Immersive Analysis of Spatiotemporal Racing Data

Nicole Weidinger
Know-Center GmbH
Graz, Austria
nweidinger@know-center.at

Neven El Sayed
Know-Center GmbH
Graz, Austria
nelsayed@know-center.at

Granit Luzhnica
Graz University of Technology
Graz, Austria
granit.luzhnica@tugraz.at

Tobias Schreck
Graz University of Technology
Graz, Austria
tobias.schreck@cgv.tugraz.at

Eduardo Veas
Graz University of Technology
Graz, Austria
eveas@tugraz.at

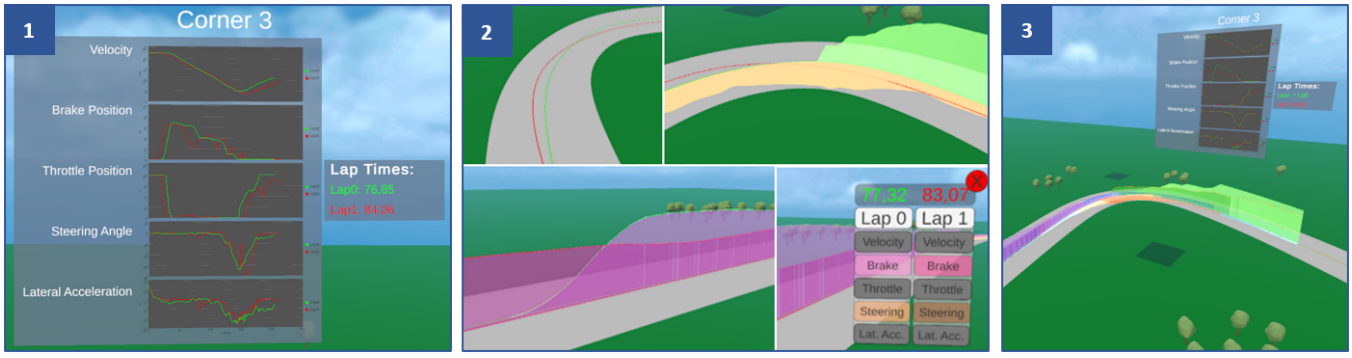


Figure 1: Our immersive application visualizes racing data in 3 different ways: with conventional line charts (left), with situated 3D graphs on a racing track (middle) and in a hybrid way by combining the line charts and the situated visualization (right).

ABSTRACT

This paper presents an exploratory study of expert behavior while analysing spatio-temporal data in an immersive environment for the racing engineering domain. The analysis of moving-object data has become crucial in diverse fields, including sports analysis, logistics and autonomous navigation. This data provides valuable insights into events occurring at specific points in space and time, enabling professionals to make informed decisions. For example, in motorsports, race engineers rely on spatio-temporal data and vehicle telemetry to identify key events and optimize performance. However, conventional stacked line charts used by race engineers offer limited spatial association. Effective visualization techniques that incorporate the spatial context are essential to fully understand and interpret the complex nature of moving-object data. To address this, we propose novel immersive designs for analyzing motorsports data. Our study uses a critical task in racing engineering—*comparing cornering performance of two drivers* to document patterns of behavior of expert analysis. Experts used conventional charts, situated 3D graphs and a hybrid with both options within an Immersive Analytics environment. Results demonstrate the potential of our approach. All experts preferred the hybrid visualization combining conventional and situated approaches. In the short study period, experts found value in the situated approach to understand differences in distances between events.

CCS CONCEPTS

• **Computing methodologies** → **Virtual reality**; • **Human-centered computing** → **Visualization, Visualization application domains**; *Visualization techniques.*

KEYWORDS

Immersive analytics, spatiotemporal data, virtual reality, racing analytics, motorsports

ACM Reference Format:
Nicole Weidinger, Neven El Sayed, Granit Luzhnica, Tobias Schreck, and Eduardo Veas. 2023. Immersive Analysis of Spatiotemporal Racing Data. In *The 2023 ACM Symposium on Spatial User Interaction (SUI '23), October 13–15, 2023, Sydney, NSW, Australia.* ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3607822.3614542

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).
SUI '23, October 13–15, 2023, Sydney, NSW, Australia
© 2023 Copyright held by the owner/author(s).
ACM ISBN 979-8-4007-0281-5/23/10.
https://doi.org/10.1145/3607822.3614542

1 INTRODUCTION

The analysis of spatiotemporal data can help to understand behavior not only of moving objects like vehicles but also of animals or humans [2, 21, 24, 32]. Collecting and understanding spatiotemporal data, like trajectories, is also an important task in the athletic and sports field to analyze and improve performance [42, 43, 58].

Presenting such data in an easy and intuitive way can be challenging. Research has been done on that topic and concepts like the space-time cube or great wall of space-time have been developed and allow effective visual analysis [20, 45].

Recently, also the potential of immersive technologies was examined to visualize and present large amounts of data. This research has shown [29, 39, 56] that immersive technologies, like Virtual Reality (VR), can have benefits like better spatial understanding, rich semantic interaction, peripheral awareness, and large information bandwidth.

In this paper, we focus on the visual analysis of racing data in the motorsport domain. Nowadays the collection and analysis of data in motorsports is a very common technique, not only used in Formula 1 but also in club sports championships and karting [38]. Data acquisition systems can provide a large amount of measurement data that the engineer needs to know about the car's behavior. This data can for example include engine performance, tire wear or track conditions. By understanding this data, engineers can find the potential for improvement of the car's performance, like finding the most suitable setup of the car for a specific scenario. It can also help to identify areas where driver's can improve their technique or driving style. The acquisition and analysis of data is not only common but also crucial in this domain, where even small improvements in performance can make a significant difference [38]. There exist software solutions that aim to support the analysis process of racing data. Examples of such software are SGB Sports Software [1] and Canopy Simulations [2]. This software is used on computers with traditional screens. To visualize the data usually line charts are used in combination with other techniques, like visualizations of the racing track from the top (bird's eye view) or camera recordings from the driver's perspective.

In our work, we make use of the potential of VR and visualize racing data in an immersive way. Our research's focus is to explore the effect of the immersive environment as such, and alternative visualizations on the analysis process of racing engineers. In this domain, an immersive approach can provide the following advantages compared to traditional desktop platforms: we can visualize the actual racing track in perceived real-life size, and present the data directly on the racing lines, enabling the engineers to see the data directly where it was generated. We assume that this encourages a better contextual understanding and improved data interpretation when experts can relate the data directly to specific parts on the track and allows them to experience the data in a more intuitive and comprehensible manner. Therefore, we conducted a user study with five racing engineer experts. Our goal was to understand the usage and effectiveness of an immersive data visualization environment for their tasks. The experts were initially exposed to traditional visualizations, which they already know from their desktop solutions. To explore the effects of our proposed solution, they were then exposed to situated visualizations (referred to as sitVis), which make use of a real-life size racing track and data visualizations directly on the racing line. Finally, they were asked to work in a hybrid environment where both visualizations were available in order to investigate their preferences and observe which one they would use for which purposes.

