3D Hypergraph-Oriented Air Flow Analysis Based On PTV

Denis Klimentjew, Nils Erik Flick, Till Bosselmann

Technische Aspekte Multimodaler Systeme, Fachbereich Informatik
MIN-Fakultät, Universität Hamburg
klimentjew@informatik.uni-hamburg.de

1. INTRODUCTION

The presented work introduces a new air flow analysis approach based on Particle Tracking Velocimetry (PTV). One of the special features of the proposed method is that after the tracer particles are detected, matching and tracing are jointly conducted. To this end, we introduce an interpretation module based on a directed hypergraph for 3D curve reconstruction. At first the 2D inter-frame locations are localised and used for the extraction and calculation of 3D keypoints. Through 3D keypoints which are evaluated by the hypergraph together with the time information in several steps, reverse curve matching for path selection can be reconstructed and the resulting trajectories visualised.
In contrast to the preceding works our approach tries to describe the measuring data by 3D trajectories directly instead of estimating first 2D trajectories and then matching afterwards. A higher precision can be achieved also with complicated trajectories. A certain independence of the reflections and lighting conditions is reached by the interpretation. Moreover, the path of particles can also be reconstructed with the minimum number of 3D keypoints under consideration of the path energy minimization.

2. THEORETICAL DESCRIPTION OF THE ORIGINATING METHOD

The PTV system we developed is based on two synchronised cameras with long exposure time.

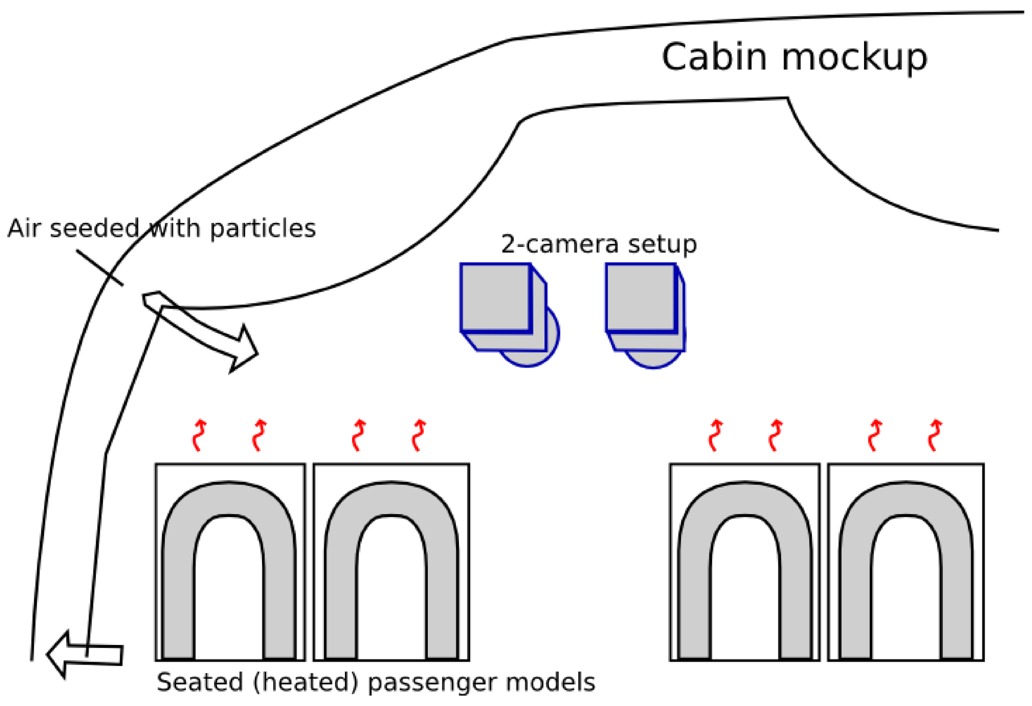

Figure 1: *Cross section of a full scale aircraft cabin mockup, as used in our experiments*

