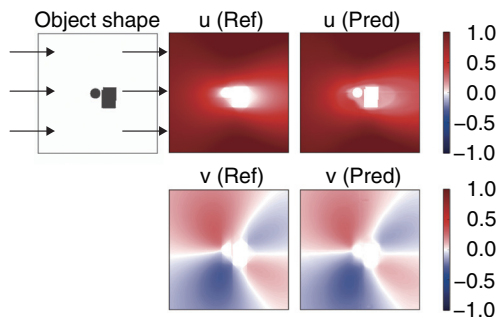
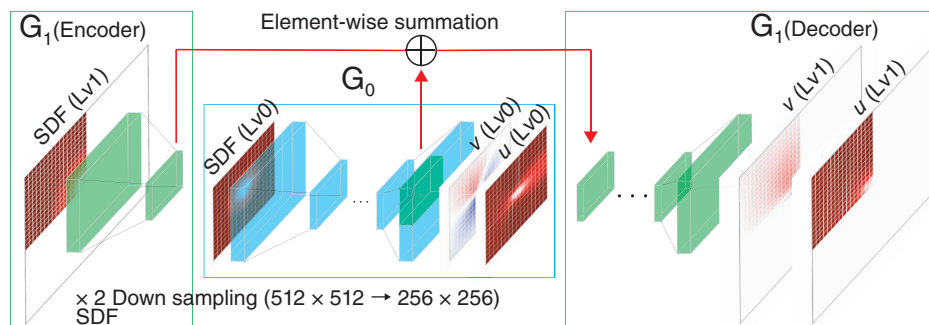


## 9-1 Deep-Learning Model for High-Resolution Steady Flow Prediction — Convolutional Neural Networks for Multiresolution Steady Flow Prediction —



**Fig.9-2 Flow field prediction with the proposed deep-learning model**

The simulation (reference) and predicted two-dimensional steady-state flow fields around objects with a resolution of  $1024^2$ . Here,  $u$  and  $v$  are the normalized flow velocity along the  $x$  and  $y$  axes, respectively. The arrows represent the directions of the in- and out-flows from left to right.



**Fig.9-3 Architecture of the proposed model**

The global low-resolution and patched high-resolution signed distance functions (SDFs) are fed to networks  $G_0$  and  $G_1$ . The patched features ( $256 \times 256$ ) from  $G_0$  are merged with the down-sampled features ( $256 \times 256$ ) by  $G_1$  to predict the patched high-resolution flow field. Since the elementwise sum of the global features from  $G_0$  and the local features from  $G_1$  allows the propagation of the global information to  $G_1$ , the predicted high-resolution flow fields maintain the consistency of the structures between the patches.

Deep-learning-based models using convolutional neural networks (CNNs) are widely used to generate photo-realistic images. These models have also been applied to surrogate models that approximate computational fluid dynamics (CFD) simulation results, which can be obtained significantly faster than CFD simulation results. A kind of surrogate models are needed for an instant prediction and large-scale parameter scans of flow fields. Because of memory-size constraints, conventional models have been applied up to a resolution of  $512 \times 512$ . For the high-resolution flow fields, a model has to predict the patched regions of flow fields independently, and this leads to inconsistency between the independently predicted flow fields.

In this work, we developed a new flow-prediction model to resolve the memory and connection issues simultaneously. A CNN-based model predicts the steady-state flow field around an object from a signed distance function (SDF), which represents both simple and complex object shapes in a universal way. Conventional models have applied CNNs to the patched SDF data to predict the patched flow field. In this work, we developed a model to use a low-resolution global SDF and a high-resolution patched SDF to predict a globally consistent high-resolution flow field (Fig. 9-2).

Here, the low-resolution SDF is constructed from a high-resolution SDF by down-sampling.

In CNNs, the input data are first encoded and then decoded to the target output data. The developed model consists of an encoder/decoder ( $G_0$ ) for low-resolution data and another encoder/decoder ( $G_1$ ) for high-resolution patched data (Fig. 9-3). Figure 9-3 shows the prediction of the flow field with  $1024 \times 1024$  resolution, where a low-resolution ( $512 \times 512$ ) global SDF and a high-resolution ( $512 \times 512$ ) patched SDF (1/4 region) are used as input data to  $G_0$  and  $G_1$ , respectively. The patched features ( $256 \times 256$ ) from  $G_0$  are merged with the down-sampled features ( $256 \times 256$ ) by  $G_1$ . By combining the global information from the low-resolution data and the local structures from the high-resolution patched data, the model can predict the global high-resolution flow field consistently. Although such a model has also been proposed in the field of image processing, it uses the global low-resolution and high-resolution data. Our model is more memory-efficient and can still predict the global high-resolution flow field by using the patched high-resolution data. Using this model, we can predict the flow fields instantly and perform large-scale parameter scans.

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### Reference

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