Budapest University of Technology and Economics
Department of Hydraulic and Water Resources Engineering

LAGRANGIAN ANALYSIS OF RIVER FLOW FROM UAV VIDEOS

FOLYAMI ÁRAMLÁS LAGRANGE-I SZEMLÉLETŰ VIZSGÁLATA DRÓNFELVÉTELEK ALAPJÁN

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ABSTRACT

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) and space-time image velocimetry (STIV), became a real alternative for direct flow measurements (Lükő and Baranya, 2016 and Lükő, 2016). These methods deal with the Eulerian analysis of the flow. Beyond this I move to the Lagrangian analysis, which is based on the particle tracking velocimetry (PTV) method. Zsugyel (2016) in his doctoral dissertation has tested the particle tracking methods, where he quantifies the chaotic mixing of the flow. He uses GPS mounted floating buoys for his field measurements, the number of which is limited and expensive. In present research an UAV is used to capture the tracers floating the water surface. Hundreds of intensive yellow tennis balls are used as tracers, which is suitable for the image processing method. This way more detailed information can be acquired about the track of the particles. After the reconstruction of the tracks, the mixing could be estimated as well, which is important in pollutant and cooling water or sediment transport analysis.

In this study an overview will be given about the PTV and other UAV based river flow measurement methods with a short review of their applications carried out in the past years. Next, attempts will be made to apply PTV at a groyne in the Danube, where there complex flow conditions. During the measurement campaign the UAV videos will be collected as well as other additional measurements, like acoustic measurement and the geodetic survey. There is an old PTV image processing algorithm in Matlab for laboratory measurements, which will be further developed to be able to apply for field measurements as well. The new PTV algorithm will be tested with the collected UAV videos. The results of the measurements will be discussed and future research ideas will be outlined.

TARTALMI KIVONAT

A drónok használata egyre elterjedtebb napjainkban a különböző mérnöki felmérések során. A víz és azon belül a folyógazdálkodás területén különösen nagy lehetőségek rejlenek a drónokkal hajtott mérésekben. Korábbi kutatásaim során lehetőségem volt a Large-Scale Particle Image Velocimetry (LSPIV) és Space-Time Image Velocimetry eljárás (STIV), újszerű indirekt videó-alapú sebességmérési eljárások tesztelésére tudományos diákköri dolgozataim készítése során (Lükő és Baranya, 2016 és Lükő, 2016), melyek alkalmas alternatívái lehetnek a hagyományos vízhozammérési eljárásoknak. Ezen eljárások az áramlások Euler-i értelmezésével foglalkoznak. Ezen túllépve, a Lagrange-i szemléletű vizsgálatokra térek át, amely alapvetően egy részecskekövető eljárásra, a Particle Tracking Velocimetry-re (PTV) épül. Zsugyel (2016) doktori értekezésében a részecskekövető eljárások tesztelésével foglalkozik laboratóriumi és kisebb léptékű folyami alkalmazásai során, ahol számszerűsíti az áramlásra jellemző kaotikus elkeveredési viszonyokat. Terepi vizsgálataiban GPS-szel felszerelt felszínen úszó szárnyas bójákat használt, melyeknek száma limitált, és igen drága. Jelen kutatásban ezzel szemben drónról készített videofelvételek és a képelemző eljárás szempontjából alkalmas, a folyó felszínén úszó nagyszámú jelzőanyag segítségével jelentősen részletesebb és nagyobb kiterjedésű (akár a folyó teljes szélességét lefedő) képet kaphatunk a részecskepályákról. A pályák rekonstruálásával képet kaphatunk az áramlási jellemzők mellett az elkeveredés jellegére is, melynek ismerete szennyezőanyag, hűtővíz vagy éppen hordaléktranszport vizsgálatokban különösen fontos.

Dolgozatomban először feltárom és áttekintem a jellemzően külföldi irodalmat, amely kitér a drón alapú áramlásmérésekre, a PTV eljárásra és a Lagrange-i szemléletű elkeveredési vizsgálatokra. Esettanulmányként egy áramlási szempontból összetett folyószakaszt, a Duna sarkantyúkkal szabályozott szakaszát választottam ki. A tanszéken elérhető műszerek segítségével mérési kampányokat hajtunk végre, hogy begyűjtsük a szükséges videóanyagokat, egyéb kiegészítő mérésekkel együtt, pl. akusztikus alapú áramlásmérések és geodéziai felmérések. A korábbi laboratóriumi vizsgálatokra alkalmazott tanszéki, Matlab környezetben fejlesztett PTV képfeldolgozó algoritmust továbbfejlesztem, hogy a terepi mérések során felhasznált jelzőanyagok esetén is alkalmazható legyen. Az esettanulmányi helyszínen készített videókat elemzésére és az áramlási pályák jellemzésére kísérletet teszek. A dolgozatom végén eredményeimet értékelem és továbbfejlesztési javaslatokat fogalmazok meg.

1 INTRODUCTION

The scientific and civilian applications of Unmanned Aerial Vehicles (UAVs) are rapidly expanding. The most common scientific uses are in the fields of archaeology, geography, mining and civil engineering. In river engineering, or in general, water resources engineering UAV based measurements have a huge potential.

These UAV measurements not only applicable for river flow estimations, but topography measurements as well to get more detailed information about the geometry of river engineering objects and to complete the geodetic surveys, such as the geometry of the flood protection dyke (Lükő, 2016). Topography measurements can be applied for even larger scales, like the geometry of a section of a river (at low water) and the detailed geometry can be used as the digital terrain model (DTM) for the hydrodynamical models (Lükő et al., 2017).

Back to the flow measurements: indirect video based velocity measurement methods, e.g. large-scale particle image velocimetry (LSPIV) and space-time image velocimetry (STIV), became a real alternative for direct flow measurements (Lükő and Baranya, 2016 and Lükő, 2016). These methods deal with the Eulerian analysis of the flow. Beyond this I move to the Lagrangian analysis in this study, which is based on the particle tracking velocimetry (PTV) method. Zsugyel (2016) in his doctoral dissertation has tested the particle tracking methods, where he quantifies the chaotic mixing of the flow. He uses GPS mounted floating buoys for his field measurements, the number of which is limited and expensive. In present research an UAV is used to capture the tracers floating the water surface. Hundreds of tennis balls are used as tracers, which are more cost-efficient and suitable for the image processing method. This way more detailed information can be acquired about the flow, since every tennis ball would go on a different path. The field measurement for this study was at a groyne pair of the Danube River. The flow around the groynes has complex flow structures (Kadota and Suzuki, 2010), which is best for testing the PTV. Some balls would go with the main flow and some would stuck in the dead zone of the groyne after caught in the vortex street. Obviously the reconstruction of the tracks is just the starting point of the research. If the measurements and the trajectory calculation works robust, many other parameters could be calculated, such as the mixing parameters, which are important in pollutant and cooling water mixing or sediment transport analysis. The resuspension of fine sediment particles caused by ship induced waves have a huge effect to the ecological habitat at groyne fields (Fleit, 2015). The resuspension of fine particles can be seen on the UAV images (**Figure 1**)

Figure 1. *Resuspension of fine sediment particles can be seen from the UAV*

The main goal of this study is to test and assess PTV in a large river. The first step of the study is to perform field measurement campaigns to capture videos from UAVs. The applied tracers are bright yellow tennis balls, which will be well-visible on the videos. Next, a multi-object tracking MATLAB algorithm will be used and improved for the PTV analysis of the video data, which has to main parts: (i) the particle detection and (ii) the particle matching. The expected results are the reconstructed trajectories of the tennis balls. ADCP control measurements will also be carried out to provide large scale flow velocity distributions in the study reach.

2 PARTICLE TRACKING VELOCIMETRY (PTV)

Velocimetry based measurements on particle tracking is one of the oldest measuring techniques in fluid mechanics, but the numerical solutions for particle tracking velocimetry (PTV) only appeared in the late 80s. (Adamczyk and Rimai (1988), Adrian (1991) and Dracos (1996)). Now, almost 30 years later, there are very few river-scale applications of the method (for example: Sukhodolov et al., (2007) used surface tea candles on the flow at night). PTV has been mostly applied in laboratory environment. This study aims to break this and apply the PTV method for a section of a large river, the Danube at a recirculation zone of a groyne field.

The other particle imaging technique, the Particle Image Velocimetry (PIV) which uses the Eulerian analysis of the flow, is way more popular, and already a practice transplanted discharge measurement technique called large-scale particle image velocimetry (LSPIV) (Fujita et al., 1998, Muste et al, 2008). Originally the PIV method was the "High Image Density PIV" and the PTV was the called "Low Image Density PIV". Obviously both methods have its pros and cons. PTV has strong advantages compared to the statistical analysis of an ensemble of particle images by means of cross-correlation approaches, like the PIV method (Fuchs, 2017). Now PIV is also possible to measure complex flow structures, like the instantaneous velocity field of a vortex street (Lükő, 2016) but the Lagrangian method is more suitable and provides more information estimating mixing parameters, not just a simple velocity field but the path of the particles.

2.1 METHODOLOGY

Step zero of the PTV method is to shoot the accurate video for the analysis. The camera needs to be orthogonal to the water surface or the images need to be orthorectified afterwards. The recorded water surface has to have visible floating small objects to track along with the flow. The PTV's logical structure is built up from the following steps (**Figure 2**):

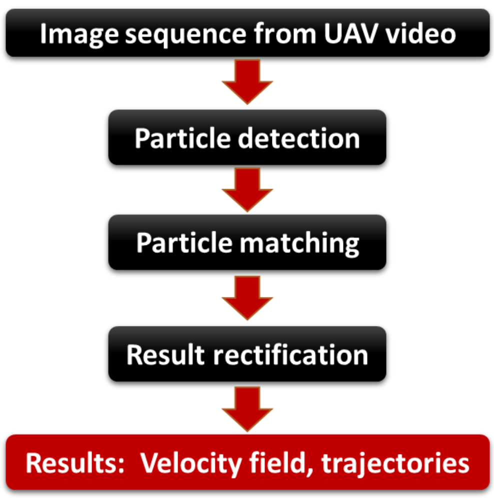

Figure 2. *Steps of PTV method*

First, the image sequence is taken. Then, on every frame of the video, each tracer's individual position needs to be found. This is most likely to be done by separating the tracers' color from the background color or looking for the unique shape of the tracers. Then each individual tracer's position needs to be found on every following frames. Knowing the particle's position on the previous frame, the searching for the position on the next frame will be done close to the previous one. Sometimes the correlation is varying between the matched particles, there will always be miscalculated positions, so some kind of rectification of the results is necessary. The result from a video is the path of particles or the velocity vectors at the calculated positions.

For PTV analysis, the presence of some kind of tracers floating along with the flow are essential. Natural tracers like foams are not very suitable because of their intense change of shape and size. Particles are needed which can be matched from the first frame till the last one. Artificial particles need to be floating with the same speed as the flow and cannot drown or be blown away by the wind.

