

Lagrangian Analysis of River Flow from UAV Videos to Characterize Mixing

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Abstract

Attempts have been made to test the river-scale particle tracking velocimetry (PTV) method using UAV videos in the River Danube. A MATLAB-based algorithm has been improved for the image post-processing, which reconstructs the trajectories of a hundred of floating particles. The PTV results are compared to ADCP measured velocity field. The resulted trajectories are analyzed both by their chaotic and mixing characterization. Calculated local Lyapunov exponents will be categorized by the trajectories' characteristic features. The particle distribution changes in time will be analyzed to characterize mixing.

Keywords

ADCP; Lagrangian flow description; Lagrangian statistics, local Lyapunov exponent; mixing; PTV; UAV

INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are increasingly used in the field of engineering surveys. In river engineering, or in general, water resources engineering UAV based measurements have a huge potential. Indirect video-based velocity measurement methods, e.g. Large-Scale Particle Image Velocimetry (LSPIV) (Muste et al., 2008; Detert & Weibrecht, 2017) and Space-Time Image Velocimetry (STIV) (Fujita et al., 2006), became a real alternative for direct flow measurements. These methods deal with the Eulerian analysis of the flow, i.e. the flow is described at fixed points. However, the airborne video recordings inherently allow us to observe the surface processes based on a Lagrangian view, i.e. to describe the flow field with moving particles in the water. In this study the Particle Tracking Velocimetry (PTV) method was applied to assess the spatially complex nature of the flow field in a large river. To the authors' knowledge no such analysis has been performed yet to describe the flow field and mixing processes in large rivers.

STUDY SITE

In the present research floating tracers has been released at a groyne field in the Danube River in Hungary, near Göd. The width of the river is about 300 m, and the mean velocity is about 1 m/s. This river section was chosen because the continuously detached eddies generated by the groynes result in complex flow dynamics here. Moreover, mixing processes in the shear zone between the main flow and the dead (recirculation) zone cannot be well described with conventional Eulerian methods. Similar PTV measurements have been made at groyne fields by Zsugyel et al. (2012a) in a simplified laboratory setup.

METHODS

Field measurements

In Figure 1 an illustration of the field measurements is shown. Hundreds of yellow tennis balls are used as tracers (released from the boat from upstream), which are suitable for the image processing

method and detailed information can be acquired about the surface flow. A *dji Phantom 3 Standard* type UAV was used to capture the tracers floating on the water surface in the study site. First, the UAV videos were taken at the tip of the groyne, then after the tracers left the UAV's field of view (FOV), the UAV has moved to another position where the tracers were in the FOV again. The FOV was about 85x130 m from 60 m altitude.

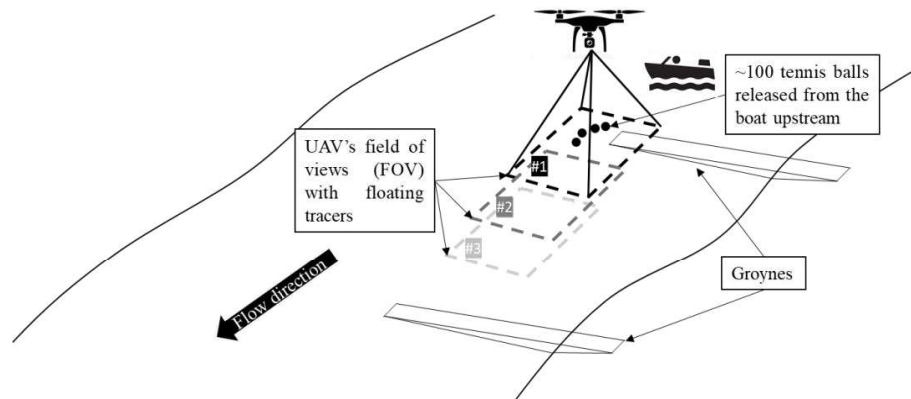


Figure 1. Schematic illustration of the UAV measurements in the River Danube

Additionally, complementary Acoustic Doppler Current Profiler (ADCP) measurements were also performed from a moving boat to capture the 3D flow velocity field. The post-processed ADCP measurements provided an Eulerian spatio-temporally averaged flow field, which could be directly compared with the Lagrangian approach.