Our work contributes to existing research by introducing a sitVis technique in the field of immersive analytics for racing team engineering to explore spatiotemporal time series data. Making use of immersive sitVis techniques is new in this domain of sports. We propose combining the situated immersive visualization techniques along with the traditional visualizations in order to allow users to take advantage of combined capabilities. Furthermore, we evaluate sitVis in combination with traditional visualization techniques in regard to the added value for experts in the race engineering domain and investigate the preferences of usage for specific tasks. Thanks to experts feedback we were also able to make out new promising fields of application in the motorsports domain that would benefit from our approach. Even though we apply the sitVis and the combined visualizations in a specific domain of race engineering, our work advocates for the exploration and the potential use of analogous immersive techniques in other domains dealing with time series data.

2 RELATED WORK

Data analysis remains one of the primary challenges in the athletic and sports fields. A key problem is understanding the performance of individuals, and the interrelations of teams. While there are different types of measurements and analysis methods possible, there are no general solutions yet. Recently, Visual Analytics (VA) has been used to analyze sports data [33, 42], allowing experts to visualize and study the performance of players and teams. However, with the significant increase in the volumes of data that can be recorded, and features that can be computed, visualizing remains a challenging task. VA merges automated analysis with interactive visualization [15, 23], utilizing machine analysis for data processing [44]. VA is commonly used for analyzing multi-dimensional big data, enabling users to analyze data from various perspectives.

Tactics analysis is an important task in the athletic field [42, 43]. Wang et al.[50] developed a VA tool called Tac-Simur. It enables experts to analyze players' tactics and performance in matches to identify player patterns. Their tool enables experts to understand the tactics and strength of each player, which can be used to enhance players' performance. Another tactic analysis tool using VA was developed by Wu et al. [53] specifically for racquet sports. This tool provides athletes with valuable insights into their opponents' playing styles, allowing them to identify systematic weaknesses and develop effective counter-strategies during matches.

2.1 Immersive Analytics

Observing the growing need to handle enormous quantities of data, immersion has been advocated for data visualization over two decades ago [47] due to its ability especially to display spatial scale, and provide spatial immersion. Immersive Analytics (IA) improves large-scale visualization, enabling users to navigate through the data intuitively [13, 25, 29, 39].

IA provides opportunities to explore data and replay events recorded in digital twins. The term immersion refers to the extent to which the system delivers a convincing sensory input, replacing normal perceptual sensations [40]. IA techniques can represent

[1] https://sbgsportssoftware.com/
[2] https://canopysimulations.com/

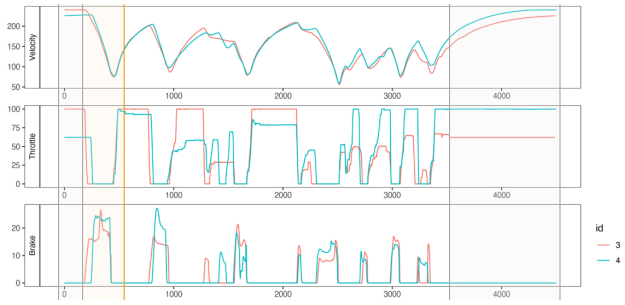


Figure 2: Distance plots with lap overlays. From top to bottom, Velocity, Throttle, Brake. The first corner is marked. Note the binary treatment of throttle and brake.

large amounts of abstract data, which may not have physical or spatial qualities [13]. Such data can have qualities that are not directly observable in reality, e.g., spatial [1, 4, 14], temporal [11, 31], multidimensional [17, 18], or graph/network [27, 28]. While visualization research has traditionally been skeptical of using 3D, recent perceptual research provided compelling evidence of the advantages of immersive analytics for presenting 3D visual representations, such as maps [57], parallel coordinates [9], scatterplots [34], provided the visualizations are designed for the new medium.

In general, 3D data visualization is used in IA as a new means to analyze data, enabling us to present a digital twin of the physical world. There are two common types of IA representation: abstract and sitVis. Abstract visualization has no spatial correlation with the scene environment [35], while sitVis is presented in a reference to space and time [19].

Abstract representation has been widely employed in IA in recent years [3, 17]. Researchers examined the visualization effect and parameters for individual [54] and collaborative analysis [26]. Cordeil et al. [16] developed IATK (Immersive Analytics Toolkit), simplifying to authorize and present data in immersive environments.

Using presently stable technology, sitVis can precisely register to the referent in space. Researchers used the perceptual representation of sitVis to present data in virtual and augmented reality [22, 52]. sitVis commonly used for Spatiotemporal data [46, 55], multidimensional data [37, 59], and streaming data [48, 49, 51], to enhance data understanding.

With the provided digital twin in immersive environments, spatial data became one of the main beneficial visualizations in IA [32, 56]. Over the past few years, with the increased interest in trajectory data in IA, a number of studies have been conducted to examine the benefits and design pipelines for trajectory implementation in IA [10, 20, 21, 58]. Shuttlespace [58] Ye et al. also implemented an immersive analytics application in the sports domain. They make use of VR and trajectory visualization to support badminton coaches in their analysis process.

2.2 Analysis of Racing Data

Race engineers generally have an excellent understanding of vehicle mechanics and dynamics. They may face the analysis of the same data with different roles: engineering the car, or coaching and trouble shooting the drive. We concentrate on the second aspect.

A racing car includes numerous sensors delivering readings continuously to a telemetry system. The engineer analyses the vehicle and the performance by looking into corresponding telemetry channels. The telemetry is broken into laps counted with a sensor when passing the starting line. In collaboration with a high-tech automotive engineering provider, this study uses telemetry data obtained with an industry gold-standard racing simulator. The main goal of the analysis is understanding, comparing and improving track racing performance by professional drivers. The simulator delivers clean data at 100Hz. Analysis is carried out predominantly on line-charts (time and distance plots), X-Y charts and histograms [38]. For a moving object, distance and time are related by velocity. Indeed, the distance plot expands fast sections of the track and compresses slow sections compared with the time-plot [38].

To analyze performance, the race engineer usually takes a reference lap. This can be the fastest lap in a stint, the fastest lap of the series or session. It is important that the lap is done with the same car. Comparisons make up for (95%) of the analysis work, which is done by overlaying graphs from separate laps [38]. The engineer would plot a velocity profile over distance as a basis for comparison. This is the outcome. To analyze what leads to this outcome, one needs to look at the input: throttle pedal, brake pressure and steering. A racing car needs to be operated at the physical limits of grip to be fast. The lateral acceleration of the car provides information about this. Fig. 2 illustrates these as per Segers J. [38], concretely:

Velocity (Speed): Most analyses use the velocity graph as reference because it is the end result and reflects any changes in vehicle set-up or driving style. An experienced engineer finds locations on the track with the velocity graph.