For the background removal an image I can be seen as the sum of several components:

$$F_{i,f}(\vec{x}) = \alpha \cdot BG_{i,f}(\vec{x}) + N_{i,f}(\vec{x}) + T_{i,f}(\vec{x}) \quad (1)$$

where F denotes the image, T_i the foreground region containing the traces, BG_i the background, and N_i the camera noise at frame number i. In a static scene, BG_i is affected only by changes in illumination (and reflections). The main of BG_i's intensity can be removed by calculating a median image over several frames. This template is then subtracted from each input image. If an effort was made to keep illumination constant, the remaining BG_i intensity is low enough to not affect further segmentation steps significantly, so that we can assume $F_i = T_i + N_i$, which simplifies the following segmentation steps.
If F is viewed as feature space, the MeanShift algorithm can be used for segmentation. It operates by following the density gradient with a kernel in the feature space until a maximum has been reached. Pixels sharing the same gradient maximum are assigned the value of that maximum. All other pixels are assigned the density estimate of the kernel centered at their position. If the kernel is chosen to be suitably large, and the noise is uniform and white distributed, the method is noise resistant.
Although by no means perfect, the MeanShift based segmentation showed the best performance of all the tested methods, due to its suitability to varying classes of input images.

2.1 Keypoints

We introduce inter-frame locations of particles as a choice of 2D keypoints, which can be detected on each view individually; the 2D keypoints introduced above are then combined to 3D keypoints, all while respecting the epipolar constraint.
There is more to the choice of such *2D keypoints* as essential significant feature:

- they are very robust against the choice of exposure time, because the aspect, except for inevitable overlaps, depends only on first order of arclength of the original trajectory, and not on curvature or other aspects of its shape
- no matter how long the duration of the integration of *intra*-frame information, these keypoints are always equally well localized

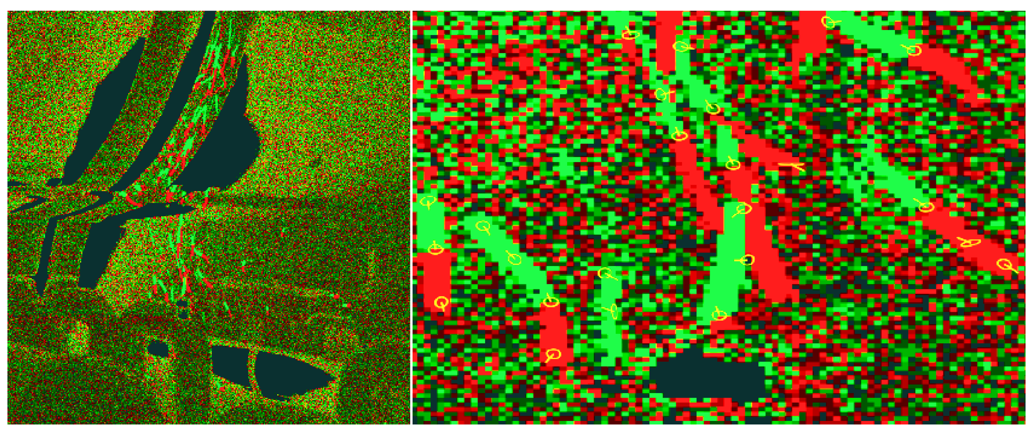

Figure 2: *Example of correctly detected inter-frame locations, superposed onto a color-coded two-frame difference image*

For the software prototype, the choice fell on Harris' and Stephens' combined edge and corner detector over other possibilities because of excellent localization and high specificity (empirical, synthetic and actual image series), and especially for its avoidance of multiple detections (which would be toxic for the accuracy of measurements).

2.2 Interpretation

In the following, we always assume that all interframe locations which are detectable with sufficient confidence have been detected. While it might be possible to achieve good results by suitably tracing out the trajectories from image information, we think it preferable not to proceed in this direct way but instead to generate hypotheses and filter them according to how well they explain the frame content. This circumvents most problems local path-following methods have with ambiguous situations, especially in the presence of occlusion.
The advantages to indirect analysis via hypotheses are manifest:

- thanks to a global, top-down, view, results are much less likely to be influenced by local fluctuations, noise and difficult situations (i.e. crossings of traces) than local approaches
- there are enhanced opportunities for a true probabilistic interpretation of the image series, as explained below
- one can unambiguously fit simple curves to just a few keypoints, which nevertheless remain accurate to high order if desired (B-splines lend themselves to it)

The third point above can be understood as an instance of Occam's Razor; moreover, it renders optimization over curve spaces completely unnecessary.