Image processing algorithm

A multi-object tracking algorithm in MATLAB has been improved to analyze our UAV videos. The structure of the algorithm is shown in Figure 2. The algorithm has two main parts: (i) the tracer particles are detected on each frame and (ii) every single detection is matched together along the image sequence. In the next paragraphs the detailed process of the algorithm is given. In order to fasten the calculations, in the first step, a color mask has to be applied on every image. Accordingly, only the yellowish pixels remained in the analyzed frame, supporting to decrease the number of failed detections. Then, the size parameter of the Gaussian filter needs to be set, which is the diameter of the tracked object in pixels. Applying this filter, the center of the tracer will be brighter than the background. Figure 3a and b show this so-called blob size setting. This Gaussian filter was applied over the whole image (Figure 3c) to detect the tracers. Tracers are recognized where the blob image has a maximum value. A local 2D maximum value finder is used to localize the center of the tracers.

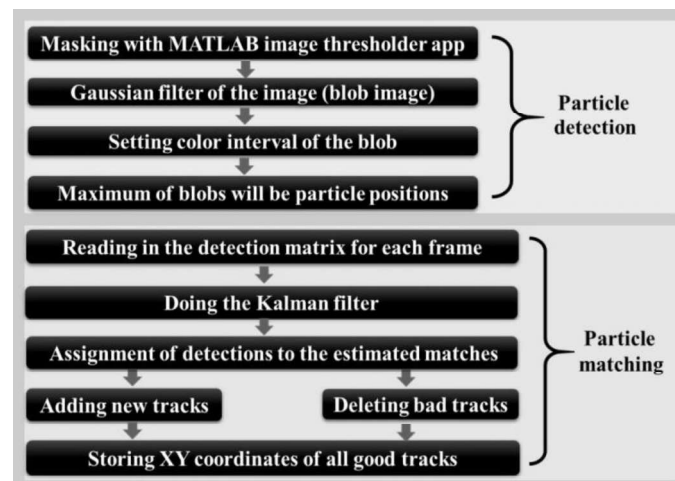


Figure 2. The structure of the improved multi-object tracking algorithm

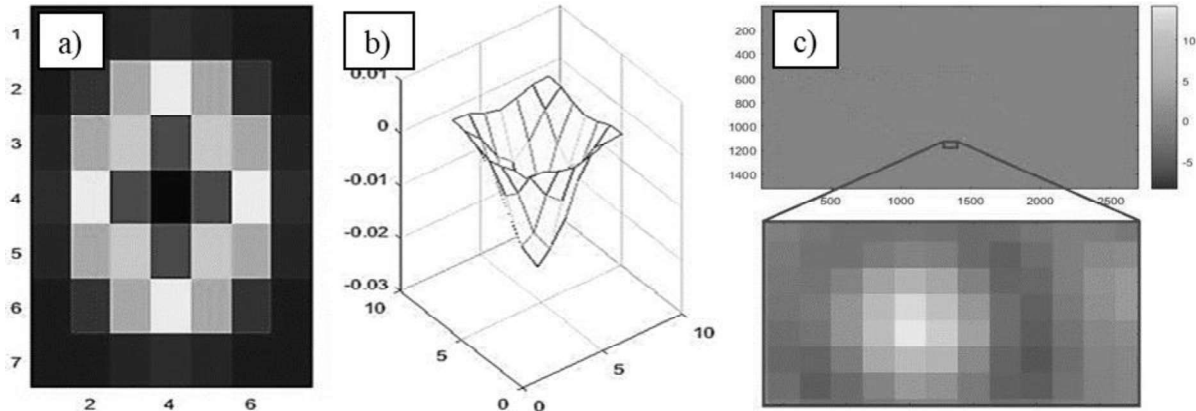


Figure 3. Gaussian filter: blob size = 7 pixel (a and b) and the whole blob image (c)

Next, knowing the tracer positions on every frame, they need to be matched together. The detections are assigned to the estimated track positions by using a cost function, resulting the X and Y trajectory matrices. If the detection is too far from the estimated position, it will be rejected. The next step is finding new detections. The tracks which did not get assigned is basically a new tracking. If the tracking did not get matched up, it gets a strike, and if a track has a strike greater than a predefined number, the tracking will be deleted from the matrix. Eventually, only the good trajectories are stored in the final X and Y matrices in pixel unit, which are converted into the local coordinate system. After testing the algorithm, the collected videos have been processed, reconstructing the trajectories of the tracers in the video.

