FreBIS: Frequency-Based Stratification for Neural Implicit Surface Representations

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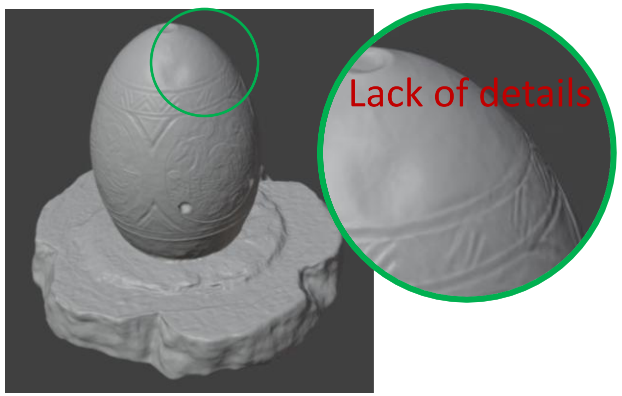
Motivation & Problem Statement

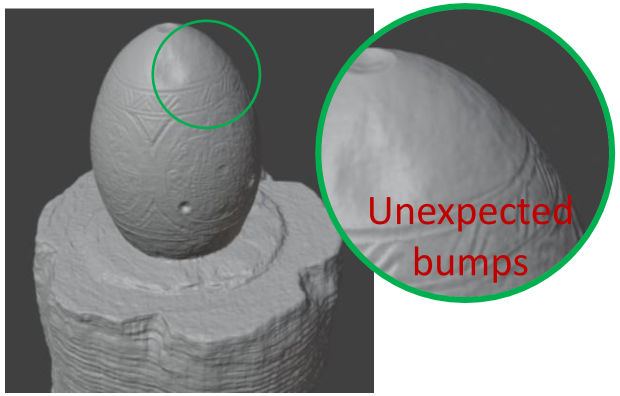
- Neural implicit surface representation enables continuous high-resolution and accurate 3D surface reconstruction.
- Existing methods use a single encoder to capture all surface frequencies.

→ **There is a tradeoff between accurate shape recovery and reconstructing the fine details.**

Reference image



Positional encoding level 6
[VolSDF, 2021]



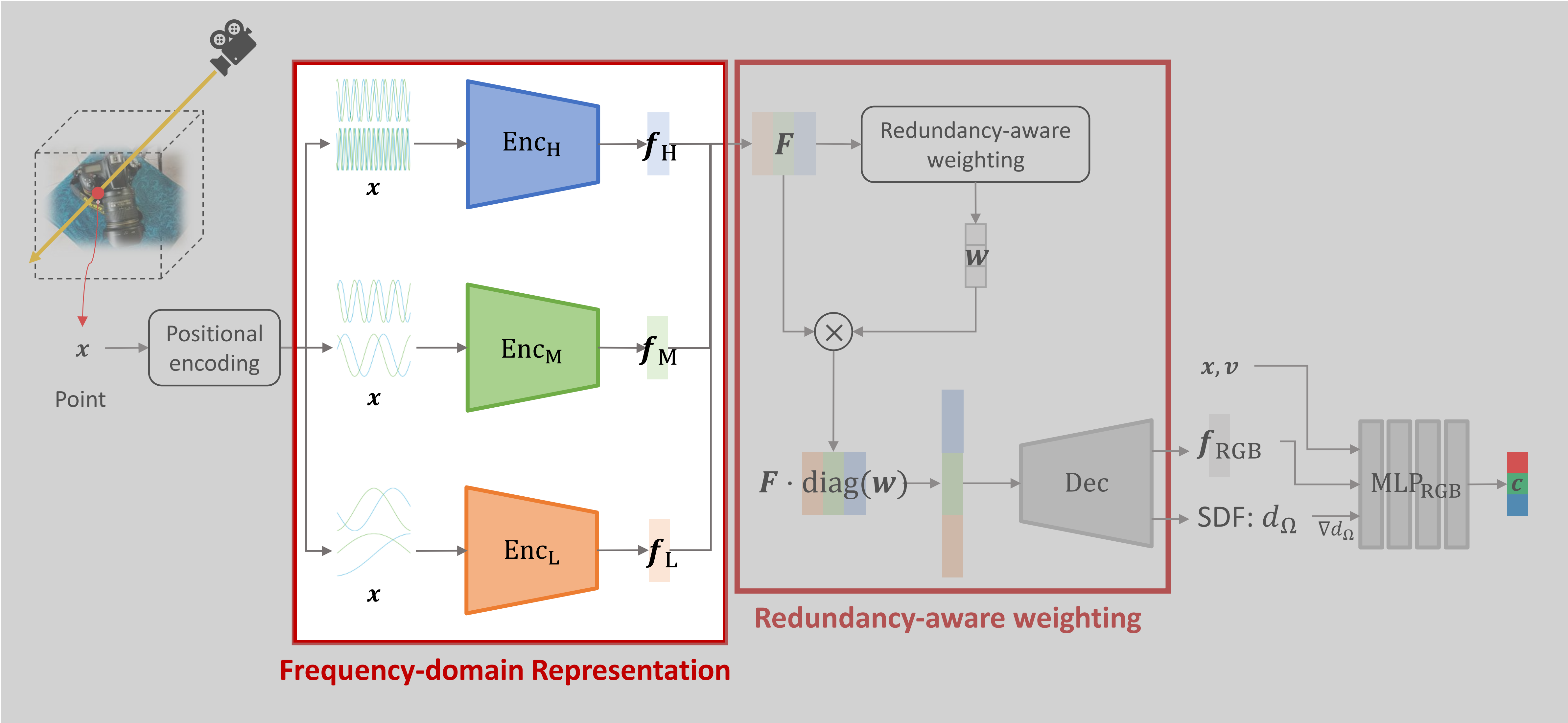
Positional encoding level 9
[VolSDF, 2021]

- **Goal**:
  Recover high-quality surfaces of a 3D scene that contains a wide variety of frequency levels.

