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GP-4DGS: Probabilistic 4D Gaussian Splatting from Monocular Video via Variational Gaussian Processes

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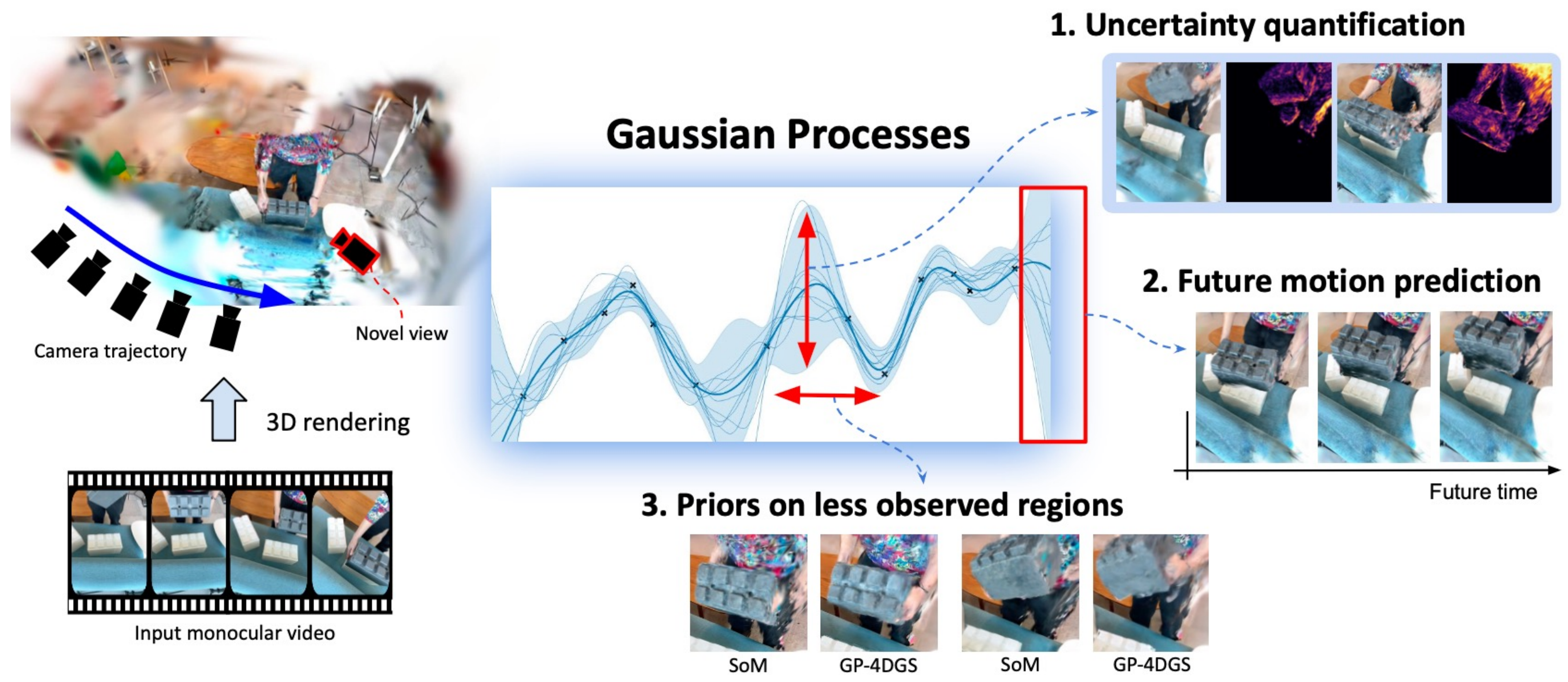
Task: Dynamic Novel View Synthesis

- **Goal:** Reconstructing dynamic 4D scenes from cell-phone monocular video
- **Challenge:**
  - **Too sparse information for reconstruction**
  - Existing 4DGS algorithms model unables uncertainty quantification, future motion prediction, and adaptive motion priors.

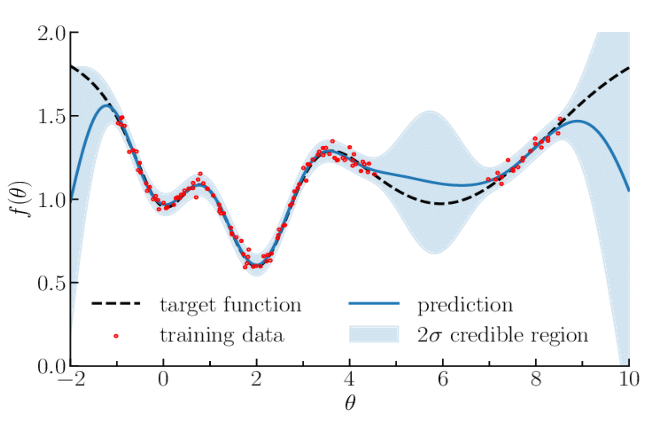


TL;DR: We introduce **probabilistic deformation modeling** of 4D Gaussian Splatting from monocular video via **Variational Gaussian Processes**.

