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DRL-EnVar: an adaptive hybrid ensemble–variational data assimilation method based on deep reinforcement learning

Key words: Adaptive data assimilation; Hybrid ensemble–variational method; Background error covariance; Deep reinforcement learning

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Motivation

- Targeting the limited effectiveness of existing ensemble–variational (EnVar) data assimilation methods under sparse observations and rapidly evolving atmospheric conditions—where fixed or empirically tuned hybrid parameters fail to adequately represent flow-dependent background-error characteristics—we propose a deep reinforcement learning-based ensemble–variational (DRL-EnVar) hybrid data assimilation framework. By integrating data-driven feature extraction and adaptive decision-making into the EnVar formulation, the proposed method aims to improve assimilation performance during transitional phases while preserving physical consistency and computational efficiency.

Main idea

- A deep reinforcement learning-based ensemble–variational hybrid data assimilation framework (DRL-EnVar) is proposed, integrating adaptive hybrid-parameter optimization into EnVar to improve assimilation accuracy under sparse observations and evolving flows.
- A DL-enhanced feature extraction architecture is introduced, where a cyclic convolution module alleviates information loss near circular equatorial boundaries and improves spatiotemporal representation completeness.
- Hybrid parameter selection is formulated as an RL-based process embedded in EnVar, enabling straightforward deployment across assimilation settings while preserving theoretical consistency and supporting 3DVar and 4DVar.

