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Integrating Deep Learning into a Hybrid Image-Based Velocimetry Framework for Flood Flow Analysis

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This study evaluates the feasibility of applying the deep learning-based optical flow model SEA-RAFT to natural rivers during flood periods. By integrating image preprocessing techniques with Large-Scale Particle Image Velocimetry (LSPIV) and Space–Time Image Velocimetry (STIV), we propose a hybrid framework for estimating river surface velocity and discharge.

We selected the Naka River in Tokushima, Japan, and the Zengwen River in Taiwan as the study sites. PTZ cameras were installed on bridges to continuously monitor river flows. Video frames were orthorectified using ground control points (GCPs). The orthorectified frames were then enhanced in ImageJ software to improve brightness and contrast for clearer flow pattern visualization, and to increase sharpness in order to strengthen the visibility of natural tracers, particularly in low flow regions. The enhanced frames were finally masked to define the region of interest (ROI) for subsequent velocity estimation.

In the surface velocity estimation stage, we analyzed the flow fields using LSPIV and three SEA-RAFT optical flow models constructed with different sets of pretrained weights (large, medium, and small). In the absence of reliable in situ surface velocity measurements during flood periods, we used LSPIV as a surrogate reference and evaluated the discrepancies between the two approaches. The results show that the estimated velocity magnitudes are highly consistent (Fig. 1). The Bland–Altman analysis further indicates a bias of 0.206 m/s, suggesting that SEA-RAFT slightly overestimates velocities compared with LSPIV. Notably, the agreement between the two methods improves at higher velocities, which indirectly implies that SEA-RAFT may offer an advantage in capturing natural tracers in low-velocity regions (Fig. 2).

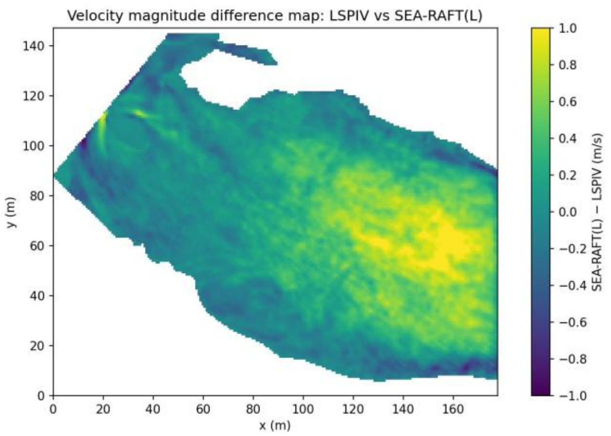

Fig. 1 Spatial map of surface velocity magnitude differences between SEA-RAFT(L) and LSPIV (Naka River, 29 Aug 2024, 12:00).

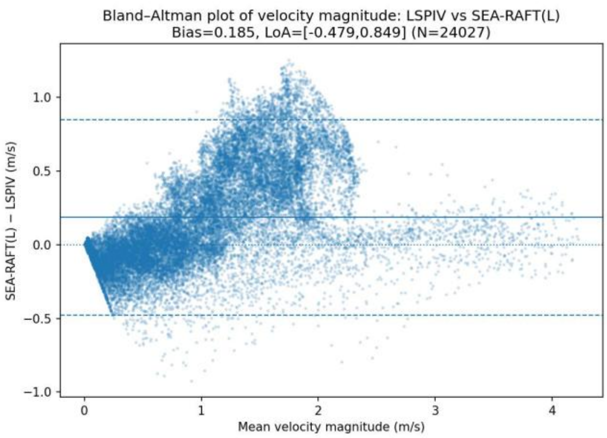

Fig. 2 Bland–Altman plot of surface velocity magnitude between SEA-RAFT(L) and LSPIV for the Naka River case (29 Aug 2024, 12:00).

Furthermore, given the absence of ground truth measurements, the absolute accuracy of the two methods cannot be directly quantified. Instead, we evaluated their temporal stability using the coefficient of variation (CV). The analysis was conducted for three spatial categories: the entire domain, the mainstream region (top 10% highest velocities), and the near-bank zone (within 4 m from the riverbank). Results show that SEA-RAFT exhibits a lower median CV of velocity magnitude within the ROI (Fig. 3). This indicates that SEA-RAFT provides more temporally stable velocity estimates than LSPIV across consecutive frames.