Characterization of mixing

In this study the mixing has been characterized using two methods. First, the probability density functions (PDFs) have been calculated of the transversal and streamwise displacement of the particle plume at six time-instants, starting from the first recorded frame. The flattening and widening of the PDFs are expected with time.

Second, the so called anomalous relative displacement according to Spydell et al. (2007) has been calculated. The relative displacement $\mathbf{r}(t)$ of a single trajectory is

$$\mathbf{r}(t) = \mathbf{r}(t_0 + t) - \mathbf{r}(t_0), \quad (1)$$

averaging this for all t_0 and all tracer particles results in the mean displacement function $\mathbf{R}(t)$.

Anomalous relative displacements are

$$\mathbf{r}'(t) = \mathbf{r}(t) - \mathbf{R}(t). \quad (2)$$

At given time-instants (t), a 2D PDF ($C(r'_1, r'_2, t)$) was determined, where r'_1 and r'_2 stand for the streamwise and transversal directions, respectively. In this study the 2D probability density function has been calculated from the 30 longest trajectory data at four time-instants, $t = 1$ s, 5 s, 10 s and 15 s. The displacements are expected to be greater in the streamwise direction because of the main flow direction of the river.

Characterization of chaos

A possible way to quantitatively describe the spatially and temporally complex nature of the flow at such locations using the PTV results, is to reveal the chaotic nature of the flow. The traditional way to characterize this chaotic feature is the determination of the standard Lyapunov exponent of chaotic advection (Tél and Gruiz, 2006). Accordingly, if the initial distance is small between two

particles, the growth of the distance in time is proportional to an exponential factor. The Lyapunov exponent (λ) is described as:

$$\Delta r = \Delta r_0 \cdot e^{\lambda t}, \quad (3)$$

where Δr is the distance between particles at t time-instant, Δr_0 is the initial distance and λ is the Lyapunov exponent. The reciprocal of the Lyapunov exponent can be interpreted as the local prediction time (τ):

$$\tau = \frac{1}{\lambda}, \quad (4)$$

which is the characteristic time scale under which information on the initial conditions is being lost in a system. While Zsugyel et al. (2012) used 3-5 particles to analyze this phenomenon, whereas in this study hundreds of particles could be analyzed, providing more detailed information on the chaotic nature of the flow. The trajectories of a 40-second-long video have been reconstructed, out of which the longest ones were chosen out. 45 particle pair's growth of distance have been calculated and analyzed.

RESULTS AND DISCUSSION

Eulerian (ADCP) versus Lagrangian (PTV) flow assessment

In Figure 4 the trajectories reconstructed from the PTV analysis (left panel) and the steady-state streamlines fitted on the ADCP based flow velocity distribution at the free surface (right panel) are shown. In the figure, the rectangle shows the UAV's FOV located downstream from the tip of the groyne. The differences between the two images clearly underline the additional information on the complex flow patterns contained by the PTV based analysis. The enhanced transversal relocation of the tracers indicates the significant mixing effect of the vortices generated by the shear layer at the groynes. Statistical analysis on the instantaneous velocity fields, a quantitative assessment on mixing parameters can be performed, which cannot be directly derived from ADCP based flow fields.