Method

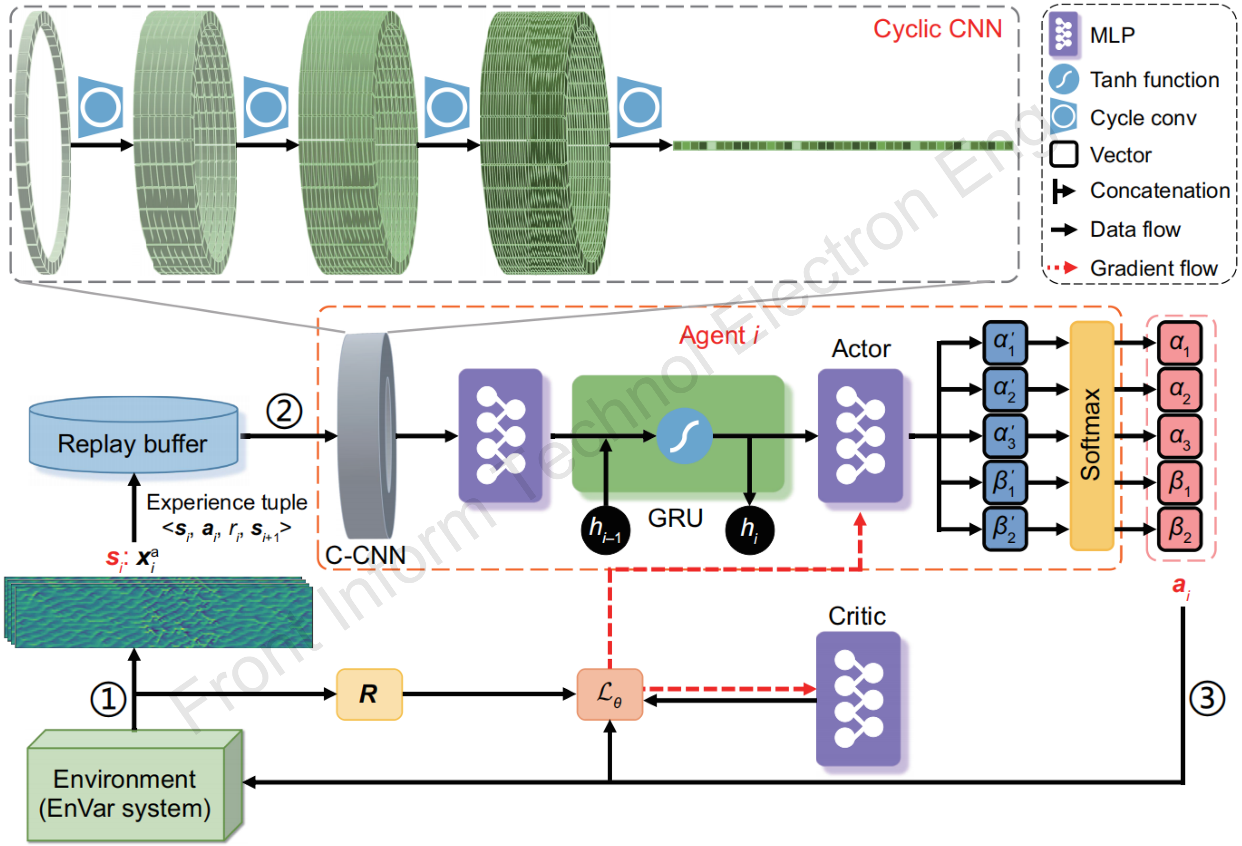


Fig. 1 The agent interacts with an EnVar-based simulation environment to learn a hybrid weighting policy, guided by a C-CNN encoder, a GRU module, and an actor–critic framework. Black solid and red dotted arrows represent data and gradient flows, respectively. References to color refer to the online version of this figure

