

Lagrangian Analysis of River Flow from UAV Videos

(Folyami áramlás Lagrange-i szemléletű vizsgálata
drónfelvételek alapján)

Lükő Gabriella BSc 4th year

Supervisors:

Dr. Sándor Baranya associate professor

Department of Hydraulics and Water Resources

Dr. Márton Zsugyel research fellow

MTA-BME Water Management Research Group

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1. Introduction

Unmanned Aerial Vehicles (UAVs) are increasingly used in the field of engineering surveys. In river engineering, or in general, in 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 and Weibrecht, 2017) and Space-Time Image Velocimetry (STIV) (Fujita et al., 2006) have become 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 carried out yet to describe the flow field and mixing processes in large rivers.

2. Study site

In the present study, floating tracers were released at a groyne field in the Danube River in Hungary, near Göd (Figure 1), where the width of the river is about 300 m, and the mean velocity is about 1 m/s. This particular 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 could not 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.



Figure 1. Study site

3. Methods

3.1 Field measurements

In **Figure 2** an illustration of the field measurements is shown. Hundreds of yellow tennis balls were used as tracers (released from a boat from upstream), which were suitable for the image processing method in order to acquire detailed information 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 was moved to another position where the tracers were in the FOV again. The FOV was about 85x130 m from 60 m altitude.

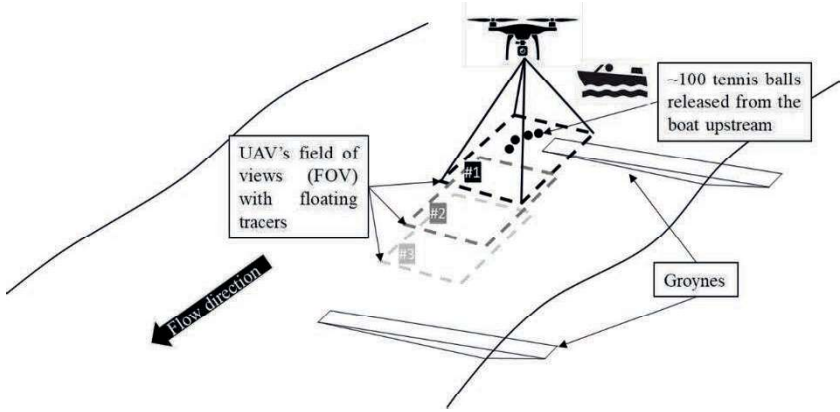


Figure 2. Schematic illustration of the UAV measurements in the River Danube.

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.

3.2 Image processing algorithm

A multi-object tracking algorithm in MATLAB has been developed to analyze our UAV videos. The structure of the algorithm is shown in **Figure 3**. The algorithm has two main parts: (i) the tracer particles are detected on each frame and (ii) every single corresponding detection is matched together along the image sequence. In the next paragraphs the process of the algorithm is detailed.

In order to fasten the calculations, in the first step, a color mask has to be applied on every image. In this case, only the yellowish pixels remained in the analyzed frame, in order to reduce 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. After applying this filter, the center of the tracer will become brighter than the background. **Figure 4** shows this so-called blob size setting. This Gaussian filter was applied over the whole image to detect the tracers (see **Figure 5**). 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.

