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Visualising the Invisible: Exploring Approaches for Visual Analysis of Dynamic Airflow in Geographic Environments Using Sensor Data

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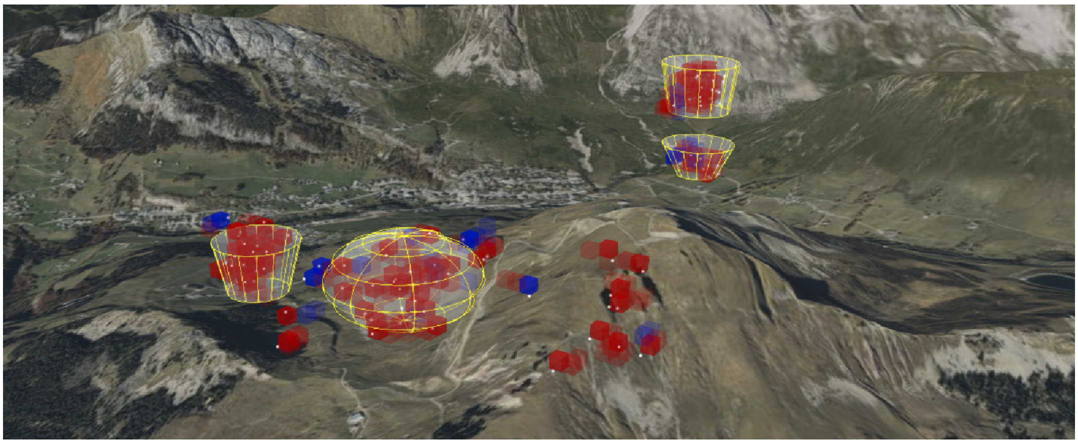

Figure 1: *Visualising the combination of our Space Partitioning and Trajectory-Centred methods within TEAMwISE [KAZ*21]. Coloured cubes show positive (red) and negative (blue) extrema of vertical speed. Transparent geometric shapes represent abstractions of the thermal shapes derived from our method.*

Abstract

Measuring, modelling, and visualising dynamics of fluids, in particular air and water flow, are important in many applications, including engineering, biology, meteorology, and sports. While there are established models of airflow in controlled conditions, we are lacking an understanding of the distinct airflows in natural environments, whose characteristics are highly influential for all forms of aerial activities. There is little data available for fine-scale analysis and representation of airflow outside the lab without the help of sophisticated and laborious airflow measurements. Here, we explore ways to exploit movement data of flying agents for this purpose, propose an approach to model and visualise thermal dynamics as a discrete localised airflow, and demonstrate our approach using data collected from paraglider pilots.

1. Introduction

Fluids, i. e. liquids and gases, have no fixed shape, and many are transparent media, such as water or air. Thus, their motion and flow patterns are often invisible to us. Flow pattern and motion visualisation can provide information on the flow field and the dynamic structure of the flow. Airflow movement impacts many applications, ranging from weather analysis over vehicle design and architecture to the flying of manned or unmanned aerial vehicles (UAVs) [ANV08, RCSV16, Fro89]. Thus, understanding the flow's dynamic structure has far reaching impacts, including economic impact (plane fuel consumption), engineering and safety (wind effect on objects), competitive performance (gliders), or combinations thereof (e.g. weather prediction). A limitation of scaling is imposed by the complexity of the existing models and by the challenge of incorporating the effect of the natural environment on flows dynamics. Computational fluid dynamics (CFD) has a rich history spanning decades, and often employs supercomputers for flow dynamics simulations [Wen13, And13]. This restricts applica-

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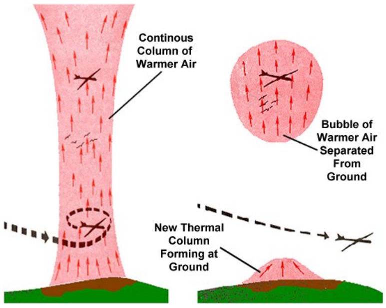

