Augmenting LSPIV Surface Current Measurement with Drifting ASVs

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***Abstract*— Large Scale Particle Image Velocimetry (LSPIV) has been successfully used in the field to gather water surface flow data, which is critical to understanding complex geomorphic, hydrologic, and ecological river processes. Its success, however, depends on lighting conditions and adequate flow seeding with trackable debris or visual features, that can be hampered by environmental disturbances such as wind or wildlife. Instead, this research proposes augmenting traditional LSPIV methods by incorporating autonomous surface vehicles (ASVs) as pieces of actuated debris. This addressses the shortcomings of artificial seeding with tracers that may not be recoverable and impractical. Our method uses initial image velocimetry flow estimates to guide an ASV to sparsely seeded or poorly illuminated regions within the survey area. There it can be set adrift and tracked from above to capture additional measurements to improve the surface flow field reconstruction. We compare conventional techniques with our augmented LSPIV system in simulation and in field tests. The results showcase performance and capability enhancements ASVs can provide.**

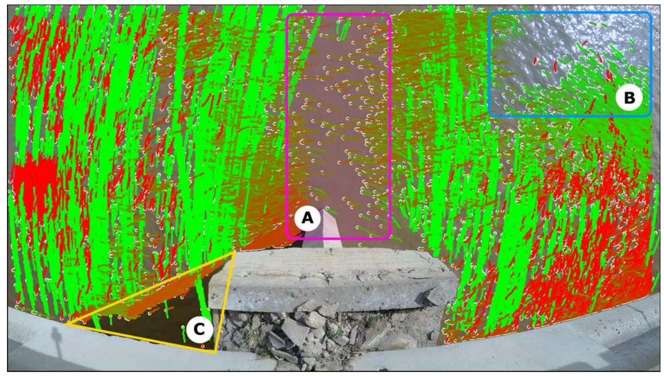

Fig. 1: Environmental illumination, disturbances, and seeding can impact the quality of LSPIV measurements

I. Introduction

Though much of the world's landmass has been mapped and studied, our knowledge of the planet's water-covered regions is strikingly limited in comparison. Much of this stems from the fact that these areas are less accessible, making data collection significantly more challenging and expensive. Further difficulty arises from the need to measure more complicated parameters than standard bathymetric readings to understand and model a hydrological system; knowledge of the movement of the water is critical to the study of a variety of hydrological phenomena and often required for many engineering applications such as channel reconfiguration, bank stabilization, floodplain reconnection, in-stream habitat improvement, and dam removal [18].

In order to characterize the currents in a body of water, there are a number of techniques and equipment available that can be used to collect individual flow measurements or velocity profiles throughout the survey region [20]. These methods range from from relatively simple approaches involving manually tracking buoyant objects drifting with the flow [13], [3], to the deployment of increasingly sophisticated instrumentation at points throughout the measurement area [8], [2], [9]. Since the efficacy and performance of these methods can vary widely with environmental conditions, the choice of appropriate current measurement technique depends on the specific survey scenario and the resources available.

A popular technique used to produce instantaneous surface flow measurements across a visible area is Large Scale Particle Image Velocimetry (LSPIV), which involves capturing video of the desired measurement region and tracking patterns on the water surface across frames [7], [16]. The performance of the computer vision algorithms that form the crux of this method, however, is highly dependent on illumination conditions and the distribution of trackable features within the flow [17]. Inadequate or changing ambient lighting conditions may cause the algorithms to lose track of surface patterns or register undesirable false positive detections due to effects such as glare or shade on the water [11]. In addition, external influences such as those due to wind, wildlife, and moving reflections can generate tracks that contradict the true surface flow of the water and adversely impact the accuracy of the flow approximation. Finally, water conditions and domain structure can conspire to limit the features that can be detected and tracked with LSPIV. Although previous research has developed techniques to mitigate this issue by using specular reflections as a seeding surrogate [4], [15] or artificially seeding the flow with tracer particles [14], [6], ambient lighting and the additional infrastructure involved with tracer deployment and recovery may not be appropriate in certain survey scenarios.

