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PTV-Stream: A simplified particle tracking velocimetry framework for stream surface flow monitoring

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ABSTRACT

Particle tracking velocimetry (PTV) is a promising image-based approach for remote streamflow measurements in natural environments. However, most PTV approaches require highly-defined round-shaped tracers, which are often difficult to observe outdoors. PTV-Stream offers a versatile alternative to cross-correlation-based PTV by affording the identification and tracking of features of any shape transiting in the field of view. This nearest-neighbor algorithm is inherently thought for estimating surface flow velocity of streams in outdoor conditions. The procedure allows for reconstructing and filtering the trajectories of features that are more likely to pertain to actual objects transiting in the field of view rather than to water reflections. The procedure is computationally efficient and is demonstrated to yield accurate measurements even in case of downsampled image sequences.

1. Introduction

In recent years, an increased attention has been devoted to multidisciplinarity and innovation in sensing the hydrological cycle (Tauro et al., 2018). Affordable and versatile sensing systems may in fact help mitigate the limitations of traditional measurement stations that currently offer poor spatial coverage but require expensive maintenance (Gleick, 1998; Hannah et al., 2011). Among the new generation of experimental instruments, optical methodologies and image analysis have contributed to advance hydrological observations in several fields. For instance, precipitation, streamflow, and plant water stress are routinely monitored using images (Allamano et al., 2015; Muste et al., 2008; Ludovisi et al., 2017; Abrantes et al., 2018). Integration of optical methods with unmanned aerial vehicle (UAV) technology (Tauro et al., 2015; Perks et al., 2016; Manfreda et al., 2018) and participatory science has also opened up new frontiers in distributed hydrological observations (LeBoursicaud et al., 2015; Le Coz et al., 2016).

Streamflow observations have highly benefitted from optical methods, and the use of image analysis for river monitoring is documented since the 1990s. For instance, large scale particle image velocimetry (LSPIV) is a promising technique that is vastly adopted in hydrology to estimate the surface flow velocity field of water bodies and may be applied to flash flood observation (Jodeau et al., 2008) and to the digital mapping of riverine features (Hauet et al., 2009). Other image-based approaches involve particle tracking velocimetry (PTV) and optical flow that have also been utilized to investigate diverse phenomena spanning from irrigation (Félix-Félix et al., 2017) to volcanic dynamics (Gaudin et al., 2014). Several image-based streamflow studies rely on the installation of permanent and cost-effective gauge-cams in the proximity of the water body of interest to continuously monitor flow dynamics (Bechle et al., 2012; Tauro et al., 2016; Huang et al., 2018). These automated systems comprise digital cameras, controlling units, and, in some cases, laser systems for fully remote photometric calibration. Gauge-cams collect a large volume of images of the water surface that can be off-line analyzed to inspect the streamflow regime at high temporal resolution. However, image-based techniques and gauge-cams are rarely systematically implemented in practical engineering operations probably due to the lack of consistent image processing protocols.

In previous streamflow studies in diverse riverine environments (Tauro et al., 2016; Tauro and Salvatori, 2016; Tauro et al., 2017), correlation-based PTV has been successfully applied to estimate the surface flow velocity field. PTV typically revolves around two phases: particle identification and tracking (Lloyd et al., 1995). In the first phase, images are enhanced to emphasize the appearance of particles in the field of view (for instance, by applying filters and thresholds) and the location of the centroid of the particles in frames is recovered. In the tracking phase, the centroid of the detected particles is identified in subsequent images to reconstruct particle trajectory. Several algorithms have been developed for PTV analysis. In Lloyd et al. (1995), Brevis

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et al. (2011), cross-correlation is implemented for both particle detection and tracking. In addition, relaxation (Wu and Pairman, 1995), heuristics based on a priori knowledge of the flow (Tang et al., 2008), and Voronoï tracking scheme (Aleixo et al., 2011) have also been utilized. Upon PTV processing, particle trajectories are reconstructed based on velocity vectors that are randomly located in the field of view. Surface flow velocity maps can be generated by interpolating particle trajectories.

PTV presents several advantages with respect to alternative approaches. Firstly, it allows for identifying and reconstructing the trajectory of individual features transiting in the field of view, thus tangibly relating velocity estimations to physical objects. By imposing conditions on the trajectories, see for instance Hassan and Canaan (1991), Tauro et al. (2017), velocity measurement accuracy can be considerably improved. Further, PTV does not involve spatial averaging and can be successfully adopted in case of velocity gradients (Fuchs et al., 2017).