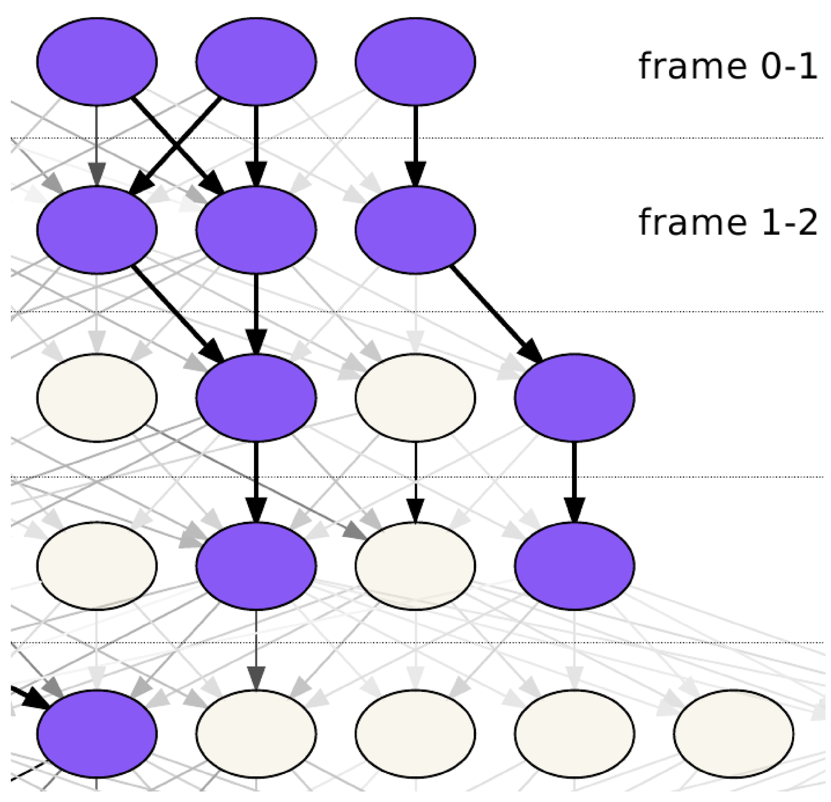

Figure 3: *Directed graph of continuations*

All possible immediate continuations form an acyclic, directed graph (fig. 3). We extend it to a directed hypergraph by considering all paths up to an arbitrary number of frames f. f can be small, of the order of about 5 frames, and longer range dependencies are disregarded, because the particle motion can be described locally. By cutting hyperedges (e.g. bottom-up, by removing edges first and enforcing transitivity under these constraints), one can partition the hypergraph of continuations into non-branching segments. These partitions are possible *explanations*, or *interpretations*, of the image evidence g and should be assigned a probability.

$$p(\beta|g) = \frac{p(g|\beta)p(\beta)}{p(g)} \quad (2)$$

An application of the Bayes theorem: in eq. 2, β represents the curve parameters and g the image evidence. The prior distribution $p(\beta)$ can be picked on physical grounds; for example, one should favor interpretations which do not require excessive kinetic energy to realize. $p(\beta|g)$ would be read as the probability of a single trajectory being supported by the image evidence; the probability of the whole hypergraph partitioning depends on the individual trajectories' probabilities, which are independent except for the interdiction of crossings and for the handling of subchains.
Each path candidate (chain) from the hypergraph is converted to a smooth trajectory candidate by means of B-splines

3. EXPERIMENTAL RESULTS

The implemented prototype comprises temporal information and the reconstructed 3D particle trajectories. In spite of the foundations the temporal information can be determined through the synchronized cameras and particle traces (blurred lines). To computate the velocity of single particles we use two different algorithms, the above mentioned physical properties or the first derivative of the resulting curvature.
To assist the developers of air conditioning systems we use different means for the vizualization of the velocity of the particles. For the visualization of single particles the direct numerical indicator can be used. For a large number of particles, the color-coded visualization of the velocities is advantageous. Fig. 4 shows the color and hue coded trajectories of the particles, the slowest particles are green, the fastest are red (color and hue coded).

