# High-Fidelity Haptic Rendering through Implicit Neural Force Representation

## **Christoforos Vlachos**

#### **Konstantinos Moustakas**

chris.vlachos@ece.upatras.gr

moustakas@ece.upatras.gr

Department of Electrical and Computer Engineering, University of Patras, Rion-Patras, Greece

#### Introduction

The refresh rate requirement for haptic rendering is very tight (1kHz).

This is an issue for the haptic rendering of complex meshes.

Analytic methods struggle to meet the refresh rate requirement while approximate methods can't maintain the right level of detail.

We would like to create a fast and scalable method, that is mesh-agnostic and produces high-fidelity results.

#### Methods

Represent the mesh implicitly using a distance function (SDF) and respective normals (UNF).

**SDF**: force magnitude **UNF**: force direction

Neural networks utilizing sinusoidal activation functions have shown potential in representing various signals[1].

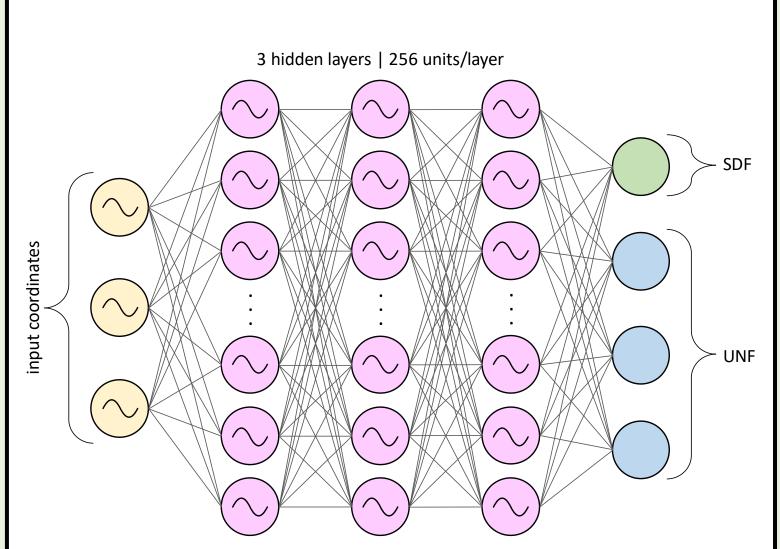
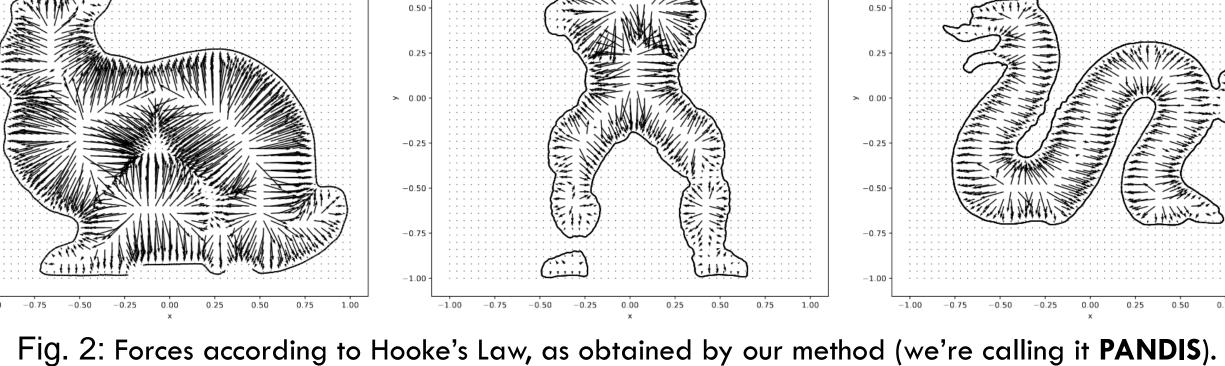


Fig.1: The architecture of our proposed method.

Pose the SDF and UNF calculation as a Boundary Value Problem in order to construct the loss function.

