contrast to the kinematics, PCA of the joint torques showed that over 90% of the variance was captured by the first three principal components (figure 5E), suggesting that despite their diverse body configurations, yoga poses produce comparatively low-dimensional patterns of joint loading.

Predictions were insensitive to randomly generated coefficient values (α_i) for 29 of the 55 poses (figure 6A,B). Twelve of these poses involved only a single body segment in contact with the ground, making the optimization problem fully determined. The remaining 17 poses involved multiple contacts but shared a continuous line of contact with the ground, which likewise resulted in coefficient-insensitive predictions. The remaining 26 poses exhibited sensitivity to the choice of α_i (figure 6C,D). Although the predicted joint torque magnitudes varied, their relative ordering remained largely unchanged and was similar to that obtained with equal coefficients ($\alpha_i = 1$). The median predictions from random coefficients closely matched those from equal coefficients (figure 6C), with 10 poses showing identical joint torque rankings and all remaining poses retaining at least 50% similarity (figure 6E). These results suggest that the relative ranking of joint torques is robust to the choice of coefficient values.

Discussion

We developed a computational framework for predicting whole-body joint torques from 2D images of yoga poses in the sagittal plane. The framework also demonstrates the use of a metabolic cost model for predictive simulations. It produces a novel dataset of joint positions, contact locations, joint torques, and contact forces for the entire body across 55 yoga poses. These data show that the poses collectively span nearly the full range of motion of the major joints while imposing a wide range of joint torques, with the greatest average demands on the lower extremities. Principal component analysis revealed a striking contrast between kinematics and kinetics: joint-angle data exhibited little dimensionality reduction, whereas over 90% of the variance in joint torques was explained by the first three principal components. Thus, yoga poses are highly diverse in body configuration while producing comparatively low-dimensional patterns of joint loading.

Our simulation framework is currently restricted to sagittal-plane poses that are symmetric about the sagittal plane. Joint angles and contact locations were obtained by manual digitization and are therefore subject to measurement error. The human model consists of rigid segments and does not account for passive muscle or ligament forces or body–body contacts, which may affect joint force predictions. We also did not experimentally validate the predicted joint torques or contact forces. Finally, because the model is joint torque based, it cannot predict individual muscle forces. While the joint-specific metabolic coefficients had some effect on the joint torques for some poses, and we do not exactly know what these coefficients should be, we found that the inference of the relative magnitudes of joint torques is largely insensitive to the choice of coefficient values.