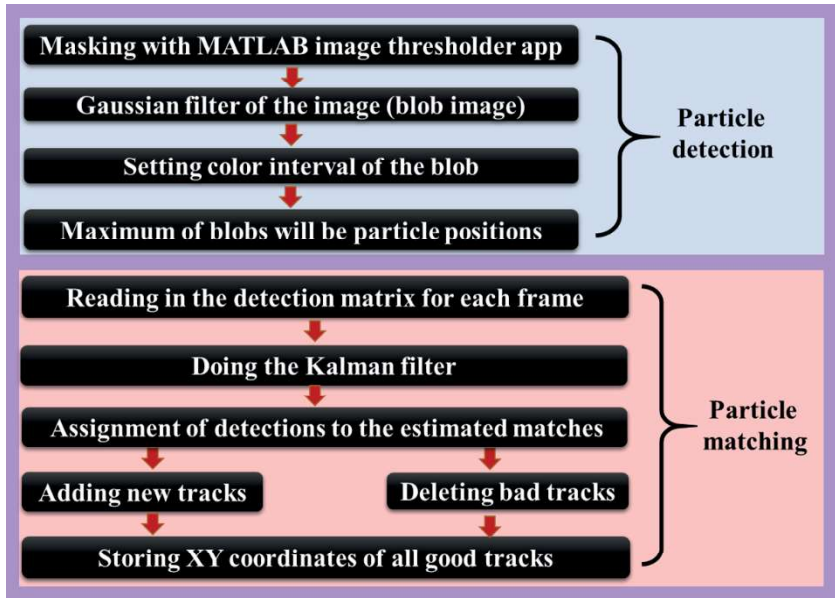


Figure 3. The structure of the improved multi-object tracking algorithm.

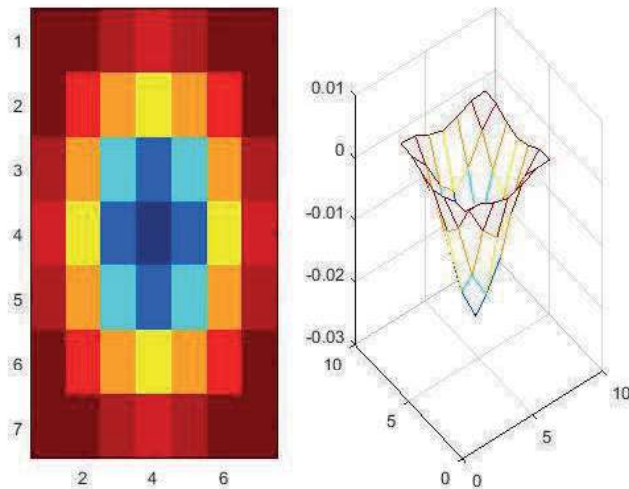


Figure 4. Gaussian filter: blob size = 7 pixels

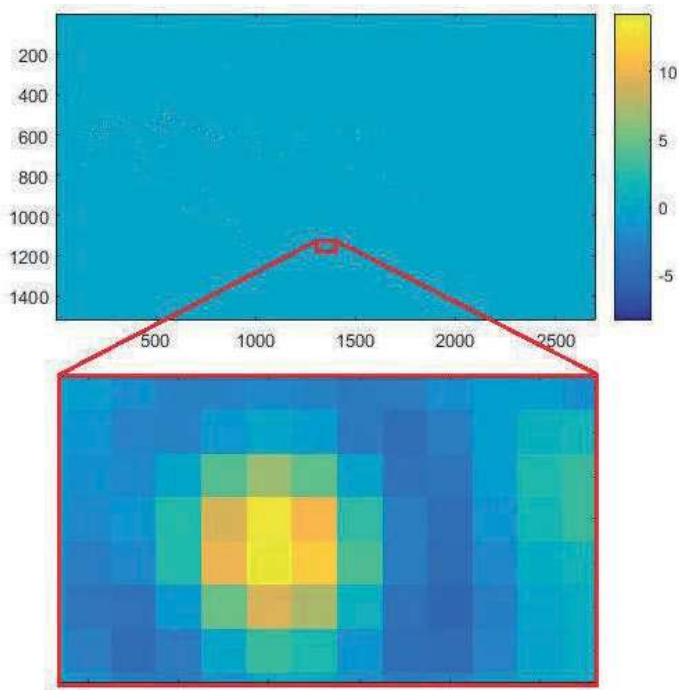


Figure 5. Gaussian filter: the whole blob image

Next, knowing the tracer positions on each frame, they need to be matched together. The detections are assigned to the estimated track positions by using a cost function, resulting in the X and Y trajectory matrices. If a detection is too far from the estimated position, it will be rejected. The next step is finding new detections. A track 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 units, which are converted into the local coordinate system. After testing the algorithm, the collected videos were processed, reconstructing the trajectories of the tracers in the video.

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

$$\Delta r = \Delta r_0 \cdot e^{\lambda t} \quad (1)$$

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):

$$\tau = \frac{1}{\lambda} \quad (2)$$

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, in this study hundreds of particles could be analyzed, thus providing more detailed information on the chaotic nature of the flow. All trajectories of a 40-second-long video were reconstructed, and the growth of distance was calculated and analyzed in case of 6 randomly assigned particle pairs.