Method

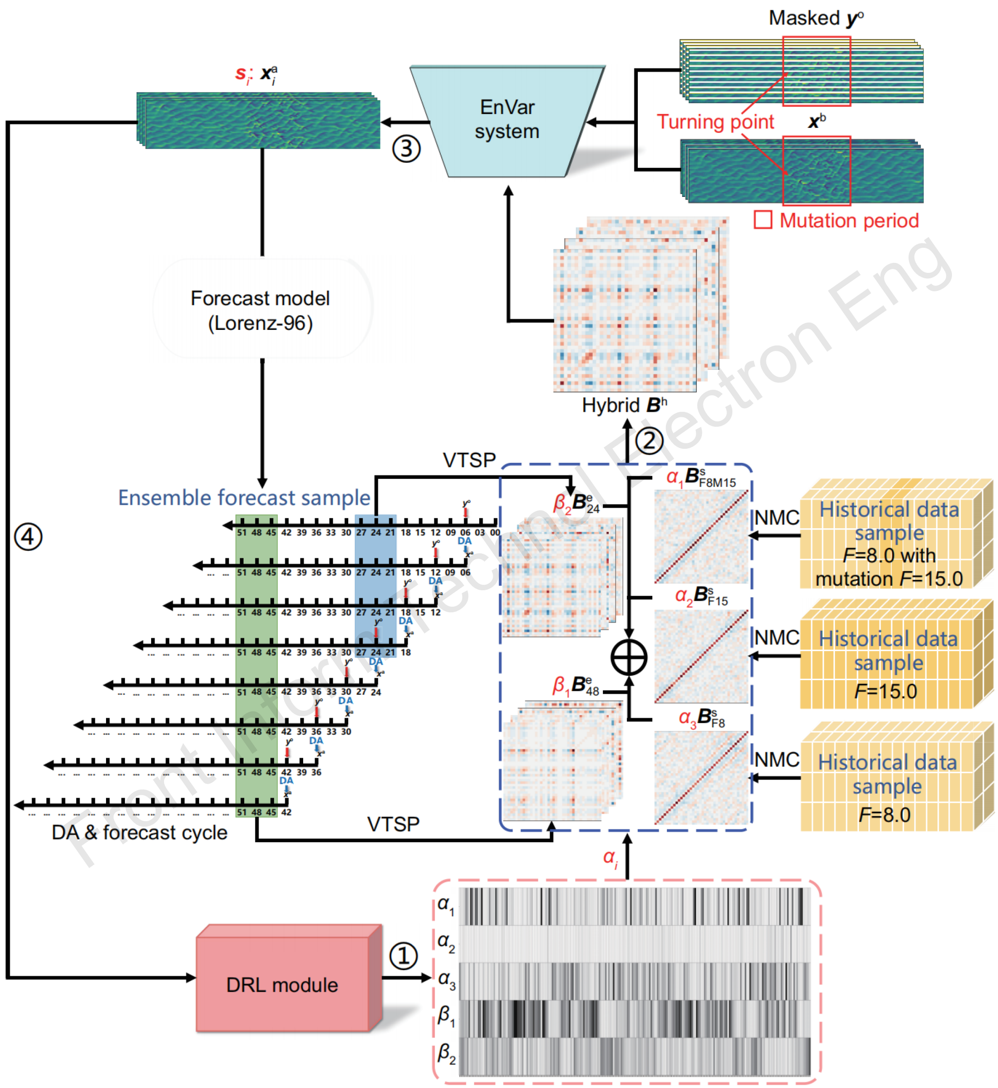


Fig. 2 EnVar assimilation phase. The DRL-output action (weights) is used to combine multiple B matrices. The resulting B^{h} is applied in the EnVar system for assimilation, and the resulting analysis state is fed back to the DRL module, forming a closed adaptive learning loop. Note that the black and white stripes correspond to the temporal change of weights across a span of 1 year. References to color refer to the online version of this figure

Results

Table 1 AM and the standard deviation for different methods, along with the percentage improvement in the performance of the three methods relative to the pure 3DVar method

Observation ratio	AM±standard deviation			
	Pure 3DVar	CTL-EnVar	MLP-EnVar	DRL-EnVar (ours)
90%	0.5792 ± 0.0085	0.5611 ± 0.0052 (3.13%)	$\underline{0.5505} \pm 0.0050$ (4.96%)	$\mathbf{0.5480} \pm 0.0054$ (5.39%)
80%	0.6439 ± 0.0130	0.6088 ± 0.0084 (5.45%)	$\underline{0.5850} \pm 0.0067$ (9.15%)	$\mathbf{0.5831} \pm 0.0079$ (9.44%)
75%	0.6695 ± 0.0131	0.6239 ± 0.0085 (6.81%)	$\underline{0.6022} \pm 0.0106$ (10.05%)	$\mathbf{0.5995} \pm 0.0089$ (10.46%)
50%	2.8550 ± 0.0992	2.4770 ± 0.1099 (13.24%)	$\underline{2.1890} \pm 0.1019$ (23.33%)	$\mathbf{2.0698} \pm 0.0833$ (27.50%)
Cost (s)	**24.87**	36.82 (1.48)	35.91 (1.44)	$\underline{31.17}$ (1.25)

The final row lists the computational cost for each method, as well as the computational cost multiples relative to the pure 3DVar in the bracket. The best results are in bold and the sub-optimal results are underlined