Yariv et al., 2021, “Volume rendering of neural implicit surfaces,” in *Proceedings of the 35th International Conference on Neural Information Processing Systems*

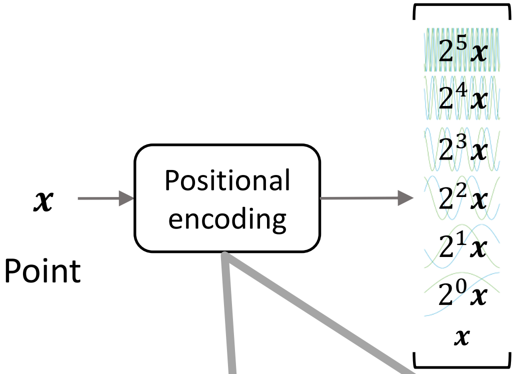
Method: FreBIS

The FreBIS framework consists of two modules:



Frequency-Domain Representation

- Three encoders convert the input to features corresponding to different frequency bands (low, middle, high).
- FreBIS uses positional encoding to transform the input coordinate into frequency domains.
  - e.g., frequency level $L = 6$



$$\mathit{Embed}(\boldsymbol{x}) = \left(\boldsymbol{x}, \sin(\boldsymbol{x} \times 2^0), \cos(\boldsymbol{x} \times 2^0), \cdots, \sin(\boldsymbol{x} \times 2^{L-1}), \cos(\boldsymbol{x} \times 2^{L-1})\right)$$

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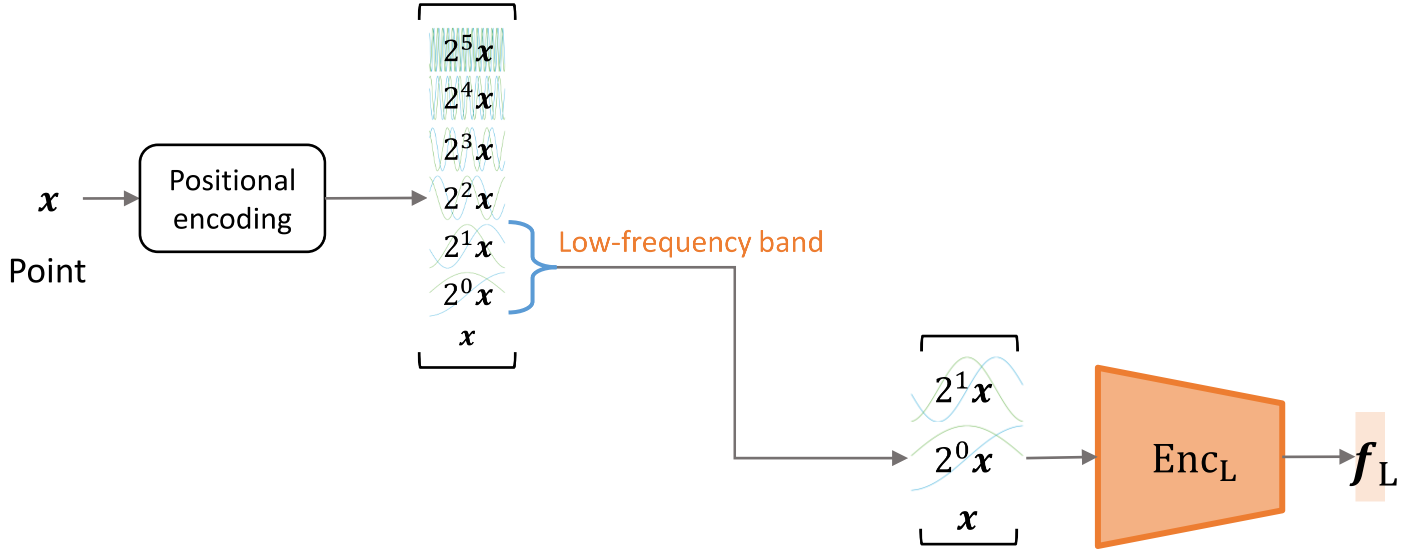