The effects of these environmental factors can be seen in the raw feature tracks collected during LSPIV presented in figure 1 above. The tracks in this image are colored on a gradient from green to red based on their alignment with the direction of flow in the river pictured, with green denoting movement with the flow and red indicating movement against the flow. Although most tracks recorded generally

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move downstream, changing wind conditions during this deployment cause LSPIV to pick up brown and red paths that do not represent the true surface currents. Figure 1 also illustrates the importance of adequate flow seeding for LSPIV; in areas where the flow is slower and less debris is present, such as region A immediately downstream of the bridge pylon, insufficient trackable features limit the number of surface current measurements a typical LSPIV system can obtain. Finally, the adverse effects of ambient illumination are also evident in the lack of detections in the region of strong glare in the top right of the image, and the false tracks detected along the boundary of the shadow cast by the bridge pylon, denoted as regions B and C respectively. Addressing some of these concerns to expand the utility and improve the performance of LSPIV is the focus of this work.

Contributions: This research seeks to augment existing LSPIV techniques by incorporating specifically configured autonomous surface vehicles to address traditional weaknesses of these methods and reduce the infrastructure required to deploy LSPIV systems in the field. ASVs outfitted with visual features and/or markers that facilitate tracking in a variety of lighting conditions, can autonomously navigate to the survey area and then be directed to drift through information-lucrative regions within the flow while being tracked from above by the LSPIV measurement system. This approach essentially allows one to use ASVs as pieces of actuated debris that are robust to illumination conditions and can provide additional data on demand in regions and scenarios problematic for standard LSPIV methods. Calibrated markings on the vehicle can also dramatically reduce the infrastructure typically used to compute the camera parameters needed to transform and scale measurements of the surface flow field collected in the image frame to the world frame, thereby reducing the cost and time to deploy or move an LSPIV system in the field. Furthermore, additional instrumentation can be deployed aboard the ASVs to concurrently sample surface flow or other environmental fields of interest. Properly outfitted, an ASV can also be utilized to generate additional surface features upstream of the survey area by churning up foam or stirring up sediment. When the measurements are complete, the vehicles can autonomously navigate to a convenient designated extraction point, eliminating the burden of artificial tracer collection and any fears of environmental contamination. In the following section we describe the architecture of a typical LSPIV system and develop the methodology for integrating an ASV.

II. Methodology

In this section we describe our LSPIV implementation and how it can be augmented to incorporate measurements obtained by visually tracking drifting ASVs in order to address typical shortcomings of LSPIV.

A. Conventional LSPIV

Traditional LSPIV systems are generally comprised of several common components, each of which can be implemented using various techniques and algorithms. Although the particulars of how these components are arranged and how information moves through the LSPIV pipeline vary across implementations, the typical process can be conveniently partitioned into stages of flow visualization, image acquisition and analysis, measurement rectification, and flow field reconstruction[16].

1) Flow Visualization: In order to successfully measure the movement of the water surface using LSPIV, one must first identify a set of proxy measurements that can be obtained from images of the scene. When applying particle image velocimetry (PIV) in a laboratory setting, the flow being studied can be specifically illuminated or densely seeded with artificial particles designed with minimal mass to reduce inertial effects and with visual characteristics that simplify detection in images [1]. For field applications in large-scale flows such as rivers, a dense seeding of this nature is impractical and ambient illumination is beyond control, necessitating an alternate approach. Instead, a common approach is to detect and track light surface debris or foam floating with the water flow. Unfortunately such natural flow seeding may be unavailable across the entire survey area in sufficient density to capture all aspects of the flow. Another feature used successfully as a surrogate for tracer particles in the field are the reflections formed by light interacting with surface perturbations in the flow [6], [15]. This approach, however, is dependent on favorable lighting conditions and susceptible to influence from environmental disturbances such as strong wind or rain. A final alternative is to artificially seed the flow taking care to choose particles that accurately follow local flow movements, minimizing effects due to inertia and particle submergence. Once an adequate source of proxy measurements has been identified or constructed, LSPIV can proceed.

2) Image Acquisition and Processing: In contrast to the complex camera systems often employed for PIV in the lab, when performing LSPIV in the field, it has been shown that video at 30 frames per second from conventional cameras is sufficient for capturing the velocities typically encountered in hydraulic and hydrologic applications [16]. Whether the image data are collected and processed offline at a later time or processed online as image frames are collected, the general procedure is the same; patterns or features are identified in an image and then searched for in the following frames. The actual implementation of this process can be accomplished with a variety of computer vision algorithms depending on the application requirements, but for the purposes of investigating the effect of incorporating an ASV, this work will detect Shi-Tomasi features and track them across frames using the Lucas-Kanade optical flow technique. Although many traditional LSPIV implementations will modify the input images to compensate for lens distortion and perspective projection effects prior to detecting and tracking features, doing so can distort noise models due to averaging and may introduce aliasing effects, thereby adversely affecting tracking performance [10]. Instead the images are processed in their raw state and once particle tracks are computed in the image frame, they can be fed into the same camera distortion and projection models to calculate actual measurements of the surface flow in the world frame.