2.2 RELEVANT LITERATURE

Ishikawa et al. (2000) crates a new PTV algorithm, which is suitable for calculating the velocity vectors of fluid flow subjected to strong deformations such as rotation, shear, expansion and compression.

Nobach and Honkanen (2005) try to increase the accuracy of displacement estimation in PTV using 2-dimensional Gaussian regression. This procedure helps to find rotated and elliptical particle image shapes. The explicit procedure avoids pixel locking in the case of elliptical, non-axially oriented particle images or correlation peaks.

Sokoray-Varga and Józsa (2008) applied the PTV for surface velocity measurements in a conventional laboratory scale model with large vortices and turbulence to take reliable measurements in flows exposed to strong deformations. They use a vertical camera axis and 30 frame per second frame rate. The particles are white small round pieces, the background and the flow is black on the images. Their algorithm reconstructed the velocity field. Some videos from this laboratory setup was used to test my new PTV algorithm for this study (see Chapter 4).

Thumser et al. (2016) introduces a new methodology for real-time particle tracking in rivers (RAPTOR). This technique performs large scale particle tracking velocimetry (LSPTV) using a combination of floating, infrared light-emitting particles and a programmable embedded color vision sensor in order to simultaneously detect the track of hundreds of objects. The main advantage that it is fast and can be done in real-time. The disadvantage is that the method requires the use of specialized light-emitting particles which in some cases cannot be retrieved from the investigation area. There are quite a lot of articles about the 3D PTV.

Willneff (2003) measures particle motion in small laboratory scale 3D object space, which are imaged as a 2D path in image space of an observing camera. If corresponding particle images were found in at least two cameras the 3D particle position can be determined. If the temporal assignment over the time is possible, the trajectory can be reconstructed. ETH Zürich developed an open source 3D-PTV software, called OpenPTV for laboratory experiments.

Weitbrecht (2001) analyzes dead zone of groyne fields and its effect on the longitudinal dispersion in rivers.

Patalano and Garcia (2016) show us their user friendly toolbox for PIV and PTV techniques applied in large scale physical models in laboratories. PIVlab and PTVlab implemented in MATLAB environment.

There are no UAV-based PTV measurements yet in the literature, but UAVs are quite popular in LSPIV measurements. The UAV measurement method is the same methodology, collecting UAV for image processing. Here are the couple of UAV-based LSPIV applications performed in the past years.

Tauro et al. (2015a) developed a lightweight quadrotor for the LSPIV. A gimbal was applied to the vehicle for the camera lens to be orthogonal to the water surface preventing the image orthorectification. Field experiments showed that the vehicle is able to stably hover an area of 1 * 1 m^2 for 4 minutes with a payload of 532 g. The UAV-based LSPIV is demonstrated through tests in an outdoor laboratory and over a natural stream.

A detailed sensitivity analysis has been done by the same researchers (Tauro et al., 2015b). They analyze the effect of tracers' visibility, and it is assessed through the index $Z=N_0/N_{TOT}$, where *N*0 indicates the number of nodes presenting velocity values less or equal to 10 % the average velocity in the entire time-averaged map, and N_{TOT} is the total number of nodes is the map. Also analyzed the stability of the experimental platform, and it is assessed through the index $D=N_d/N_{TOT}$, where N_d refers to the number of nodes presenting negative velocity values, that is, vectors in the opposite direction of flow. In case of fixed configurations, the *D* index is found to be equal to zero. Structural similarity index (*SSIM*) is largely used in image analysis to quantify differences between images in terms of luminance, contrast, and structure. *SSIM* is computed on the time-averaged velocity maps obtained for each experimental replicate. Also, the maximum velocity values were analyzed, so the velocity range values for cross-sections.

Patalano et al. (2015) applied the flying LSPIV because of the wide rivers at flood events and too high angles for the fixed LSPIV**.** The tests have been done during a river flood of the Suquia River in Argentina. Accurate velocity measurements were also been carried out at the same time with an acoustic Doppler current profiler (ADCP). The UAV was equipped with a camera (recording 30 frames per second), and it was placed on a gimbal that absorbs vibrations of the vehicle. The discharge measured with the LSPIV was 73 m^3/s versus 74 m^3/s with ADCP, which represents a difference of 1.35 %.

The same researchers introduced a new toolbox (RIVeR) used in rivers, channels and also large physical models (Patalano and García, 2016). The toolbox uses the results from conventional 2D large-scale image-based flow velocimetry techniques orthorectifying them instead of orthorectifying the images first, which reduce dramatically the computational cost. RIVeR is fully operational and has already been used in many applications with extreme conditions such as stream gauging during flash-flood events and low water level.

Detert and Weitbrecht (2015) proved the applicability of a low-cost airborne velocimetry system to measure large-scale velocity field. The measurement equipment consisted of an ultra-light action-cam and a ready-to-fly low-cost quadcopter. Video recordings were performed from heights between 45-74 m covering a total length of 310 m, while spruce chips were added as tracer particles. Each lens-corrected frame was automatically orthorectified to riparian ground reference points. The positional error of each point was computed to be within 0.17-0.39 m, so that the magnitude of the related descaling error was below ±2%, and the error of apparent found velocity is approximately 0.03 m/s. These values describe the uncertainty added to the subsequently calculated particle image velocity profiles measured by ADCP indicates that the proposed new type of velocimetry system is capable of measuring with relatively high accuracy.

Also an optimized application of a low-cost airborne surface velocity system has been developed by Detert (Detert et al., 2016). At Surb Creek, Switzerland, on a reach length of 650 m surveying flights and PIV analysis had been performed. The remaining velocity error due to orthorectification for the example given was estimated to <0.01 m/s, and the total error was estimated to be <0.1 m/s. The raster resolution was 0.5*0.5 m with 50% overlap. The optimized system was capable to provide flow fields with high resolution in time and space, a high potential tool for data acquisition in the field.

There is a specifically-developed UAV system to remotely and safely gain high-resolution images of the water surface (Blois et al., 2016). It presents details of a Scale Invariant Feature Transform (SIFT) that permits accurate rectification of the images. These data are key to informing and calibrating predictive tools that can reconstruct potential emergency scenarios. They discuss the concept and technology employed to render these measurement systems effective, and provide examples of applications that show the fidelity of the data that can be extracted from aerial images, and thus the vast potential of this technology.

Several helicopter based measurements were also performed in the past years (e.g. Detert and Weitbrecht, 2014; Fujita and Hino, 2003; Fujita and Kunita, 2011). These prove the robustness of the aerial LSPIV methods again, but the helicopters cannot be included in the group of cheap or cost-efficient measurements.

It is assumed that if UAV-based LSPIV works robust, the UAV-based river-scale PTV application will too. Of course the presence of the essential visible, trackable particles are essential in this case too.

3 UAV MEASUREMENT CAMPAIGNS

3.1 MEASUREMENT FIELD

The official measurement campaigns took place on the 6th and the 20th of October (after many UAV testing) at a groyne pair of the Danube, at Göd (**Figure 3**). The river flow was 1360 m^3/s (10/06/2017) and 1080 m^3/s (10/20/2017), which are both low water, the water levels were below the top of the groyne. On the second measurement campaign about the half of the dead zone was fully dry because of the very low water. The complex flow structures were captured at the nose of the groyne and the dead zone between the two groynes.

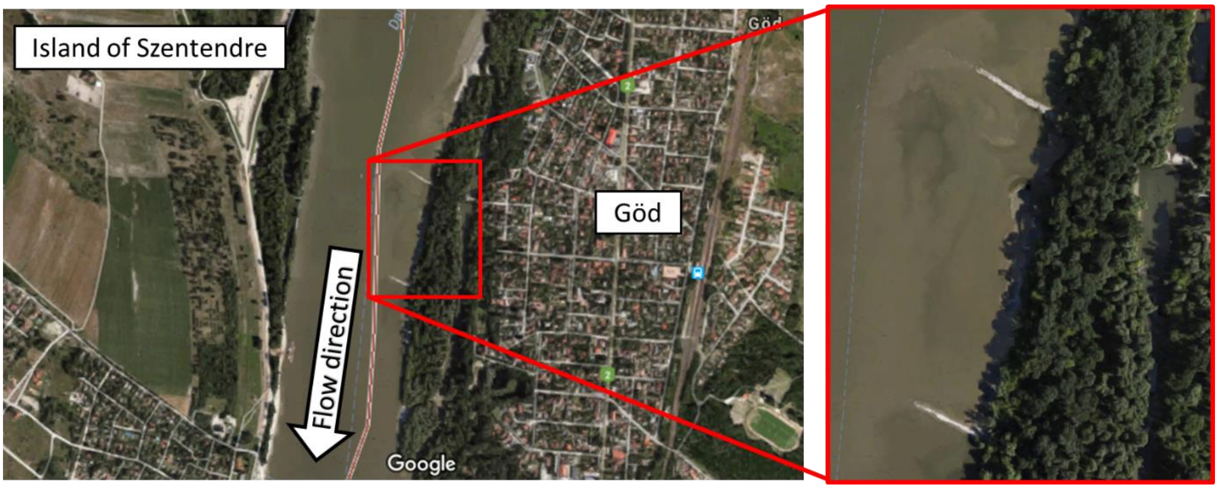

Figure 3. *Measurement field*

3.2 MEASUREMENT METHOD

The measurement was carried out in two separate parts. First, the UAV measurements have been done to capture the river surface for the PTV analysis. Second, the river discharge was measured along with the 3D velocity distribution using ADCP (Baranya, 2009) as control measurement.

Each UAV measurement had the following steps (**Figure 4**):

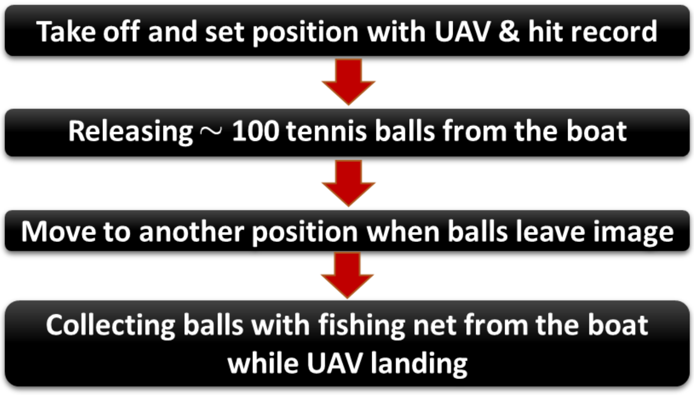

Figure 4. *Steps of UAV measurement*

A video of the measurement campaign had 3 UAV positions while following the tennis balls (**Figure 5**). The #1 video position is usually next to the groyne, right after releasing the balls from the boat (**Figure 6**). First the balls are very close to each other, then they get more scattered while moving down with the flow. During the #2-#3 UAV positions, almost the whole image is full of balls floating far from the other balls. **Figure 6** is also here to show that the balls are visible perfectly on the images. The view of an image from the UAV is about 128 x 85 m from 60 m high altitude.