4D Gaussian Splatting

- **3D Gaussian Splatting** represents static scenes as a set of primitives.
- **4D Gaussian Splatting** adds per-primitive motion over time to model dynamic scenes.

Modeling



[Gaussian Processes]

- **A probabilistic model over functions** that provides mean prediction and uncertainty estimate via kernel-based correlation.
- **Kernel**: Encodes smoothness and periodicity through correlations between inputs.

1. Probabilistic Deformation Modeling

$$f_i(\mathbf{x}) \sim \mathcal{GP}(m_i(\mathbf{x}), k_i(\mathbf{x}, \mathbf{x}'))$$

Model Gaussian primitive deformation as a probabilistic function over space and time, where we adopt multi-input / multi-output Gaussian Processes.

- **Input:** canonical position & target time t $\quad \mathbf{x} = (x_0, y_0, z_0, t) \in \mathbb{R}^4$
- **Output:** deformation offset $\quad \mathbf{y} = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_d(\mathbf{x})) \in \mathbb{R}^d,$

2. Spatiotemporal Correlation

$$k_i(\mathbf{x}, \mathbf{x}') = k_{i,\text{spatial}}(\mathbf{x}_s, \mathbf{x}'_s) + k_{i,\text{temporal}}(\mathbf{x}, \mathbf{x}')$$

- **Decomposed kernel:**
  - **Spatial kernel:** matern only
  - **Temporal kernel:** matern&periodic

$$k_{i,\text{spatial}}(\mathbf{x}_s, \mathbf{x}'_s) = \sigma^2_{s,i} \frac{2^{1-\nu_i}}{\Gamma(\nu_i)} r^{\nu_i}_{s,i} K_{\nu_i} r_{s,i};$$

$$k_{i,\text{temporal}}(\mathbf{x}, \mathbf{x}') = \sum_{j \in \{x,y,z\}} k_{i,j}(j, j')\, k_{i,\text{periodic}}(t, t').$$

Training & Inference

1. Scalable Variational Inference

Variational GPs: *Inducing point approximation reduces complexity from $O(N^3)$ to $O(NM^2+M^3)$, enabling scalable GP inference over numerous primitives.*

- **Training:** Variational posterior $q(\mathbf{u}_i) = \mathcal{N}(\mathbf{m}_i, \mathbf{S}_i)$ over inducing points is optimized jointly with kernel hyperparameters θ via ELBO.

$$\mathcal{L}_{\text{ELBO}} = \sum_{i=1}^{d} [\mathbb{E}_q[\log p(\mathbf{y}_i|\mathbf{u}_i)] - \text{KL}[q(\mathbf{u}_i)\|p(\mathbf{u}_i)]]$$

- **Inference:** $\bar{\mu}^*_i = \mathbf{k}^{(i)\top}_*(\mathbf{K}^{(i)}_{ZZ})^{-1}\mathbf{m}_i$ and $\bar{\sigma}^{*2}_i = k^*_i - \mathbf{k}^{(i)\top}_* \boldsymbol{\Sigma}_i \mathbf{k}^{(i)}_*$

2. Self-Reinforcing Optimization

- **GP-GS optimization:** GP is trained on high-confidence primitives (Stage 1) and GS is guided from GP posterior (Stage 2).
- **For training GPs**, selecting the confident data from 4D Gaussian Splatting.

Stage 1: GP Optimization

Stage 2: GS Optimization

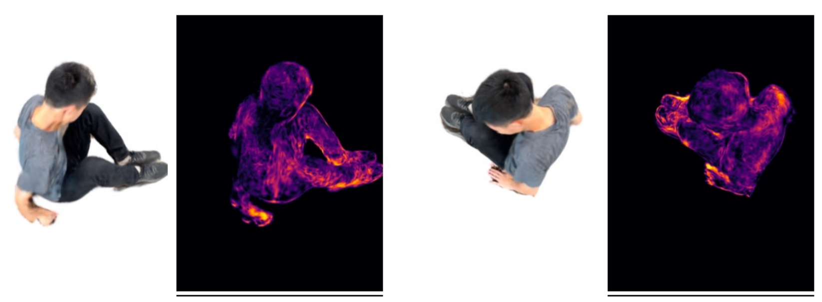
Algorithm 1 GP-GS Optimization Strategy

Input: Training images $\mathcal{T}$, Gaussian primitives $\{\gamma_k\}_{k=1}^N$
Output: Optimized GS model with GP regularization

```
while not converged do
    Stage 1: GP Training        // For every N_GP iterations
    Compute confidence: C_k = Σ_{I∈T} Σ_{r∈I} ω_k^π(r)
    Select confident data: D_C = {(x_i, y_i) : C_k > τ_C}
    Train variational GPs on D_C with Eq. (14)
    Stage 2: GS Optimization
    Infer variational GP posteriors and cache μ̄_(k,t)(x)
    Compute loss: L_GP = E[δ_k · ||y_(k,t) − μ̄_(k,t)||^2]
    Update GS: L_total = L_recon + λ_GP L_GP
end while
return optimized GS and GP models
```