Joint kinematics and kinetics of 55 yoga poses

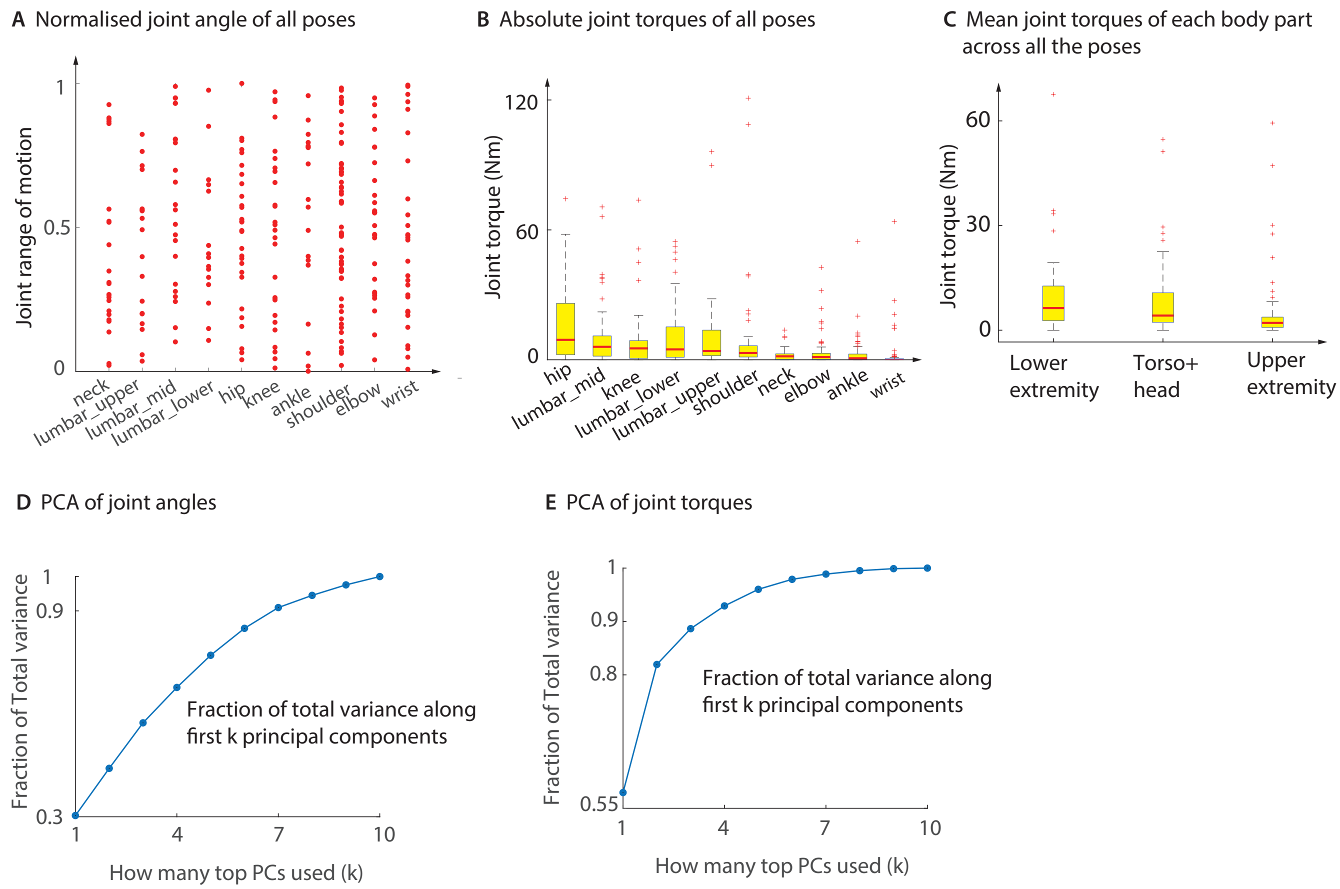

Figure 5. Joint angles and torques of 55 yoga poses. **A)** Joint angles for all joints across all poses, normalized by each joint's range of motion[34]. Zero and one denote the minimum and maximum values, respectively. **B)** Absolute joint torques for all joints across all poses. **C)** Mean absolute joint torques for the upper extremities, lower extremities, and torso. **D)** Principal component analysis of joint angles across all poses. **E)** Principal component analysis of joint torques across all poses.

Future work could extend the framework to three-dimensional poses by combining computer vision methods for estimating 3D joint kinematics, examined with a 3D MuJoCo model. Incorporating passive joint mechanics and body–body contact would further improve biomechanical realism. Model predictions should also be validated experimentally using measurements of joint torques and ground reaction forces. More broadly, the dataset of joint kinematics and kinetics generated here provides a foundation for designing yoga-based rehabilitation protocols and evaluating the biomechanical demands of individual poses for different movement disorders and injuries.

