Paper title: **Deep reinforcement learning for turbulence modeling in large eddy simulations.**

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1. Summary

1.1 Motivation/Purpose/Aims/Hypothesis

The motivation behind this research stems from the inadequacies of traditional supervised learning in turbulence modeling, particularly in the context of implicitly filtered Large Eddy Simulations (LES). The purpose is to revolutionize turbulence modeling by adopting a reinforcement learning (RL) paradigm, aiming to overcome challenges posed by unknown closure terms and filter forms in LES. The hypothesis is that RL, by directly interacting with the dynamic LES environment, can provide a more robust and accurate approach to turbulence modeling.

1.2 Contribution

The primary contribution of this work lies in applying the RL framework, specifically Relexi, to derive data-driven turbulence models for implicitly filtered LES. By incorporating a modern high-order discontinuous Galerkin scheme, the research demonstrates the adaptability of RL in training models to dynamically adjust the eddy viscosity in both time and space. This shift from traditional approaches showcases a novel way to tackle longstanding challenges in turbulence modeling.

1.3 Methodology

The methodology involves implementing the RL paradigm using the Relexi framework. The choice of a high-order discontinuous Galerkin scheme serves to demonstrate the applicability of the approach to modern, high-fidelity discretizations. The RL agent is trained using the Proximal Policy Optimization (PPO) algorithm, with a policy network based on three-dimensional convolutional layers. The training focuses on achieving long-term stability and superior accuracy in turbulence simulations.

1.4 Conclusion

In conclusion, the research successfully applies RL to turbulence modeling in implicitly filtered LES. The trained models exhibit stability and accuracy, outperforming traditional analytical LES models. The generalization of these models to different resolutions and higher Reynolds numbers highlights their potential for real-world applications. The study lays the foundation for future advancements in data-driven turbulence modeling.

2. Limitations

2.1 First Limitation/Critique

One limitation of the approach is the reliance on a specific high-order discontinuous Galerkin scheme. While this choice demonstrates the methodology's effectiveness in modern discretizations, it may limit the generalizability of the approach to other numerical schemes or computational domains. Addressing this limitation would involve exploring the adaptability of RL-based models to different discretization methods.

2.2 Second Limitation/Critique

Another limitation lies in the computational complexity associated with RL training. Training RL models can be resource-intensive, especially with complex simulations. This may hinder the scalability of the approach to large-scale simulations or real-time applications. Future work could focus on optimizing the RL training process for efficiency without compromising accuracy.

3. Synthesis

The ideas presented in the paper open avenues for potential applications and future scopes in turbulence modeling. The successful application of RL to implicitly filtered LES suggests broader implications for real-world fluid dynamics simulations. The adaptability of the trained models to different resolutions and Reynolds numbers indicates their potential use in diverse engineering and environmental scenarios. Future research could explore the integration of RL-based turbulence models into practical applications, optimizing them for efficiency and scalability. This synthesis highlights the transition from theoretical advancements to real-world implementations, paving the way for advancements in data-driven turbulence modeling.