

OMNIPHYSGS: 3D CONSTITUTIVE GAUSSIANS FOR GENERAL PHYSICS-BASED DYNAMICS GENERATION

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Paper under double-blind review

REBUTTAL APPENDIX

We provide additional details and results to address the reviewers’ concerns and comments.

- **For Reviewer 7Xoc.** Section C provides experiments comparing our method to directly optimizing coefficients for different constitutive models, which demonstrates the difference and contribution of our work compared to related methods (Nagasawa et al., 2019; Su et al., 2023). Detailed analysis of these works is provided in the OpenReview comments. Section E provides more qualitative results, with prompts that do not describe motions, to demonstrate the robustness of our method.
- **For Reviewer h6D1.** Section B provides an analysis and improved results of the artifacts in the can-duck collision scene. Section E provides more qualitative results regarding the same material with different material parameters.
- **For Reviewer ktNn.** Section A provides the detailed results of the user study as a complement to the metrics in the main manuscript. Section B provides an analysis and improved results of the artifacts in the can-duck collision scene. Section C provides experiments comparing our method to directly optimizing a vector representing the probability of different pre-defined constitutive models. Section E provides more qualitative results regarding real-world scenes.
- **For Reviewer S54K.** Section E provides more qualitative results regarding both multiple objects and real-world scenes.
- **For Reviewer kAsd.** Section C provides experiments comparing our method to directly optimizing coefficients for different constitutive models, which demonstrates the difference and contribution of our work compared to the related method (Su et al., 2023). Detailed analysis of the work is provided in the OpenReview comments. Section D provides the revised version of the original Figure 3.

For other comments and concerns, we provide detailed responses in the OpenReview comments. We appreciate the reviewers’ valuable feedback and suggestions. Thank you for your time and input.

A USER STUDY

As a complement to the metrics in the main manuscript, we conducted a user study among 20 participants to evaluate the quality of the generated dynamics by different methods. In the study, the participants were asked to rank the videos based on two criteria: the text alignment and physical plausibility of the dynamics. Table 1 shows the detailed results of the user study, where the numbers indicate the average ranking of each method. A lower ranking reflects better performance. The results indicate that our method achieves better performance in modeling various dynamics while the baseline methods achieve comparable performance only in the pure elasticity case. This conclusion aligns with the quantitative and qualitative findings discussed in the main manuscript. Figure 2 presents the user interface of our user study.

B ANALYSIS OF ARTIFACTS IN COLLISION

We analyze the artifacts occurring in the generated dynamics, particularly those involving complex interactions such as collisions. Our findings indicate that the number of grids in the MPM simulator is a key factor influencing the quality of generated dynamics. Figure 4 (see the supplementary video for better visualization) compares the dynamics generated with varying grid resolutions. The results

demonstrate that increasing the number of grids effectively reduces aliasing artifacts and enhances the physical plausibility of the generated dynamics.

C DISCUSSION ON THE NETWORK ARCHITECTURE

In the main manuscript, we implement the proposed physics-guided network with a neural network composed of two components, a 3D feature encoder and a physics-aware decoder. A naive way to simplify the network is to directly optimize a vector representing the probability of different pre-defined constitutive models for each particle. However, our preliminary experiments revealed that this straightforward method struggles with convergence and is prone to numerical instability. Figure 3 shows the predicted softmax probability during training of both the naive method and our proposed approach. we used the prompt “*a sand wolf collapsing*”, where the model is expected to converge to the non-elastic sand constitutive model. The results show that the naive method fails to converge, as the probabilities for both elastic and non-elastic models remain close to 0.5.

D REVISION OF THE ORIGINAL FIGURE 3

We have revised the original Figure 3 to illustrate how the decoder assigns different materials to different parts of the scene. Figure 1 shows the revised version of the original Figure 3.

E MORE EXPERIMENT RESULTS

We provide more qualitative results in this section, including the visualization of **the same material with different strengths** (Figure 5), **multiple objects** (Figure 6), and **real-world scene** generated using our method (Figure 7). In some cases, we remove the verb describing motions from prompts to demonstrate the robustness of our method when using material-only prompts. For better visualization, please refer to the supplementary video.