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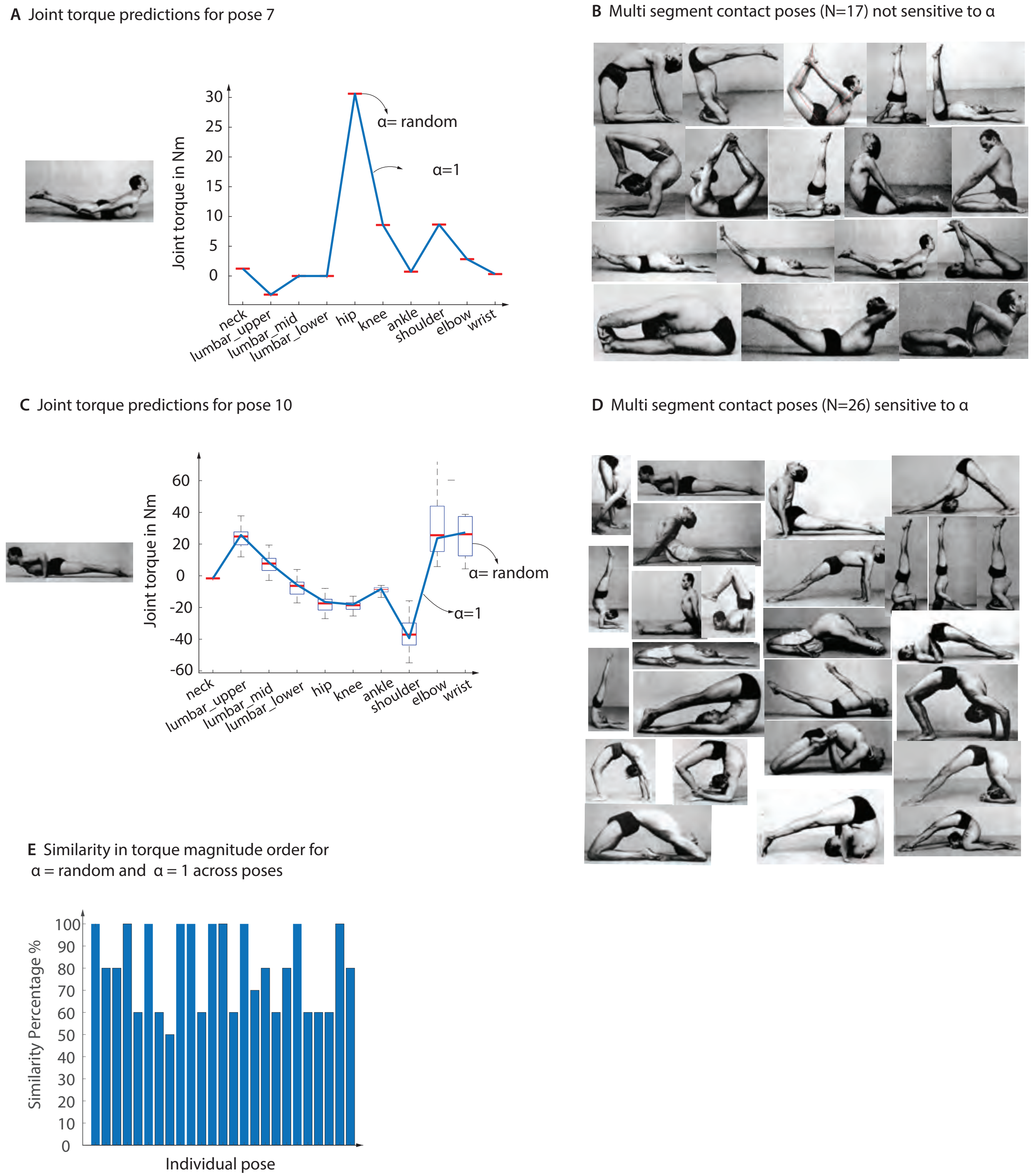

Figure 6. Predictions with random coefficients $\alpha_i \in (0,1)$ and equal coefficients $\alpha_i = 1$. A) Joint torque prediction for a pose insensitive to changes in α_i. **B)** Poses insensitive to changes in α_i. **C)** Joint torque prediction for a pose sensitive to changes in α_i. **D)** Poses sensitive to changes in α_i. **E)** Similarity in the relative ranking of joint torque magnitudes between the median predictions with random coefficients and the predictions with equal coefficients.

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