#### Results

# 1 Calculate forces that would be generated (for validation).



2. Implement haptic rendering pipeline.

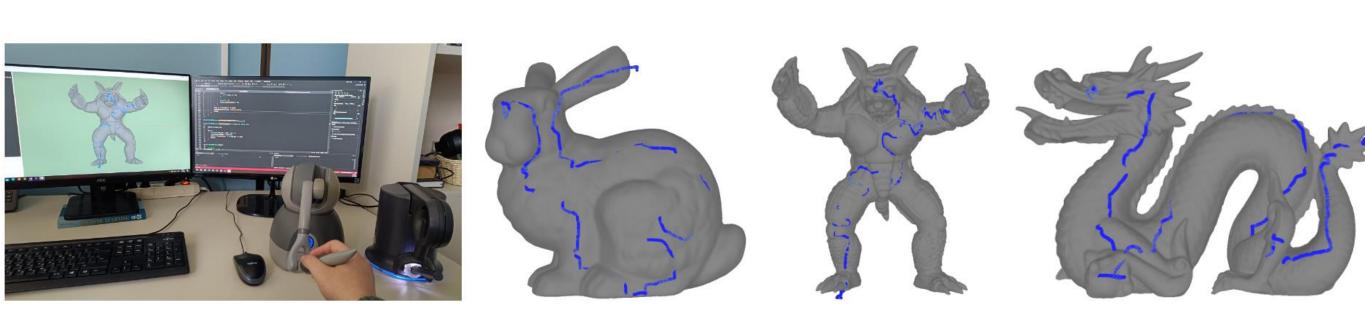


Fig. 3: Experimental setup and probe trajectories that were used for testing.

Setup time and storage space: Comparable to calculating forces on a 32<sup>3</sup> grid and interpolating.

<u>Update rate</u>:  $\sim 1.3$  kHz (97% of frames above 1kHz) independent of mesh choice.