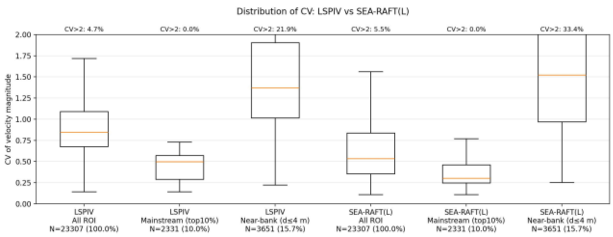

Fig. 3 CV distribution of surface velocity magnitude for SEA-RAFT(L) and LSPIV (Naka River, 29 Aug 2024, 12:00).

For discharge estimation, since both SEA-RAFT and LSPIV showed a tendency to underestimate surface velocities in low-velocity regions, we used surface velocity estimates from STIV as the primary input, as STIV is relatively less dependent on natural tracers. Discharge was then computed using a velocity index (α), which represents the ratio between surface velocity and depth-averaged velocity.

To investigate the plausible distribution of α at the study sites, the cross section was divided into five zones based on relative submergence, turbulence structure, cross-sectional geometry, and the spatial distribution of velocity. We then applied the proposed importance sampling–based Bayesian workflow as a stochastic approach to obtain the posterior distribution of α for each zone (Fig. 4) and the probabilistic distribution of the total discharge Q. Finally, the estimated discharge was compared with the upstream dam release, and the results showed that the estimation biases was within 10% (Fig. 5).

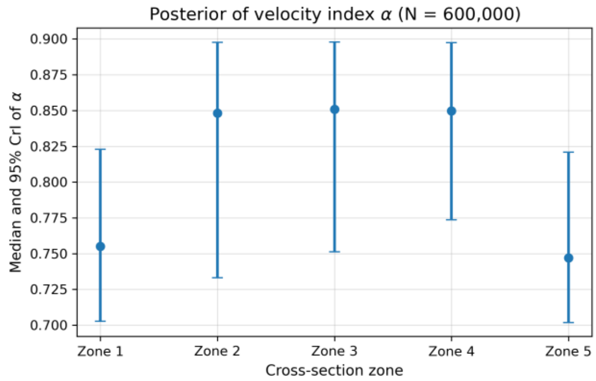

Fig. 4 Posterior median and 95% credible interval (CI) of the velocity index (α) for each zone, estimated using all observations at the Naka River site.

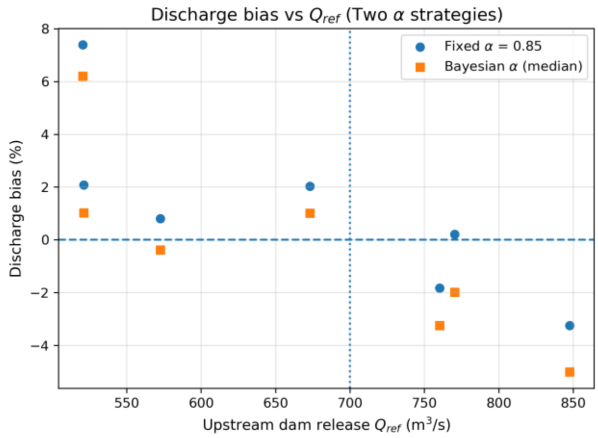

Fig. 5 Percentage bias of the estimated discharge relative to upstream dam release records under two estimation strategies at the Naka River site.

In conclusion, during flood periods, SEA-RAFT demonstrated strong agreement with LSPIV for surface velocity estimation while providing higher resolution flow field and improved temporal stability. Furthermore, the proposed importance sampling–based Bayesian workflow offers a stochastic approach to explore the velocity index (α) for converting surface velocity to depth-averaged velocity. Overall, this study presents an integrated framework ranging from image enhancement and surface velocity estimation to discharge computation, supporting robust and nonintrusive flood flow analysis in natural streams.