Throttle: Throttle pedal position is expressed in percentage (0% : completely off pedal, 100% full-throttle).

Brake: The brake channel records the amount of pressure put in the brake pedal. Brake pressure must be built up quickly to reduce the loss of time. The brake and throttle should have a binary, inverse relation. Usually, the brake data refers to the pressure, in our case we use the brake (pedal) position as this information was provided by the dataset (see section 4.1 for more information regarding the dataset).

Steering angle: It records the angle at which the steering wheel is turned, expressed in deg. or steering rack travel in mm, with 0 : vehicle traveling straight. In our application, a positive value indicates a left-hand turn.

Lateral acceleration (referred to as latA): It measures cornering force as the g-force or acceleration perpendicular to the car's center line. As with steering, positive latA indicates a left turn. The latA is used to analyze handling behavior and absolute cornering power.

The data mentioned above is most commonly used for analysis of performance and coaching, that is why we decided to focus on these channels for our first study.

2.2.1 Racing line. The path traversed by the racing car around the race course is called racing line. An optimal racing line exist that allows a car with specific physical properties to traverse the track with the lowest possible time [5]. Note that optimal in this case

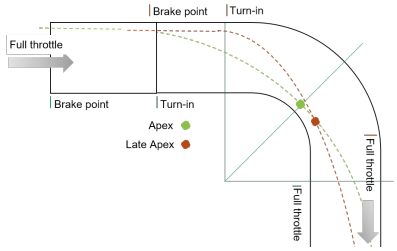


Figure 3: Cornering a right angle corner. With a late apex, brake has to be aggressive, corner is slower, but exit speed is higher.

refers to time. In principle optimal lines exist that minimize fuel consumption, maximize energy recovery, optimize brake usage or tire wear, and so on. A racing strategy requires the team to be able to balance these. Qualifying requires lower lap times and is the topic of this discussion. Here, the racing line is the compromise between the shortest path and the path that leads to achieving the highest speeds [7], and depends on factors such as the track geometry, the vehicle's aerodynamics, power characteristics, tire degradation, and grip[12]. Calculation of the racing line is a bounded optimization problem that requires taking into account track geometry and vehicle dynamics [36]. The professional driver performs such optimization constrained by perceptual and motor capabilities [41].

2.2.2 Cornering. The optimization of the racing line stretches the radius of turns by spanning the width of the track. Fig. 3 shows two possible lines to traverse a corner, where the driver enters from the left and exits at the bottom. In green, the geometric apex is defined by a perfectly circular path. In red, the driver turns in later and hits a late apex. Often, the fastest solution minimizes the time for both corner and subsequent straight [41]. For the purpose of analysis, a corner is broken down in corner entry, which is the deceleration marked by the aggressive application of the brake, the apex, and corner exit, which marks the acceleration phase [8]. The points and form in which the driver brakes, the grip and downforce while steering, the point when the driver gets on the throttle, all these and other factors determine success in cornering.

2.2.3 Implications for spatiotemporal data. Cornering exploits the full width of the track. On the approach at full throttle the car positions on the outside. The aggressive application of the brake leads a drastic reduction of speed to carefully position the attack on the apex. Going over the apex at the right speed to wind the car across to the outside at full throttle again. The race engineer analyzes the telemetry charts to determine the application of the brake at entry, the frequency and form of steering and the application of throttle. The points in space at which these events occur in reference to the track have a major influence in the outcome.

3 IMMERSIVE ANALYTICS DESIGN

To implement an application that visualizes racing data in an immersive environment we made use of the Unity 3D engine [3] and the Mixed Reality Toolkit (MRTK)[4]. We designed the application for the HP G2 Omnicept headset [5]. To visualize line charts we incorporated the 'E2Chart' unity asset from Ice Pond Studio [6] and adapted it to fit our needs.

We derived the applications requirements from our experts feedback. The following 5 channels need to be included, as they are most commonly used by the experts: velocity, brake, throttle, steering and latA. Also, they need to be able to highlight points of interest, e.g. the braking point. Additionally, we decided to focus on one subtask specifically: cornering analysis. This allows them to spent more time with the task and we are able observe their behaviour in more detail. We also confront them with just two laps to compare, instead of letting them choose out of a pool of laps like they are used to. This, again, increases the time they can spent for the task and we can make sure that the laps have significant differences.

3.1 Visualization Types

The application offers three ways to visualize racing data. The first method involves conventional line charts, a representation of the data that racing experts are familiar with. The second method, on the other hand, involves a sitVis using 3D graphs that are displayed on a racing track. This approach offers an immersive experience for the users, allowing them to see the data in context with the space where the data was generated. We assume that this encourages a better contextual understanding and improved data interpretation when experts can relate the data directly to specific sections or parts of the track and allows them to experience the data in a more intuitive and visually comprehensible manner.

Additionally, the application offers the possibility to combine both conventional and sitVis types, giving the users more flexibility in exploring and analyzing the data.

3.1.1 Abstract Visualization. Our first visualization type is abstract which makes use of conventional line charts and is inspired by data representations that experts in the field are already used to. The familiar visualization should make the expert feel comfortable and encourage them to act naturally. This allows us to observe how experts typically analyze the information so that we can better understand their thought processes, decision-making strategies, and patterns of interpretation.

We created a line chart for each data channel: velocity, brake position, throttle position, steering angle and latA. Section 4.1 provides more information regarding the used dataset. As shown in Figure 1 (left) a chart shows the data of 2 laps. In the industry it is common to use green for the reference lap and red for the second lap, this is why we also decided to choose this color coding in our application. We are aware that it is not an optimal solution for users with color-vision deficiency but we wanted to stay as close as possible to the industry standard. The x-axis represents the value, such as km/h (velocity), percent (brake and throttle position), degree (steering angle) or newton (latA), while the y-axis displays the distance covered since the start of the curve. The data is plotted against distance and not against time as it is more valuable to compare the data at the same spot in the track. For datasets in this

