BIGE: Biomechanics-informed GenAI for Exercise Science

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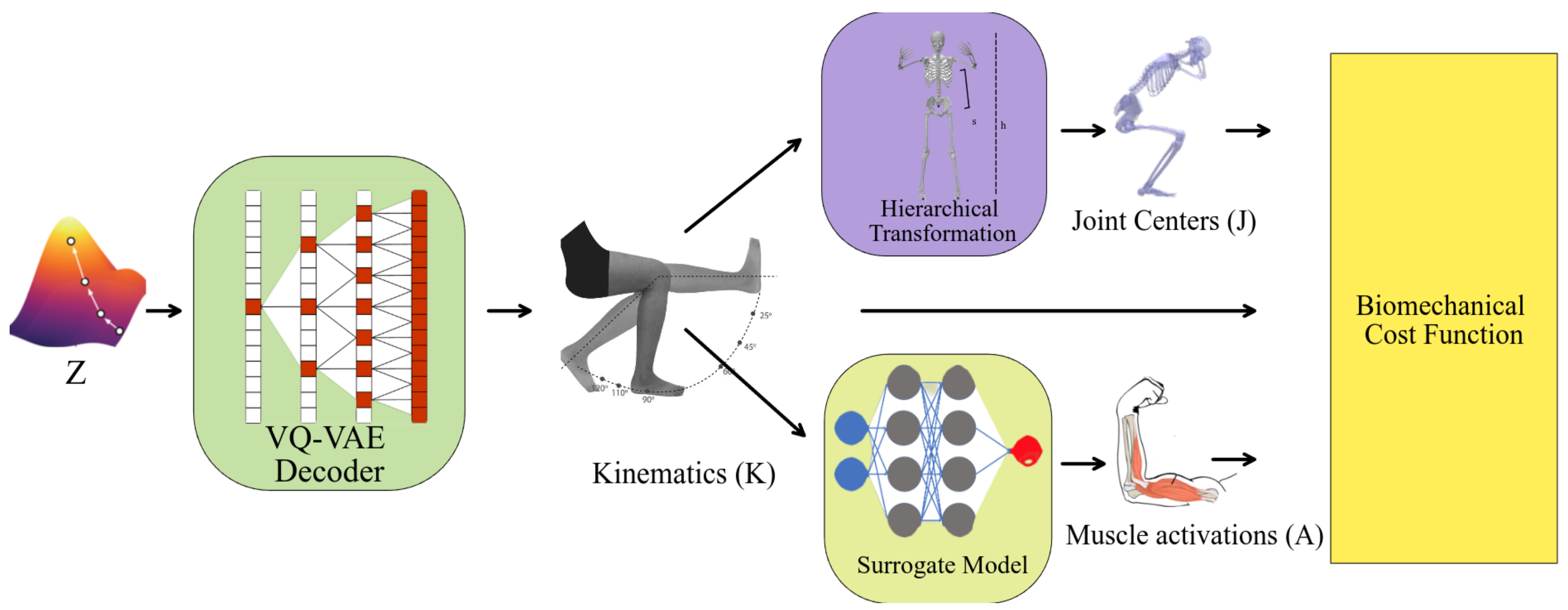
How it works



Latent variables are decoded using a VQ-VAE decoder to generate joint kinematics. Hierarchical transformations are applied to the biomechanical model, to compute joint centers. A surrogate model predicts muscle activations. Finally, clinician-defined constraints are imposed on the derived variables.

