3D Tomographic Reconstruction of Dynamic Gas Bubbles from Dual-Perspective Imaging

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The dynamics of gas bubbles, such as flames and interstellar clouds, during interaction with shock waves is an important topic of research for better understanding gas-dynamic instabilities that have strong implications on applications such as supersonic combustion and supernova explosions [1]. Shock-bubble interaction often leads to the gas bubble evolving into complex 3D shapes in millisecond timescales, making experimental characterization of bubble morphology challenging. Additionally, experimental investigations of shock-bubble interactions often utilize apparatuses with limited optical access [2], and therefore, the number of view perspectives that could be used for observing shock-bubble interaction is restricted. In this context, accurate 3D tomographic reconstruction of dynamic gas bubbles from just two orthogonal views becomes desirable.

Many previous works have explored tomographic reconstructions with limited viewing angles. Sparse-view computed tomography (CT) has been explored by many in medical imaging through compressive sensing [3] and deep learning [4]. Those studies noted that reconstructions from sparse views using approaches developed for abundant views (e.g., filtered back projection) give rise to streaking defects, and therefore, an effective image prior is essential. Zang et al. [5] used optical-flow-based view interpolation of two projected images as a regularizer for 3D reconstruction optimization of fluid flow. Zang et al. particularly pointed out the challenge of applying neural-network-based methods for reconstruction of fluid flows due to the lack of representative training data.

In this project, 3D tomographic reconstruction of dynamic gas bubbles using two orthogonal projection will be explored. The target bubble geometry will be representative to that resulted from planar shock wave interaction with an initially spherical bubble. The bubble geometry can be assumed as largely axially symmetric. First, 3D model of a dummy bubble will be constructed to provide the ground truth for the reconstruction algorithm. Two orthogonal projections of the model will then be calculated as the input images. A loss function can be constructed by computing the difference between the input projections and the guess geometry. A milestone of the project will be implementing a regularizer for the optimization. Several approaches could be considered in the construction of regularizers. The fact that the bubble geometry is expected to be roughly axially symmetric means that revolving the projection from the view perpendicular to the symmetry axis yields approximately the bubble geometry. The axially symmetric approximation can be exploited in constructing a regularizer. The optical-flow-based view interpolation proposed by Zang et al. could also be explored. Another milestone will be implementing regularizers in the optimization algorithm to successfully compute a reconstruction and evaluate the performance of the reconstruction against the ground truth. Finally, real experimental data could be tested with the reconstruction algorithm.

References

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