[3]https://unity.com

[4]https://github.com/microsoft/MixedRealityToolkit-Unity

[5]https://www.hp.com/us-en/vr/reverb-g2-vr-headset-omnicept-edition.html

[6]https://assetstore.unity.com/packages/tools/gui/e2chart-147893

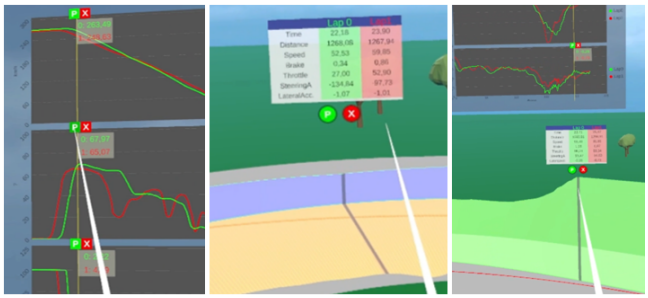


Figure 4: In each condition the users are able to select points in the visualization. To highlight the points persistently they can also pin the points. In the hybrid visualization (right) the visualizations are linked. This means a point marked in the chart is also marked in the sitVis and vice versa.

domain, overlaying data against time does not provide any useful insights, as events happening at the same time could be taking place at different locations, and the traces tend to diverge over the length of the lap [38]. It also ensures a fair comparison with the sitVis, where the data is shown directly on the location where it was generated. The individual line charts for each channel are combined on a large billboard (Figure 1 left), offering further information like a heading that indicates the corner of the track and the overall lap time for each lap. Section 3.2 describes what kind of interactions the abstract visualization offers to the users.

3.1.2 Situated Visualization. Our application also offers the possibility to present the racing data in a situated approach. We want to show the exact same data as in the abstract visualization just in relation the track and the racing line. The user should be able to perform the exactly same analysis tasks.

The given dataset (see section 4.1) includes the position of the racing car which is used to extract the racing line. Like in the abstract visualization, we present two laps to be able to compare them. The racing line of the reference lap is shown in green while the other line is colored in red (to match with the abstract visualization). We also extracted and visualized the track limits. Unfortunately we had to interpolate points from the given dataset, therefore the limits are not 100% accurate but we want to overcome this limitation for future projects.

There has already been done research in visualizing trajectories in immersive applications [20, 21, 24, 58]. When we created our sitVis, we thought about the following: As the new kind of visualization and probably also the technology is quite new to the experts we wanted to stay close to the traditional abstract visualization as possible to avoid overwhelming the users. We also wanted to keep the relation to the racing line clearly visible. This is why we decided to use simple 3D graphs on the corresponding racing lines. The shape of the graphs look familiar to the experts usual chart visualization and are just expanded in length and bent according to the curves course.

As all data channels are visualized on the corresponding racing lines, the view gets cluttered and it gets hard to distinguish the individual data channels. Figure 1 (middle) shows how the channels are presented on the racing lines. A solution would be to distribute the plots spatially to divide them more clearly. We decided to solve this problem in two ways: Different alignment of the graphs and a menu to toggle visibility. We chose a vertical alignment for all channels that just consist of positive values and have no reference to a left or right direction. These channels are velocity, brake and throttle position. The remaining channels, steering angle and latA, are plotted horizontally (flat on the racing track) as their values do relate to a left or right direction (plus or minus values) and we think that it also gives the viewer a better understanding of the presented values. We also created a menu, that allows the user to control the visibility of each data channel and lap. Compared to the chart visualization, this creates additional steps to see and analyse all data channels, but we think the advantages of seeing the data at the space where it was generated out-weights the disadvantage of the additional steps. The menu is also shown in Figure 1 (middle). The different buttons of the menu are color-coded according to their corresponding channel, which makes it easier to distinguish them and select/deselect the desired graph. Additionally it also offers the possibility to toggle the visibility of all channels of a lap. The menu can be easily accessed by pressing a button on the left controller. The user can then simply select the channels that they want to see or hide.

In the abstract visualization, we could color the data lines in green and red to reference the corresponding lap. In the sitVis all the channels of one lap are plotted on the corresponding racing line. When more channels are shown, users could get confused by what graph shows what information. That is why we decided to use different colors for the data channels. We chose one color for each channel, where the reference lap (green lap) has a brighter tone of color and the red lap is kept in a darker shade. To still be able to easily distinguish the laps, we create a small outline on each plot in green or red. Figure 1 (middle) shows the sitVis in more detail.

3.1.3 Hybrid: Chart and Situated Visualization. The third visualization type combines the data representations of the first two conditions: abstract and sitVis. Figure 1 (right) shows the layout of the third condition, where the billboard is positioned next to the racetrack where the sitVis are shown. By combining the traditional line chart with the sitVis on the race track, we give the user the flexibility to choose how they want to explore and analyze the data. Confronting experts with this visualization gives us the possibility to observe how they would include the different visualization types in their analysis process. If they favor one visualization over the other or if there is a preference of visualization for specific tasks.

3.2 Locomotion and Interactions

We make use of both controllers to enable basic interactions and movement possibilities [6]. The user is able to move freely in all directions, allowing them to see the scene also from a higher viewpoint. To enable a faster movement and change of perspective we also created two predefined teleportation points: inside and outside of the corner.

To interact with the presented data, the application offers the following interaction possibilities: select point, pin point (to mark a point persistently), and cancel point. Once a point is selected with raycast selection, details about the point are visualized. In the hybrid visualization, we linked both visualization types [30]: A

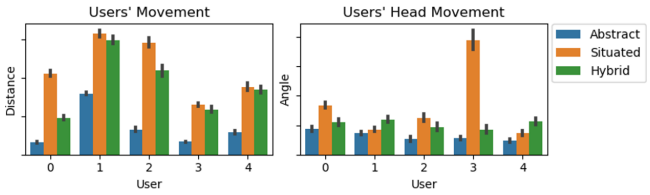


Figure 5: Relative body and head movement (angular) for each user and condition. It shows that the experts moved the most in S, followed by H and A. The A condition concentrates all information in a packed figure. Participants only need to fly in front of it. In S the points of interest are clearly separated and participants need to move in the environment to inspect them.

point that is selected in the chart is also selected in the sitVis and vice versa. Figure 4 shows what a selected/pinned point looks like in the different visualization types.

4 EVALUATION

The goal of the study is to observe the patterns of behavior of the participants during performance analysis in the comparison of two laps: a fast one (reference) and a slower lap. As mentioned before (Section 3) we focus on observing the task of cornering analysis.

We organized the study in three conditions: abstract, situated, and hybrid. The abstract visualizations present the information in line charts, a common format experts use for analysis in their daily business. The focus was to observe how participants work with sitVis and whether they transfer behavior learned in situated to hybrid visualizations.

4.1 Dataset

The dataset used for the evaluation was collected with a professional driver using a motorsports industry gold standard racing simulator. The simulation environment comprises the physics simulation software VSM, used for bench-marking in motorsports (e.g., Formula 1), the graphics simulation software Fastlap [7], and the simulator hardware. The latter consists of a Formula 3 cockpit supported by hexapod motion platform mounted in front of a 210deg 6m radius screen. The physics simulation software drives the motion platform in synchrony with the graphics. The dynamics model simulation can deliver up to 800 channels of vehicle telemetry from vehicle sensors at 100 Hz. We used data commonly used for analysis of performance and coaching, the input (throttle, brake pressure, steering) and the performance (velocity, lap time, distance, and latA) and the vehicle position in 2D used to extract the racing line.