PTV is designed for low seeding density flows and does not require assumptions on flow steadiness nor on the relative position of neighbor particles. Its applications in hydrological sciences are diverse and involve dispersion in porous media (Moroni and Cushman, 2001), exchange processes between rivers and groynes (Uijttewaal et al., 2001; Yossef and deVriend, 2011) and tidal patterns (Kimura et al., 2011), and sediment transport (Radice et al., 2017; Ballio et al., 2018). In most algorithms, PTV is dependent on the presence of tracers whose shape is a priori known. Such a feature has considerably limited the implementation of PTV in outdoor experimental studies where the controlled deployment of particles may be challenging. In fact, the instance of naturally occurring round features is rare, and deploying a large amount of particles in difficult to access riverine environments can be impractical. On the other hand, the alternative LSPIV approach has been extensively applied (Fujita et al., 1997). This technique applies the principles of classical Particle Image Velocimetry (PIV) (Adrian, 1991, 2005; Raffel et al., 2007; Peterson et al., 2008) to recognize and track patterns on the water surface of natural streams, and may be applied also without deploying objects in the current (Tauro et al., 2017). For a comparison between LSPIV and PTV, refer to Tauro et al. (2017).

Experimental PTV applications entail: i) definition and imaging of the field of view; ii) orthorectifying images through transformation schemes that rely on the known coordinates of a minimum of six ground control points (GCPs; in this phase, photometric calibration and camera lens distortion removal may also occur); and iii) image processing. In Tauro et al. (2014), image orthorectification and GCPs surveying are prevented by maintaining the camera optical axis perpendicular to the field of view and by utilizing medium-power lasers to create reference points at known distance in images, thus enabling fully remote photometric calibration.

In this work, we propose a novel simple PTV approach, PTV-Stream, specifically aimed at estimating the surface flow velocity of natural water bodies in outdoor conditions. The procedure functions as a nearest-neighbor algorithm, whereby low seeding density is assumed in the field of view. Tracers of any shapes can be identified and tracked in images based on their luminance with respect to the background. The algorithm requires a priori known direction of the flow average velocity that should be approximately perpendicular to the cross section, and allows for reconstructing and filtering tracer trajectories that are more likely to pertain to actual objects transiting in the field of view rather than to water reflections. The procedure is developed in Java and offers a computationally efficient alternative to correlation-based PTV schemes. In this study, we apply PTV-Stream to experimentally controlled videos taken on the Brenta River and to a video of a moderate flood in the Tiber River. We compare our PTV-Stream findings to the cross-correlation-based PTV procedure developed by Brevis et al. (2011) and implemented in Tauro et al. (2017) (correlation-based PTV in the rest of this manuscript) and to independent benchmark data collected with a current meter or with radar technology.

Particle recognition

1. Luminance threshold
2. Relative pixel distance grouping

Particle tracking

1. Parent-child association
   1. Parent-child trajectory parallel to flow
   2. Consistent parent-child areas
2. Trajectory filtering
   1. Trajectory covers most of field of view
   2. Trajectory is parallel to flow

Velocity estimation

1. Frame-by-frame velocity
2. Iterative procedure to remove velocity outliers

Fig. 1. Flowchart of PTV-Stream.

2. PTV-Stream

PTV-Stream is a particle tracking procedure that aims at identifying the trajectories of objects floating on the stream surface and passing through the field of view. The method can be applied on a sequence of images recorded at a fixed acquisition frequency with an RGB camera. The outputs of the procedure include the objects' trajectories and velocities in pixels per frame. The metric dimension of pixels must be independently estimated to obtain output velocities in meters per second. The sequence of images may be obtained from video captured with permanent cameras, mobile setups, and aerial platforms. Photometric calibration may be attained by a priori determining the camera intrinsic parameters and through camera geometric calibration in laboratory conditions. Alternatively, similar to Tauro et al. (2016, 2014), the system of low power lasers may be used.

PTV-Stream is organized in three main phases: particle recognition, particle tracking, and velocity estimation, see Fig. 1. Different from traditional PTV approaches, PTV-Stream does not involve interpolation of results. Rather, trajectory-based average velocities are computed in the region of interest. This is related to the fact that homogeneously and densely seeded water surfaces are rarely encountered in field settings. Therefore, interpolating sparse instantaneous velocities may result in significant uncertainty. Towards a correct implementation of the algorithm, it is assumed that the camera field of view is directed with its width along the river cross-section and that the height of the field of view is approximately orthogonal to the cross-section. Further, particles are assumed to follow the stream average flow direction and, therefore, their trajectories should be fairly orthogonal to the river cross-section. These simple assumptions are consistent with previous work by Hassan and Canaan (1991) and can be easily verified by properly orienting the camera in the experimental setup or rotating captured images. It is also advisable to preliminarily take a look at experimental videos to roughly determine the average dimension of the tracers transiting in the field of view, their luminance in varying illumination conditions, and the average frame-to-frame pixel displacement.

The particle recognition phase is an appearance-based method that detects objects based on their luminance without searching for specific geometric shapes. Object detection is directly conducted on RGB images. Specifically, since floating material can be lighter or darker than the background, in the experiments, we arbitrarily choose to track light tracers and discard dark ones, even though the opposite choice is also possible. Therefore, all pixels whose luminance is higher than a certain threshold value are regarded as pertaining to a potential