ABSTRACT

In a turbulent flow velocity field and its gradients at small scales are closely related to key nonlinear turbulence processes like mixing, intermittency, energy cascade, material element deformation, etc. Thus, the velocity gradient tensor has been a subject of fundamental interest. Various studies have been performed to understand the evolution of velocity gradients in turbulent flows primarily for incompressible flows. These studies have not only contributed to an improved understanding of small-scale motion in turbulent flows, but they have also helped in the development of useful turbulence closure models for incompressible flows. However, very limited studies have been performed for compressible flows.

Compressibility adds more complexity to the dynamics of velocity gradients due to the interaction of shock with turbulence processes. While in incompressible flows, the pressure field depends on the velocity field alone, in compressible turbulence pressure field depends on the temperature and density field as well. Further, in compressible turbulence a significant level of dilatation can exist, which is absent in incompressible flows. Hence, it becomes important to understand the influence of compressibility on the dynamics of velocity gradients.

To perform fundamental study of velocity gradient dynamics at small-scales, we need access to compressible turbulence data at varied Mach numbers and Reynolds numbers. However, very limited experimental data is available for compressible flows; thus, there is a need to perform direct numerical simulation (DNS) of canonical compressible turbulent flows. To generate these canonical compressible turbulence datasets, an appropriate numerical scheme must be employed that can robustly handle the presence of extreme discontinuities in the flow-field. Further, these methods need to be ported on parallel computing platforms like graphical processing unit (GPU) clusters to perform high-fidelity DNS simulations.

The Lagrangian approach is known to be more insightful in understanding the dynamics of velocity gradients. However, it is very difficult to generate Lagrangian flow fields. Alternately, the Lagrangian field can also be produced with the help of simulated Eulerian field data and a Lagrangian particle tracker. Following this approach, we generate Lagrangian field data from DNS data of compressible turbulent flows and perform Lagrangian analysis of velocity gradients and its associated processes.

In recent years, machine learning-based techniques have evolved as a viable tool for discovering key relationships from data. Recently, data-driven techniques have become very popular in the turbulence community, motivated by the recent success, which has led to improved accuracy of turbulence models assisted with machine learning. These machine learning methods can be of paramount importance in learning hidden physical mappings between velocity gradients and the processes governing its dynamics.

In this work, we identify three studies (Study A, B and C) towards both understanding of velocity gradient dynamics and modelling the governing processes. In Study A, we develop a direct numerical simulation (DNS) solver for isotropic compressible turbulent flow integrated with a Lagrangian particle tracker (LPT).

The Lagrangian field data produced using this solver will be utilized for performing Lagrangian analysis of the velocity gradient tensor (Study B). We extensively compare and evaluate DNS results against high-order accurate Navier-Stokes based DNS results. Further, we evaluate the speed-up and scalability of our solver on GPU platform using compute unified device architecture (CUDA) application programming interface (API) developed by NVIDIA. At last, we integrate a cubic-spline based Lagrangian particle tracker (LPT) with the DNS code which saves immense Lagrangian post-processing time.

In Study B1, we investigate the influence of compressibility on vorticity-strain rate dynamics. We obtain time correlations between the instantaneous vorticity vector and the strain-rate eigenvector system of an appropriately chosen reference time. We parametrize compressibility in terms of turbulent Mach number and normalized dilatation-rate and flow field topology. Our investigations reveal that local dilatation rate significantly influences these statistics for selected topologies. We attempt to provide physical explanations of these observations (in terms of the moment of inertia and angular momentum) by performing detailed calculations following the Tetrad approach in a compressible flow field.

In Study B2, we perform Lagrangian investigations of the dynamics of velocity gradients in compressible decaying turbulence. Specifically, we examine the evolution of the invariants of the velocity gradient tensor. We examine the trajectories of fluid particles in the space of the invariants of the velocity gradient tensor. This allows us to accurately measure the lifetimes of major topologies of compressible turbulence and provide an explanation of why some selective topologies tend to exist longer than the others. Further, the influence of dilatation on the lifetime of various topologies is examined. Finally, we explain why the so-called conditional mean trajectories (CMT) used previously by several researchers fail to predict the lifetime of topologies accurately.

In Study B3, we focus specifically on two models meant for the incumbent viscous process: the linear Lagrangian diffusion model (LLDM) and the recent fluid deformation closure model (RFDM). We subject these models to scrutiny in non-stationary turbulence. We find that in the compressible regime, both the models show inadequacies. For compressible flows, we propose an alternative modelling strategy which shows improvement over both LLD and RFD models.

In Study C, we first demonstrate the limitations of the RFDM in estimating the pressure-Hessian. Further, we employ a tensor basis neural network (TBNN) to model the pressure-Hessian from the velocity gradient tensor itself. The neural network is trained on high-resolution data obtained from direct numerical simulation (DNS) of isotropic turbulence at Reynolds number of 433. The evaluation of the neural network output is made in terms of the alignment statistics of the predicted pressure-Hessian eigenvectors with the strain-rate eigenvectors. Our analysis leads to the discovery of ten unique coefficients of the normalized tensor basis of strain-rate and rotation-rate tensors, the linear combination over which accurately captures key alignment statistics of the pressure-Hessian tensor.