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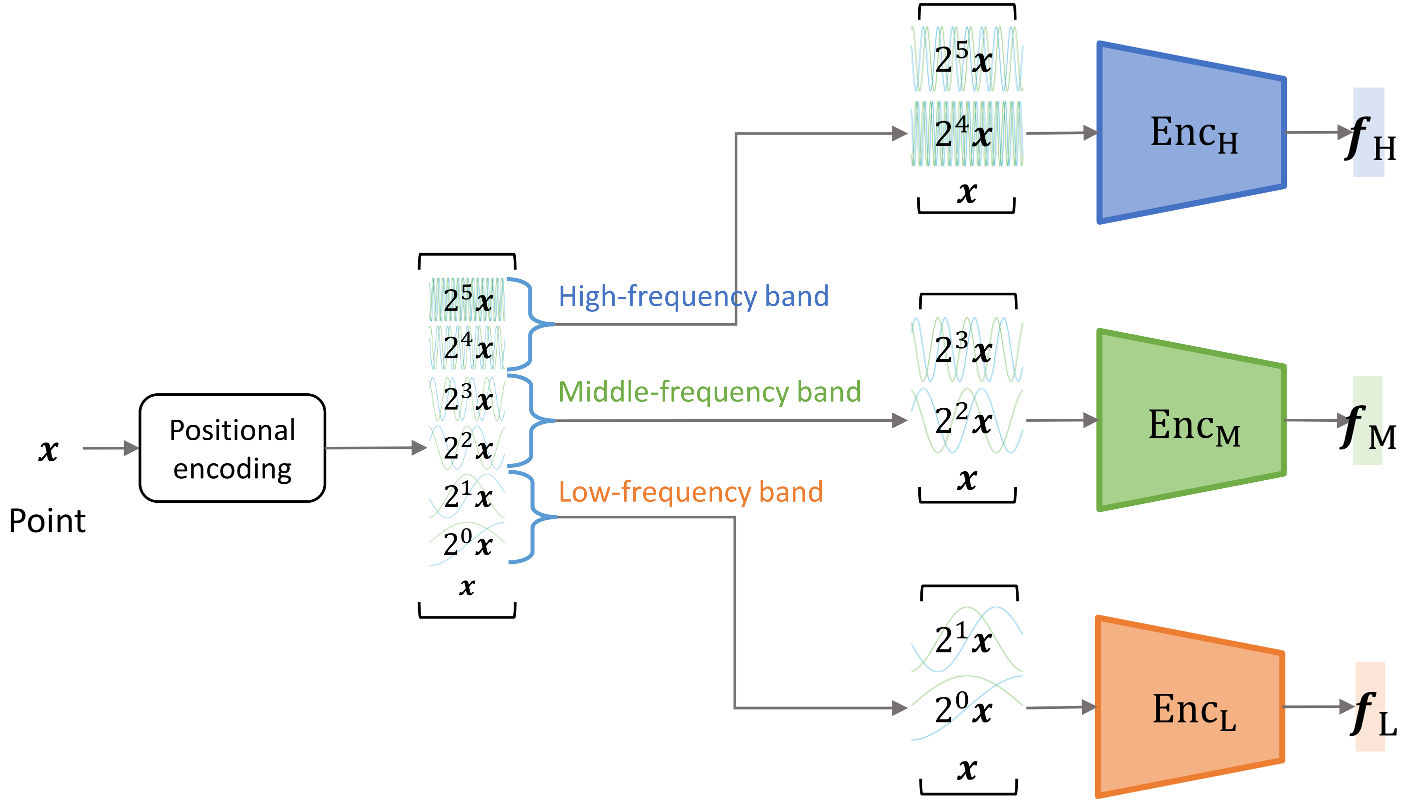

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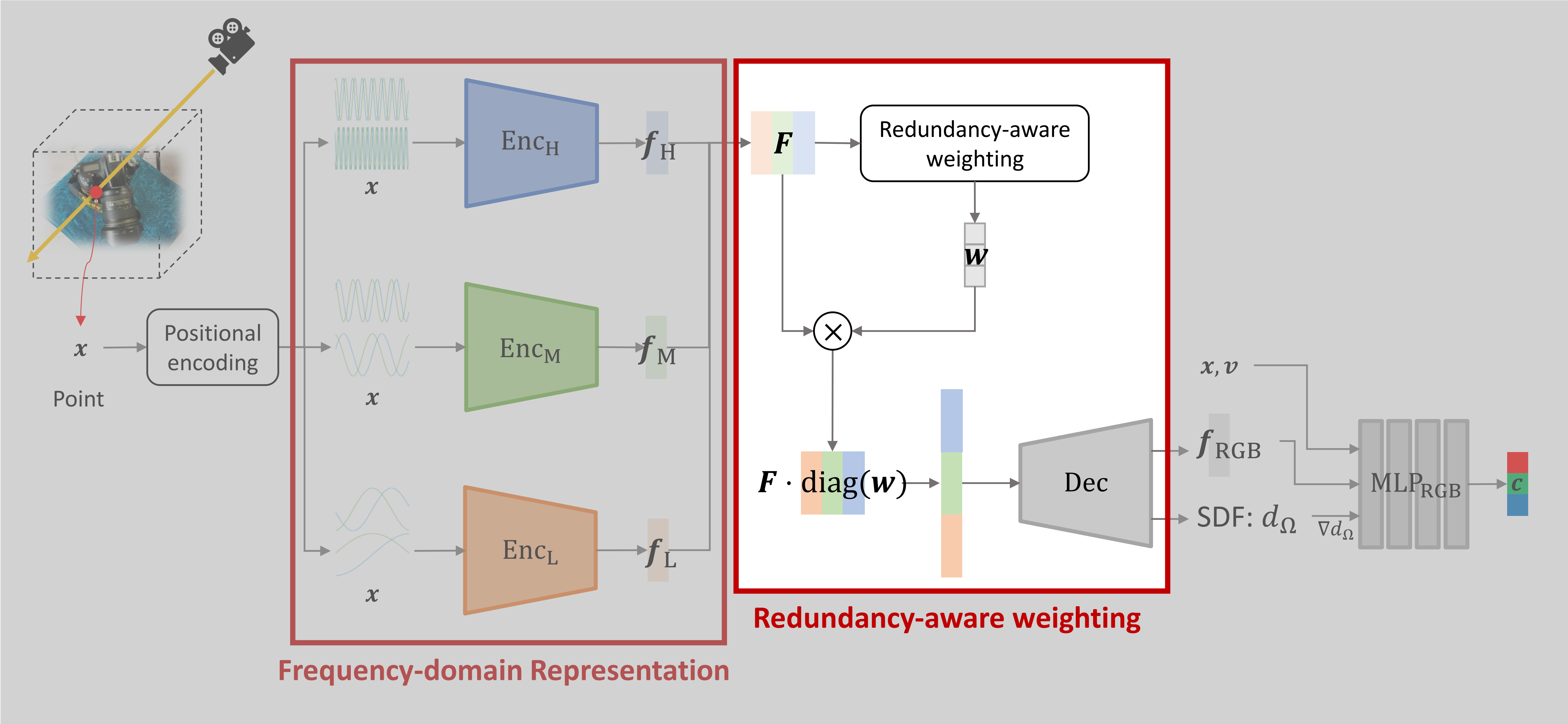
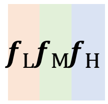