Application & Results

1. Uncertainty Quantification



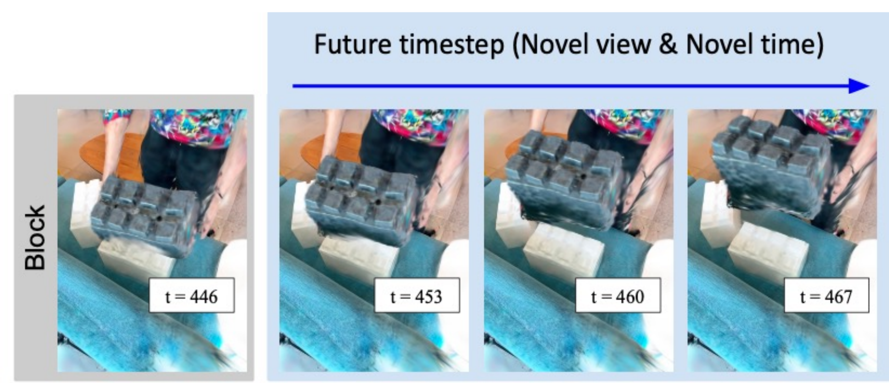
- GP posterior variance naturally provides uncertainty estimates for motion prediction, where less-observed regions exhibit higher uncertainty

$$U_k = \text{Var}(\{\mathbf{p}^{(s)}_k\}^S_{s=1}) \quad \hat{\mathbf{U}}(\mathbf{r}) = \sum_{k=1}^{K} U_k\, \omega^{\pi}_k(\mathbf{r})$$

Method	AUSE-MSE [40] ($\times 10^{-2}$) ↓ Top 20 frames	Top 40 frames	All frames
Random	9.76	9.30	10.98
UA-4DGS [19]	7.60	8.11	8.62
GP-4DGS (ours)	**7.22** (-0.38)	**8.00** (-0.11)	**8.49** (-0.13)

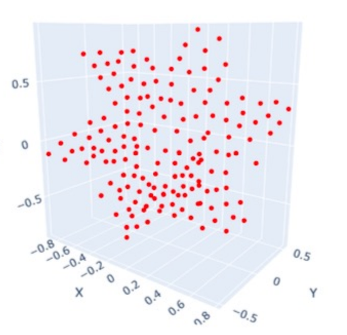
2. Future Motion Prediction

- Querying the trained GP at **future timestamp t'** (x_0, y_0, z_0, **t'**) enables motion prediction beyond the observed training sequence without additional training.



3. Adaptive Motion Priors for Less Observed Area

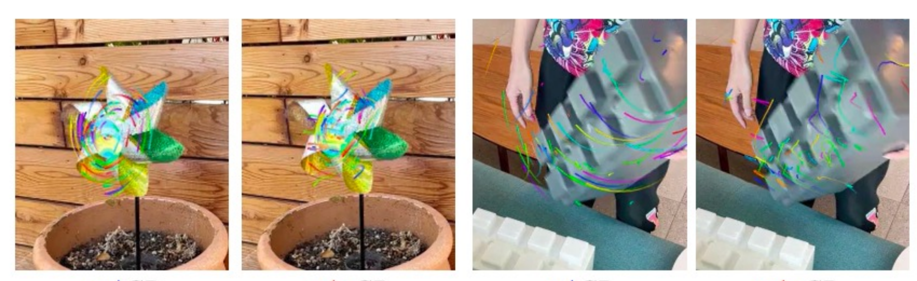
- GP-4DGS outperforms baselines and improves 3D tracking from 82.3% to 85.7%.



Inducing points visualization (canonical space)

Data	Method	mPSNR ↑	mSSIM ↑	mLPIPS ↓
All	Gaussian Marbles [42]	15.84	0.54	0.57
	SoM [46]	17.09	0.65	0.39
	GP-4DGS (ours)	**17.38**	**0.65**	**0.37**
SoM 5	SC-GS [23]	14.13	0.48	0.49
	D-3DGS [51]	11.92	0.49	0.66
	4DGS [48]	13.42	0.49	0.56
	T-NeRF [46]	15.60	0.55	0.55
	HyperNeRF [34]	15.99	0.59	0.51
	DynIBaR [22]	13.41	0.48	0.55
	Gaussian Marbles [42]	16.03	0.54	0.58
	SoM [46]	16.73	0.64	0.43
	GP-4DGS (ours)	**16.92**	**0.66**	**0.41**
Challenging subset [14]	Gaussian Marbles [42]	14.05	0.40	0.61
	SoM [46]	14.56	**0.46**	0.53
	GP-4DGS (ours)	**15.02**	**0.46**	**0.51**

Ground Truth Gaussian Marble SoM GP-4DGS (ours)



w/ GP w/o GP w/ GP w/o GP

Conclusion

- **Conclusion:** Our novel probabilistic framework capture spatiotemporal correlations by leveraging GP-based motion priors.
- **Impact:** Uncertainty and future-motion outputs can inform downstream decision-making modules, such as planning in autonomous driving.

Organizers

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