The data were collected following a protocol for physiological data collection while driving in different conditions: normal, cognitive load, physical load, wet track. After getting familiar with the track, the driver was asked to drive ten laps as fast as possible while staying in the track (qualifying session). For the purpose of this paper, only data from session normal and wet track were used because of the significant difference in performance. Wet track is simulated by the physics and graphics environment. Three pairs of laps were used for performance comparison, each pair having a lap from normal and a lap from wet track session. This choice was made to ensure the existence of a clear difference in the driving patterns. Participants were not informed of the type of conditions, instead the instructions were to compare two different laps, a fast and a slow lap and draw conclusions.

[7] http://fastlap.tech/

4.2 Participants

Five experts (M) took part in the study (see table 1). Two of them with 20+ and one with about 9 years of experience as racing engineers analyzing vehicle and driver performance. One junior expert has 5 years of experience as motorsports computer scientist developing simulation software. The experts volunteered their time to discuss the analysis process and to participate in the study. The experts are familiar with the type of data, which they use in their daily routine work. But, they were not familiar with this particular dataset.

4.3 Procedure

Each participant had a schedule of max. 2h for the study. Studies were conducted in five different days. They were first introduced to the study: *In this study you will be analyzing cornering performance of two driven laps on a single corner. The goal is to study which information is needed and how you access it.* They signed a consent form describing effects of using HMD for VR and were instructed to stop should there be any discomfort. Participants filled out a demographics questionnaire and started the study. There, they were asked about the analysis task in the context of analyzing cornering performance:

- How would you define a braking point? What information is important to compare around a braking point?
- How would you define/identify the apex? What information is important to compare at the apex?
- How would you define/identify the exit? What information is important to compare at the exit?

In each case, we referred information within: throttle, brake, steering, velocity, latA, distance time.

The mentioned points (braking point, apex, exit) are important points to analyse when looking at cornering performance. Every expert can have their own definitions and assessment of what is important to consider at that points. That is why we had to make sure that we are aware of the experts assessment scheme.

After the questionnaire about analysing cornering performance, participants were instructed to wear the HMD and handed over the controls. We encouraged them to give feedback and speak their thoughts out loud. A brief training was carried out with a reduced environment showing the track, one lap only in the specified corner. Participants were introduced to the controls and allowed to practice the following in order: i) camera navigation controls (turning, flying, teleporting to vantage points), ii) marking POIs in line-chart, iii) situated layer menu (on/off, activating data layers), iv) pointing and marking POIs in sitVis .

After the training session, the actual study started. It was split in three conditions: i) abstract (A), ii) situated (S), iii) hybrid (H).

Table 1: Five experts participated in the study. The table lists their age and experience (in years) in the racing domain.

	User 0	User 1	User 2	User 3	User 4
Age	51	48	39	33	43
Experience	27	25	5	9	18

Condition A represents the condition the experts are most familiar with, as it shows the information in stacked line-charts. Experts analyze data in desktop applications in their normal business. It was decided that this condition is shown in the immersive setting, a billboard in VR, to avoid the effect a different control modality may have on behavior, and to constrain the actions to those available in our demo. S presented information onto the track only. In H, the linechart billboard is combined with the situated information.

The three conditions were shown to all participants in the same order: A-S-H. The reasoning for this choice was that experts perform their task in an environment similar to A and having A as the first condition allowed them to familiarize with the task faster. S holds some previously unseen elements, but by the time they start with it, they know how the trial unfolds. H is our target condition, as we believe participants would use different tools for different purposes. We intend to find out which tools they use when having all options available. Having done A and S before H allowed participants to experience their strengths and weaknesses and then deploy them in H. We varied the used data among conditions but not among participants. Thus, all participants saw the same two laps in A, a different set of two laps in S, and another set in H. Each condition was carried out once as we preferred to give the experts more time in each session to let them talk more freely instead of rushing them through. Due to this approach we were not able to gain a high number of trials but we got more insights on the individual experts thought processes.

Each condition included a trial showing the cornering performance of two different laps (L0, L1) (see Sec. 4.1) with four tasks:

T1. Marking the braking point in L0 and L1 and comparing telemetry information at this point.
T2. Marking the apex in L0 and L1 and comparing telemetry information at this point.
T3. Marking the exit in L0 and L1 and comparing telemetry information at this point.
T4. Summary and recommendations to improve the performance of the slowest lap.

The tasks are aligned to the usual analysis process where experts examine the different parts of the corner. It is important to note, that this procedure was put in place as a scaffold for the study, but was not strict. The analysis was a fluid process. If a participant moved on to discuss the next points without marking e.g. the braking points, the experimenter would intervene asking the participant to please mark the braking point in each lap, and then continue.

After going through the analysis of important points, the participant was asked to conclude with a summary and recommendation. Participants were encouraged to take breaks after every session. After the study the participants were asked which condition they liked the most.

The whole session was video recorded from the HMD viewpoint (screen capture and audio). We recorded the users' position and viewpoint (translation, rotation) throughout the study as well as interaction with the different assets that make the tools (interaction with the menu: show, activate/deactivate data/lap, interaction with data: select, pin, cancel, and type of visualization (abstract/situated)).

4.4 Apparatus

The study was run in an experiment room ($20m^2$) equipped with a desk and two chairs for the experimenter and participant, and with sufficient free space for moving ($14m^2$). The practice and trial sessions were done standing. The application was deployed in a HP Reverb G2 Omnicept and driven by a desktop PC with a NVidia RTX 3080 GPU.

5 RESULTS

The user study was set to be approx. $45m$. Participants took between $28m$ and $59m$ in VR, where two decided to take a break ($5m$) before the last session and three participants went through all sessions without a break.

The study questions provided a loose structure organizing the exploration of spatiotemporal data for racing in points of interest and the measures that are important to compare – a sort of scaffold for the study. Due to the subjectivity of the task and the low number of trials, there is no measure of accuracy in performance (each expert follows a slightly diverse definition of what is important). Instead, for the purpose of assessing performance, we will inspect agreement (or lack thereof) in proposed recommendations and also assess their confidence when they marked the points of interest. As the participants were encouraged to speak their thoughts out loud we could clearly detect when they felt insecure or irritated.