Redundancy-Aware Weighting

- The redundancy-aware weighting module **maximally utilizes the encoder capacity** and effectively combines the learned complementary information by encouraging **dissimilarity between the learned representations**.
  - i.e., the higher weights are on features that are dissimilar to other features, while the lower weights are on features that are similar to other features.



Feature matrix
$\boldsymbol{F}$

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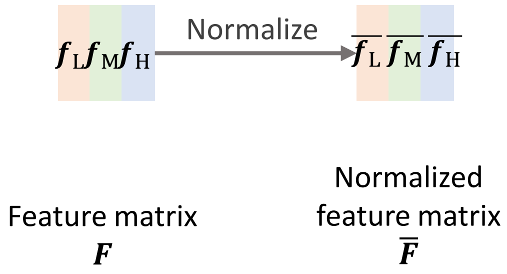
Feature normalization



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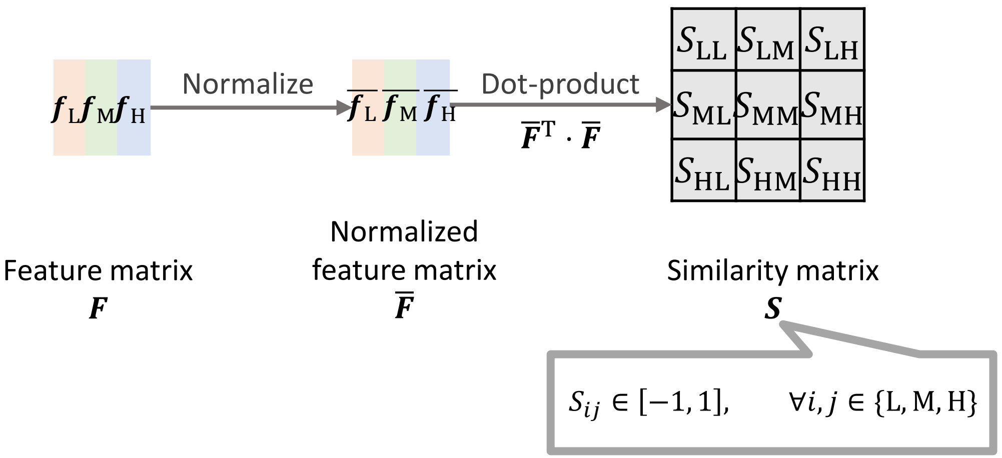
Similarity between features



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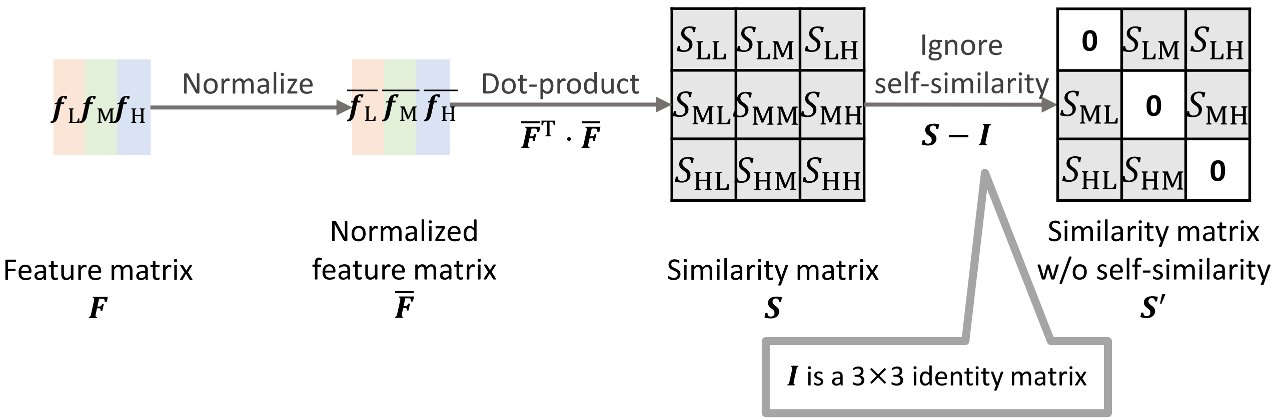
Off-diagonal similarity