4. Results and discussion

4.1 Eulerian (ADCP) versus Lagrangian (PTV) flow assessment

In **Figure 6** 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 this figure, the rectangle marks the UAV's FOV located downstream from the tip of the groyne. The differences between the two images clearly indicate 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 and a quantitative assessment on mixing parameters can be performed, which cannot be directly derived from ADCP based flow fields.

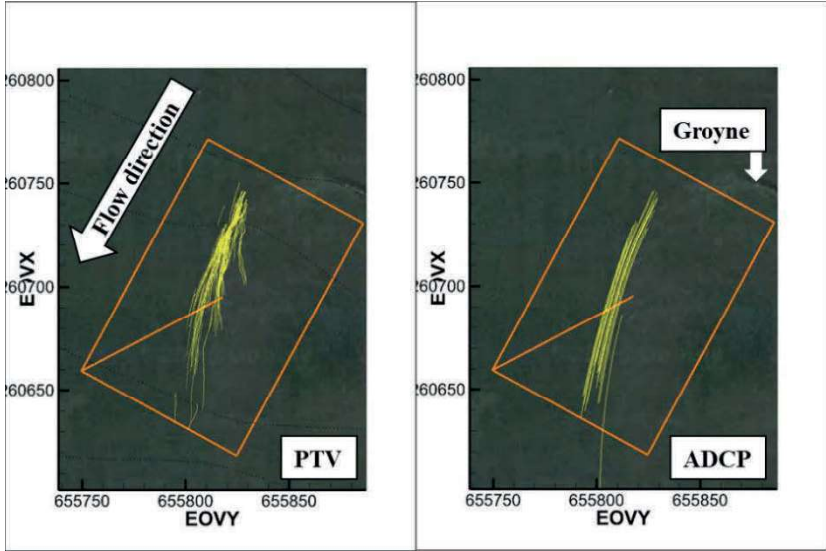


Figure 6. Comparison of the trajectories resulted from the PTV reconstruction and the ADCP velocity field.

4.2 Characterization of chaos

Zsugyel et al. (2012) use the same local Lyapunov exponent to understand more of the chaotic motion. They used 3 particles to analyze, whereas the hundreds of particle trajectories available in the present study provide for a significant improvement of the analysis. In the study of Zsugyel et al., the separation of the 3 particles was also analyzed. Here, 4 particles were chosen randomly from the derived trajectories, with ID #3, #5, #15 and #36, and all possible combinations of the pairs and their separation along their journey were analyzed (**Figure 7**). Local Lyapunov exponents were calculated for the straightest sections too. The great advantage of the tracer-based PTV method introduced in our study is that this sort of analysis could be performed for a high number of tracers resulting in thousands of such functions. Once the estimation of the local Lyapunov exponent values can be automatized, the method can provide a more detailed description of chaotic parameters than before.

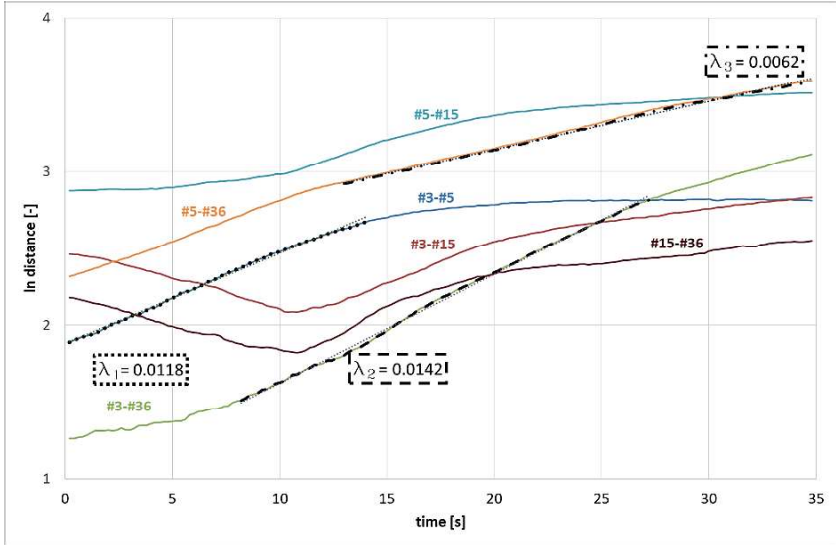


Figure 7. Separation of particles #3, #5, #15, #36 with the local Lyapunov exponents