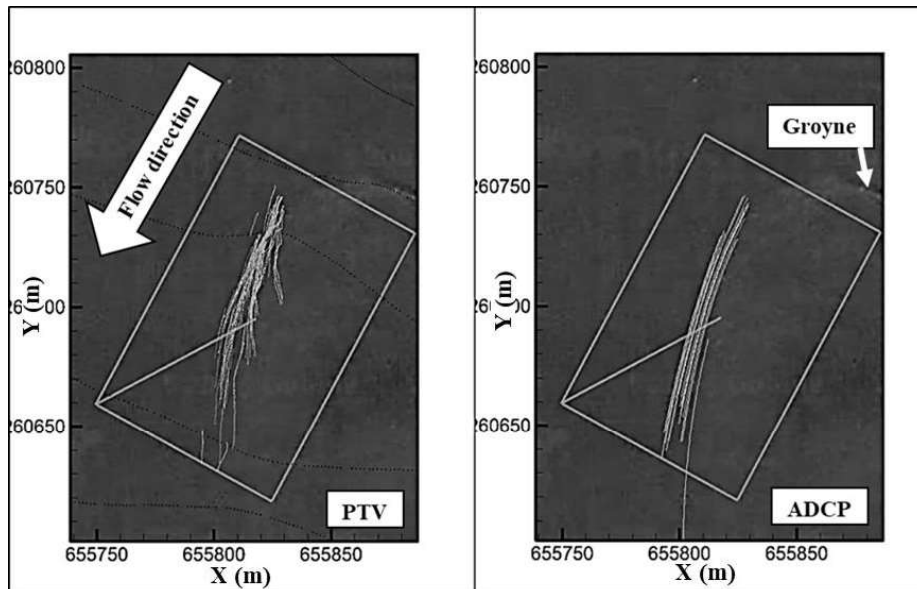


Figure 4. Comparison of the trajectories resulted from the PTV reconstruction and the ADCP velocity field

Characterization of mixing

Probability density functions (PDFs), or normalized histograms of the transversal and streamwise displacements have been calculated at $T = 0$ s, 30 s, 60 s, 90 s, 150 s and 210 s, starting from the

first recorded frame (Figure 5). In Table 1 the spatial extension changes of the tracer plume are summarized. Note, that the UAV's FOV was 130 x 85 m so at $T = 210$ s, the plume might be larger than 130 m but could not be measured.

Table 1. The changes of the transversal and streamwise extension of the plume

Time (T)	0 s	30 s	60 s	90 s	150 s	210 s
Transversal	<10 m	40 m	45 m	50 m	60 m	75 m
Streamwise	<10 m	70 m	75 m	80 m	110 m	>130 m

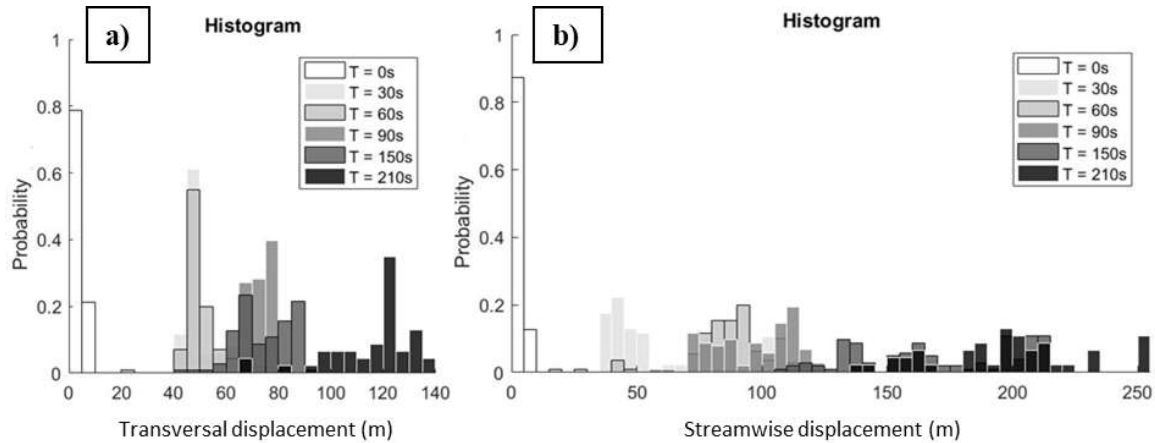


Figure 5. Probability density functions of the transversal (a) and streamwise extension (b) of the particles

