FAKULTÄT FÜR INFORMATIK

DER TECHNISCHEN UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatik

# Perceptual Losses for Deep Learning on Fluid Simulations

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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

# Acknowledgements

**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 percetual 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 Pixelniveauunterschiede 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 Percetual 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.*

# Contents

**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 Fluid simulation

### 1.1.1 Navier Stokes Equation

The state of art Fluid simulation is based on the famous incompressible equation Navier-Stokes equation

$$\frac{\partial \vec{u}}{\partial t} + \vec{u} \cdot \nabla \vec{u} + \frac{1}{\rho} \nabla p = \vec{g} + \nu \nabla \cdot \nabla \vec{u} \tag{1.1}$$

$$\nabla \cdot \overrightarrow{u} = 0 \tag{1.2}$$

where $\nabla$ denotes the gradient, $\nabla\cdot$ denotes the Divergence, $\overrightarrow{u}$ denotes the velocity of the fluid, $t$ denotes the time step, $\rho$ denotes the density of the fluid, $p$ denotes the pressure, $\overrightarrow{g}$ denotes the gravity and $\nu$ denotes the viscosity of the fluid.

The equation (1.1) is actually a transformation of the $\overrightarrow{F} = m\overrightarrow{a}$ and the equation (1.2) describes the incompressibility of the fluid.

### 1.1.2 Grid Stucture

The way of storing the velocity and the density is based on two different grid structure. We store the dencity in the center of each cell, we call it centeredgrid or scalar grid. However for storing the velocity, we sample them at the face centers of each cell [**?**]

## 1.2 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.*

## 1.3 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.*

# Chapter 2

# Related Work

similar goal area methods

# Chapter 3

# Metrics and 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.*

## 3.1 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.*

## 3.2 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.*

## 3.3 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.*

## 3.4 Lpips

# Chapter 4

# Datasets

## 4.1 Autoencoder

## 4.2 Superresolution

## 4.3 Solver in the Loop

# Chapter 5

# Tasks and Experiments Setup

## 5.1 Autoencoder

## 5.2 Superresolution

## 5.3 Solver in the Loop

# Chapter 6

# Results and Analysis

## 6.1 Comparison

### 6.1.1 Numerical evaluation

### 6.1.2 Time cost evaluation

## 6.2 Limitaions

# Chapter 7

# Conclusion

## 7.1 Future work

## 7.2 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

# List of Tables

# 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.