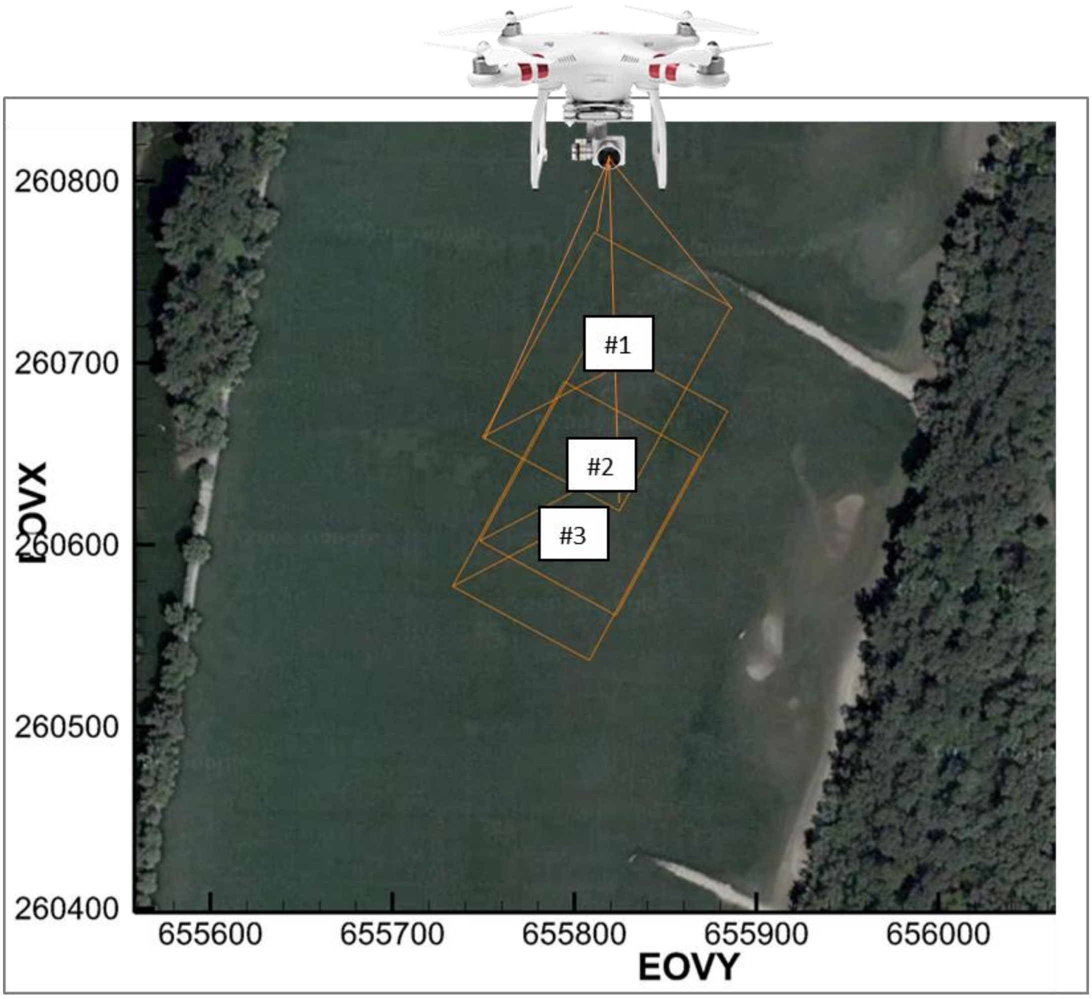

Figure 5. *UAV measurements with the rectangles standing for the collected UAV videos*

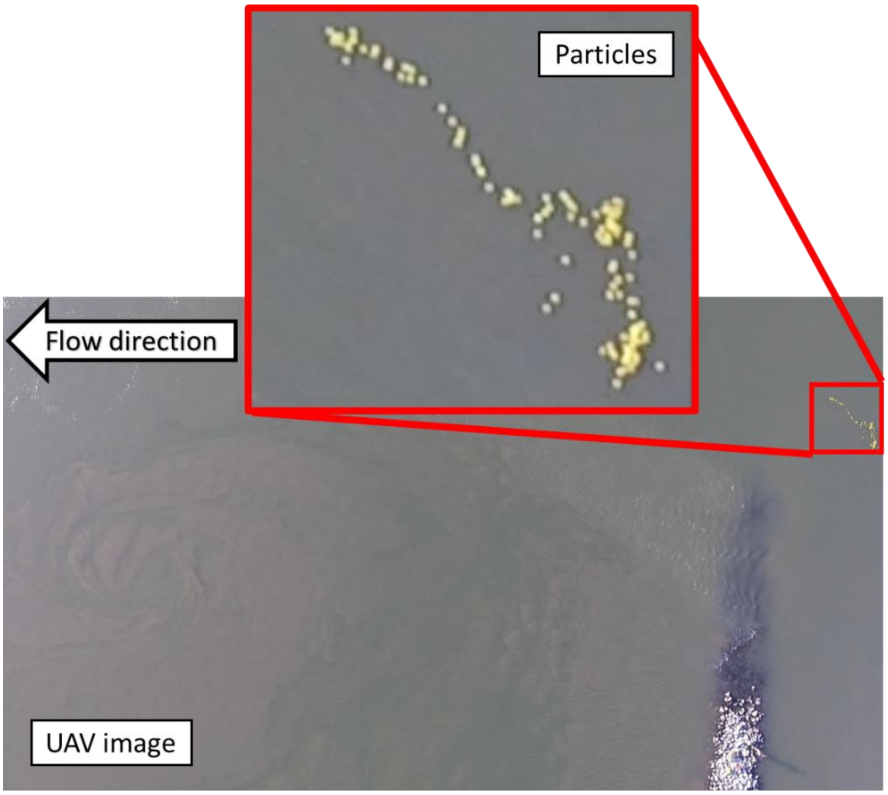

Figure 6. *Tennis balls almost reaching the groyne, after releasing them from the boat*

3.3 UAV

In this study the UAV which have been deployed is a DJI Phantom 3 Standard UAV (**Figure 7**). It is a low-cost, lightweight and user-friendly tool for the airborne PTV analysis. The main features of the Phantom 3 Standard are shown in **Table 1**. The UAV has factory-mounted 2.7K camera with a gimbal. The vehicle can be remote controlled while using DJI Go App with a tablet or a smartphone. There are different flight settings and functions in the application, as well as on the UAV. The pilot communicates with the UAV via the DJI Go interface. The camera position and the video recordings are also controlled from the tablet or phone. The flight routes are saved and available for further analysis on the SD card as well as the recorded videos in MOV file format.

Figure 7. *DJI Phantom 3 Standard /www.dji.com/*

Diagonal size (excluding propellers)	350 mm
Total weight (including the camera).	1216 g
Intelligent flight battery	LiPo 4S (4480 mAh, 15.2 V)
Hovering time	25 min

Table 1. *The main features of the DJI Phantom 3 Standard*

The camera's image resolution is 2704 x 1520 pixels and the focal length is 2.9 mm, which means if the drone is 50 m high in the air, the recorded surface will be 107 x 60 m2.

Experiences showed that in usual weather conditions the highest safe flying altitude is about 70 m. Flying higher then this level results in unstable connection between the pilot and the UAV. However, during the second measurement campaign which was happened in sunny and calm weather conditions, the connection was stable even at 90 m high.

4 IMAGE PROCESSING IN MATLAB

For the image processing of the PTV videos there were attempts made to use Sokoray's (Sokoray-Varga and Józsa, 2008) MATLAB algorithm but it cannot run with the new MATLAB versions, some serious changes will be necessary to renew it. Instead of doing that, a new ideas were searched and finally Student Dave's (2013) multi-object tracking tutorial video was used as a start. His algorithm can track the path of a bunch of flies flying overlapped as well. The algorithm was completed with some features to be able to use it at our conditions and detect our tennis balls.

For testing the algorithm I used some old video data from the laboratory of the Hydraulic and Water Resources Engineering Department originally recorded for Zsugyel's (2016) measurements. This way I could compare my results with his trajectories. The laboratory environment avoids the noisy image data and let me concentrate on the accuracy of the particle matching algorithm and the correctness of the calculated particle paths. One of the first frames of the analyzed video can be seen on **Figure 8**. There were only 8 white particles on the dark background, so they are easily recognizable. There is a built in groyne in the channel, so some of the particles are going with the main flow, some of them are trapped in the vortex street and the dead zone behind the groyne.

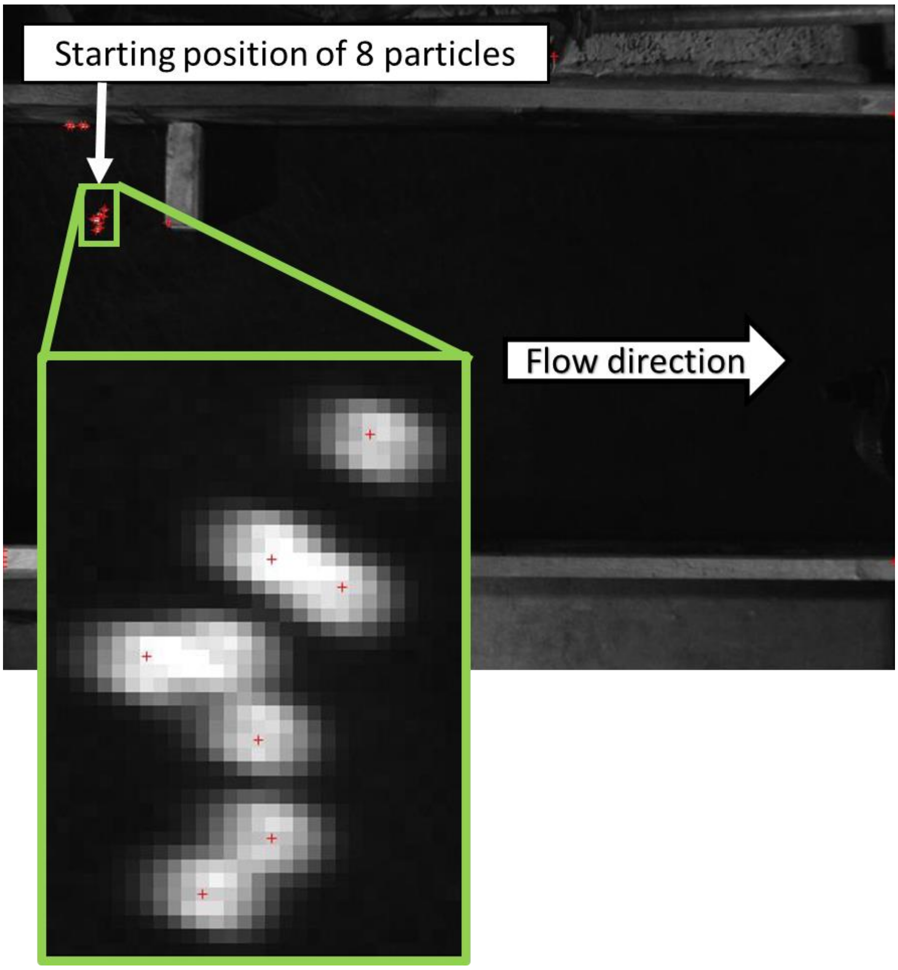

Figure 8. *Testing the new algorithm with old labor videos with very few number of particles*