The 2D PDFs of the anomalous relative displacement have been calculated and shown in Figure 6 at $T = 1$ s (a), 5 s (b), 10 s (c) and 15 s (d) using up the 30 longest trajectories of the analyzed UAV video. Figure 6a shows that the average displacement of all the trajectories is about 1.5 m in each direction. Figure 6b, c and d show that the displacements become progressively greater in the streamwise direction compared to the transversal ones, which is due to the known stronger mixing effect of the main flow direction. However, transversal displacements are still quite significant, which explains the strong mixing effect of the eddies at the shear layer.

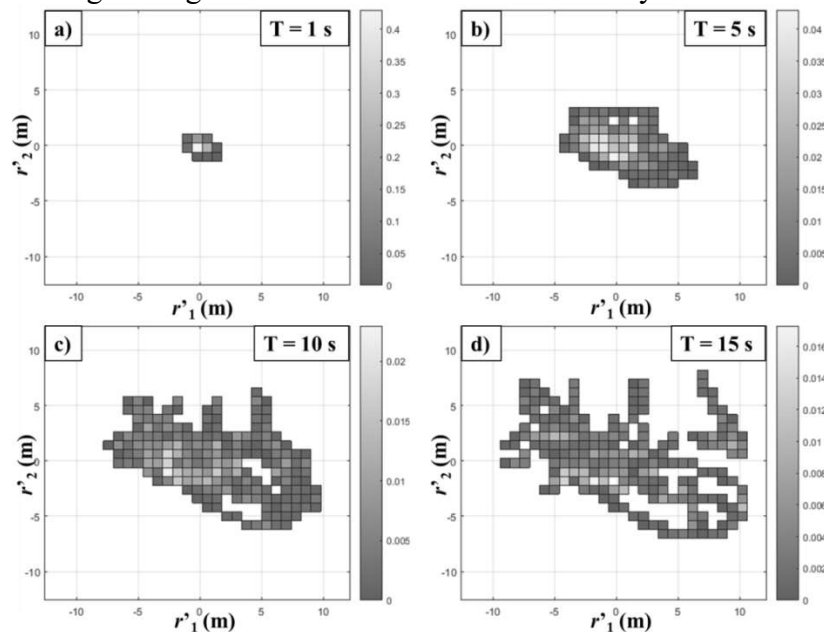


Figure 6. Anomalous relative displacement PDFs at $T = 1$ (a), 5 (b), 10 (c) and 15 (d) s

Characterization of chaos

The 10 longest trajectories were selected, which resulted in 45 possible particle pairs for follow-up analysis. The time evolution of the pair distances was plotted on a semi-log diagram, i.e. the linear segments mean exponential separation. The slope of these segments are defined in equation (3) as the local Lyapunov exponents (λ). Some particle pairs floated together during the whole observation time with $\lambda \sim 0$ 1/s. Most pairs have separated 1, 2 or 3 orders of magnitude further from their initial distance. The most typical curves together with their typical Lyapunov exponents are shown in Figure 7. For instance, nine tracer pairs separated similar in time, and so we classified them into Type 3 (Figure 7c). Every separation in this group starts with an $\lambda = 0.06$ 1/s local Lyapunov exponent, i.e. $\tau = 16.67$ s local prediction time, following by a longer section with a characteristic $\lambda = 0.04$ 1/s, i.e. $\tau = 25$ s prediction time scale.

