

Aerodynamic shape optimization by combination of VAE and PINN

—Hybrid SDF and point-cloud for shape representation—

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We propose a new aerodynamic shape optimization (ASO) framework that combines a Variational Autoencoder (VAE) and Physics-informed neural networks (PINN), employing hybrid Signed Distance Function (SDF) and point-cloud representations for geometry. By introducing a VAE, the body shapes can be reduced to small number of latent variables that are efficient for the optimization problem. Also, the VAE enables us to easily impose constraints on body design range in the ASO framework. Regarding the shape representation, the SDF is introduced to flexibly impose the boundary condition as an equivalent body force in the Navier-Stokes equation. The point clouds are used to precisely express the body shape as zero SDF points.

Figure 1 shows the overall framework of our proposed method. Regarding the VAE, PointNet is employed as its encoder, whereas standard MLP is used as a decoder. The VAE is preliminary trained to minimize the loss function defined as the sum of Density-aware Chamfer Distance (DCD) and the Kullback-Leibler divergence. Then, the SDF-PINN is trained with physics loss function of the Eikonal equation. This way the SDF function corresponding to latent variables λ can be immediately calculated by SDF-PINN. After both VAE and SDF-PINN are trained, the NS-PINN is trained for the initial values of latent variables to minimize the loss function defined as the sum of residuals of the Navier-Stokes equation and boundary conditions. In the optimization phase, the NS-PINN and latent variables are alternately updated. The latent variables are updated to the direction as C_D reduces. Instead of the standard wall boundary condition for the flow past bodies, the equivalent body force term is introduced in the Navier-Stokes equations, and the SDF function is used to evaluate this body force.

The proposed method was demonstrated through shape optimization of two-dimensional airfoils. Point clouds representation of 47 NACA airfoils are trained by VAE and reduced to only two latent variables with sufficient accuracy. The initial and improved shapes calculated through this optimization method are shown in Fig. 2. For corresponding geometries, flow fields were also calculated using conventional CFD (ANSYS Fluent), showing that the C_D value decreased by approximately 4%, from 1.14 for the initial shape to 1.08 in the improved shape.

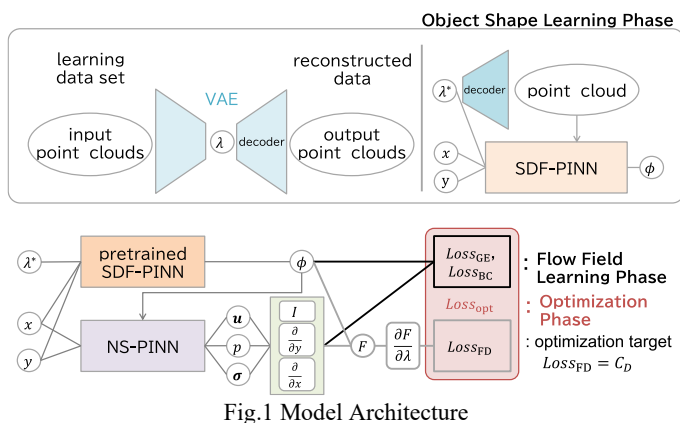


Fig.1 Model Architecture

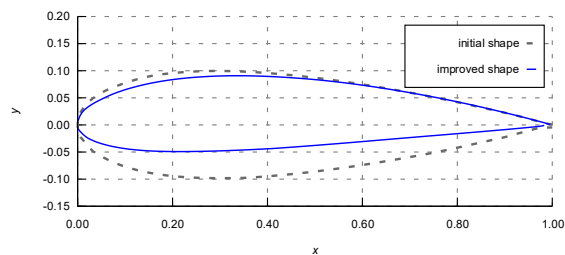


Fig.2 Comparison of the initial shape and the improved shape. A blue line is an improved shape; a line of grey points is the initial shape.