REFERENCES

- Kentaro Nagasawa, Takayuki Suzuki, Ryohei Seto, Masato Okada, and Yonghao Yue. Mixing sauces: a viscosity blending model for shear thinning fluids. *ACM Trans. Graph.*, 2019.
- Haozhe Su, Xuan Li, Tao Xue, Chenfanfu Jiang, and Mridul Aanjaneya. A generalized constitutive model for versatile mpm simulation and inverse learning with differentiable physics. *Proceedings of the ACM on Computer Graphics and Interactive Techniques*, 2023.

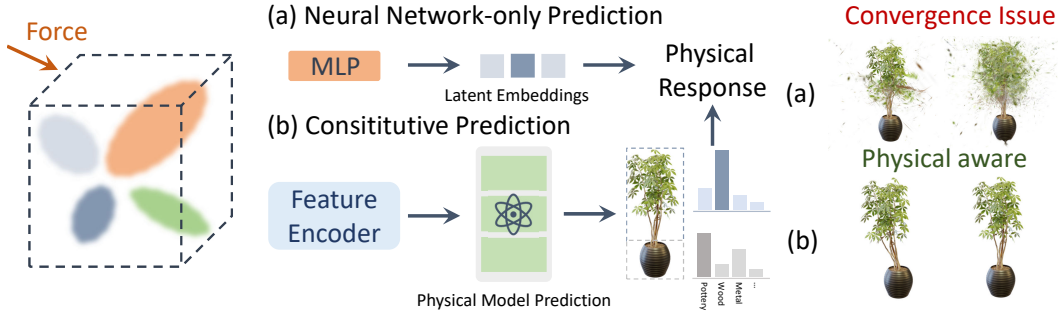


Figure 1: Constitutive Gaussian Network (Revised version).

Table 1: Quantitative results of the user study. The table shows the average ranking of each method for each scene and the overall average ranking. **Lower** values indicate better performance. The best results are highlighted in bold.

Method \ Scene	Swinging Ficus	Collapsing Ficus	Rubber Bear	Sand Bear	Jelly Cube	Water Cube	Average
PhysDreamer	3.1579	3.1250	2.0588	2.7692	2.1765	2.5385	2.6376
Physics3D	2.1579	2.7500	2.8824	3.0000	2.6471	3.0000	2.7396
DreamPhysics	2.4737	3.0000	2.2353	2.7692	2.3529	3.3077	2.6898
Ours	2.2105	1.1250	2.8235	1.4615	2.8235	1.1538	1.9330

Method \ Scene	Rubber and Sand	Duck and Pile	Rubber hits Metal	Bear into Water	Average
PhysDreamer	2.8000	3.1250	2.8125	3.0588	2.9491
Physics3D	2.7333	2.7500	2.8750	2.8824	2.8102
DreamPhysics	3.0667	2.6875	3.0625	3.0588	2.9689
Ours	1.4000	1.4375	1.2500	1.0000	1.2719

Evaluation of Physical Plausibility and Text Alignment

Video A

Video B

Video C

Video D

Please read the video description
Prompt: A swinging ficus tree

Please rank the videos based on physical plausibility and text alignment (1 is the best, 4 is the worst)
Please ensure each video has a different ranking!

Ranking of Video A
☐ 1 ☐ 2 ☐ 3 ☐ 4

Ranking of Video B
☐ 1 ☐ 2 ☐ 3 ☐ 4

Ranking of Video C
☐ 1 ☐ 2 ☐ 3 ☐ 4

Ranking of Video D
☐ 1 ☐ 2 ☐ 3 ☐ 4

Submit and watch next video

Figure 2: The user interface of our user study.