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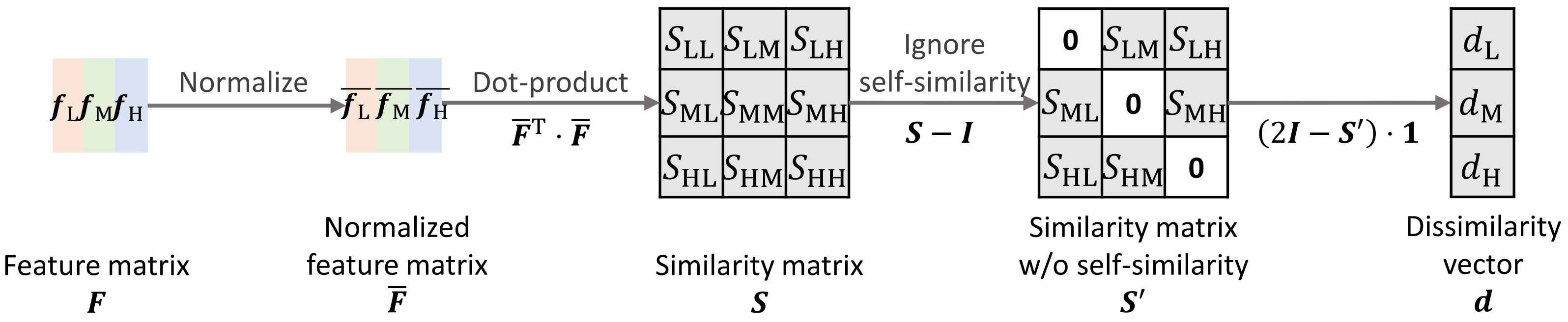
Dissimilarity between features



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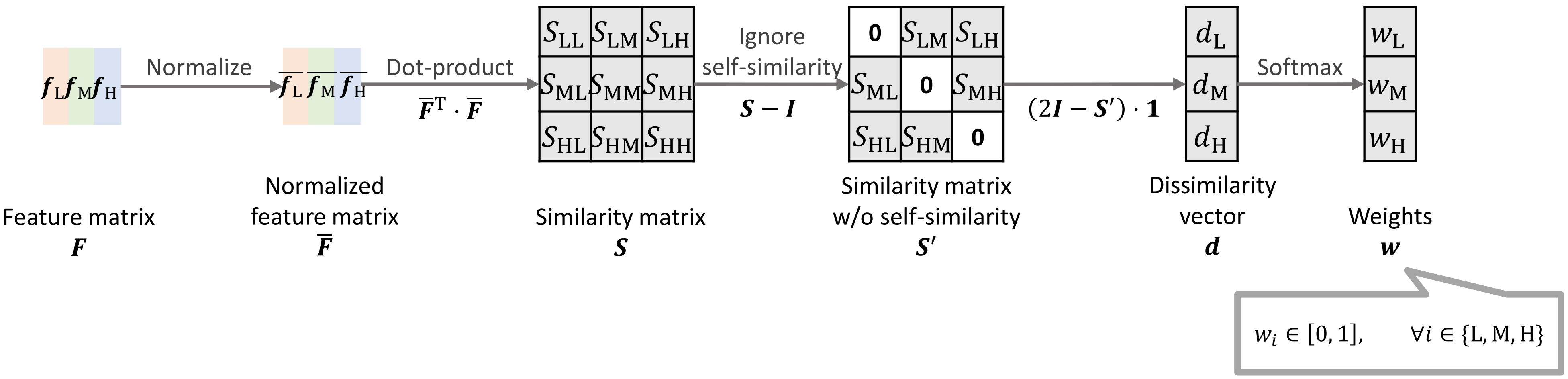
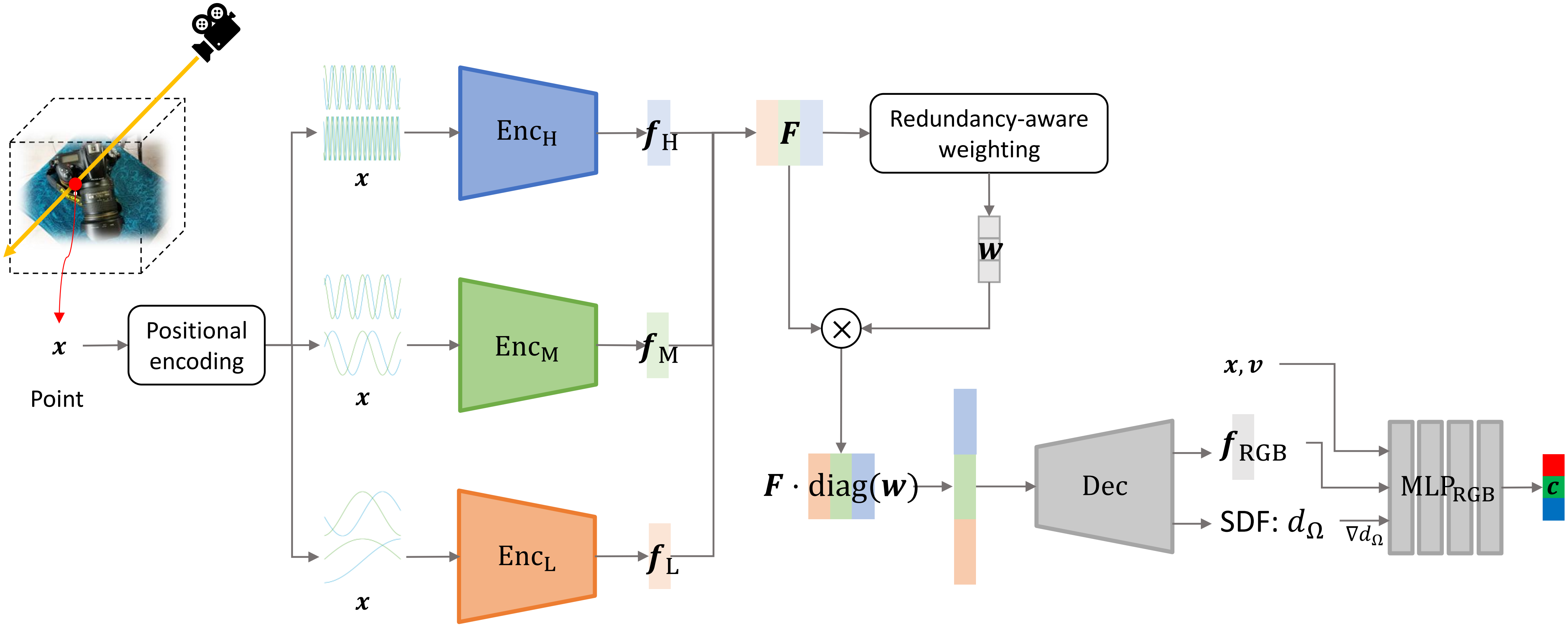
Rescaled dissimilarity