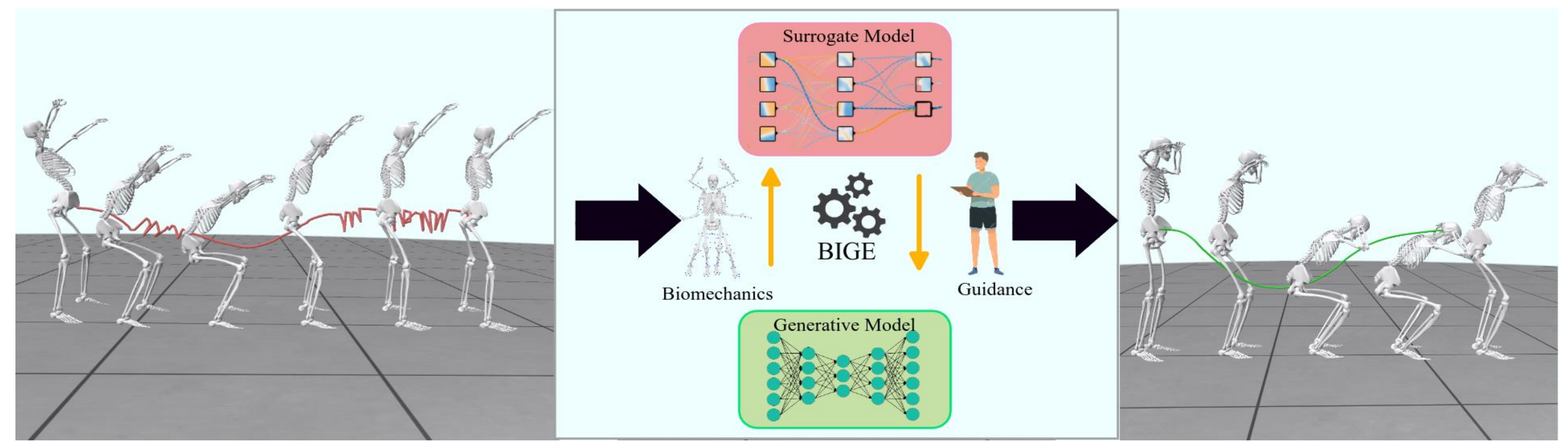
Biomechanical Constraints

Metric	Definition	Guidance Loss
Pelvis Tilt (degs)	$\max(K_{\text{pelvis}})$, where K_{pelvis} is the pelvis tilt angle at peak activation	$\mathcal{L}_{\text{tilt}} = \frac{1}{T}\sum_{t=1}^{T}\hat{K}_{t,\text{peak\_timestep,pelvis\_tilt\_index}}$
Asymmetry (degs)	$\text{mean}(\sum_{(j_l,j_r)\in\text{leg joints}}\lvert K_{j,\text{left}} - K_{j,\text{right}}\rvert)$, comparing the angles of left and right leg joint	$\mathcal{L}_{\text{asymm}} = \frac{1}{T}\sum_{t=1}^{T}\sum_{j_l,j_r\in\text{leg joints}}(\hat{K}_{\text{left}} - \hat{K}_{\text{right}})^2$
Angular vel. (degs/s)	$\text{mean}(\sum_{\theta\in K^{\text{angles}}}\frac{d\theta}{dt})$, where K^{angle} is joint angles in Kinematics	$\mathcal{L}_{\omega} = \frac{1}{T}\sum_{t=1}^{T}\sum_{\theta\in K^{\text{angles}}}(\hat{K}_{t,\theta} - \hat{K}_{t,\theta})^2$
COM vel. (m/s)	$\text{mean}(\frac{\lvert\lvert dK^{trans}\rvert\rvert}{dt})$, where $K^{trans}\in\mathbb{R}^3$ pelvis translation relative to the ground	$\mathcal{L}_{v_{\text{COM}}} = \frac{1}{T-1}\sum_{t=1}^{T-1}(\hat{K}^{trans}_{t+1} - \hat{K}^{trans}_{t})^2$ is the
COM acc. (m/s^2)	$\text{mean}(\frac{\lvert\lvert d^2K^{trans}\rvert\rvert}{dt^2})$, where ∇^2 is the Laplacian operator	$\mathcal{L}_{a_{\text{COM}}} = \frac{1}{T-2}\sum_{t=2}^{T-1}(\nabla^2\hat{K}^{trans})^2$
Foot Sliding	$\text{mean}(\lvert\lvert\frac{dp_{\text{lowest}}}{dt}\rvert\rvert)$, ensures the lowest point p_{lowest} does not slide on the ground	$\mathcal{L}_{\text{slide}} = \frac{1}{T-1}\sum_{t=1}^{T-1}(\mathbf{p}_{\text{lowest},t+1} - \mathbf{p}_{\text{lowest},t})^2$
Muscle activation constrain (MAC)	Ensure vastus medialis muscle activation $\hat{A}_{\text{vas\_med}}$ remains in the given range [low,high]	$\mathcal{L}_{\text{MAC}} = \frac{1}{T}\sum_{t=1}^{T}\max(x - \text{high}, \text{low} - x, 0)$

Our framework allows clinicians to impose multiple biomechanical constraints and criteria on the generated motion, ensuring adherence to physiologically meaningful properties. These constraints can target various aspects of the motion, including joint kinematics (pelvis tilt, angular velocity ω), joint center dynamics (center of mass (COM) velocity and acceleration) and muscle activations.