5.1 Definitions & Used Information

Experts gave definitions for the points of interest before the experiment as mentioned in section 4.3. We would like to find out: i) should we expect a unified interpretation for each point? ii) what information experts believe is important to analyze at each point. 4 experts define the braking point as the position on the track where the driver presses the brakes (where the pressure starts). One expert defines it as the position where the brakes are pushed more than 50%. There were more differences when defining the apex: 2 participants define it as the closest location of the racing line to the (inside) border of the track, the three other experts define it as the position with minimum speed at the corner, or where latA is at min/max. The exit was 2 times defined as a point: One expert defines it as the point where the driver is starting to apply the throttle and stops steering, the other describes it as the point where the driver is back at 100% throttle. The 3 remaining experts define it as a range: Once, from apex to 100% throttle, once from 100% throttle to end of curve (sector) and once from throttle at about 30% to 100%. As diverse as the definitions are also the data channels that the experts use to analyze the points. They uniformly use the brake channel and check the distance to the apex as well as the intensity and continuity of the braking. Most of them (4 experts) also use the speed as a reference, steering was mentioned 3 times and latA

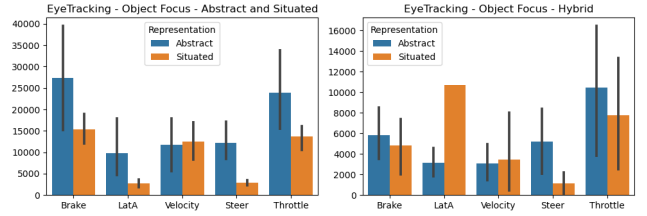
once. An important information that is checked by 4 experts at the apex is the velocity. For two of the experts the racing line and the positioning of the apex within the track is crucial. The steering angle and latA is also considered by two experts. A channel that is used by all experts at the exit is the throttle, further important information (for 3 experts) is velocity , while latA and steering are considered by 2 experts. One expert also looks at the brake pressure.

5.2 Qualitative Observations

As expected, the participants were used to the abstract visualization and had no problems getting into it and solving the task. When first confronted with the sitVis, they needed time to get used to it. Nevertheless, two participants made positive remarks like 'It's good, I like the visualization. It shows me how he's braking in which part of the track and at the same time I see in which line' and 'This is nice (...) you can clearly see this guy brakes later'. This indicates that the participants recognized and appreciated the visualization of the data in spatial relation to the track. While no participant had problems finding the braking point and exit, the detection of the apex was more difficult for 4 of the 5 experts. They made comments like 'This task here is tricky'. P2 made this comment also in the abstract condition. A reason for this can be that the visualization appears more expanded in length due to the larger occupying space. This makes it harder to detect the minimum of a graph (e.g. of velocity) compared to the traditional line chart. An exception is P3 who was not able to mark the apex in the abstract charts as he required the racing line in relation to the track to solve the task.

All participants mentioned that they preferred the hybrid visualization. Although there were individual differences in which visualization was used more for selecting the points (see Figure 8), all experts mentioned they like the possibility to combine both visualizations and to see marked points on the chart as well as on the track. For the overall comparison and summary, the chart was preferred as it gives the experts a better overview of the data, as they can see the data in a more compressed view. P2 explicitly mention that he preferred the sitVis for the brake and throttle and the chart for detecting the apex. He said: 'Here you can see it better' [pointing at sitVis of throttle] 'for the exit this type of visualization is better'. P1 almost exclusively used the sitVis and stated that he preferred to explore the new kind of data representation over working with what he is already familiar with. Even P0, who used the abstract visualization more extensively than the other participants still used the sitVis to confirm his assessment. P3 mentioned in the beginning of H that he will use the abstract visualization as he is used to it but started to use the sitVis from task 2 till the end (as he preferred to see the racing line). Experts also mentioned the value of collaboration that they see in the sitVis. Especially when working with drivers they feel like that this techniques has great potential to enhance the communication and understanding between the different user types.

All the participants agreed in their recommendations for the drivers, e.g. braking later and with more intensity. There were just small individual differences, e.g. one expert mentioned additionally to reduce the gap between brake and throttle what others didn't. For us, this was no surprise as we intently selected laps with a clear difference.



	Condition A + S				Condition H			
	A		S		A		S	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Brake	27322.2	15677.0	15428.4	4288.9	5826.8	3403.3	3858.4	3341.2
LatA	9869.4	8776.8	2199.4	1608.4	3143.4	1772.6	2140.4	4786.1
Velocity	11693.4	8054.4	9964	7320.4	3093.0	2221.5	2775.2	4488.5
Steer	12219.2	5572.4	2350.6	1460.3	5227.8	4167.0	465.4	962.7
Throttle	23850.4	11574.5	13698.2	3433.7	10420.2	8588.6	7756.2	7003.7

Figure 6: The diagrams show the gaze duration for objects, measured from eye-tracking (unit: number of frames). The left figure combines condition Abstract (A) and Situated (S) while the right figure presents the results of condition H. The table below shows the mean and standard deviation results.

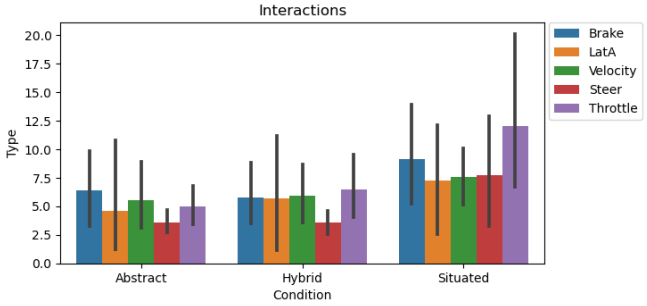


Figure 7: The total number of interactions for each condition. Most interactions were performed in condition S, followed by H and A. In A the experts possessed more confidence and marked points without questioning it. In S and H they felt more insecure at the apex and needed multiple tries mark the point. Another reason for the difference is also that the experts liked to explore the new visualization type and marked points out of curiosity. In H they also liked to mark points in the chart to see where the point is located in the sitVis and vice versa.

5.3 Motion analysis and attention

We analyze movement in the VR environment to investigate the process of exploration and head movements for the possible deployment of attention. Figure 5 shows the amount of movement of participants within the VR environment for each condition excluding the teleportation. Users moved more in the VR environment in conditions (S and H) where the situated visualisations were active. A similar trend can be observed from the head angle movement presented in Figure 5 (right). The A condition concentrates all information in a packed figure. Participants only need to fly in front of it. The condition where most of the movement happens for all participants is S. Clearly, in S the points of interest are separated

and participants need to move in the environment to inspect them. But also, S is the first time participants experience the situated representation and therefore they explore more. P0 started "whoa!, you know, one spends 20 years looking at things one way [referring condition A]…this is so nice [referring condition S while flying]". The more extensive need of controls that are needed for the S can be problematic for people that have less experience in VR. This could also be observed in our study. For 3 out of 5 participants it was easier to adjust to the VR environment. P3 for example experienced more head movement than the others in the situated approach as he needed time to get used to the controls. He preferred to move his head instead of using the rotation control. This let to some discomfort and at the beginning of H he announced to solely use the charts. Interestingly he then still used the sitVis but only once he reached a good observer position where no movement was necessary (see Figure 8).