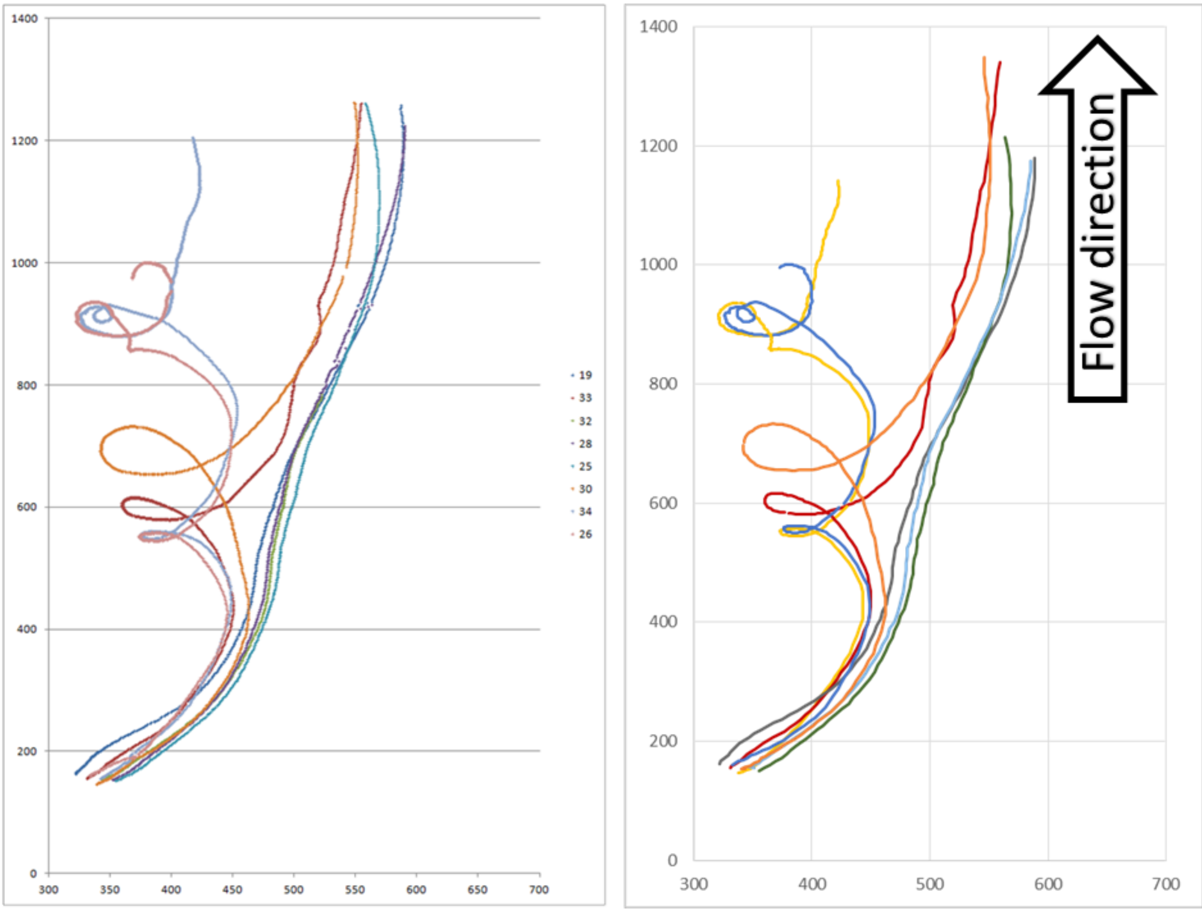

Figure 9. *Trajectories by Zsugyel (2016) (on the left) and with the new algorithm (on the right)*

The reconstructed trajectories of Zsugyel's (2016) and with the new algorithm can be seen on **Figure 9**. The algorithm calculates the trajectories good enough to use it for the UAV videos from the field measurements. The structure of the algorithm will be shown with illustrations from the UAV video processing.

4.1 STRUCTURE OF PTV ALGORITHM

The structure of the algorithm can be seen on **Figure 10** which has 2 main parts, the image detection and the particle matching.

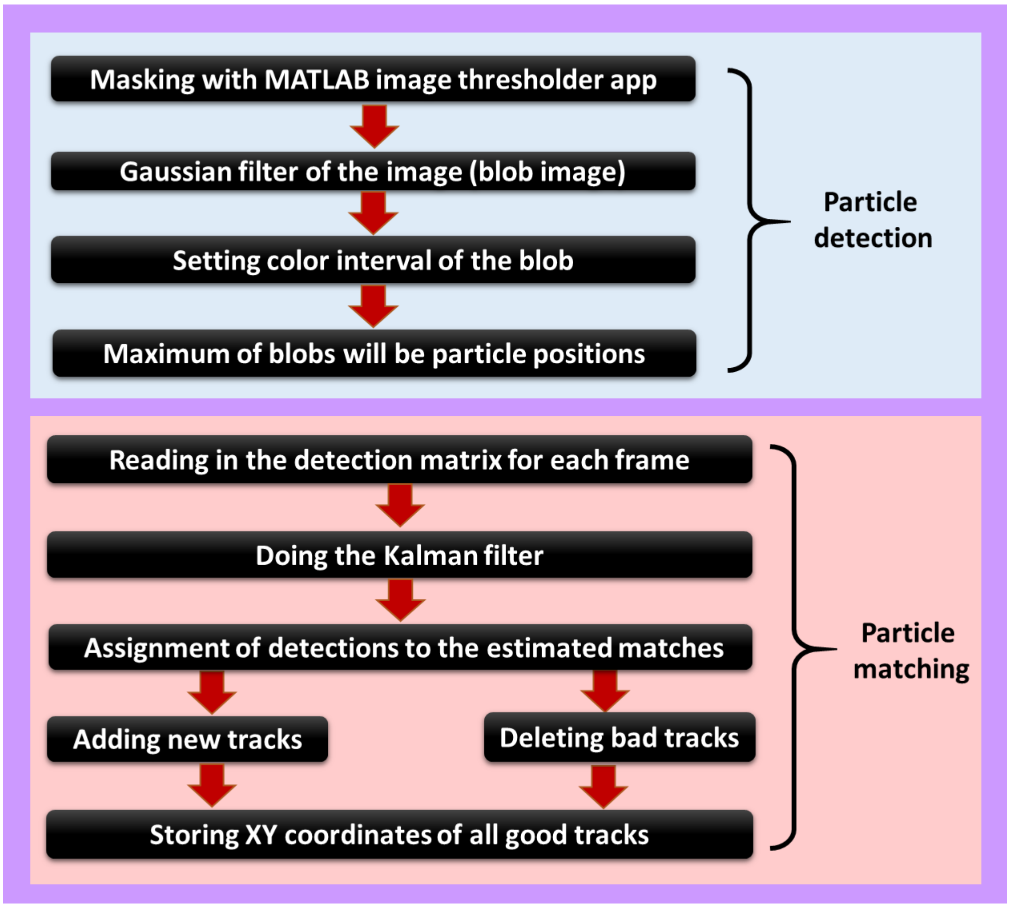

Figure 10. *Structure of the algorithm*

4.1.1 PART 1 (PARTICLE DETECTION)

The next steps need to be done on each frame of the image sequence, so the particle positions will be known on every frame.

4.1.1.1 MASKING WITH MATLAB IMAGE THRESHOLDER APP

In the case, masking means some color dimensions will be blacked out, so most likely only the tennis balls will be seen on the image. This helps decreasing the number of failed detections, like shimmering on the water surface. Not only we'll get less bad detections, but the algorithm is not even searching for detections there either, the processing will be faster using masks. The MATLAB image thresholder application was used for this task. Obviously it is not likely that no other pixels than tennis balls will be on the mask image, some of the picture might have similar colors too. The mask image can be seen on **Figure 11**. The image is not fully homogeneous black, but mostly just the area of the balls can be seen, and the other bright pixel arrangement are different from the balls.

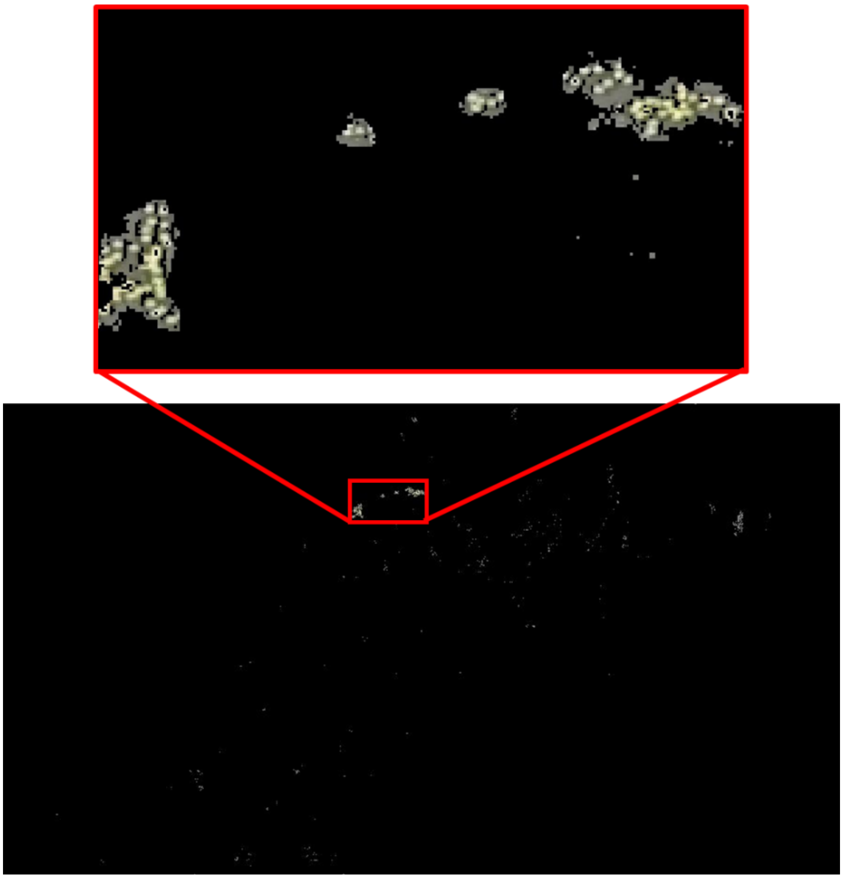

Figure 11. *Mask image*

4.1.1.2 GAUSSIAN FILTER (BLOB IMAGE)

First the parameters of the Gaussian filters need to be set. This means that the size of the balls is needed, which can be estimated from the image resolution and by zooming in the image and calculating the diameter on the image. Of course the center of the ball will be brighter, then by the edge it is starting look like the water surface more greyish colors**. Figure 12** shows this so called “blob” size setting.

