NiLBS: Neural Inverse Linear Blend Skinning

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Abstract

In this technical report, we investigate efficient representations of articulated objects (e.g. human bodies), which is an important problem in computer vision and graphics. To deform articulated geometry, existing approaches represent objects as meshes and deform them using “skinning” techniques. The skinning operation allows a wide range of deformations to be achieved with a small number of control parameters. This paper introduces a method to invert the deformations undergone via traditional skinning techniques via a neural network parameterized by pose. The ability to invert these deformations allows values (e.g., distance function, signed distance function, occupancy) to be pre-computed at rest pose, and then efficiently queried when the character is deformed. We leave empirical evaluation of our approach to future work.

1. Linear Blend Skinning (LBS)

Linear blend skinning is widely used in computer games and other real-time applications to deform a character’s skin following the motion of an underlying abstract skeleton [3].

Given a deformable surface mesh model whose vertices in homogeneous coordinates are $\mathbf{V} = \{ \mathbf{v}_n \in \mathbb{R}^4 \}$

Let us define the LBS deformation process as:

$$ \tilde{\mathbf{v}}_n = \sum_b w_{bn} \mathbf{B}_b \mathbf{v}_n $$

(1)

where the collection of $B$ homogeneous transformations $\{ \mathbf{B}_b \in \mathbb{R}^{4 \times 4} \}$ are blended by the weights $w_{bn}$. These weights are typically painted by a digital artist on the surface of the model, although automated algorithms exist for cases when less control and quality is needed [1]. Each of these transformation matrices are typically factored into the product of two transformations $\mathbf{B}_b = \tilde{\mathbf{B}}_b \mathbf{B}_b^{-1}$. In what follows, we will use $\tilde{\mathbf{v}}$ to denote quantities in the rest coordinate frame, and $\mathbf{v}$ in a deformed coordinate frame. The homogeneous transformations $\mathbf{B}_b^{-1}$ are expressed in rest pose and kept fixed throughout deformation, while $\tilde{\mathbf{B}}_b$ are typically computed as a function of the pose degrees of freedom $\theta$ – we can abstract this process via the pose function $\{ \tilde{\mathbf{B}}_b \} = \text{pose}(\theta)$. Given a vertex in rest pose $\tilde{\mathbf{v}} \in \mathbf{V}$, the transformation:

$$ \tilde{\mathbf{v}}_b = \tilde{\mathbf{B}}_b \mathbf{B}_b^{-1} \mathbf{v} $$

(2)

first encodes the point in the (local, rest) $b$-th coordinate frame as $\tilde{\mathbf{v}}_b = \mathbf{B}_b^{-1} \mathbf{v}$, and then decodes it in the $b$-th (global, posed) coordinate frame as $\tilde{\mathbf{v}}_b = \tilde{\mathbf{B}}_b \tilde{\mathbf{v}}$. Finally, once we represent the weights $w_n = \{ w_{bn} \}$, as well as the transformations $\mathbf{B}(\theta) = \{ \mathbf{B}_b \}$ in tensor form, we can summarize the skinning of a single vertex as:

$$ \tilde{\mathbf{v}}_n = \left[ w_n \mathbf{B}(\theta) \right] \tilde{\mathbf{v}}_n, $$

(3)

where $\mathbf{B}(\theta)$ has dimensionality $B \times 4 \times 4$, $w_n$ has dimensionality $1 \times B$, and we highlight the dependency of $\mathbf{B}$ on the pose parameters $\theta$. Further, $w_n$ are typically normalized so that they are positive and sum to one.

2. Neural inverse LBS (NiLBS)

We seek a method to query the occupancy function of a posed character. Occupancy evaluates to 0 outside and 1 inside; see Figure 1. We employ the pre-computed rest pose occupancy as a cache. This cache can be used to query the
obtain an inverse mapping as:

\[ \omega = \begin{bmatrix} \omega_1 & \cdots & \omega_B \end{bmatrix}, \]

i.e. weights bounded to \([0,1]\) and with unit sum. For each \(n\), we define a softmax output layer to mimic the typical LBS setup, \(W\), where for each \(w\), achieved by replacing the artist-painted weights \(w_{\text{orig}}\) by a neural function \(\mathcal{V}_\omega(x) : \mathbb{R}^3 \rightarrow \mathbb{R}^{1 \times B}\) with parameters \(\omega\):

\[
x = \mathcal{F}_\omega(x; \theta) = \left[ \mathcal{V}_\omega(x) \mathbf{B}(\theta) \right] x
\]

where for \(\mathcal{V}_\omega\), we use an MLP with \(B\) output channels, and a softmax output layer to mimic the typical LBS setup, i.e. weights bounded to \([0,1]\) and with unit sum.