In **Figure 7**, the #5-#15 particles are far from each other and the distance growth is not exponential. The #5-#36 and #3-#15 both move away exponentially from each other following a quite similar path. #3-#15 and #15-#36 particle pairs both start with getting closer to each other for a short time, then the distance is growing exponentially with varying degrees of intensity. However, they may not exceed the initial distance, since the analyzed time is short. #3-#36 is the most exemplary pair, as the initial distance is very small and then the distance is growing 2 orders of magnitude with a very similar Lyapunov exponent value as that of the buoys in the study of Zsugyel et al.. If every pair and their corresponding Lyapunov exponents were calculated, the spatial distribution of the Lyapunov exponent values could be shown over the whole analyzed area. This means PTV can help us to characterize coherent structures and understand more about the parameters of chaotic motion. Consequently, a more detailed analysis of the trajectories will be strived for in the future.

5. Conclusions

In the present study, UAV based river flow measurements were carried out with Lagrangian approach and an algorithm was developed to perform the image processing in MATLAB environment. Also, a detailed literature review was done on the relevant topic, including the applied Lagrangian flow measurements and other Eulerian flow measurements which use images from UAV measurements. To the authors' knowledge no UAV based particle tracking velocimetry (PTV) have been applied before, so this study aimed for testing its applicability. During the field measurements, UAV videos were collected of a hundred tennis balls floating in a groyne field. Then these videos were analyzed using the new PTV algorithm, and ~100 trajectories were defined, following a sensitivity analysis on some particular image processing parameters. Application of a river scale PTV is a huge step in the Lagrangian approach of river flow measurements. Compared to the previous methods, where a limited number of intelligent buoys were applied as tracers, in this study hundreds of second-hand tennis balls were used which is a more cost-efficient practice, especially considering the increased spatial information it provides. Besides the PTV measurements, ADCP measurements were also carried out, and the results were compared. It was shown that although flow velocity field reconstructed from an ADCP survey contains significant information on the flow field, it could not be applied for the analysis of the fine scale, unsteady nature of the flow which can be detected through the PTV measurements. PTV can reveal even very fine-scale spatiotemporal flow structures. For example, while the developing plume at the end of the groyne cannot be seen from the ADCP streamlines of the velocity distribution, the reconstructed trajectories by PTV can detect and quantify these chaotic natures of dynamic flow structures too. As the chaotic structures are usually characterized by the finite-size Lyapunov exponents, a few random particles were chosen to analyze their distance from each other, and the Lyapunov exponents of these trajectory pairs were calculated. The exponents correspond to the previous results of the relevant literature, however, the novel approach presented in this study contributes to the characterization of the complex flow structures in a very detailed and quite cost-efficient way.

UAV based measurements have a huge potential for future research in river engineering, since videos with very valuable data can be collected from places where measurements would not be possible any other way manually.

The application of the techniques introduced in this study need to be further analyzed, since this was a first attempt in this field. The applied MATLAB algorithm can be further developed, also getting closer to the automatization of the processing. Nonetheless, follow-up UAV measurements need to be carried out, considering the already gained experiences. As introduced above, the chaotic characterization of the flow field can be well described with parameters like the Lyapunov exponent and the analysis of these can be applied to the trajectories calculated in the present study.

The PTV method could be used, for example, for assessing sediment resuspension caused by the breaking of ship induced waves (Fleit, 2015) and littoral erosion, since the phenomenon is visible on the UAV videos. Moreover, PTV can reveal the eddy structures in the vicinity of different structures, such as river groynes, as demonstrated in this study, but there is a need for further research for quantitatively assessing the chaotic nature, which is important in cooling water and pollutant water mixing.

The calculation of instantaneous flow velocity vectors based on the revealed trajectories could also contribute to the better understanding of flow structures. In fact, this information is inherent in the trajectories, as the displacement of the tracer and the time step is known. The analysis of temporally varying flow velocity fields would mean a significant step towards the quantitative description of mixing processes in rivers.

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