Figure 2: *Illustration of column and bubble type thermal structures [Avi65].*

tions in practice often to smaller projects. Air flow itself is difficult to observe, but we can observe its dynamics indirectly via the movement of agents within the environment - such as smoke particles carried by flow - as long as we can determine its impact on them to a reasonable extent. For some agents (e. g. weather balloons) the movement is fully driven by the air movement. Other agents (e. g. birds or glider pilots) modify their behaviour to exploit updrafts and avoid downdrafts as a movement strategy to gain distance or altitude with reduced movement costs. One highly dynamic and unpredictable updraft is the thermal, which greatly influences agents in the air, see Fig. 2. However, it is a particular challenge to quantify the impacts of flows on movement strategies given the intricate dynamic nature of thermals and the sensitivity of behaviour or performance based on thermal characteristics (e.g. [WDH*18]). As many of the current models and visualisations are targeting weather analysis and forecast [Stu98], there is a gap for the visualisation of fine-scale airflow information in a natural environment. Some recent approaches combine 2D heat-map representations with elevation (e. g. [Par]) but do not consider 3D airflow dynamics within the aerial environment above the terrain.

We propose the use of movement data, including ground and vertical speed, collected from flying agents, specifically densely packed agents (such as flocking birds and groups of gliders) for detecting and modelling distinct updrafts and airflows in an automated analysis. We investigate how to define the limits of updrafts and their cycling nature, and how to visualise them to support their analysis. This can support the analysis of energy minimisation in bird migration or decision-making algorithms by UAVs, or can aid in glider pilot training. As a first step, we use the vertical speed of flying agents to create a dynamic model of the airflow and suggest ways to enhance visualisation and analyses with additional environmental parameters recorded onboard the agents. As a use-case, we apply our method to a data set of a paraglider pilots in competition.

Our investigation aims towards the following research questions:
RQ1: How may we extract the dynamic structure of airflow from the movement data of flying agents moving collectively?
RQ2: How may we model and visualise dynamic structures for subsequent analysis in an intuitive manner?

2. Background and Related Work

Flow visualisation is an important topic in scientific visualisation and has been a research subject for many years [AAFW17, BCP*12, WE05, Smi12, Rus11]. Most of the flow visualisation methods for controlled environments can be grouped in three categories [Mer12]:

1) making the flow visible by introducing some visible additive materials into the main stream of gaseous or liquid materials
2) using the optical index of refraction to represent density of the medium;
3) a combination of the above two, i. e. artificially change the fluid density by introducing energy, e. g. in the form of heat

Each of these methods utilise an agent in the flow field for visualisation. Despite recent technological advances, this principle of flow visualisation is still relevant, even as categorisations may be extended. For example, the commonly used Laser Doppler Velocimetry (LDV) or Particle Image Velocimetry (PIV) methods, employ lasers to visualize the flow field via a molecule tagging that serves as an agent. [Smi12].

In small and controlled environments, thermal-like updrafts may be simulated by a man-made setup, where air movement is detected and visualised using planar visualisation technique, lidar or radar techniques. Dennis and Siddiqui [DS21] describe algorithms for automatic thermal-like airflow detection in a lab setting applying image segmentation technique to investigate the three-dimensional behaviour of buoyant updrafts. Christmann et al. [CFM*22] describe a user-centred design to airflow visualisation.

For large, natural environments, predicting fluid movements becomes complex, making flow visualisation a unique challenge. Projects usually involve many resources, including specific skills and high-tech equipment. Restricting the area to a large, flat landscape [AGHD98] helps to simplify the environmental variables, but also restricts versatility of phenomena and generalisability of results. In meteorology and related areas, animated 3D visualisation is an informative tool to understand the nature of the underlying process [HBH*00]. In a survey paper on techniques and tools for meteorology visualisation, Rautenhaus et al. [RBS*18] pointed out that many advanced techniques have been proposed for flow visualisation, however, only a few directly target atmospheric airflow. Helbig et al. [HBR*14] detailed a workflow for visualising atmospheric data in Virtual Reality (VR), but their large-scale approach is not directly applicable to our meso-scale setting and requirements for further analyses.

Our approach is based on exploiting collected evidence on airflow by groups of moving entities and is related to the investigation of collective motion. For an overview of this topic including mathematical methods and simulation models see the work by Vicsek and Zafeiris [VZ12]. There are some conceptual thermal structure models related to movement, in particular for animal movement analysis [NCF*18], but they focus on the analysis of behaviour of the entities within the rising air, not the analysis of the airflow itself. The interplay between uplift airflow and bird soaring has been a research topic over many decades [Fro89, RCSV16].