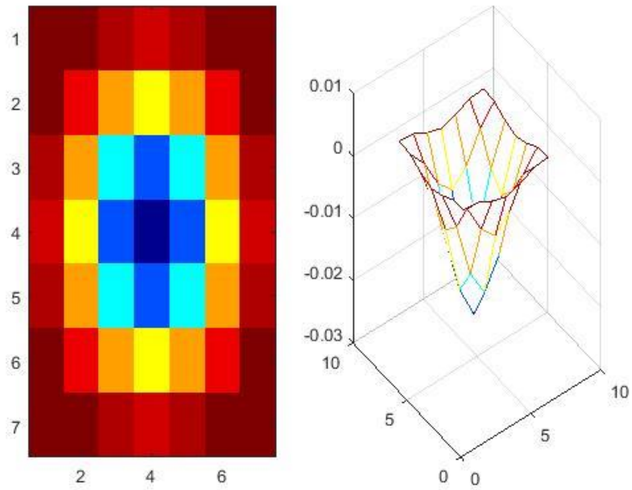

Figure 12. *Parameter of the Gaussian filter: blob (tennis ball) size = 7 pixel diameter*

This Gaussian "blob" filter is calculated over the whole image to detect the tennis balls. Where there is a ball recognition, the blob image has a maximum value there.

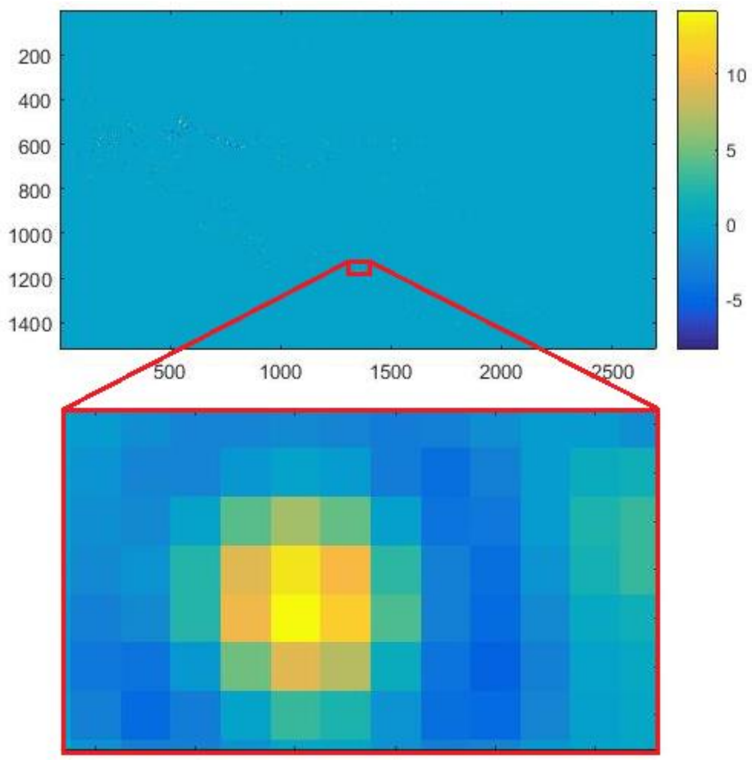

Figure 13. *Blob image*

4.1.1.3 COLOR INTERVAL OF TENNIS BALLS ON THE BLOB IMAGE

On the blob image pretty much where the pixels are blue that is the water, which will not be needed, and the yellow pixels are what we need, the tennis balls. There are also other less yellow, i.e. greenish pixels, which we do not want to count as our particles. In **Figure 13** the colorbar shows us which values need to be set, so this blob image will be blanked, and only those "tennis ball" high values will matter.

4.1.1.5. MAXIMUM OF BLOBS WILL BE PARTICLE POSITIONS

A local 2D minimum/maximum finder is used to find the maximum of the blobs on the image. Every maximum values will be stored as the XY coordinates of the tennis ball positions, which can be seen on **Figure 14**. However, the blob image automatically recognized maximum values all over the edge of the image, as the applying of the filter results in local maximums at the edges which indicates false tracer positions. These wrong particles positions are removed before the particle matching.

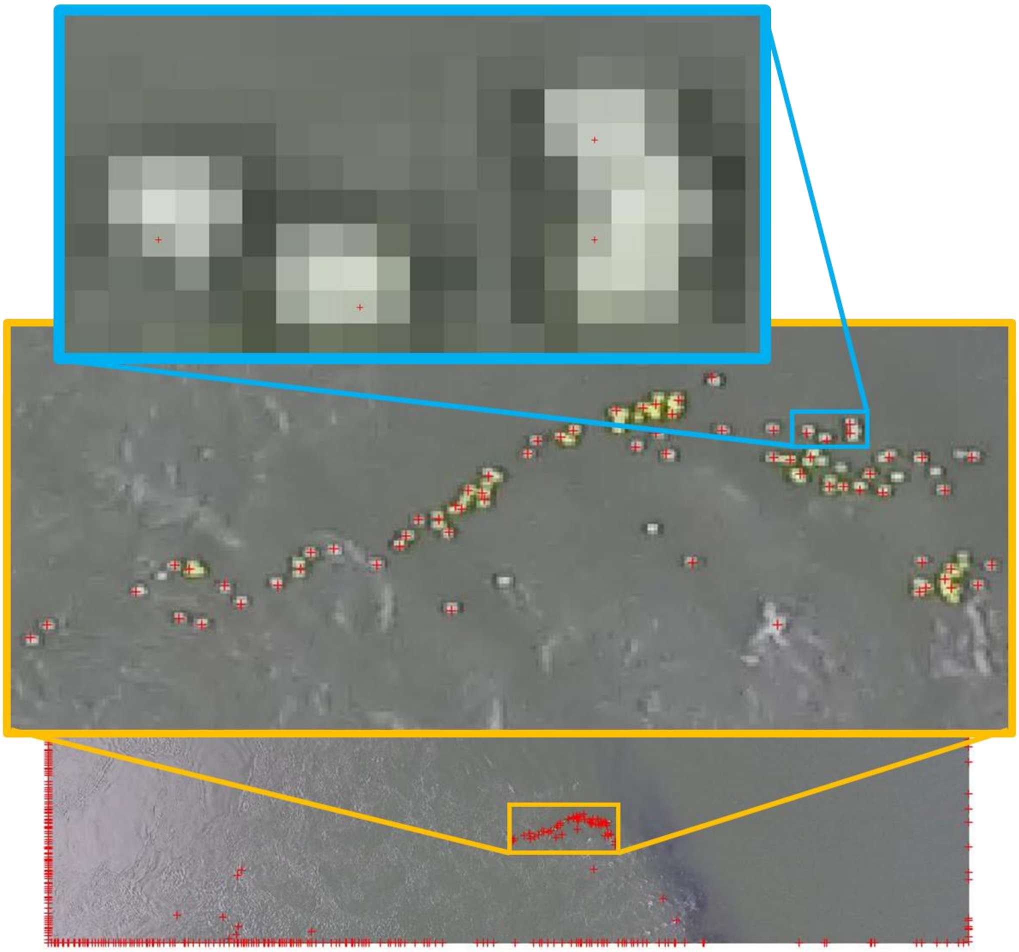

Figure 14. *Particle positions*

4.1.2 PART 2 (PARTICLE MATCHING)

Now the particle positions are known on every frame, they just need to be matched together.

4.1.2.1 KALMAN FILTER

The algorithm needs to have changing number of estimates because balls might float in and out of the image at some point, and the algorithm may loses it at some point then it finds again, but that does not mean they are bad tracks. The main variables of the Kalman filter are given, for example the particles estimated positions from their expected velocity. The variates are calculated in 3D originally and meant to track overlapping particles as well, so there is a 2D updating step. Then comes the initialization of the 2D variables, such as creating a large matrix full of "NaN" for the XY positions, and the good values will be filled in here later on. The next state is that the next positions of the balls are predicted from the last state and the predicted motion. Then the next covariance is predicted then the Kalman Gain is done.

4.1.2.2 ASSIGNMENT OF DETECTIONS TO THE ESTIMATED MATCHES

The detections are assigned to the estimated track positions by making a distance (cost) matrix between all pairs, the rows are estimated tracks and columns are detections. The track number is limited by the number of frames. If the detection is too far from the estimated position it will be rejected. The covariance estimation will be updated with the assignment.

4.1.2.3 ADDING NEW TRACKS AND DELETING BAD TRACKS

Found tracks are already stored and filled in the matrix. 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 X, the tracking will be deleted from the matrix.

4.1.2.3 GOOD TRAJECTORIES

Now we have only the good trajectories stored in XY matrices. Plotting so many trajectories are not the most convenient in MATLAB environment, so the results will be shown using MS Excel and Tecplot 360 softwares.

4.2 CONVERSION OF COORDINATES

The image data and the trajectories calculated by the PTV algorithm are in pixel units. The exchange to meter units is straightforward. Knowing:

- the flight altitude (h),
- the size of the camera lens (c),
- and its focal length (f),
- and image resolution,

the size of a pixel can be calculated (**Figure 15**). For example, if the Phantom 3 UAV is at 60 m altitude, the size of image seen will be 128 · 85 m, using 2704 · 1520 px image resolution, a size of a pixel will be 0.047 meter.

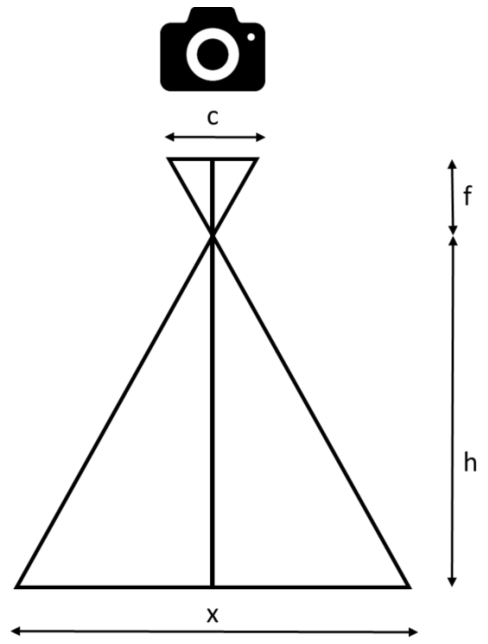

Figure 15. *Size of image recorded from UAV*

Also the flight records are stored in the UAV's DJI account, so the XYZ coordinates of every flight route is available. This way the flight altitude and the UAV positions are known. Flight altitude is necessary for pixel size calculation, and the UAV positions will be used when the resulted trajectories need to be georeferenced, since we do not use any reference points. A simple coordinate transformation is done from the image's own coordinate system to the Hungarian EOV system as the last step.

5 SENSITIVITY ANALYSIS

There are a few parameters of the image processing method, which required some kind of sensitivity analysis. There are probably many more parameters, but the following ones should be the most important ones to be analyzed:

- Image resolution
- Image distorsion
- Frame rate

5.1 IMAGE RESOLUTION

This is obviously an important parameter, since the computational time of the image processing is significantly more when we have high image resolution. But since we have kind of short videos and a tennis ball takes only a few pixels, now the maximum image resolution was chosen.