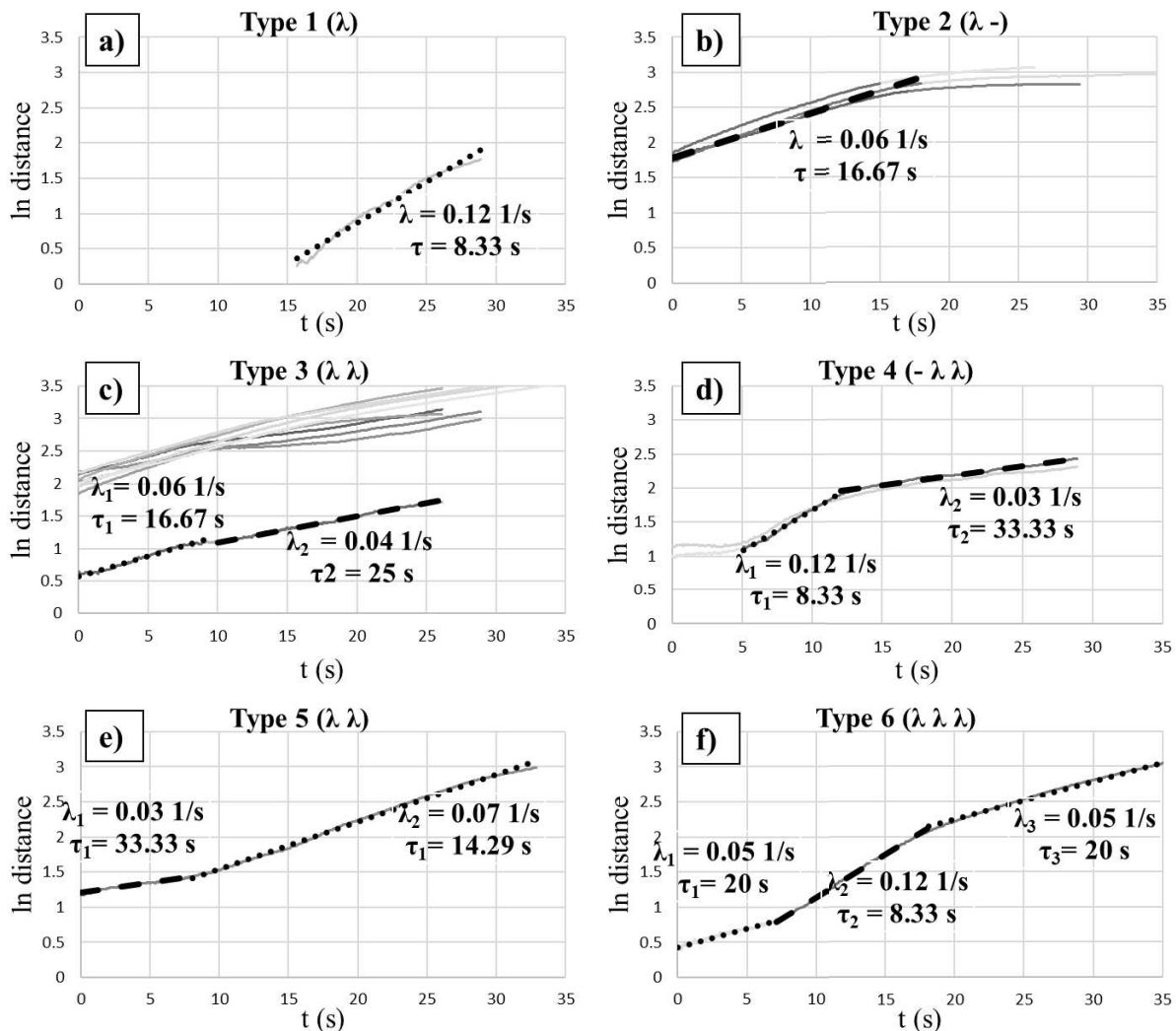


Figure 7. The six types of characterized particle pair separation curves with typical local Lyapunov-exponents (λ) and prediction time scales (τ)

DISCUSSION AND CONCLUSIONS

In this study, large river scale UAV-based PTV measurements have been carried out and a new MATLAB algorithm has been improved for the image post-processing, to enable the quantitative description of mixing processes. The Lagrangian approach was successfully applied to describe the flow field by calculating relative displacements of tracers as well as characterizing the chaotic

nature of the flow, both containing relevant information on the mixing processes. As a subsequent step, the characteristic dispersion parameters will be estimated based on the gained information. Furthermore, experiences learnt during the technical implementation of the method contributes to boost the spatial and temporal resolution of the analysis as, for instance, higher UAV altitude would help to extend the field of view yielding longer tracer trajectories.

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