3. Modelling and Visualising the Airflow/Thermal

For open, natural environments, we propose using the movement of tagged objects as a sensory system for airflow visualisation. Tagged objects could be animals (e. g. birds), humans (e. g. paragliding pilots), or UAVs. Birds have the ability to utilise the airflow very efficiently, especially thermals, to gain altitude and save energy [RCSV16,SLVW11]. A well trained paraglider pilot has a very similar movement as birds in thermals [ANV08]. Given the characteristics of updrafts as dynamic airflow in form and uplift mechanism, and the corresponding assumptions (e. g. on basic structure and diffusion/attenuation) we can exploit the movement data of flying entities in an informed way. Our hypothesis is that the air dynamics of the phenomena of interest, including thermals, can be sufficiently detected and characterised by the evidence derived from such data, including but not limited to vertical velocity of the agent when moving passively. The proposed methods follow two main approaches, where one takes a region-based perspective while the other takes a trajectory-based perspective, similar to the Lagrangian and Eulerian approaches for tracking kinematics. Using these complementary approaches, we create models of the shape, strength, and direction of flow of thermal bubble-like structures over time and 3D space.

The data collection and pre-processing for our evaluation use case involved collecting movement data from paraglider pilots via multi-sensory devices attached to their equipment (including a GPS tracker and bio-logging unit [WWT*23]). This data includes location (GPS at 1 Hz), activity intensity and magnetic direction (50 Hz), as well as environmental measures of temperature, humidity, and air pressure (1 Hz). We use pre-processed data for the investigation of flow visualisation and analyses, where data had undergone

1) integration and consolidation: where data are time matched if collected at different frequencies

2) cleaning: often small data errors exist that need to be corrected, such as outliers and missing data

3) transformation: where spatial data require alignment onto the same global projection

4) calculation: of data derivatives, e. g. vertical speed from GPS.

3.1. Airflow Modelling

Space Partitioning

At a basic level thermals are regions of uplift, and we can create an uplift model by using space-partitioning and collecting the uplift evidence from the movement of agents within partitioned cells. The partitioning can be based on simple rules, such as uniform cube-cells that enclose all movements, or can be data-driven, e. g. regions of higher movement activity (uplift evidence) are treated differently to regions with lower activity. A function f of time is then applied to aggregate activity within a cell to map (discrete or continuous) an airflow value : $f(t, cell) = v_{airflow}$. For example, we could map each point in time in the data set range to the average corresponding uplift velocity value of entities in the cell at that point in time. Alternatively, we could aggregate uplift values over a certain time window whose size is informed by the expected duration of an uplift phenomenon (although this adds complexity and further assumptions). For subsequent visualisation, these values then can be mapped to visual variables, e. g. the colour of the partition cells. Such a mapping allows both static and dynamic views, where the former shows all cells that at some point in time are above a certain threshold value, while the latter shows at each time point only the cells with a higher value at this time point.

We investigated different instances and visualisations of such a model and found that a simple cube model with uniform cells allows for informative animations of the dynamics, where we map cells with positive and negative vertical velocity to corresponding colours, e.g. red and blue, respectively and higher absolute values are mapped to higher colour intensity. This allows the user to firstly identify regions of high uplift from collective movements, and secondly the edges of updrafts during animations to gain some perspective on structure. Although this first approach does not provide an overview on the dynamics this space-partitioning method can serve as a base case for comparison with more sophisticated methods.

We integrated the implementation into the TEAMwISE movement analysis tool [KAZ*21] (Fig. 1) as follows:

1) **Grid Generation:** We create a spatial partitioning by defining a 3D grid that encompasses the entire area of interest, with the grid cell size being adjusted to the sensor resolution and expected entity speed, and number of active agents - to reduce the number of empty cells while preventing cells from being so large that they obscure significant movement patterns and thereby hinder the identification of thermal boundaries.

2) **Data Association:** The recorded speeds are then associated with the specific grid cells where the objects were located at the time of measurement or in a short time window.

