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R. Borgo, G. E. Marai, and T. Schreck
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Neural Flow Map Reconstruction : Supplemental Material

S. Sahoo, Y. Lu & M. Berger
Vanderbilt University

1. Reduction Rate Experiment

1.1. Experimental Details

We perform an additional experiment wherein we vary the reduction rate for the heated cylinder dataset [Pop04, GGT17], in order to study the differences between optimizing for flow map samples and fitting directly to vectors. For the experiment, we choose reduction rates of 50, 100, 200, 300, and 400, relative to the total size of the time-varying vector field. We set the network capacity to be 0.5 times the size of the total number of flow map samples. We generate flow map samples by integrating particle using Euler integration scheme with a step size of 0.1, measured in grid units, for a duration of 10. We train the models using Adam optimizer with a starting learning rate of 10^{-4}, decaying every 60 epochs by a factor of 0.2. We train the models for a total of 150 epochs.

1.2. Experimental Results

We compare fitting to vectors vs fitting to flow map samples both qualitatively and quantitatively for different reduction rates. In Figure 1 the top row shows the FTLE generated using flow map samples seeded at timestep 1100, and integrated for a duration of 80 (grid units). In the bottom row we show the FTLE error maps with respect to ground truth. We can see that optimizing for flow samples outperforms directly fitting to vectors across all reduction rates. In Figure 1 we show the flow map error for different durations. All the points are seeded on the grid at time step t=0 and integrated using Euler integration scheme. Consistent with the FTLE plots, we observe an improvement in performance with our method in representing the flow map. We find that when the reduction rate is comparatively low (e.g 50) both methods are able to learn a good representation of the underlying vector field and thus the flow map error is rather low. However, the difference between the two optimization techniques is more prominent under aggressive reduction rates (e.g 300 and 400). We can see that flow map-based optimization better preserves the features (e.g the swirling motions in the FTLE) as compared to optimizing for the vectors directly.

References

[GGT17] GÜNTHER T., GROSS M., THEISEL H.: Generic objective vortices for flow visualization. *ACM Transactions on Graphics (Proc. SIGGRAPH) 36*, 4 (2017), 141:1–141:11. 1

[Pop04] POPINET S.: Free computational fluid dynamics. *ClusterWorld 2*, 6 (2004). URL: http://gfs.sf.net/. 1

Table 1: *We list the total training time in minutes, Inference time (time taken to integrate 10,000 particles for a duration of 100 grid-time) in seconds, and the model size for different reduction rate.*

Reduction Rate	Training Time	Inference Time	Model Size
50	209.68	53.81	5.4
100	92.75	40.05	2.7
200	40.3	23.06	1.3
300	26.11	18.72	0.90
400	20.40	14.23	0.67

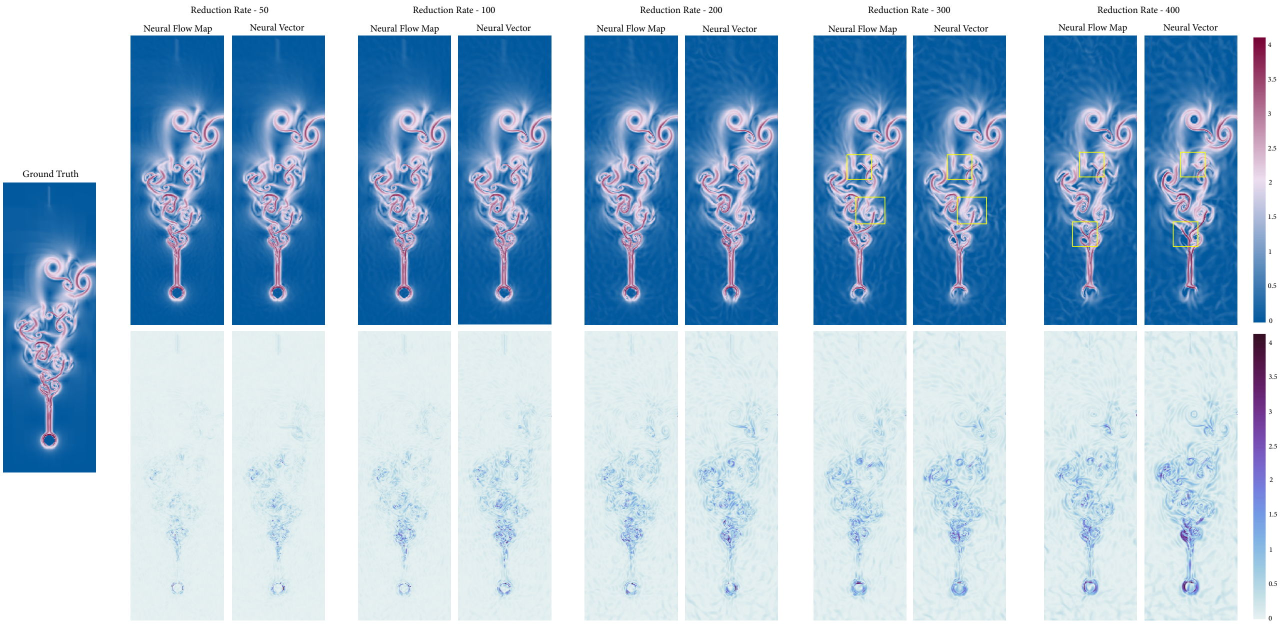

Figure 1: We qualitatively compare our method – Neural Flow Map to Neural Vector across different reduction rates. We show (top) the FTLE (generated by integration particles seeded at $t = 1100$ and for a duration of 80 in grid-time, and (bottom) difference images between the approximated FTLE and the ground truth FTLE. We find that optimizing for flow map samples yields better performance across all the reduction rates as compared to optimizing for the vectors themselves. We highlight the differences in purple.

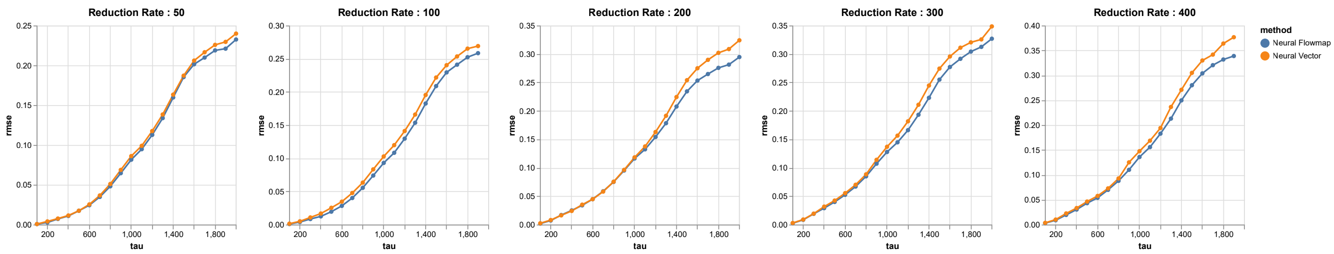

Figure 2: We show quantitative results for our reduction rate experiment, where we measure the RMSE of flow map error across different integration durations.