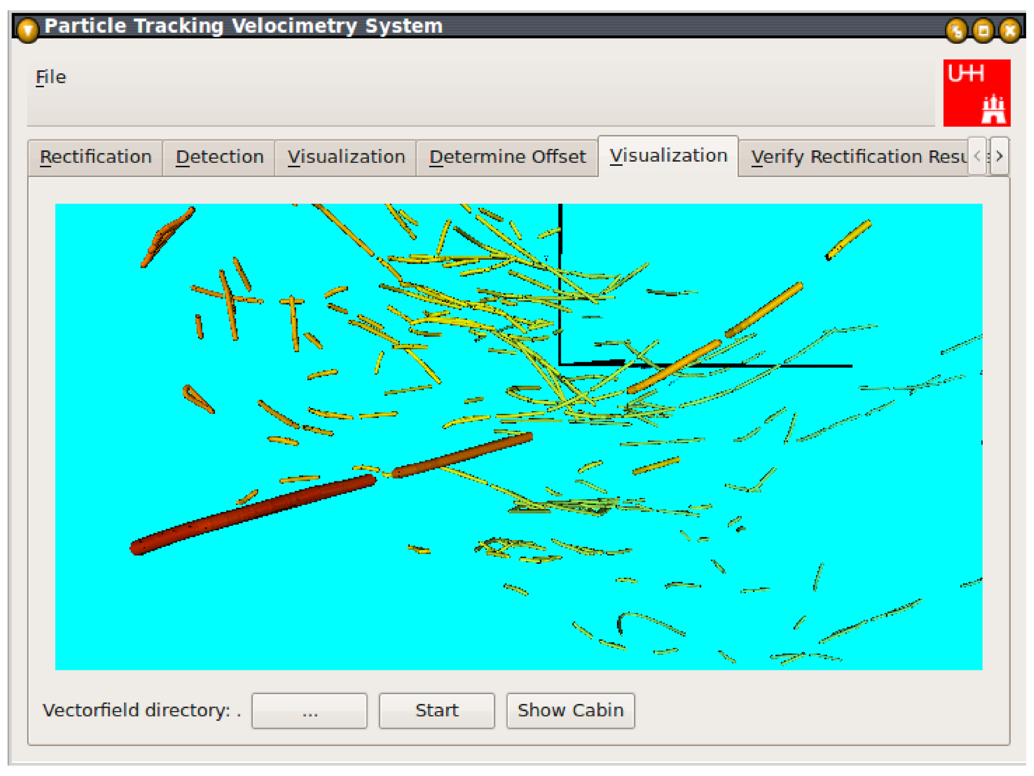

Figure 4: *Color and hue coded velocities of reconstructed 3D trajectories. The slowest particles are green, the fastest are red*

Exact evaluation of fluid experiments needs ground truth, which is not always easily obtainable: however, for validation, one can resort to synthetic images, employing ray tracing in order to use the observational model as a generative model. Experimental results are encouraging: the detection process, when run on a synthetic image series showing a portion of a circular motion, reports after hyperedge selection only two candidates for motion, one corresponding closely to the true motion (with very low average deviation from it of about 1%).

4. CONCLUSION

This work demonstrated that depth reconstruction of sparse flow information is practical using a stereo camera setup. Furthermore, tracking of individual particles can be done by generating a graph of possible paths and matching generated curves. After the summary of the results also known problems of the developed method are shown briefly. The selecting a suitable background mask to limit the number of candidate points and prevent the problem from becoming unmanageable from state explosion (super linear growth of possible choices).
As a summary, the direct description of the measuring data by 3D trajectories instead of estimating first the 2D trajectories and this matching afterwards offer oneself as advantageous. A higher precision can be achieved also with complicated trajectories. The presented system is capable of making essentially one-dimensional measurements of a fully 3 + 1 - dimensional spatio-temporal phenomenon.