3) **Airflow Value Calculation:** For each cell, an indicator value for the airflow is calculated to implement airflow value function f. In our current implementation, the velocities of all objects within that cell are averaged to calculate the cell's "average vertical velocity" at a time point or during a short time window.

4) **Visualisation:** Visualising the grid statically as a large cube enclosing smaller cubic cells might create occlusion. As an alternative, an animation over time can show only the cells that have a high data value in a certain time window around the current animation time, either independent of or together with track animation.

Uplift Airflow Extraction

In our second, trajectory-centred, approach we analyse the agent trajectories with the assumption that thermal updrafts form from bubble-like structures that merge into columns of rising air in which flying entities can soar within to gain altitude. Flying through a bubble or column, either straight or by circling, will create stretches of positive vertical velocity. Each such stretch provides evidence of an uplift phenomenon. The more evidence is gathered within the spatial and temporal limits of a phenomenon, the higher our confidence of the thermal structure , e. g. a short-termed bubble or a long-term column of rising air. Given our assumption on the scale of bubbles and columns, we can thus cluster these stretches and analyse the results for the type and size of phenomenon they could indicate. In the visualisation, we can then represent the findings by corresponding shapes (e. g. spheres and clipped cones for bubbles, and cylinders for thermal columns).

The data collection for flying entities, e. g. by GPS sensors, is not perfect, and at the same time (missing) uplift might not be the only reason for measured vertical speed. For example, a bird or glider might perform some steering manoeuvre, e. g. a direction change. Thus, we can extend the evidence from the uplift stretches to sequences of movement points that might contain some downward sinking points between uplift stretches. While high vertical velocity is an indicator of thermal uplift, sinking stretches can help identify boundaries and gaps between thermals. We assume that switching from uplift sequences to dropping sequences (or the other way around) is a strong indicator of thermal boundaries at which the glider leaves (or enters) the thermal. Note that there could also be other reasons, e.g. reaching the top or a collapse of the thermal uplift at a point of time.

Depending on the morphometrics and behaviour of the flying entity, and the environmental conditions, values of vertical velocity that correspond to the airflow can vary, e.g. the angle of the bank affects the sink rate of an agent and thus the final vertical velocity that it experiences for a given updraft [WDH*18]. Thus, our method allows to set parameters for such values. These parameters include a threshold t_{up} on the vertical speed, above which we assume an uplift, the minimum length l_{slen} of a stretch of data points to be considered an uplift sequence, the difference d_{vv} of vertical velocity at entry and exit points, and the maximum length l_{maxgap} and overall percentage p_{maxgap} of intermediate gaps in uplift sequences allowed. Conceptually, it works as follows:

1) **Airflow Stretch Detection:** We extract maximum stretches of consecutive data points on each trajectory that are either above (S_{above}) or below (S_{below}) the vertical velocity threshold t_{up}.

2) **Uplift Sequence Assembly:** We assemble maximum sequences $seq = s_1, \dots, s_k$ of stretches $s_i \in S_{above} \cup S_{below}$ where the length of the stretches in S_{below} is below threshold l_{maxgap}

3) **Uplift Clustering:** We cluster the points in the uplift sequences, or the sequences as a whole, using either spatial or spatio-temporal clustering depending on time and space scales. Clustering is performed once for the whole time period for an overview and for sliding time windows to cover fine-scale dynamics.

4) **Breaking Point Analysis:** We collect data points for which in a short time window before there was positive vertical velocity, and in a short time window after negative vertical velocity, or vice versa, to detect evidence for uplift boundaries.

5) **Thermal Shape Reconstruction:** Based on assumptions of the physics of thermals and entity movement, we estimate thermal type and shape using the information from the breaking points, but also points of negative vertical velocity in the vicinity of clusters.

6) **Visualisation:** We add geometric shapes that represent thermal shapes to a movement visualisation, see Figs. 1 and 5, and represent cluster transitions as 2D diagrams or enrichment in 3D.