#### Quality:

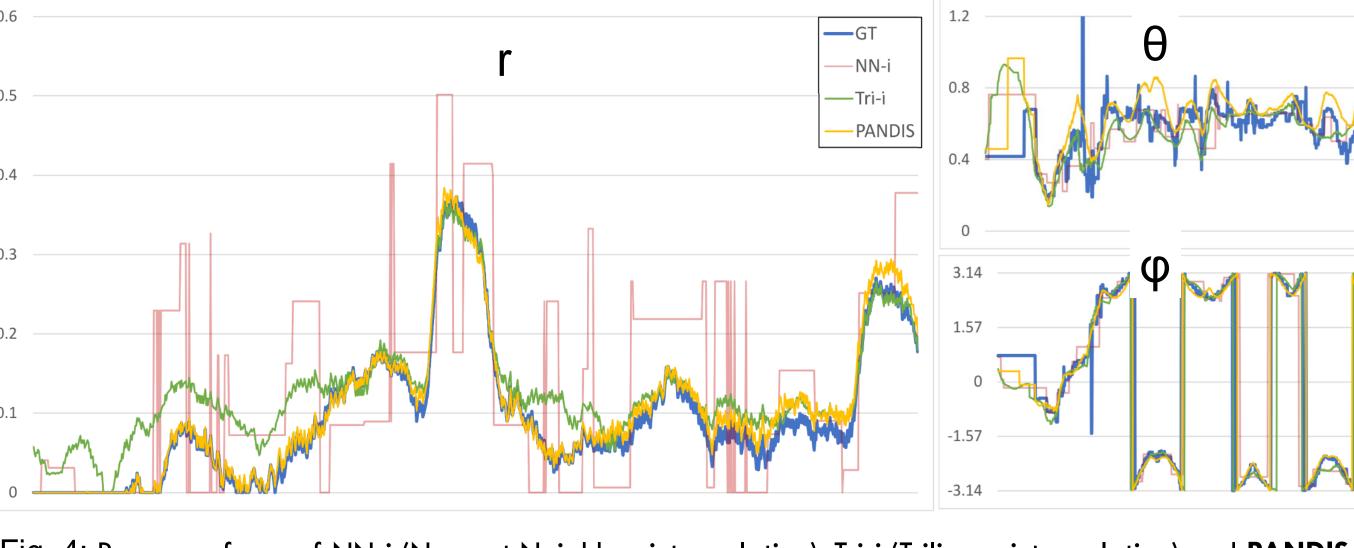


Fig. 4: Response force of NN-i (Nearest Neighbor interpolation), Tri-i (Trilinear interpolation) and PANDIS compared to GT (Ground Truth).

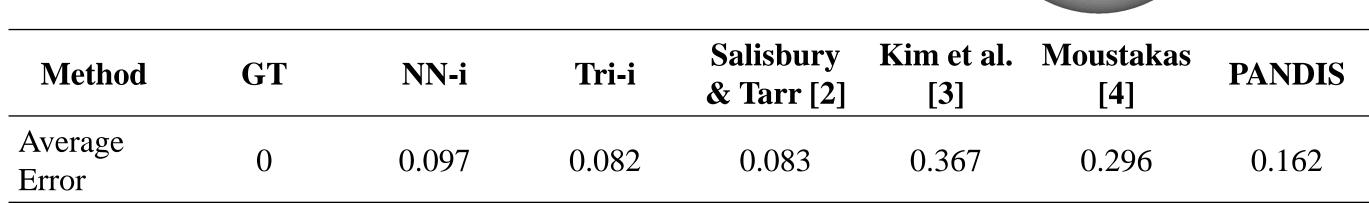
Quantitative Results:

	Model	$\operatorname{GT}$	NN-i		Tri-i		PANDIS
			$-32^{3}$	$64^{3}$	$32^{3}$	$64^3$	TANDIS
Average Error	Bunny	0	0.086	0.031	0.057	0.026	0.006
	Armadillo	0	0.139	0.081	0.099	0.046	0.022
	Dragon	0	0.176	0.054	0.171	0.041	0.068

Average  $\text{Error}_i = \sum_{i=1}^{n} (\|\text{force}_{i,j} - \text{force}_{\text{GT},j}\|), i = \{\text{GT, NN-i, Tri-i, PANDIS}\}$ 

**3.** Further validation (theoretical).

The SDF and UNF of a sphere can be calculated analytically.



#### Conclusion

# We have successfully:

- embedded both the SDF and the UNF into a Neural Network.
- created and implemented a method of fast, accurate, and highly scalable haptic rendering.
- validated the results against ground truth data and other stateof-the-art methods and found PANDIS to be on par or better than the competition.

#### Discussion

While the groundwork to support machine learning based haptic rendering is there, some issues still exist that should be researched further:

- The inability to effectively model nonlinear mesh deformations in a robust manner, avoiding the current necessity to retrain the neural network.
- The very nature of the SDF as a mathematical distance function and its innate crudeness in representing nonwatertight meshes.

#### References

- [1]: Sitzmann, V. et al.: Implicit neural representations with periodic activation functions. NeurIPS 2020, 7462–7473
- [2]: Salisbury, K., Tarr, C.: Haptic rendering of surfaces defined by implicit functions. ASME IMECE 1997. 61–67.
- [3]: Kim, L., et al.: A haptic-rendering technique based on hybrid surface representation. IEEE CG&A 24(2), 66-75.
- [4]: Moustakas, K.: 6dof haptic rendering using distance maps over implicit representations. MULTIMED TOOLS APPL 75(8), 4543-4557.

## Acknowledgments

The research project is implemented in the framework of H.F.R.I call "Basic research Financing (Horizontal support of all Sciences)" under the National Recovery and Resilience Plan "Greece 2.0" funded by the European Union - NextGenerationEU (H.F.R.I. Project Number: 16469.).





#### **Further information**



Loses only to 64<sup>3</sup>,

which use way more

storage space and

preprocessing time.