Results

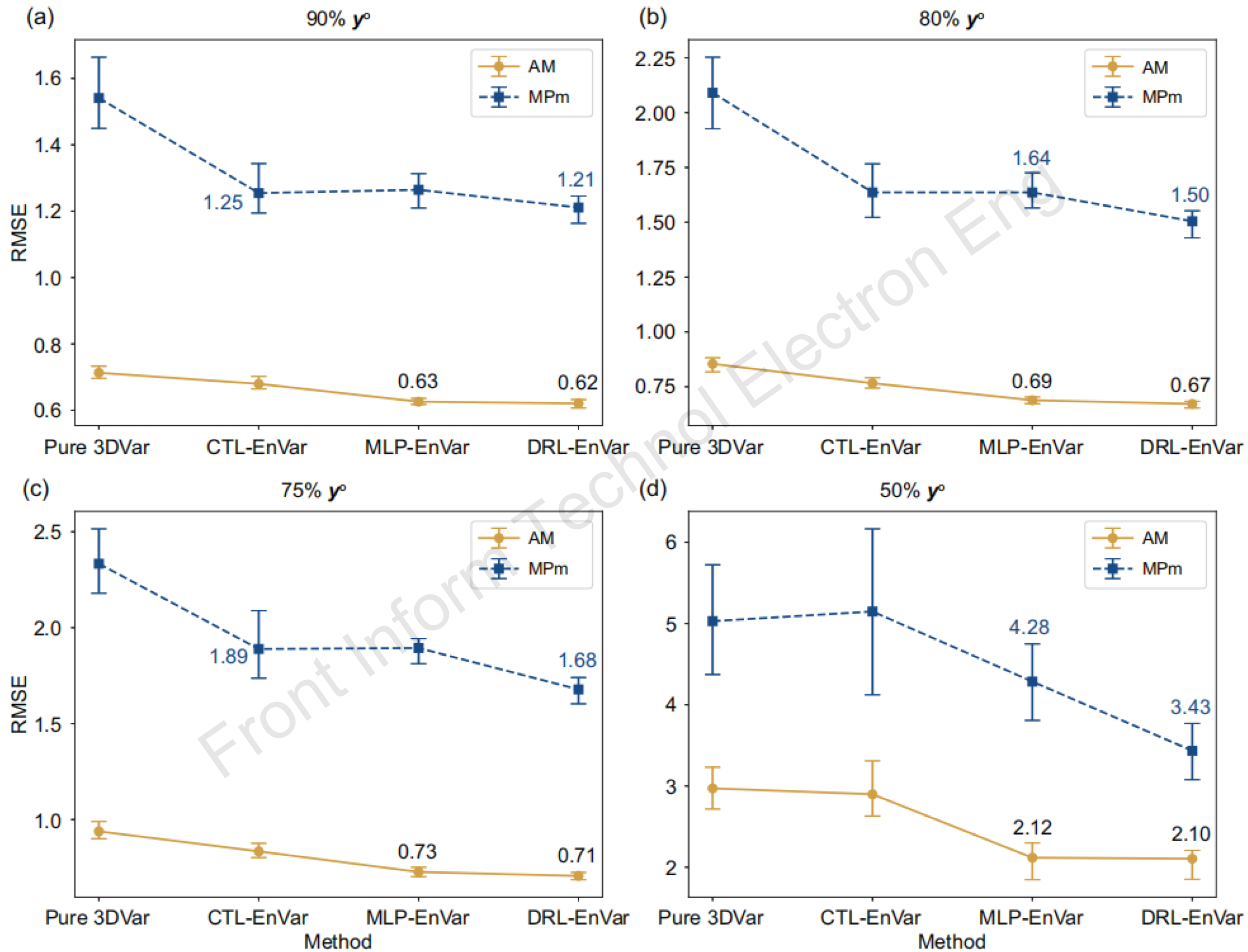
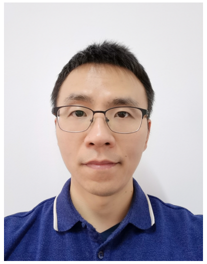


Fig. 7 RMSE of assimilation methods under varying observation sparsity, with an anomaly occurring in the state variable during 1 month of the annual assimilation cycle: (a) 90% y^o; (b) 80% y^o; (c) 75% y^o; (d) 50% y^o. The solid yellow-orange line represents the AM, while the dashed dark blue line represents the MPm. Error bars are shown for each value. References to color refer to the online version of this figure

Conclusions

In this work, we propose a novel deep reinforcement learning-based hybrid ensemble–variational data assimilation framework (DRL-EnVar), which enhances flow-dependent background-error representation through intelligent hybrid-parameter optimization under sparse observations and rapidly evolving weather conditions. By embedding DRL into the variational assimilation process with low computational overhead, this approach improves assimilation accuracy and stability while maintaining practical efficiency, offering a promising pathway for extending traditional variational methods toward adaptive and scalable real-world weather assimilation.



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