An exhaustive eye tracking analysis is left for future work. However, we aggregated information of what data objects in the analytics environment were more time in focus for each user. Figure 6 summarizes the number of frames that a user looked at a particular visualization in A, S, or H. With it, we intend to anticipate the strategies users deploy for analysis. Figure 6 (left) compares A and S. The channels that most in focus in A are brake and throttle. Whereas latA and steering receive less attention in S. Figure 6 (right) compares abstract and situated within the H condition. In this case, it is interesting that latA was more in focus in the sitVis, but steering not that much. During the study we noted that latA was often used as a control value when the position of the apex was not clear. This insecurity and possibility to check the correctness (thanks to the chart) could explain the more extensive use of this data channel in the sitVis of H.

5.4 Behavior and strategies

We also analyzed interactions to unveil what information users relied upon for solving their tasks. Figure 8 illustrates user interactions over time (normalized) in conditions H and it shows which channels were used to mark points as well as which channels and when were made visible for the sitVis. In H both abstract and sitVis were present. Each user relied on different visualization, all of them combined interactions in both representations to solve the tasks. P0 relied more heavily on the abstract visualization but still used the situated to explore the data even further. P1 used the sitVis almost exclusively. He stated that he liked to explore the new kind of data representation and only checked the chart once, when marking the apex. P2 used both visualizations, while he preferred the situated for marking the braking point and exit and the abstract visualization for determining the apex. P3 interestingly preferably used the sitVis more often although he announced in the beginning of the session that he prefers the charts (as less movement is necessary). Once he had a good view on the situated, where no movement was needed, he preferred it over the abstract charts. P4 used both visualizations to solve the tasks, but relied more heavily on the abstract for the summary task as it presents the data in a more compressed view.

Figure 7 presents the amount of interactions on each data channel for each condition. It shows that more interactions happened in S, followed by H and A. This is due to the stronger confidence that experts possessed in A - they marked points without questioning it. In S and H they felt more insecure at the apex and needed multiple tries to mark the point. But another reason is that the experts liked to explore the new visualization type and marked points out of curiosity. In H they also liked to mark points in the chart to see where the point is located in the sitVis and vice versa.

6 DISCUSSION

We proposed designs of an IA technique for motorsports experts, for the task of comparing cornering performance of two laps. This is a common task for racing engineers and we invited 5 experts to an analysis session to investigate how they access information with our novel tool. Participants analyzed three cases using different techniques: a conventional line chart, a sitVis that presents the data on the track, and a hybrid that combines both visualizations. Before starting, they defined points of interest (PoI) and intentions for analysis.

We hypothesized that having analyzed data for more than 20 years with a conventional mode and after only 20m of using sitVis and being exhausted from working in VR for ca. 30m, in the last condition, participants would return to the methods they are confident with. Our assumption turned out to be wrong. Although two experts relied more heavily on the abstract visualization, all experts made use of the sitVis. One expert even almost exclusively marked points in the sitVis. Despite the short exposure to sitVis, participants understood its value.

6.1 Favourite Condition: Hybrid

All users preferred the Hybrid Condition. Two of them already mentioned it during the analysis, e.g., user 1 said 'it's good to have both'. After the session they were also asked about which condition they liked the most.

The main advantage of the hybrid representation is information granularity and as it offers both, the overview and the details. The conventional chart compresses all the information at a glance, whereas the situated expands the information onto the track for details. The hybrid visualizations enables the users to take advantage of both granulates. Another interesting granular effect of the hybrid mode is that depending on the visualization (situated or abstract), the signal compression is different. The abstract visualizations have less space to present the entire signal and thus the signal is more compressed. Whereas the sitVis can occupy much more space and thus the signals are more expanded. This allows the users to explore in more detail the sitVis and still have e more compact view of the abstract visualizations which might make it easier to precisely locate the minimum points.

Although experts are used to the chart representation, they still liked to have the racing line in relation to the track available. Even the experts who relied more heavily on the abstract representation still used the sitVis in their analysis. The hybrid condition gave them the opportunity explore the new data representation with support of the visualization that they are familiar and confident with.

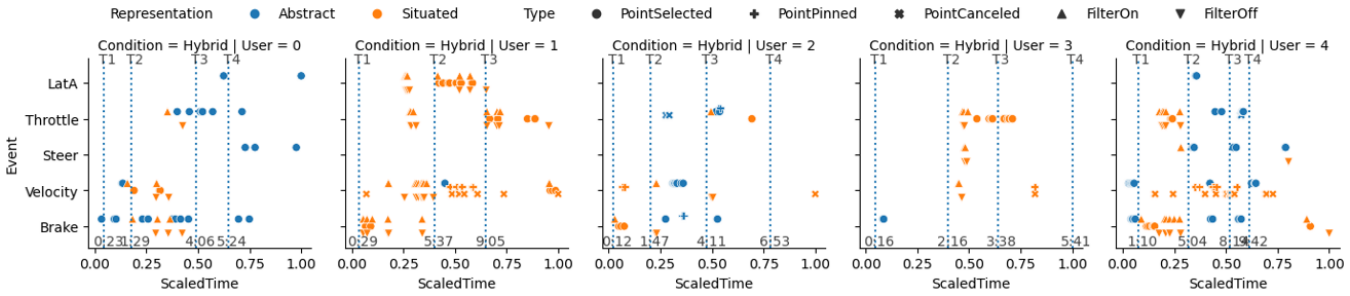


Figure 8: User interactions for the hybrid condition. The vertical dotted lines represent the start of a task. The channels that participants stated are relevant for solving the task in the pre-questionnaire are highlighted for those tasks. The time (x-axis) is scaled from the beginning to the end of the session within a condition and the absolute time (in minutes) is printed along the start of the task. Each expert had individual preferences regarding what type of visualization they used to interact with. P0, for example, relied more heavily on the abstract visualization, while P1 relied more heavily on sitVis. Despite these individual differences all experts mentioned they like the possibility to combine both visualizations and to see marked points on the chart as well as on the track.

6.2 Limitations

Despite the positive feedback we still believe that there are shortcomings in the proposed designs. One important direction for improvement is facilitating the comparison by making differences more explicit and emphasizing them. For instance, computing and plotting the difference between two channels (e.g., brake L0 - brake L1). Differences between points are also important. For instance, when marking points, it would be important to compute and register differences with the previous point marked. We also realized that it can be beneficial to mark ranges (e.g. for the exit). Additionally, the sitVis could be improved in a way that makes less interactions (show/hide) needed and allows to observe more data at once. Then, also more data could be presented on the track.Besides more data regarding the car, also human telemetry of the driver (e.g., muscle activity, eye tracking) would be relevant to explore. Moreover, the proposed solution addresses an isolated subtask. The racing engineer has to observe the performance at a larger scale, look at the full lap, and look at collections thereof. Our work was intended to scaffold that which requires attention to spatial details.