5.1 IMAGE DISTORSION

It is assumed that since the camera is orthogonal to the water surface, there is no need of orthorectification of the UAV images. Maybe the camera is not 100% orthogonal due to bad gimbal work or too high wind or other conditions. Analysis have been done to see how much the same objects change on different images. 8 random images were chosen when the boat has different positions (**Figure 16**). The length of boat in pixels were measured manually in AutoCad software. The results of the boat sizes on every image can be seen in **Table 3**. The relative deviation is about 4%. This 4% might be coming from the uncertainty of the boat size measurement, and low enough to say that the images do not need any orthorectification.

Figure 16. *The boat on different frames*

Image ID	Boat size (px)
1	175
2	174
3	176
4	174
5	173
6	169
7	170
8	170
Average:	**173**
Deviation:	**7**
Relative deviation:	**4%**

Table 3. *Size of the boat on different frames*

5.2 FRAME RATE

The original frame rate is 30 frames per second (fps), in case of a 10 second long video section this already means 300 images to process. This should be reduced as long as the resulted frames are still usable for the particle matching and reconstructing trajectories. Particles cannot be too far from each other, if they change too much between image pairs, the results will be messed up. Frame rates = 1 and 15 fps have been analyzed. The analyzed video was 24 second long, which means there are 360 images at 15 fps, and there are 24 images at 1 fps to process. The resulted trajectories can be seen on **Figure 17**. Results from using 1 fps is unacceptable, the algorithm loses too many tracks. Using 15 fps results very good trajectories but the number of images to process is a little bit high. For the image processing 5 fps was chosen to reduce the calculation time but they are definitely more detailed than 1fps.

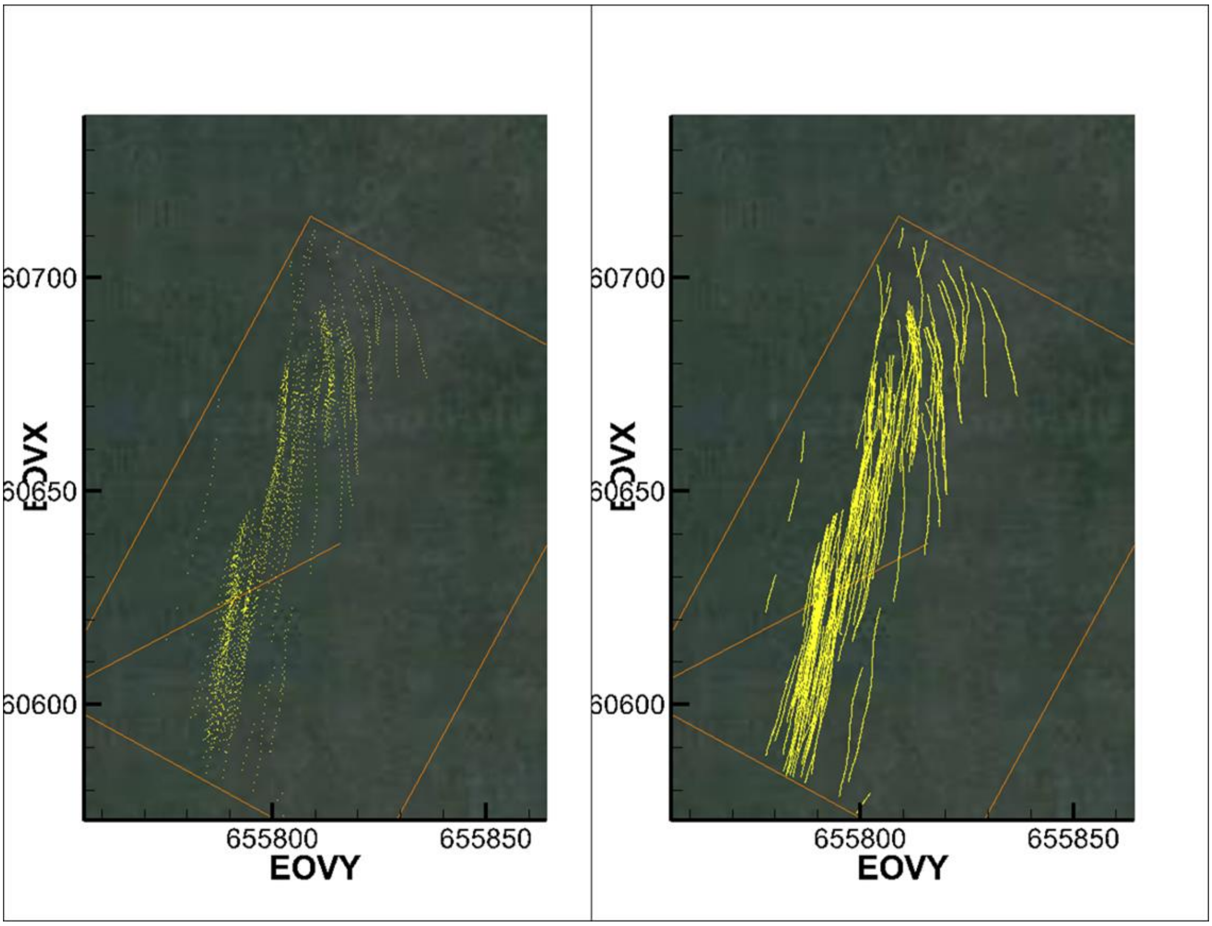

Figure 17. *Trajectories using frame rate = 1 fps (on the left) and 15 fps (on the right)*

6 RESULTS

First, the ADCP measurements from the second field campaign are shown in **Figure 18**, because the PTV results from the same campaign will be analyzed later on. The orange rectangle represents an analyzed UAV image. The black dots show where the moving boat ADCP measurements took place. The spatially interpolated velocity distribution closest to the free surface can be seen, where the color indicates the velocity magnitude. The increasing flow velocities due to the groynes can be well detected, moreover, the recirculation zone with low velocities can also be observed. Between these two zones the flow can be characterized with high shear, which leads to the formation of vortices. Despite the fact that the vortex street can easily be seen by eye at such locations, streamlines fitted to a steady flow field will not indicate the spatially complex behavior of the flow. The figure shows streamlines at the tip of the groyne, which, in general, show well the flow acceleration (denser lines) and main flow directions. ADCP measurements provide large scale information on the flow field, but due to the measurement method and the procedure, it is not capable to reveal the fine scales, both space and time wise, of the flow field.