We also perform a spatial-temporal clustering of the resulting sequences or data points to capture the dynamics of thermal updrafts over the full measurement period and thus visualising the pathways of short-lived yet strong bubbles of vertical uplift and their convective cycling. Depending on the characteristics of the flying entities, e. g. their capability to actively stay in a thermal and their speed and manoeuvrability, and of the collected data, different clustering methods and parameters might be suitable. For an overview of spatio-temporal clustering, see [AAK*20, KMNR10]. The global clustering also allows us to perform an analysis of the cluster transition behaviour of entities, i. e. between which thermal hotspots they are switching over time. We use a Sankey diagram, or arrows in 3D, between cluster shapes for a static visualisation of the transition patterns, see Fig. 3. Leaving and reentering can inform the analyst about thermal ceilings and cycling duration (availability).

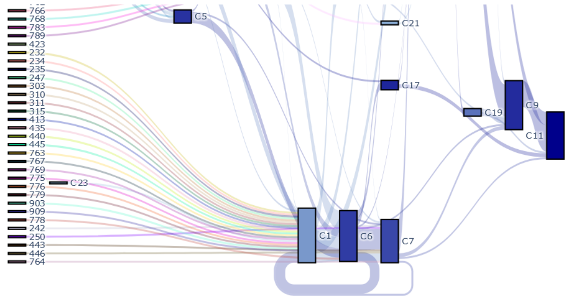

Figure 3: *Sankey diagram of paraglider movement through thermals during a practice task (cutout). We can identify main clusters for soaring and return patterns (cycles) to clusters, indicating that pilots consider a previous cluster more promising than the current one. Cluster maximum altitude is mapped to a colour gradient.*

Cluster duration or altitude can be mapped on the representation to further facilitate the analysis.

The shape reconstruction highlights differences in thermal type and shape beyond the convex hull, and allows the user to establish a confidence level in the otherwise complex flow dynamics. However, our investigation on well-separating rules is ongoing, we currently distinguish columns by long-term uplift without intermediate sinking evidence in a region with a large vertical span (a few hundred meters), with bubbles indicated by sinking evidence or smaller vertical span, and the further shape and size based on the uplift movement position extrema and breaking point analysis. The resulting uncertainty could be visually indicated in the future and more fine-tuned thermal building rules included. We currently assign a core set of geometric shapes to represent thermal types: columns, spheres, and cones for stationary stable or bubble-type thermals, wedges for moving thermals that indicate the movement direction for short-distance movements (a few hundred meters), and cones connected by arrows for long-distance movements, to indicate the movement path without too much occlusion, see Fig. 1. For our use-case data set, we performed a sensitivity analysis on several clustering methods, including ST-DBSCAN, ST-OPTICS, ST-HDBSCAN [CPC*21], with regard to the clustering parameters (e. g. spatial and temporal distance), resulting in parameter settings that allow clear distinction between potential thermal regions for our data set. ST-DBSCAN results were used for the presentation here. Turning this semi-automatic approach into a data-driven parameter selection for other data will require a deeper investigation.

3.2. Case Study

For the case study we use a data set collected from a group of paraglider pilots flying without motors and so constrained to gain height within updrafts for cross country flight [RCSV16, FAA16], see Fig. 2. The pilots are flying simultaneously prior to the start of a competitive race, within in a restricted cylindrical airspace, and thus provide a sensor array to sample evidence for airflows at high spatial-temporal resolution. The size of around 800,000 data points (position at 1 Hz), covering 114 gliders over four hours, constitutes a large data set that is hard to tackle with simple scatter point or trajectory visualisation. We have implemented and applied both meth-

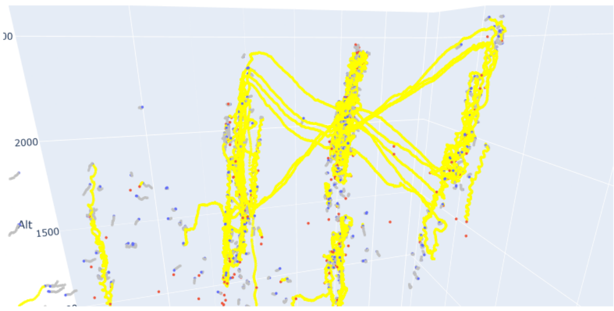

Figure 4: *3D plot of breaking points in paraglider trajectories, from high to low vertical speed (blue) and vice versa (red), indicating thermal entry and exit points. Points between corresponding entry and exit points are shown in yellow to support shape identification (altitude exaggerated 10x). Gray points show sinking phase after exit. As the identification cannot perfectly find all actual entry and exit points, there are some yellow sinking stretches that show transition of a glider from one thermal to the next. Pillars correspond to uplift regions exploited by multiple pilots. The gap between two stacked pillar segments potentially indicates bubbles.*