3) Measurement Rectification: In order to compute the movement of particles in the real world from the movement of their projection in the collected images, an LSPIV system must transform the coordinates of each particle track detected. In addition, any lens distortion from the camera used to capture the data must also be accounted for to obtain accurate flow velocities in world coordinates. By calibrating the camera used for data collection, the distortion coefficients and camera intrinsics can be determined and used to convert particle trajectories in image coordinates to trajectories in the camera frame. To obtain more accurate results, particularly when the camera is mounted at an angle to the surface of the water, the camera extrinsics must be computed to correctly account for perspective effects. In LSPIV systems this is often accomplished by including a number of marked ground reference points in the camera field of view for which the real world coordinates are known. After the particle trajectories have been transformed from the image frame to the world frame, they can be differentiated to obtain surface flow velocities along the trajectories.

4) Field Reconstruction: The final stage of the LSPIV process is to aggregate and process the velocity measurements that have been computed and produce the desired representation of the flow field. This stage varies depending on the application requirements ranging from a simple interpolation across the survey area using the computed measurements to building a more complete model of the flow. In this work we chose to feed measurements collected into a Gaussian Process Regression in order to build a model of the flow field, which can be used to predict flow velocity at arbitrary points across the survey area and additionally provide the uncertainty of a predicted flow velocity, which could be used to identify regions requiring additional seeding. Through extensive simulation and analysis of real-world data, we determined a mixture of multiple Matern 5/2 kernels with varying lengths scales, input dimensions, and constraints as well a rational quadratic kernel performed well and produced reasonable field reconstructions in a variety of scenarios.

B. ASV Augmented LSPIV

As previously suggested, the introduction of a properly configured ASV into a LSPIV system can produce benefits across multiple stages of the LSPIV process. In this work we focus on tracking an unpowered drifting ASV in order to produce additional particle trajectories that are then transformed and integrated with measurements acquired with traditional LSPIV to improve the surface flow velocity field reconstruction. The ASV is outfitted with two colored panels that are initially used to segment the boats from the river surface using color segmentation in the HSV color space. The ASV detection is then used to initialize multiple KCF trackers to track each colored panel and the ASV as a whole, which we use to estimate a track for the center of mass of the vehicle [12], [5]. Figure 2 shows an example of the new data collected while tracking the ASV during several passes through the survey area.

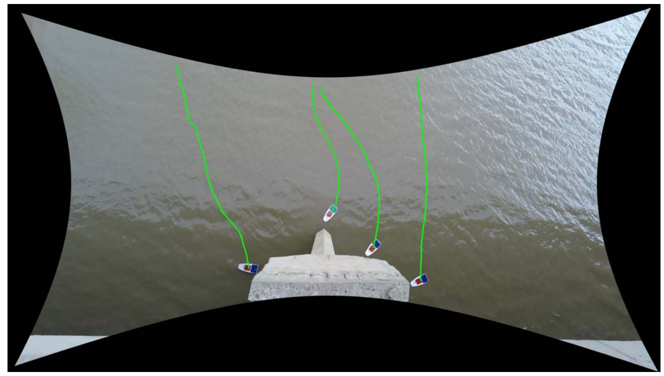
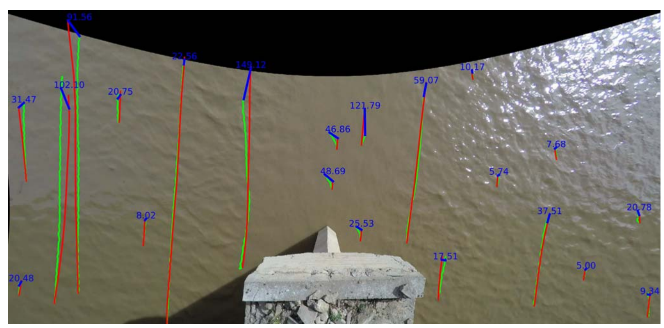


Fig. 2: Using the LSPIV camera to track an ASV drifting with the current provides additional surface flow information

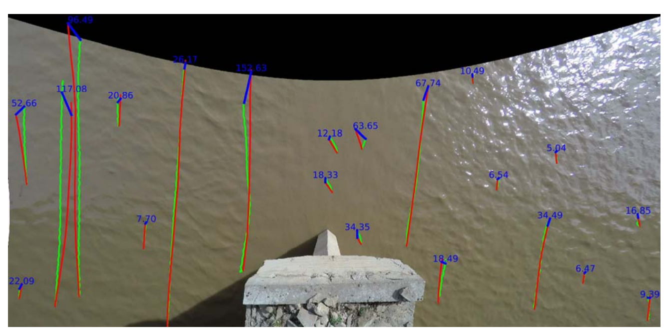
III. Field Experiment Results

We consider two preliminary field experiments, which aim to justify the reasoning behind augmenting LSPIV with an ASV and show that is it feasible to incorporate measurements extracted from an ASV track into the field reconstruction.

