HOOD-report

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Abstract

A report after reading HOOD [1]. Including the analysis of its method and possible improvements.

1 Innovations

- Using graph neural networks. Learning local states. Based on MeshGraphNets [2].
- Build a message-passing scheme over a hierarchical graph that interleaves propagation steps at different levels of resolution.
- Using physics-based loss function which is an incremental potential for implicit time stepping.
- Using a simple and efficient graph coarsening strategy which allowed the network implicitly learn transition etween graph levels.

2 Garment Preprocessing

2.1 Build up basic graph and extensions

In computer graphics, a common method to model garments is to build a garment mesh of vertices and edges. Apparently, this structure is easy to translate into a graph consisting of the same vertices and edges. Moreover, the graph augments *body edges* : the edge between vertices and nearest body node.

Feature vectors:

- To nodes, v_i includes velocity $\vec{v}$, normal vector $\vec{n}$, mass $\vec{m}$, node type, and local material parameters($\mu_{Lame}, \lambda_{Lame}$ and $k_{bending}$).
- To edges, e_{ij} includes the relative position between their two nodes.

2.2 Hierarchical graph construction

In MeshGraphNets [2], the simulation was implemented by the message passing through the graph. But in cloth simulation, the result is sensitive to the number of message passing steps, which makes it hard to manually set the number of steps. To address this problem, a message-passing scheme over a hierarchical graph that interleaves propagation steps at different levels of resolution was applied.

The hierarchical graph is a combination of several levels of coarsened garment graphs which were built by recursively applying the algorithm below:

input : fine graph $G_f(V_f, E_f)$
output: coarse graph $G_c(V_c, E_c)$ $\triangleright$ $G_c \subseteq G_f, V_c \subseteq V_f, E_c \subseteq E_f$
$v_{center} \leftarrow$ center of G_f $\triangleright$ *v_{center}'s eccentricity is equal to the graph's radius.*
for v_i in V_f **do**
  $d_i \leftarrow distance(v_{center}, v_i)$
$V_c \leftarrow \{v_i \in V_f | d_i \mod 2 = 0\}$
$E_c \leftarrow \{\}$
$V^{interm} \leftarrow \{v_i \in V_f | d_i \mod 2 = 1\}$
for $v_i \in V^{interm}$ **do**
  $V^{from} \leftarrow \{v_j \in V_f | e_{ij} \in E_f \ \& \ d_j = d_i - 1\}$ $\triangleright$ $V^{from} \subseteq V_c$
  $V^{to} \leftarrow \{v_j \in V_f | e_{ij} \in E_f \ \& \ d_j = d_i + 1\}$ $\triangleright$ $V^{to} \subseteq V_c$
  for v_j in V^{from} **do**
    for v_k in V^{to} **do**
      $push(e_{jk}, E_c)$ $\triangleright$ *e_{jk} connect nodes in V_c, thus $e_{jk} \in E_c$*

Through this algorithm, we build coarsened graph G_c from the input graph G_f, and this coarsened level is the cornerstone of Section 3.2.

3 Message Passing

In the GNN for simulation series, the GNN is built up by MLPs which learn the relationship between edges and nodes. And the model predict next time step through N message-passing steps.

The full model of HOOD consists of:

- Several encoder MLPs: 1 for nodes, 1 for body edges, 1 for each level's edges.
- N message-passing steps: 1 for nodes, 1 for body edges, 1 for each level's edges(levels processed in current step).
- Decoder MLP: only 1, predict the acceleration, preparing for next time steps.

3.1 Basic message passing

In each single message-passing step, edge feature are first updated as:

$$e_{ij} \leftarrow f_{v \to e}(e_{ij}, v_i, v_j),$$

And then, node feature are updated as:

$$v_i \leftarrow f_{e \to v}(v_i, \sum_j e_{ij}^{body}, \sum_j e_{ij}),$$

$f_{v \to e}$ and $f_{e \to v}$ are both multi-layer perceptions. All nodes share the same MLP, and each set of edges share the separate MLPs.

3.2 Multi-level message passing

4 Physical Supervision

4.1 Physical garment model

4.2 Novel terms in the loss function

4.2.1 Collision term

4.2.2 Friction

4.2.3 Vertex mass and canonical geometries

5 Conclusion

5.1 Enhancement

- Computationally cheap, compared to physics-based approaches.
- Train once, simulate every dynamic cloth, compared to other learning-based approaches.
- Be able to handle changes in topology and dynamic material parameters.
- Truly unsupervised, without the need of ground-truth data.
- State-of-the-art.

5.2 Problems remain

- Cannot simulate high speed animation, especially when body motions exceed the velocity seen at training time.
- Weak on solving garment self-collision.
- (Based on my observation) Low accuracy on prediction of inertia & creases in motion.
- Batch size was locked to 1, which means low reasoning speed.

6 Possible Improvements

6.1 Details change

6.2 Model structure

6.3 "Serialization"

6.4 Hypergraph

References

[1] A. Grigorev, M. J. Black, and O. Hilliges, "Hood: Hierarchical graphs for generalized modelling of clothing dynamics," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 16 965–16 974.

[2] T. Pfaff, M. Fortunato, A. Sanchez-Gonzalez, and P. Battaglia, "Learning mesh-based simulation with graph networks," in *International Conference on Learning Representations*, 2021.