Overall FreBIS Framework



Experimental Setup

Dataset

- **BlendedMVS** : Object-centric real-world scenes with complex backgrounds
  - **Number of Scenes** : 9 scenes
  - **Number of views** : 31~144 views
  - **Resolution** : 768 × 576

Baselines

- VolSDF [Yariv et al., 2021] : 0.5M parameters
- Scaled-up VolSDF : 1.4M parameters (roughly the same as Ours)

*Scaled-up VolSDF: An adaptation of VolSDF, where the number of parameters is increased to be roughly the same as Ours

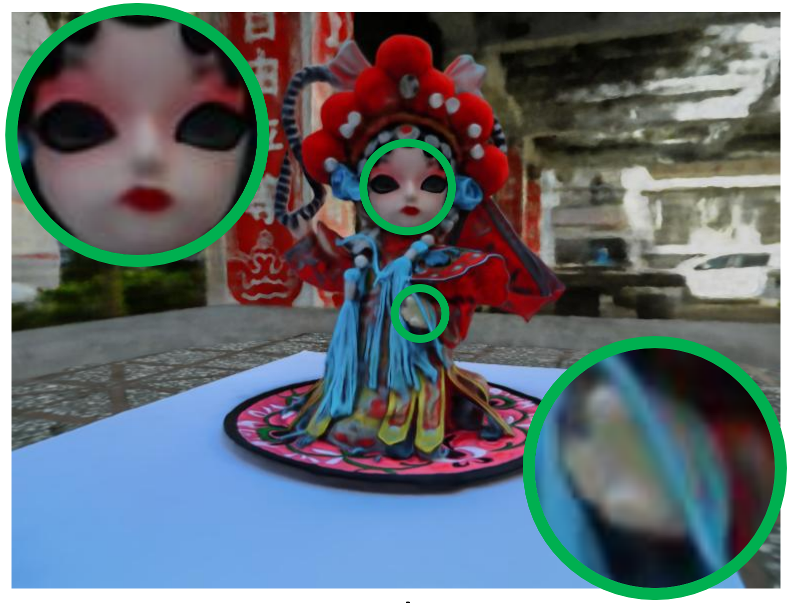
Quantitative Results: BlendedMVS

	Method (no. of parameters)	Doll	Egg	Head	Angel	Bull	Robot	Dog	Bread	Camera	**Mean**
	VolSDF [52] (0.5M)	25.43	27.23	26.94	30.28	26.18	26.39	28.44	**31.18**	22.96	27.23
PSNR(↑)	Scaled-up VolSDF (1.4M)	26.07	27.15	26.62	30.37	26.08	25.07	28.32	29.44	23.02	26.90
	Ours (1.4M)	**26.22**	**27.48**	**27.29**	**30.52**	**26.33**	**26.69**	**28.56**	30.22	**23.08**	**27.38**
	VolSDF [52] (0.5M)	0.911	0.943	0.959	0.989	0.970	0.957	0.950	**0.988**	0.928	0.955
SSIM(↑)	Scaled-up VolSDF (1.4M)	0.925	0.943	0.956	**0.990**	0.970	0.946	0.949	0.980	0.929	0.954
	Ours (1.4M)	**0.928**	**0.946**	**0.961**	**0.990**	**0.971**	**0.962**	**0.952**	0.983	**0.930**	**0.958**
	VolSDF [52] (0.5M)	0.041	0.032	0.017	0.007	0.021	0.032	0.027	**0.006**	0.045	0.025
LPIPS(↓)	Scaled-up VolSDF (1.4M)	**0.035**	0.032	0.018	**0.006**	0.021	0.043	0.028	0.011	0.045	0.027
	Ours (1.4M)	**0.035**	**0.030**	**0.015**	**0.006**	**0.020**	**0.030**	**0.026**	0.009	**0.044**	**0.024**