A. LSPIV Holdout Validation



(a) Analysis of field reconstruction approximated using data subset



(b) Analysis of field reconstruction approximated using complete data

Fig. 3: Predicted and actual drift paths of test particles

In this experiment we collect and process LSPIV data from a fixed location on a bridge overlooking as section immediately downstream of the bridge pylon obstructing the flow. In order to validate our methodology and motivate ASV augmentation, we first purposely withhold all data collected in the region downstream of the pylon and compute the surface current field approximation without this data, simulating inadequate seeding in a region of the flow. We then evaluate our results by using this field approximation to predict the drift of a disjoint set of test particles that were tracked by our system but not taken into account during reconstruction. The results of this analysis are presented in figure 3a where we denote the true test particle tracks in green, the tracks predicted using the field reconstruction in red, and the maximum error that occurs between the two in blue.

We next repeated the same procedure, this time without withholding any LSPIV measurements collected during the experiment and performed the same drift prediction analysis using the same disjoint set of test particles to evaluate the updated field approximation. The results of this analysis are presented in figure 3b alongside results from the previous approximation.

From these results, we can observe that the test tracks behind the pylon where data was withheld in the reconstruction clearly exhibit a higher drift error relative to their length as compared to tracks in other regions where measurements were available to the approximation. As hypothesized, when the measurements in the region behind the pylon are incorporated into the field reconstruction, the maximum drift error of test tracks in the region was in general reduced and the direction of the predicted tracks showed better agreement with the ground truth data.

TABLE I: Simulated Insufficient Seeding Drift Prediction

Error Metric	Data Subset	Complete Data
Average Mean Error (px)	20.44	**19.45**
Average Max Error (px)	41.03	**38.08**
Average Mean Normalized Error (px)	10.81	**8.01**
Average Max Normalized Error (px)	14.92	**12.12**

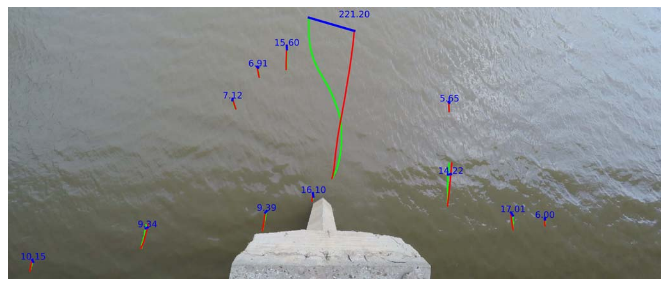
This analysis is borne out by the quantified results, which are presented in table I which show decreased errors across the board. Future iterations of this analysis will examine the average drift errors of the tracks within and without the region behind the pylon separately to discover to what extent large improvements in the region cancel worse performance in other areas of the reconstruction domain.

Several metrics used to quantify the results are provided in table I. In particular, we present the mean and max errors between true and predicted tracks, averaged across all test tracks as well as a normalized version of these metrics that accounts for the test track's length. The normalized variant is useful when the test tracks are of varying lengths, as is the case in this experiment.

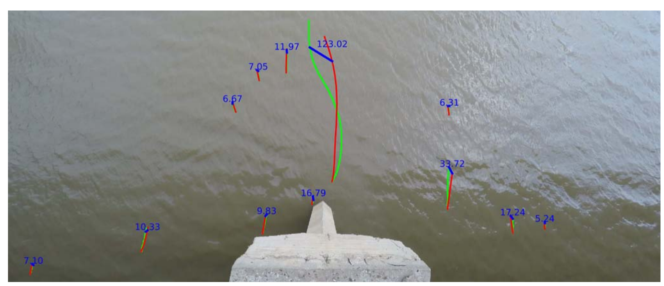
B. ASV Augmented LSPIV

With the results from the LSPIV holdout experiment seemingly indicating we can improve field reconstruction by gathering additional data in sparsely seeded regions, we consider a scenario in the same location but with stronger wind and varying lighting conditions, which introduce significant disturbances and vastly reduce the number of valid tracks our LSPIV system can detect. As in the previous experiment a disjoint set of test particles that was detected and tracked by the LSPIV system is held out of the approximation and used to evaluate the quality of the reconstruction, however this time a single test track produced by tracking the ASV is also included. In order to achieve more accurate results, we assume some simple dynamics to model the movement of the ASV based on an approximation of the vehicle's drag, as opposed to the massless assumption used to predict particle movement. We first ran the field reconstruction algorithm on data produced by LSPIV alone. The results are presented in figure 4a and quantified in table II below.