Model	Pelvis tilt(degs) →	Asymmetry(degs) →	ω (degs/s) →	COM vel.(m/s)→	COM acc. (m/s^2) →	Constrain (0-1)↓
Reference	−23.40	2.42	90.04	0.54	2.65	0.08
MoCap	$-28.13^{\pm 6.03}$	$\underline{2.76^{\pm 0.59}}$	$\mathbf{96.24^{\pm 13.96}}$	$\underline{0.67^{\pm 0.14}}$	$\underline{30.45^{\pm 5.55}}$	$0.03^{\pm 0.03}$
MDM	$0.42^{\pm 1.87}$	$\mathbf{2.25^{\pm 0.28}}$	$554.10^{\pm 112.77}$	$3.39^{\pm 0.79}$	$335.86^{\pm 81.37}$	$\underline{0.03^{\pm 0.02}}$
T2M-GPT	$4.16^{\pm 2.42}$	$4.73^{\pm 0.29}$	$918.14^{\pm 42.06}$	$6.09^{\pm 0.48}$	$597.95^{\pm 54.60}$	$\mathbf{0.02^{\pm 0.01}}$
VQVAE	$\underline{-20.69^{\pm 0.51}}$	$1.12^{\pm 0.03}$	$37.78^{\pm 0.42}$	$1.59^{\pm 0.08}$	$128.24^{\pm 6.49}$	$0.16^{\pm 0.01}$
BIGE	$\mathbf{-23.09^{\pm 1.54}}$	$2.09^{\pm 0.14}$	$\underline{56.95^{\pm 1.94}}$	$\mathbf{0.51^{\pm 0.04}}$	$\mathbf{27.32^{\pm 3.88}}$	$0.06^{\pm 0.01}$

BIGE effectively adheres to clinician-accepted constraints, highlighting its efficacy in producing physiologically meaningful motion.