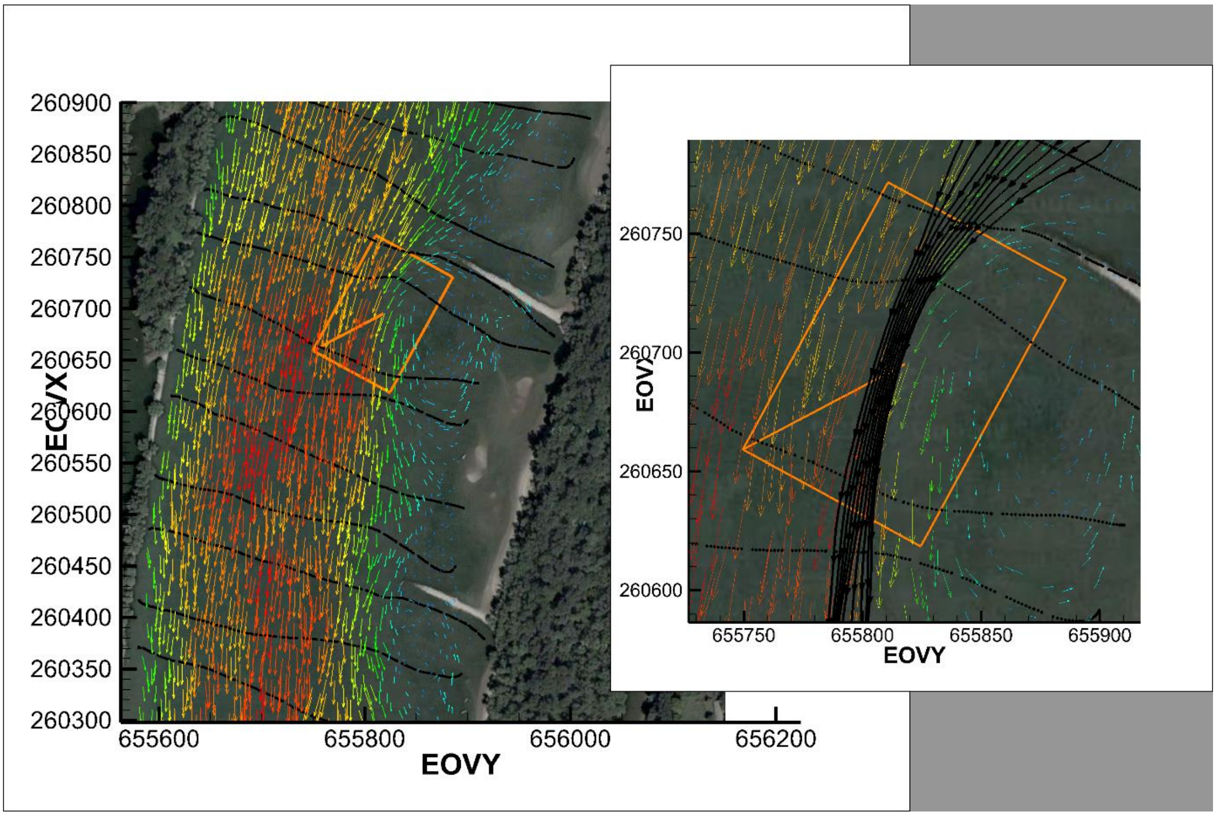

Figure 18. *Spatially averaged velocity distribution from the ADCP measurements*

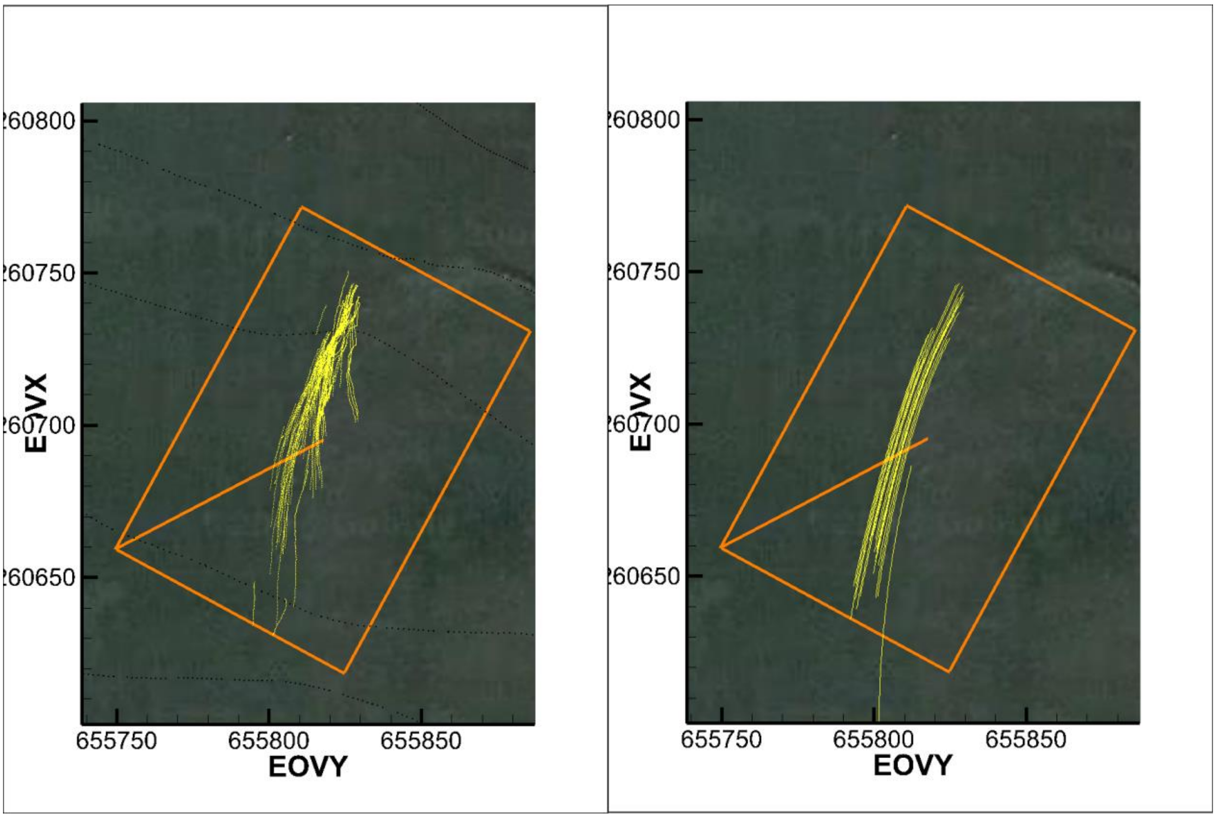

Figure 19. *Comparison of trajectories calculated from PTV (left) and ADCP (right) measurements*

Figure 19 shows the trajectories reconstructed from PTV analysis together with the streamlines fitted on the ADCP based flow velocity distribution. The difference between the two images can be very well seen as the PTV based trajectories show a more complex pattern. The transversal movements of the tracers indicate the mixing effect of the vortices, which means that a quantitative assessment on the mixing can most probably be performed based on the calculated trajectories.

The PTV results of the analyzed UAV videos are shown in **Figure 20 and 21**. PTV provides more fine scale and more detailed flow structures. Zsugyel (2016) was able to reconstruct 3 trajectories with floating buoys to quantify these complex structures. Using the PTV algorithm and hundreds of tracers, much more detailed information was gained about the same flow structures. The mixing calculation will be more accurate as well if there are more data available. **Figure 20** shows that the particles move and spread like a plume while floating. In **Figure 20**, the trajectories from all 3 UAV positions are shown. The trajectories are not continuous since some time is lost when the UAV was moving to another position, usually about 10-30 seconds. The UAV could track the tracers further too, but later on the tracers will spread out too much. **Figure 20** shows the displacements of the tracers through their positions at every 4 seconds from a video, T = 12, 16, 20 and 24 sec. Once the tracers reached the end of the frame, the UAV moved to another place.

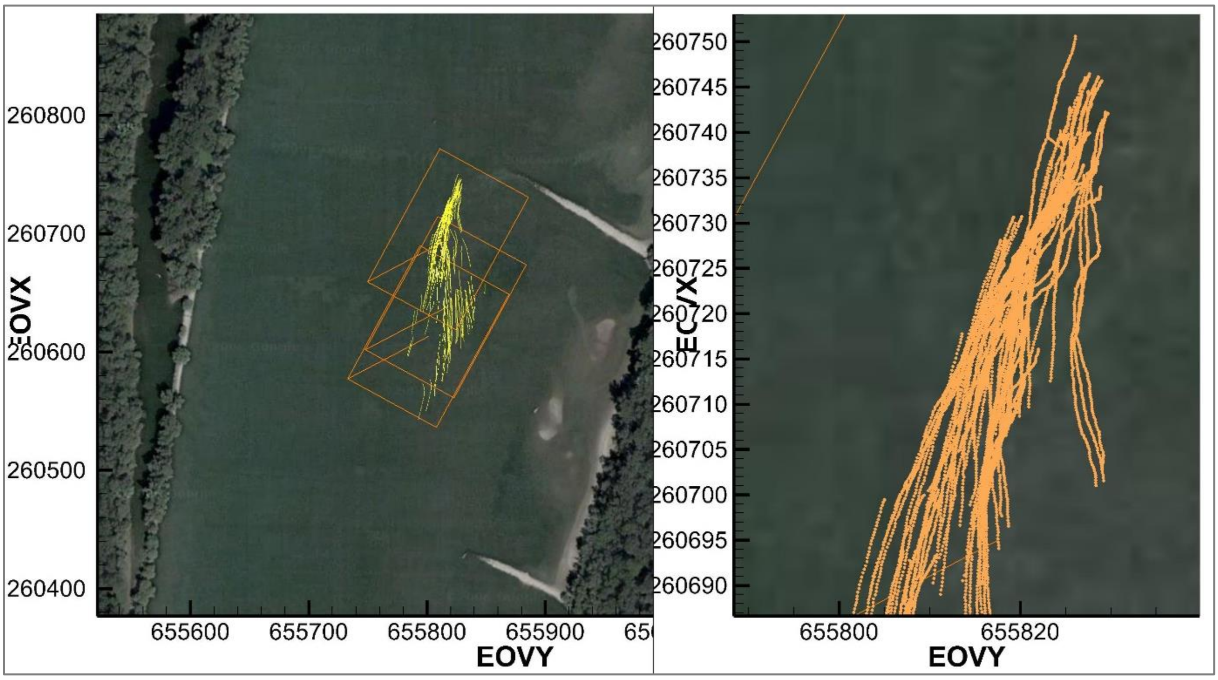

Figure 20. *Trajectories calculated from PTV measurements*

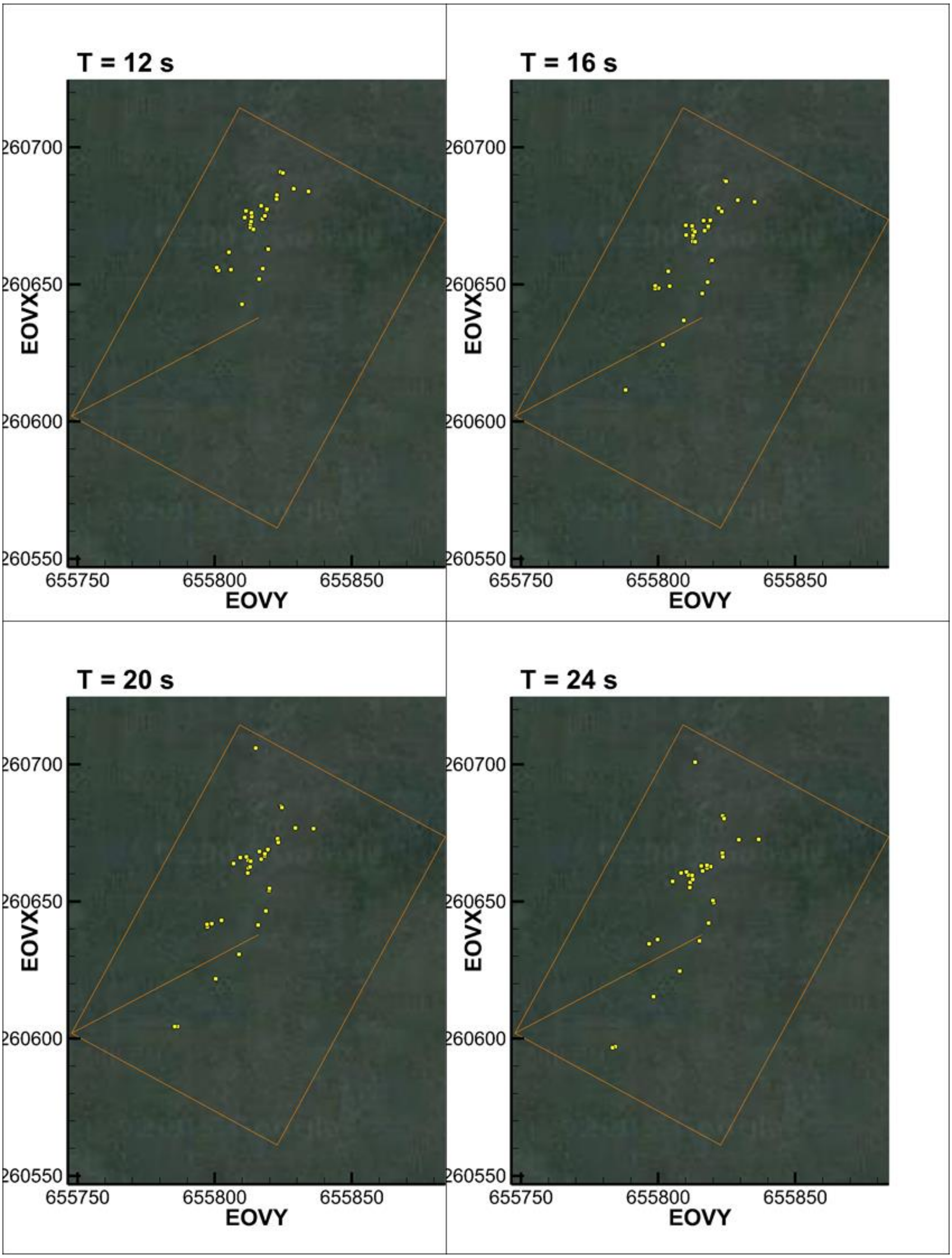

Figure 21. *Result of the PTV measurement: Animation of detected and matched tracers*

It is possible to identify the zones of strong shear based on the ADCP measurements where the vortex structures and the consequent strong mixing is expected. There are several methods exist to identify eddies in flows (e.g. Nyers et al., 2008; Holmén, 2012). One of the simpler methods is to the calculation of the so called vorticity (around the vertical axis) according to the following formula:

$$\Omega = \frac{\partial v}{\partial x} - \frac{\partial u}{\partial y}$$

- where: Ω is the Z vorticity
  - *u* and *v* are velocity vector components of *x* and *y* directions.

The Z vorticity distribution calculated from the ADCP results can be seen in **Figure 22**. The vorticity field indicates high values at the tips of both groynes. Again, these are the locations where the formation of vortices is expected leading to an increased mixing behavior. Indeed, this mixing effect can be captured looking at the tracer trajectories from PTV (see the right image). In contrast with the streamlines reconstructed from the ADCP based flow velocity field a much stronger transversal spreading if the tracers appears.