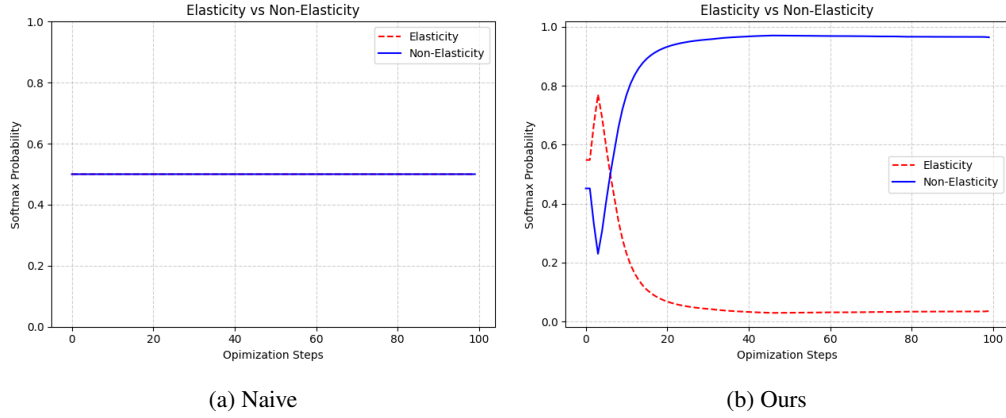


Figure 3: The predicted softmax probability of naive vector optimization and our method during the optimization process.

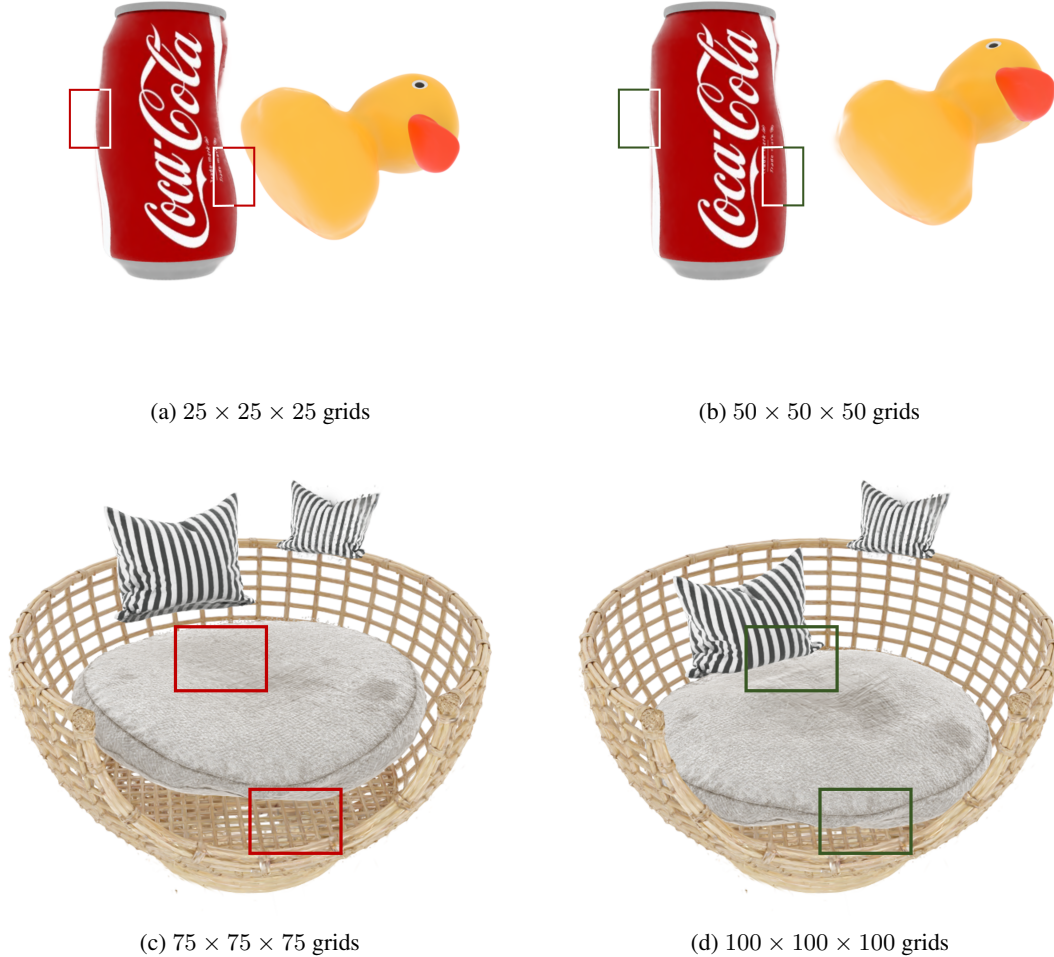


Figure 4: Comparison of the dynamics generated by different numbers of grids. We present the frame at the same time step for each grid size. Artifacts are highlighted in the red box.