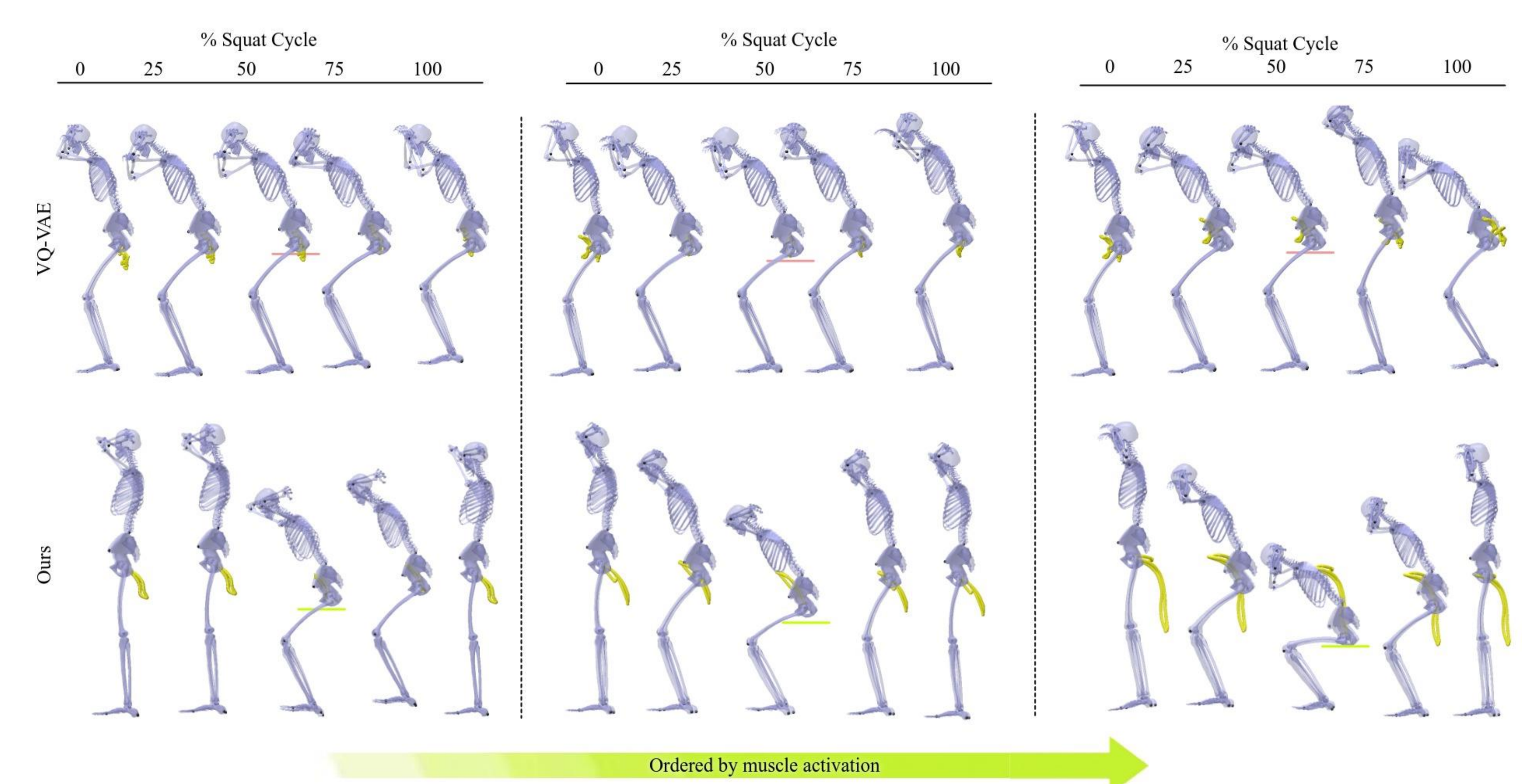


BIGE is a framework for generative models to adhere to clinician-defined constraints. To generate realistic motion, our method uses a biomechanically informed surrogate model to guide the generation process..

Summary

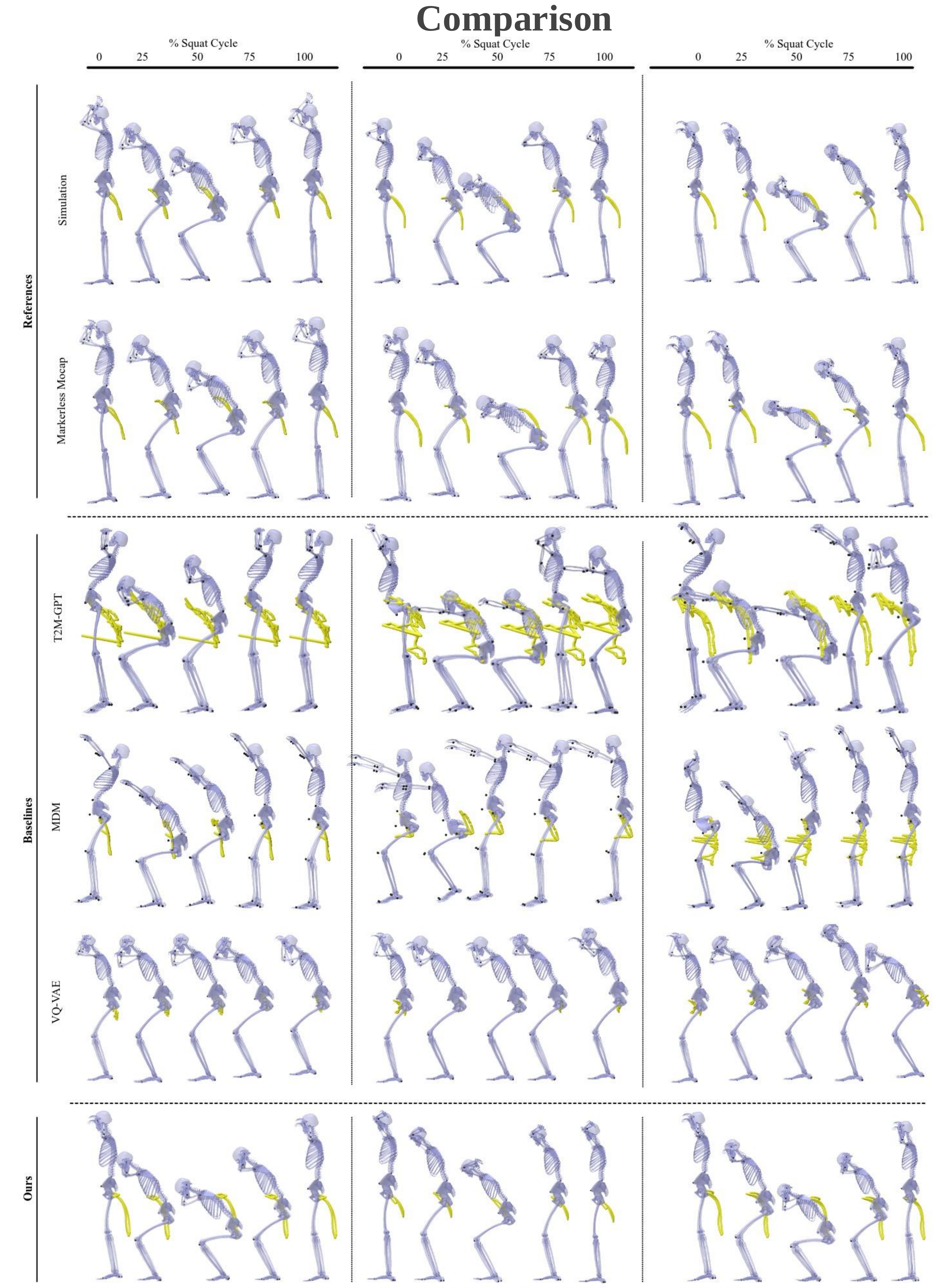
Proper movements enhance mobility, coordination, and muscle activation, which are crucial for performance, injury prevention, and overall fitness. However, traditional simulation tools rely on strong modeling assumptions, are difficult to set up and computationally expensive. On the other hand, generative AI approaches provide efficient alternatives to motion generation. But they often lack physiological relevance and do not incorporate biomechanical constraints, limiting their practical applications in sports and exercise science. To address these limitations.