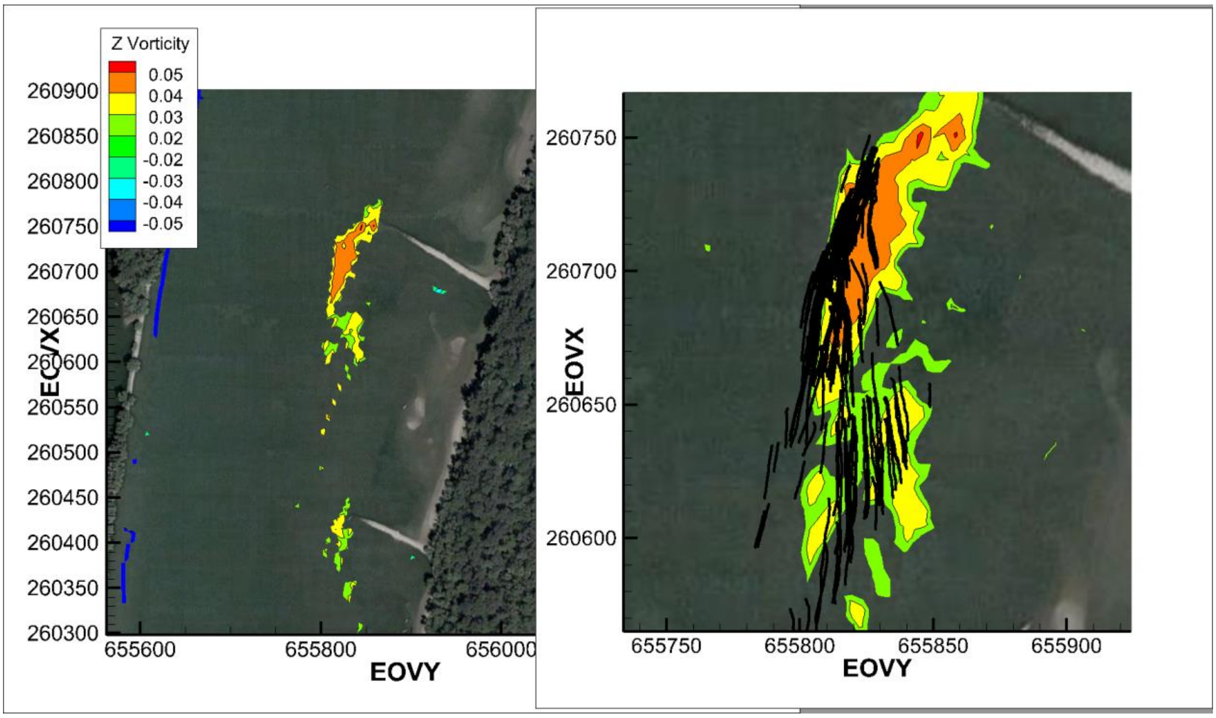

Figure 22. *Calculated vorticity field from ADCP measurements and tracer trajectories from PTV.*

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. As Zsugyel et al. (2012) said "The most characteristic feature of chaotic motion is its (exponential) sensitivity to initial conditions. The traditional way to characterize this feature is the determination of the standard Lyapunov exponent of chaotic advection (see e.g. Tél and Gruiz, 2006). In a fluid dynamical application, chaotic motion manifests itself in an exponential growth of the distance between nearby fluid particles; if the initial distance Δr_0 is small, the growth of the distance in time t is proportional to an exponential factor:

$$\Delta r = \Delta r_0 \cdot e^{\lambda t}$$

where:

- Δr is the distance between particles at t instant,
- r_0 is the initial distance and λ is the Lyapunov exponent.

This rule implies a very rapid increase resulting in strong spreading of particles and stretching of pollutant patches. The growth rate λ is called the local Lyapunov exponent, which can serve as a quantitative measure of the strength of particle dispersion to characterize mixing. The reciprocal of the Lyapunov exponent can be interpreted as the local prediction time: the characteristic time scale under which information on the initial conditions is being lost in a system. After this time, the prediction of the fluid particle positions is not possible with traditional tools."

Zsugyel et al. (2012) use the same finite-size Lyapunov exponent to understand more of the chaotic motion. They used 3 particles to analyze, compared to which the hundreds of trajectories in this study mean a significant improvement of the analysis. In the referred study the distance of the 3 particles was also analyzed. Here, 4 particles were chosen randomly from the resulted trajectories, with ID #3, #5, #15 and #36, and all possible combination of pairs were analyzed how far they went from each other along their routes (**Figure 23**). Lyapunov exponents were calculated for the straightest sections too. The great advantage of the herein introduced tracer based PTV method 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 much detailed description of chaotic parameters than before.

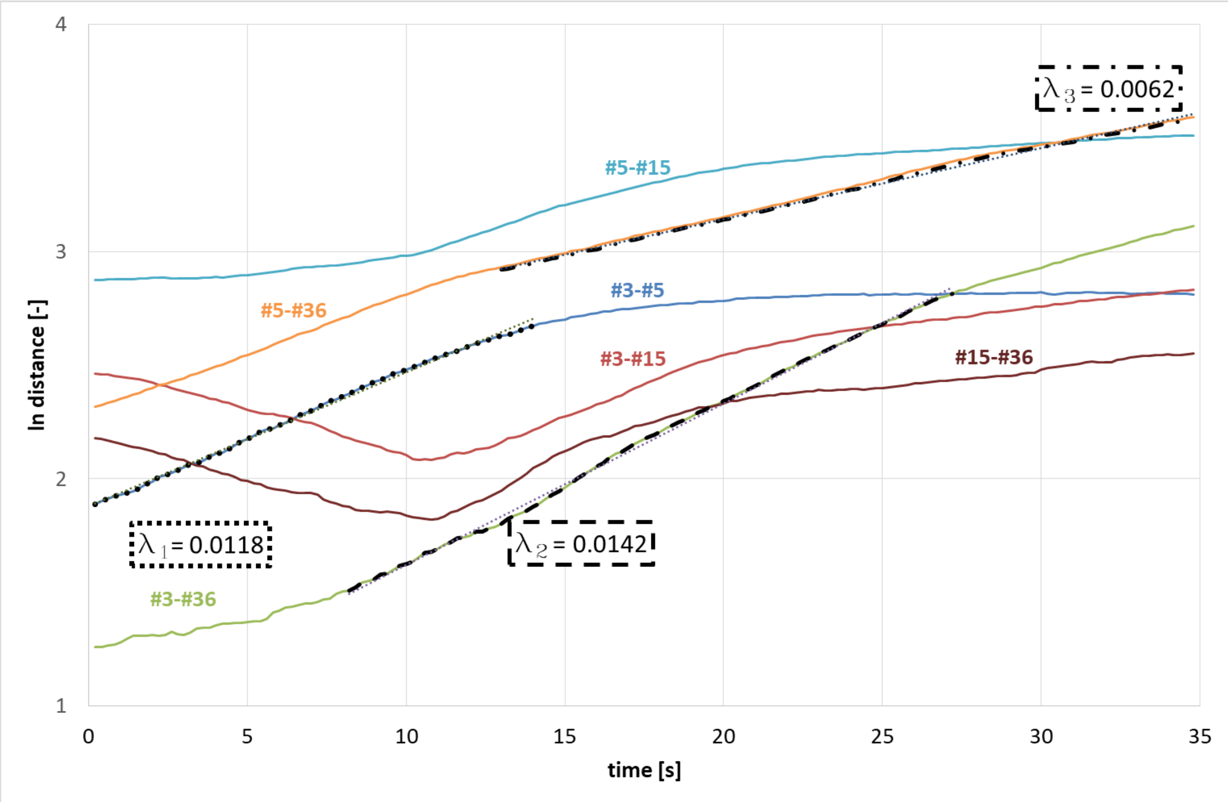

Figure 23. *Distance of particles #3, #5, #15, #36 from each other with the Lyapunov exponents*

In **Figure 23**, particles at #5-#15 and #5-#36 are not very close to each other but the distance is growing slowly, same as #3-#5, but that pair is a little closer at the start. #3-#15 and #15-#36 both start being quite far from each other, then the distance is getting smaller for a while then they start moving away from each other. #3-#36 is the most exemplary, where they are almost next to each other at the start and then the distance is growing exponentially with very similar Lyapunov exponent value as the buoys' in Zsugyel et al.'s (2012) work. If every pairs and their Lyapunov exponents were calculated, the spatial distribution of Lyapunov exponent values could be shown over the whole analyzed area, which means PTV can help to characterize these coherent structures and understand more of the chaotic motion.

7 SUMMARY AND CONCLUSIONS

UAV based river flow measurements have been carried out with Lagrangian approach and an algorithm was further developed to perform the image processing in MATLAB environment in this study. Detailed literature research was performed of the relevant topic as well including the applied Lagrangian flow measurements and other Eulerian flow measurements which use images from UAV measurements. No UAV based particle tracking velocimetry (PTV) have been applied before, so this study is testing if it is applicable. During the field measurements UAV videos have been collected of a hundred tennis balls floating in the area of a groyne. These videos were then analyzed using the new PTV algorithm and about a hundred trajectories have been reconstructed, after the sensitivity analysis have been done to some image processing parameters. Application of the river scale PTV is a huge step in the Lagrangian approach of river flow measurements. Compared to the previous methods, where a limited number intelligent buoys could be applied as tracers, in this study hundreds of second hand tennis balls were used which are much more cost-efficient, considering the increased spatial information. Besides the PTV measurements, ADCP measurements have also been carried out around at the study reach and the results have been compared. It was shown that flow velocity field reconstructed from ADCP survey contains significant information on the flow field, but cannot be applied for the analysis of fine scale, unsteady nature of the flow which can be seen from the PTV measurements. PTV can reveal those very fine spatiotemporal scale flow structures. The developing plume at the end of the groyne cannot be seen from the ADCP streamlines of the velocity distribution, but the reconstructed trajectories by PTV can detect and quantify these chaotic natures of dynamic flow structures too. The chaotic structures are usually characterized by the finite-size Lyapunov exponents, so few random particles were chosen to analyze their distance from each other, and the trajectory pairs' Lyapunov exponents have been calculated. The exponents match to the other's results in relevant literature, but the novel approach which was presented in this study contributes to the characterization of the complex flow structures very detailed and quite cost-efficiently.

8 FUTURE RESEARCH IDEAS

UAV-based measurements have huge potential for future research generally in river engineering, since very valuable videos can be collected from places where it would not be possible any other way manually. The application of the introduced techniques in this study need to be further analyzed since this was a first attempt in this field. The applied MATLAB algorithm can be improved while getting closer to the automatization of the processing. Also, 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 which can be applied to the trajectories calculated in this study.

The PTV method could be used for assessing sediment resuspension caused by the breaking of ship induced waves (Fleit, 2015) and littoral erosion, since the phenomenon is visible from the UAV videos. PTV is able to reveal the eddy structures in the vicinity of different structures, such as river groynes applied in this study, but this needs further research to quantitatively assess the chaotic nature, which is important 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 inherently consisted in the trajectories as the displacement of the tracer and the time step is known. The calculation of temporally varying flow velocity fields would mean a significant step towards the quantitative description of mixing processes in rivers.

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