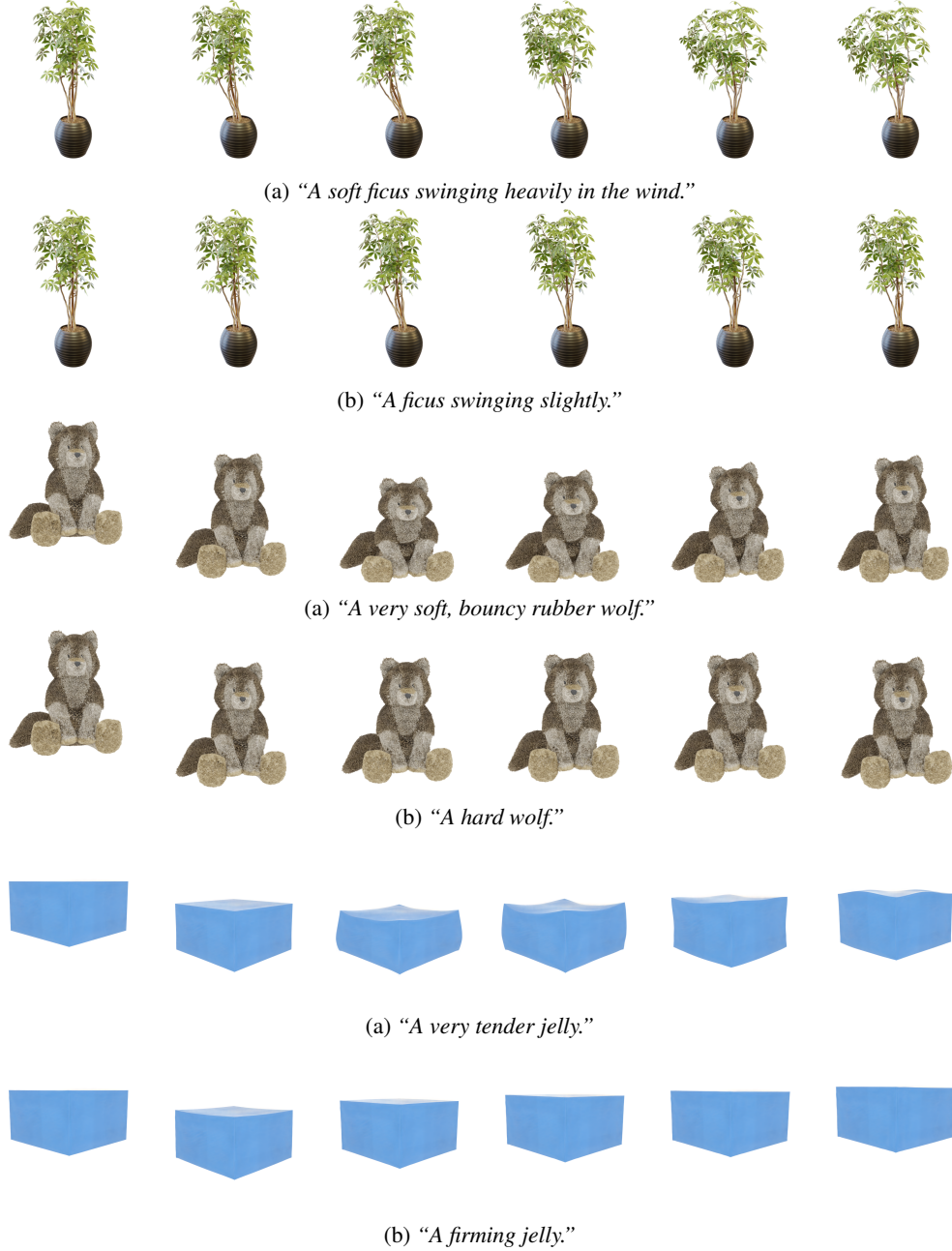


Figure 5: Qualitative visualizations of 3D dynamic synthesis for a single object in the same material but with different strength levels. We present the results of our method.



(a) “Different kinds of materials on the table”



(b) “Pillows falling into a basket.”

Figure 6: Qualitative visualizations of 3D dynamic synthesis for more than 2 objects. We present the results of our method.



(a) “Flowers swinging gently.”



(b) “A fox shaking its head.”

Figure 7: Qualitative visualizations of 3D dynamic synthesis for real-world scenes. We present the results of our method.