In order to evaluate the effectiveness of using ASV tracks to augment our LPSIV performance, we repeated the analysis, this time incorporating measurements from three ASV tracks into the reconstruction. The results of this analysis are shown in figure 4b and quantified in table II.



(a) Analysis of field reconstruction approximated using LSPIV data alone



(b) Analysis of field reconstruction approximated using LSPIV and ASV data

Fig. 4: Predicted and actual drift paths of test particles using surface flow approximations computed from LSPIV data and ASV track data

TABLE II: LSPIV and ASV Augmented Drift Prediction

Error Metric	LSPIV	LSPIV + ASV
Average Mean Error (px)	12.61	**10.54**
Average Max Error (px)	28.23	**21.27**
Average Mean Normalized Error (px)	4.01	**3.98**
Average Max Normalized Error (px)	5.27	**5.24**

From these results, we can conclude that the field approximation performs well when the test tracks happen to fall close to better seeded regions where more measurements are available. Unfortunately, because the test set is in large part reliant on tracks themselves detected with LSPIV, few are available in the problematic areas with insufficient seeding. For this reason, a single track produced with the ASV was added to the test set and in future experiments more passes with the ASV will be performed to generate enough tracks to create a disjoint test set that better spans the domain while allowing for sufficient ASV data to be included in the reconstruction.

Looking at the augmented LSPIV results, we can observe a moderate improvement across all evaluation metrics when the ASV data is incorporated into the approximation. The most dramatic improvement occurs with the ASV test track prediction, which suggests the measurements extracted from other ASV tracks may have some effects from vehicle dynamics that are not yet adequately accounted for. Several of the other test tracks, however, clearly experience modest improvements from the ASV data, motivating the need for additional experiments with denser ASV tracks and additional analysis comparing particle test tracks separately from ASV test tracks.

IV. Conclusion

In the results of our first field experiments we have demonstrated a clear value to collecting additional data in sparsely seeded regions when using LSPIV and showcased a real world scenario where traditional LSPIV data collection fails to produce adequate coverage of a region when adverse environmental effects are present. Furthermore, we have shown that ASV track data can successfully be incorporated into field reconstruction techniques potentially improving the field reconstruction near the new data and with minimal adverse effects to the rest of the approximation. We have also shown that an ASV can be tracked with relative ease through regions of strong glare or environmental disturbances, undeterred by changing ambient scene lighting conditions. These preliminary results suggest that ASVs can be a valuable tool to improving surface flow field estimation over traditional LSPIV techniques alone, and motivate several avenues of future work.

V. Future Work

Going forward, we hope to revisit the data from our field experiments and consider the localized vs. global effects of collecting additional data for use in approximation to obtain further insight into which areas should be targeted for ASV data collection. This information along with the variance of the reconstructed fields will be incorporated into a path planner that can guide the ASV autonomously to maximize information gain. Furthermore, we hope to make use to the current knowledge of the flow field to plan energy efficient trajectories, with the ultimate goal of creating a system that can minimize the energy needed to exhaustively map a region within a moving flow field with incomplete prior knowledge of the field.

We hope our work in this area can facilitate the convenient gathering of large amounts of surface flow field data across various domains worldwide. These large datasets will open up interesting applications of using machine learning techniques to learn the correlations between bathymetric maps or overhead river imagery and the type of surface flow distribution that may be present, giving, potentially providing a surface flow prior for unsurveyed areas given only satellite imagery or topographical maps of the area. Coupled with a UAV, this system could further reduce the infrastructure needed to collect surface flow field data and speed up field approximation [19].

We also see the potential of learning to automatically adapt ASV dynamics models to changing environmental conditions, vastly simplifying the difficulty in accurately modeling fluid dynamics and accounting for environmental disturbances. The same techniques could be applied to classify and estimate particle characteristics to further improve current field measurement extraction.

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