- We propose a novel framework, BIGE, that combines bio-mechanically meaningful scoring metrics with generative modeling.
- **BIGE** integrates a differentiable surrogate model for muscle activation to reverse optimize the latent space of the generative model
- Enables the retrieval of physiologically valid motions through targeted search.
- Through extensive experiments on squat exercise data, our framework demonstrates superior performance in generating diverse, physically plausible motions while maintaining high fidelity to clinician-defined objectives compared to existing approaches.



Our guidance strategy leads to a more physiologically accurate squat motion as evidenced by the increased depth of the squat.

Comparison



BIGE produces motions closely aligned with the reference data and free of unnatural artifacts. The biomechanical constraints enforced in BIGE enable the model to perform deep, natural squats throughout the cycle.

Model	Realism		Floor metrics		
	Fidelity ↓	Diversity →	Penetration (cm) ↓	Floating (cm) ↓	Sliding ($\frac{m}{sec}$) ↓
Reference	-	1.736	$0.003^{\pm 0.057}$	$0.000^{\pm 0.021}$	$0.035^{\pm 0.024}$
MoCap	$\underline{7.855^{\pm 9.902}}$	$\underline{1.773^{\pm 0.015}}$	$\mathbf{0.501^{\pm 0.987}}$	$\mathbf{0.759^{\pm 1.649}}$	$\mathbf{0.209^{\pm 0.161}}$
MDM	$257.95^{\pm 105.92}$	$1.26^{\pm 0.05}$	$2.685^{\pm 3.840}$	$3.216^{\pm 4.636}$	$1.395^{\pm 2.672}$
T2M-GPT	$459.49^{\pm 257.30}$	$1.45^{\pm 0.05}$	$\underline{1.997^{\pm 2.938}}$	$2.440^{\pm 3.606}$	$3.770^{\pm 4.758}$
VQVAE	$45.99^{\pm 4.67}$	$1.82^{\pm 0.03}$	$2.035^{\pm 3.016}$	$\underline{2.331^{\pm 3.506}}$	$1.351^{\pm 0.830}$
BIGE	$\mathbf{6.48^{\pm 4.46}}$	$\mathbf{1.76^{\pm 0.03}}$	$2.327^{\pm 3.659}$	$2.379^{\pm 3.561}$	$\underline{0.291^{\pm 0.255}}$

BIGE achieves the closest fidelity and diversity to reference data.

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- Code: https://github.com/Rose-STL-Lab/BIGE
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