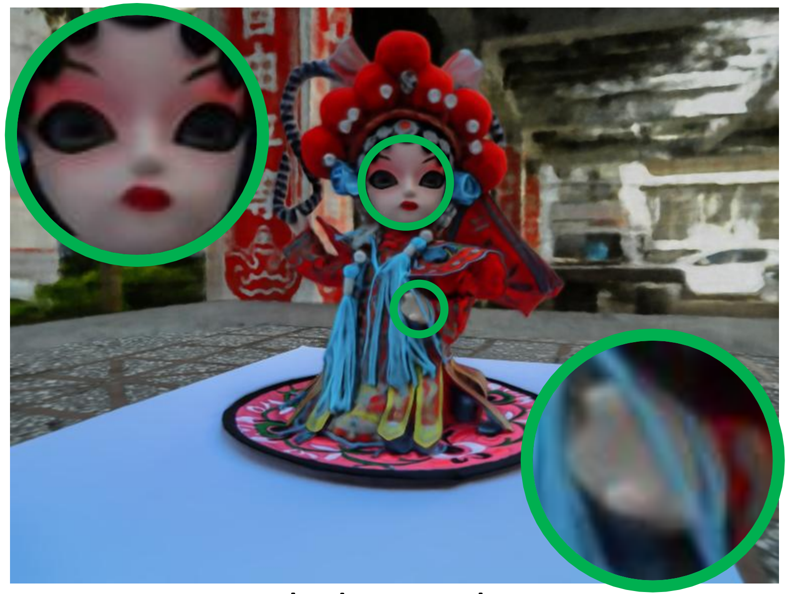
The proposed method improves the rendering quality in terms of PSNR, SSIM, and LPIPS.

Qualitative Results: BlendedMVS (Doll)

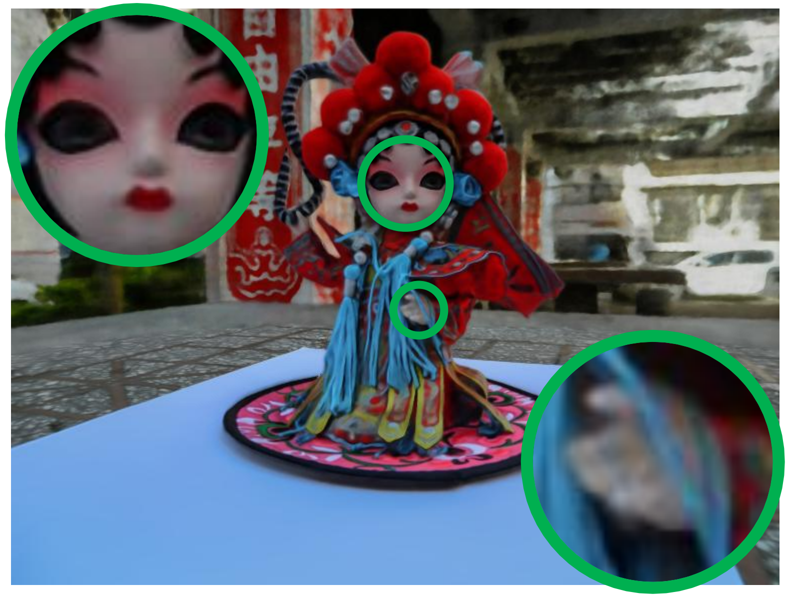
Ground truth



VolSDF



Scaled-up VolSDF

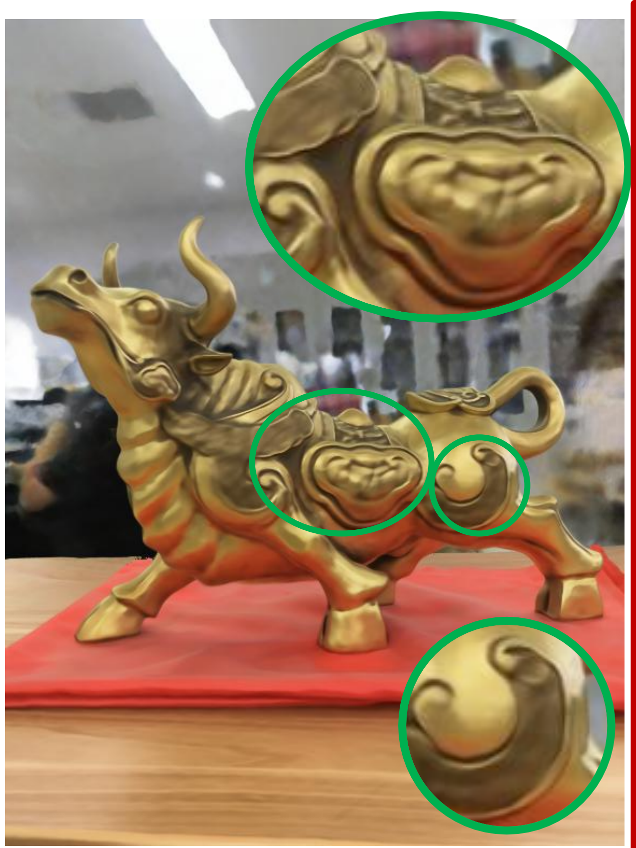


Ours

Qualitative Results: BlendedMVS (Bull)