2.2. Learnable inverse mapping

One would be tempted to invert the bracketed term in (4) to obtain an inverse mapping as:

\[
x = \mathcal{R}_\omega(x; \theta) = \mathcal{V}_\omega(x) \mathbf{B}(\theta) \] (5)

In the above equation, note the term \(\mathcal{V}_\omega(x)\) cannot be computed, as it is parametric in the unknown \(x\). We address this by replacing \(\mathcal{V}_\omega(x)\) with \(\mathcal{V}_\omega(x; \theta)\); see Figure 2. Hence, the network \(\mathcal{V}_\omega\) is provided with all the available test time information – query \(x\) and pose \(\theta\):

\[
x = \mathcal{R}_\omega(x; \theta) = \mathcal{V}_\omega(x; \theta) \mathbf{B}(\theta)^{-1} x
\] (6)

2.3. Pose representation

There are different ways to represent the pose parameters required in input to \(\mathcal{V}_\omega\). One could use the pose parameters defined by an artist and concatenate it to \(x\). Alternatively, one can also employ the “rig-agnostic” representation suggested by [2] as \((\tilde{x}; \theta) = \{ \mathbf{B}_0^{-1} \tilde{x} \}. We find this simplifies learning, as the network is directly provided with an encoding of the query in the local coordinate frame of each bone.

2.4. Ghost bone corrective

One can use the inverse mapping (6) to query the occupancy function from the cache:

\[
\tilde{O}(\mathcal{R}_\omega(x; \theta)) = \tilde{O} \left( \left[ \mathcal{V}_\omega(x; \theta) \mathbf{B}(\theta) \right]^{-1} x \right)
\] (7)

However, due to the fact that the weights in output from \(\mathcal{V}_\omega\) satisfy a partition of unity property, the resulting occupancy can contain artefacts; see Figure 3 (middle). To address this, we create an additional “ghost bone” modeled by an additional weight network channel, whose transformations are cloned from the root \(\mathbf{B}_{B+1} = \mathbf{B}_0\).

\[
\tilde{O}_\omega(x; \theta) = \left( 1 - \mathcal{V}_\omega^{B+1}(\tilde{x}; \theta) \right) \tilde{O}(\mathcal{R}_\omega(x; \theta))
\] (8)

where \(\mathcal{V}_\omega^{B+1}(\tilde{x}; \theta) : \mathbb{R}^3 \rightarrow \mathbb{R}^{1 \times B+1}\). As illustrated in Figure 3, this extra degree of freedom improves results by allowing explicit handling of background regions via the ghost bone.

2.5. Training

We train \(\omega\) on a “gingerbread” dataset consisting of 100 different poses sampled from a temporally coherent animation with poses \(\Theta\). We are only interested in overfitting performance, so we have no dataset splits. We train by jointly minimizing two losses:

\[
\mathcal{L}_{\text{occupancy}}(\omega) = \sum_{\theta \in \Theta} \mathbb{E}_{x \sim \mathcal{R}^3} \left[ \| \tilde{O}_\omega(x; \theta) - \tilde{O}(x; \theta) \| \right]
\]

\[
\mathcal{L}_{\text{weights}}(\omega) = \sum_{v_n \in \mathcal{V}} \text{CE}(\mathcal{V}_\omega(v_n; \theta), w_n)
\]

where \(\text{CE}(\cdot)\) is cross-entropy, and \(\mathcal{L}_{\text{weights}}\) helps to significantly speeds up convergence by asking \(\mathcal{V}_\omega\) to reproduce LBS deformations on the surface vertices\(^2\). We employ \(\{ w_n \}\) only at training time. An example of predicted deformed occupancy is visualized in Figure 3.

\(^2\)Note \(w_n[B+1] = 0\) as \(v_n\) is on the surface.
References

[1] Ilya Baran and Jovan Popović. Automatic rigging and animation of 3d characters. ACM TOG, 2007.

[2] B. Deng, JP Lewis, T. Jeruzalski, G. Pons-Moll, G. Hinton, M. Norouzi, and A. Tagliasacchi. NASA: Neural Articulated Shape Approximation. arXiv:1912.03207, 2019.

[3] A. Jacobson, Z. Deng, L. Kavan, and J.P. Lewis. Skinning: Real-time shape deformation. In ACM SIGGRAPH Courses, 2014.