

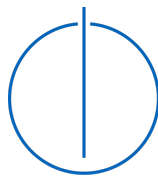


FAKULTÄT FÜR INFORMATIK
DER TECHNISCHEN UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatik

Perceptual Losses for Deep Learning on Fluid Simulations

Hanfeng Wu





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Perceptual Losses for Deep Learning on Fluid
Simulations

Perceptual Losses für Deep Learning von
Flüssigkeitssimulationen

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I confirm that this bachelor's thesis is my own work and I have documented all sources and material used.

Munich, 15.09.2021

Hanfeng Wu

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Abstract

This thesis studies the integration of perceptual loss into several models that are related to fluid simulation. Perceptual losses are used to compare high level differences, while traditional loss functions like MSE and MAE only compare the pixel level differences which is more brute force.

Now some famous perceptual loss functions like comparing the intermediate layers of pretrained vgg network already improve its performance in some image related tasks. [JAFF16] We want to show that in the context of fluid simulation, the integration of some pretrained perceptual losses should also outperform the traditional loss functions.

We tested some fluid simulation tasks in SOL [UBF⁺20] to improve the performance of the perceptual loss functions. Meanwhile we also integrate such loss functions into models like autoencoder and superresolution to compare their results with those from the same models but trained by MSE loss functions

Finally we combined the result of SOL and superresolution model to conduct some fluid simulations at a lower cost to show the advantage of integrating perceptual losses in such tasks.

Zusammenfassung

Diese Dissertation untersucht die Integration von Wahrnehmungsverlusten in verschiedene Modelle, die sich auf die Fluidsimulation beziehen. Wahrnehmungsverluste werden verwendet, um Unterschiede auf hohem Niveau zu vergleichen, während herkömmliche Verlustfunktionen wie MSE und MAE nur die Pixelniveaunterschiede vergleichen, was roher ist.

Einige berühmte Wahrnehmungsverlustfunktionen wie der Vergleich der Zwischenschichten eines vortrainierten VGG-Netzwerks verbessern bereits seine Leistung bei einigen bildbezogenen Aufgaben. [JAFF16] Wir wollen zeigen, dass die Integration einiger vortrainierter Wahrnehmungsverluste im Kontext der Fluidsimulation übertreffen auch die traditionellen Verlustfunktionen.

Wir haben einige Fluidsimulationsaufgaben in SOL [UBF⁺20] getestet, um die Leistung der Perceptual Loss Functions zu verbessern. Inzwischen integrieren wir solche Verlustfunktionen auch in Modelle wie Autoencoder und Superresolution, um deren Ergebnisse mit denen aus den gleichen Modellen zu vergleichen, die jedoch mit MSE-Verlustfunktionen trainiert wurden

Schließlich haben wir die Ergebnisse von SOL und Superauflösungsmodell kombiniert, um einige Fluidsimulationen zu geringeren Kosten durchzuführen, um den Vorteil der Integration von Wahrnehmungsverlusten in solchen Aufgaben zu zeigen. *Note: Insert the German translation of the English abstract here.*

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SOL Solver in the Loop

LSIM Learning Similarity Metrics for Numerical Simulations

Chapter 1

Introductions

Note: Introduce the topic of your thesis, e.g. with a little historical overview.

1.1 Perceptual loss functions

Note: Describe the problem that you like to address in your thesis to show the importance of your work. Focus on the negative symptoms of the currently available solution.

1.2 Physical simulation

Note: Motivate scientifically why solving this problem is necessary. What kind of benefits do we have by solving the problem?

1.3 Deep learning tasks

Note: Describe the research goals and/or research questions and how you address them by summarizing what you want to achieve in your thesis, e.g. developing a system and then evaluating it.

1.4 Related Work

Note: Describe the outline of your thesis

Chapter 2

Perceptual Losses

Note: Describe each proven technology / concept shortly that is important to understand your thesis. Point out why it is interesting for your thesis. Make sure to incorporate references to important literature here.

2.1 Learning Similarity Metrics for Numerical Simulations

Note: This section would summarize the concept User Feedback using definitions, historical overviews and pointing out the most important aspects of User Feedback.

2.2 VGG-16 loss network

Note: This section would summarize the architectural style Representational State Transfer (REST) using definitions, historical overviews and pointing out the most important aspects of the architecture.

2.3 triditional loss function

Note: This section would summarize the agile method Scrum using definitions, historical overviews and pointing out the most important aspects of Scrum.

Chapter 3

Datasets

3.1 Autoencoder

3.2 Superresolution

3.3 Solver in the Loop

*Note: Describe related work regarding your topic and emphasize your (scientific) contribution in **contrast** to existing approaches / concepts / workflows. Related work is usually current research by others and you defend yourself against the statement: “Why is your thesis relevant? The problem was already solved by XYZ.” If you have multiple related works, use subsections to separate them.*

Chapter 4

Tasks and Experiments Setup

4.1 Autoencoder

4.2 Superresolution

4.3 Solver in the Loop

Chapter 5

Results and Analysis

5.1 Comparison

5.1.1 Numerical evaluation

5.1.2 Time cost evaluation

5.2 Limitations

Chapter 6

Conclusion

6.1 Future work

6.2 Summary

Appendix A

e.g. Questionnaire

Note: If you have large models, additional evaluation data like questionnaires or non summarized results, put them into the appendix.

List of Figures

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Bibliography

- [JAFF16] Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In *European conference on computer vision*, pages 694–711. Springer, 2016.
- [UBF⁺20] Kiwon Um, Robert Brand, Yun Fei, Philipp Holl, and Nils Thuerey. Solver-in-the-Loop: Learning from Differentiable Physics to Interact with Iterative PDE-Solvers. *Advances in Neural Information Processing Systems*, 2020.