Ground truth


VolSDF


Scaled-up VolSDF


Ours

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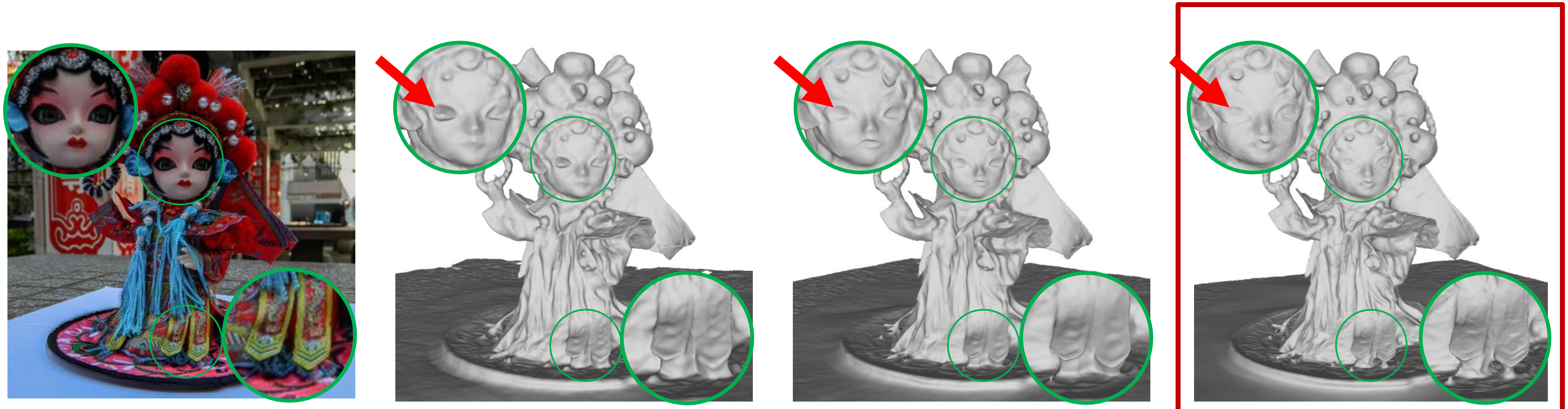
Qualitative Results: BlendedMVS (Doll)



Ground truth VolSDF Scaled-up VolSDF Ours

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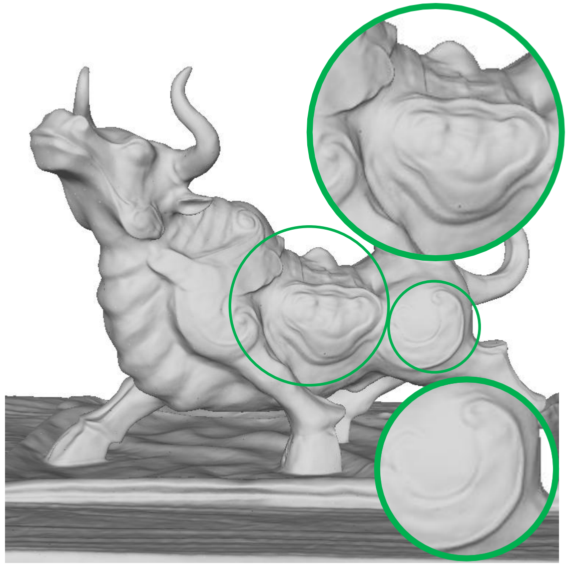
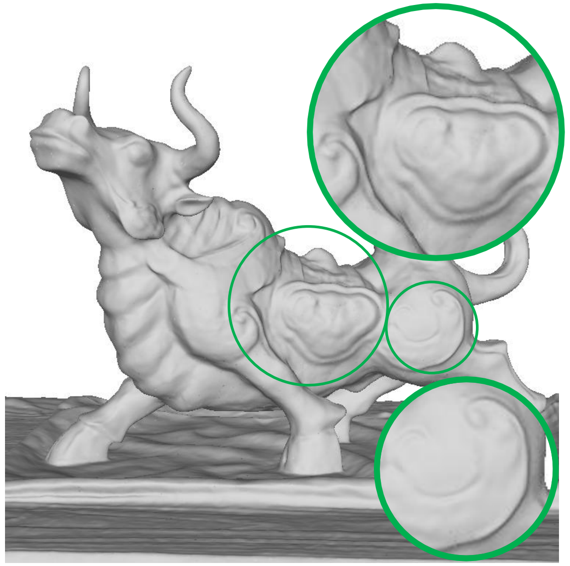
Qualitative Results: BlendedMVS (Bull)

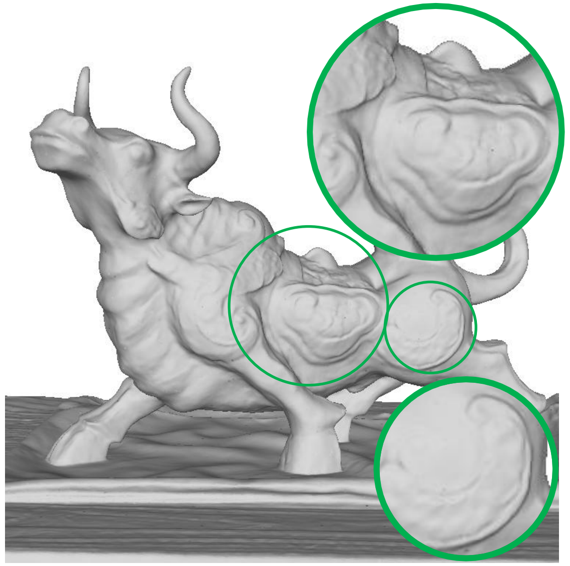
Ground truth



VolSDF



Scaled-up VolSDF



Ours

Conclusion

- We propose FreBIS, which **stratifies a scene into multiple frequency levels** according to the surface frequencies and leverages a novel **redundancy-aware weighting module,** to effectively capture complementary information.
- FreBIS improved the qualities of the reconstructed meshes, as well as rendered images.
- For future work, we plan to evaluate FreBIS on other datasets and backbones.

Thank you for your attention!

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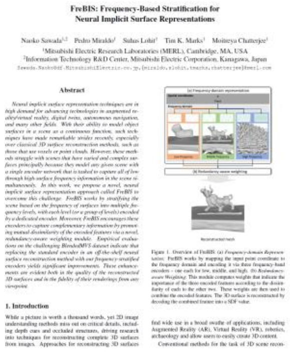
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Abstract

SCAN ME

For more details, please check out our paper and poster.