



Skinned Motion Retargeting with Residual Perception of Motion Semantics & Geometry

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Problem Statement

Motion retargeting



Mapping the motion of a source character to a target character without losing plausibility.

Traditional methods:

- Optimization with kinematic constraints
- Motion-specific and hand-designed constraints
- Post-processing and hand-tuning steps

Deep neural network methods:

- Data-driven
- End-to-end solution



Related Work

Previous learning-based methods

Full mapping and without consideration of geometry:

- NKN (CVPR 2018), Ruben Villegas, et al.
- PMnet (BMVC 2019), Lim Jongin, et al.
- SAN (TOG 2020), Kfir Aberman, et al.
- ItMRnet (C&G 2022), Shujie Li, et al.

Post-processing for geometry preserving:

• Contact-aware (CVPR 2021), Ruben Villegas, et al.



Enable the network to perceive both the semantics of the motion and the geometry of the character during the inference process without requiring post-processing.



Motivation & Challenges



We observe that artists usually copy the motion of the source character, and then manually modify it to preserve motion semantics and avoid translation artifacts, e.g., interpenetration, during motion reuse in new characters.

Challenges



- Lack of paired motion data from different characters.
- Differences in bone lengths and proportions.
- Various of shape geometries.
- Motion should be plausible and realistic.

Residual RETargeting network (R²ET)



Key designs

- A residual network structure for neural motion retargeting
- A *skeleton-aware modification module* for motion semantics perceiving.
- A *shape-aware modification module* for shape geometry perceiving.
- A balancing gate for to make a trade-off between two modifications.
- Distance-based measurements for motion semantics and geometry learning method.

Residual RETargeting network (R²ET)



Distance-based measurements:

- Normalized Distance Matrix
- Repulsive Distance Field
- Attractive Distance Field

Loss Functions:

Semantics Similarity Loss

$$\mathcal{L}_{sem} = \left\| \eta \left(\frac{\boldsymbol{D}_A}{h_A} \right) - \eta \left(\frac{\boldsymbol{D}_B}{h_B} \right) \right\|_2^2,$$

Repulsive Loss

$$\mathcal{L}_{rep} = \frac{1}{N_l} \sum_{e \in E_l} \psi_R(e),$$

Attractive Loss

$$\mathcal{L}_{att} = \frac{1}{N_h} \sum_{e \in E_h} \psi_A(e),$$

Results



Results



Figure 5. Qualitative results of skeletal motion retargeting. ΔD indicates the DM difference between the motion copy and our result.



Table 1. Comparison with the state-of-the-arts. MSE^{lc} is the local MSE. $R^2 ET_{w/oGW}$ is the model with the skeleton-aware module only. $R^2 ET_{w/oW}$ is the model without the balancing gate. Copy† is the motion copy without the global motion normalization.

Methods	Inp.	MSE↓	$\mathrm{MSE}^{lc}{}_{\downarrow}$	Pen.↓	$ ext{Con.}^{cm}_\downarrow$	
GT	-	-	-	9.02	4.92	
NKN [25] PMnet [16]	Pos.	2.298 0.806	0.575 0.281	8.96 7.11	4.42 14.7	
Copy Copy† SAN [1] PMnet*	Rot.	0.267 3.087 0.321 0.374	0.060 0.060 0.118 0.120	9.23 9.23 8.91 9.03	4.95 4.95 4.86 5.24	
$\frac{R^2 E T_{w/oGW}}{R^2 E T_{w/oW}}$ $\frac{R^2 E T (Ours)}{R^2 E T (Ours)}$	Rot.	0.297 0.378 0.318	0.094 0.178 0.116	9.09 4.68 5.94	4.93 5.31 3.57	

Copy

Right Arm

Time

Left Leg

 $R^2 ET_{w/oW}$

R²ET (Ours)

Right Leg

■ NKN ■ R²ET

GT

SAN

Table 2. Ranking results of the user study. We invite 100 users to compare our retargeting results to that of the recent methods from three aspects, i.e., overall quality (Q), semantics preservation (S), and motion details (D).

Methods	Skeletal Motion			Skinned Motion			
	Q↓	S_{\downarrow}	D_{\downarrow}	Q↓	S↓	D_{\downarrow}	
Сору	1.88	1.83	1.84	1.84	1.84	1.93	
NKN [25]	3.37	3.45	3.40	3.44	3.44	3.42	
PMnet [16]	3.06	3.06	3.06	3.10	3.07	3.00	
R^2ET (Ours)	1.69	1.67	1.70	1.63	1.65	1.64	

Thanks for watching!