ods described in this paper to the practice task of the competition and to the main event (ca. 177,000 / 799,000 data points). For the analysis, given the paraglider uplift use and flying behaviour, we set t_{up} to $1.5m/s$ to identify the strong core uplift of a thermal, l_{slen} to 4 seconds, and d_{vv} to $2m/s$ to have a clear distinction of thermal entry and exit. We allow $l_{maxgap} = 2s$ up to a limit of 10% of the sequence time.

Our trajectory analysis extracted 5643 uplift sequences, with a maximum of 99 sequences for a pilot, and 54,967 seconds covered by sequences. We experimented with clustering either all single uplift sequence data points individually or all uplift sequences. For the latter, we used the Hausdorff distance for clustering. We found only minor differences in the results for our use-case data set, but had a larger ratio of outliers for the sequences. This might be due to the parameterisation, which we will investigate as future work. We continued the analysis with the point-based clustering, leading to 130 clusters indicating uplift regions. Five of the pilots did not contribute to any of the clusters, with either short recorded time periods only or mainly downward movements. Fig. 4 shows the result of the breaking point analysis, with clearly visible uplift pillars. Cluster and timing analysis reveals that the two stacked pillars are roughly 5,000 seconds apart, indicating bubble-type thermals.

4. Discussion and Future work

A challenge for the analysis of airflow is the potential diversity of phenomena in combination with the missing ground truth information. While flying entities such as birds or human gliders probably exploit different types of uplift in a similar fashion, the uplift might stem from different mechanisms of uplift power, e. g. thermals or ridge lift. The more information we have on the mechanism, the more detailed our assumptions can be that inform our methods, e. g. regarding size and duration of uplift. Making use of the combination of landscape structure and other variables such as air temperature and coarse-grained air speed could help extract a more sophis-

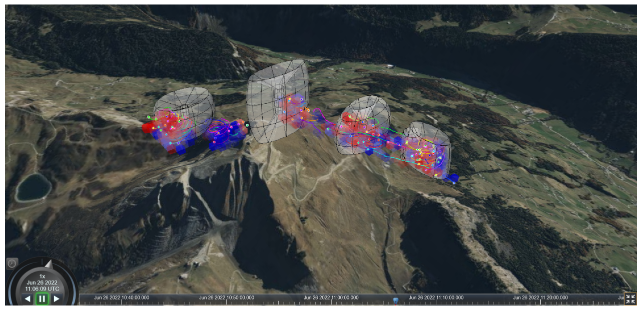

Figure 5: *Trajectory movement visualisation mapped into our uplift visualisation: Transparent geometric shapes represent potential thermal shapes, cubes represent extremal uplift values.*

ticated thermal model, and might enrich the visualisation. As the behaviour of the entities might have a large impact, an additional analysis, e. g. for soaring patterns, could be combined with our current approaches. While we model and visualise the transition of entities between clusters by investigating the individual trajectories, it is a more intricate problem to model movement relations between uplift regions, e. g. drifting thermals. Close-by clusters might refer to the same moving or two independent thermals.

Given the 3D nature of the data, a promising avenue for further extension is to transition to augmented reality (AR) for the interactive visualisation [ZKSS23] and to immersive analytics (IA) [MSD*18]. In particular, 3D exploration of animal collectives such as [NSK*17, KSN*19] and collaboration in virtual spaces might be facilitated by shared IA and mixed-reality explorations of airflow data. However, we need to investigate the gain that is provided by 3D visualisations compared to classical 2D representations from a user perspective.

5. Conclusion

We presented a promising first approach to analyse and visualise airflow dynamics by using movement data from multiple tagged flying entities. We described methods to extract airflow information from the data as well as visualisation designs. Given the large and growing amount of such data currently collected [KW23], there is an unprecedented opportunity to exploit them and moreover, to explore the collective dynamics at play in the movement strategies of these groups [WS21].

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