6.3 Potential Extensions

Future work will focus on exploring potential solutions regarding the previously mentioned limitation as well as exploring other ideas to further improvement. One aspect of exploration would be the adaptive situated visualisation based on the viewpoint of the user. For instance, if the user is looking from above, the visualisation will be dynamically adjusted for different representation based on the viewpoint (e.g., heatmaps).

Additionally, we plan to explore a replay mode representation where a virtual car would replay the whole track and the user could observe it either from the driver's or third person's perspective. Such a mode could foster collaboration between the racing engineer and the driver. Our experts already saw great potential in this regard: they believe our approach could enhance the communication and collaboration between drivers and race engineers.

Our locomotion and interaction system can be supported by a proxy (or a world in miniature) to give users quick selection for the track or to highlight points. Additionally, gaze interaction can be used to invoke the Details on Demand (DoD) view for quick data exploration.

As sports analysis often considers trajectories and their interactions [42, 43, 58], our work could be extended to other fields of motorsport. For instance, in air races where track limitations are less constricted, or non-speed competitions where the trajectories are more important to overcome obstacles. Moreover, we think our approach could also be used in other domains. Other factors could be optimized, like fuel consumption, e.g. by analyzing driving behavior in the mining industry.

7 CONCLUSION

This work deals with the analysis of spatio-temporal data related to moving objects. Motorsports experts face the task of uncovering potential for improvement of a drivers or cars performance by comparing their maneuvers on the track. We proposed designs for immersive analysis of motorsports data and studied how and when experts rely on sitVis that hold a reference to space. When they used abstract visualizations, they still preferred to have situated available for validation. We presented advantages and limitations; and offer a view of the next avenues for research. Our work suggests that the use of situated immersive visualization and especially when combined with traditional visualizations can be beneficial in exploring time series data in the motorsports race engineering domain. As such, it advocates for exploring the potential use of similar situated immersive visualization techniques for analytical purposes of time series data for experts in other domains.

REFERENCES

[1] Daniel Acevedo, Eileen Vote, David H Laidlaw, and Martha S Joukowsky. 2001. Archaeological data visualization in VR: Analysis of lamp finds at the Great Temple of Petra, a case study. In *Proceedings Visualization, 2001. VIS'01.* IEEE, 493–597.

[2] G. Andrienko, N. Andrienko, U. Demar, D. Dransch, J. Dykes, S. Fabrikant, M. Jern, M.-J. Kraak, H. Schumann, and C. Tominski. 2010. Space, Time, and Visual Analytics. *International Journal Geographical Information Science* (2010), pp. 1577–1600.

[3] Benjamin Bach, Ronell Sicat, Johanna Beyer, Maxime Cordeil, and Hanspeter Pfister. 2017. The hologram in my hand: How effective is interactive exploration of 3D visualizations in immersive tangible augmented reality? *IEEE transactions on visualization and computer graphics* 24, 1 (2017), 457–467.

[4] Hrvoje Benko, Edward W Ishak, and Steven Feiner. 2004. Collaborative mixed reality visualization of an archaeological excavation. In *Third IEEE and ACM international symposium on mixed and augmented reality*. IEEE, 132–140.

[5] Ross Bentley. 2011. *Ultimate Speed Secrets*. inn: Motorbooks: MBI Publishing Company.

[6] Doug A. Bowman, Ernst Kruijff, Joseph J. LaViola, and Ivan Poupyrev. 2004. *3D User Interfaces: Theory and Practice*. Addison Wesley Longman Publishing Co., Inc., USA.

[7] Francesco Braghin, Federico Cheli, Stefano Melzi, and Edoardo Sabbioni. 2008. Race driver model. *Computers & Structures* 86, 13 (2008), 1503 – 1516. https://doi.org/10.1016/j.compstruc.2007.04.028

[8] Adam Brouillard. 2016. *The Perfect Corner: A Driver's Step-By-Step Guide to Finding Their Own Optimal Line Through the Physics of Racing*. Paradigm Shift Motorsport Books.

[9] Simon Butscher, Sebastian Hubenschmid, Jens Müller, Johannes Fuchs, and Harald Reiterer. 2018. Clusters, trends, and outliers: How immersive technologies can facilitate the collaborative analysis of multidimensional data. In *Proceedings of the 2018 CHI conference on human factors in computing systems*. 1–12.

[10] Wolfgang Büschel, Anke Lehmann, and Raimund Dachselt. 2021. MIRIA: A Mixed Reality Toolkit for the In-Situ Visualization and Analysis of Spatio-Temporal Interaction Data. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. ACM, Yokohama Japan, 1–15. https://doi.org/10.1145/3411764.3445651

[11] Alma Cantu, Thierry Duval, Olivier Grisvard, and Gilles Coppin. 2018. Helovis: A helical visualization for sigint analysis using 3d immersion. In *2018 IEEE Pacific Visualization Symposium (PacificVis)*. IEEE, 175–179.

[12] Luigi Cardamone, Daniele Loiacono, Pier Luca Lanzi, and Alessandro Pietro Bardelli. 2010. Searching for the optimal racing line using genetic algorithms. In *Proceedings of the 2010 IEEE Conference on Computational Intelligence and Games*. 388–394. https://doi.org/10.1109/ITW.2010.5593330

[13] Tom Chandler, Maxime Cordeil, Tobias Czauderna, Tim Dwyer, Jaroslaw Glowacki, Cagatay Goncu, Matthias Klapperstueck, Karsten Klein, Kim Marriott, Falk Schreiber, et al. 2015. Immersive analytics. In *2015 Big Data Visual Analytics (BDVA)*. IEEE, 1–8.

[14] Dane Coffey, Nicholas Malbraaten, Trung Bao Le, Iman Borazjani, Fotis Sotiropoulos, Arthur G Erdman, and Daniel F Keefe. 2011. Interactive slice WIM: Navigating and interrogating volume data sets using a multisurface, multitouch VR interface. *IEEE Transactions on Visualization and Computer Graphics* 18, 10 (2011), 1614–1626.

[15] Kristin A Cook and James J Thomas. 2005. *Illuminating the path: The research and development agenda for visual analytics*. Technical Report. Pacific Northwest National Lab.(PNNL), Richland, WA (United States).

[16] Maxime Cordeil, Andrew Cunningham, Benjamin Bach, Christophe Hurter, Bruce H Thomas, Kim Marriott, and Tim Dwyer. 2019. IATK: An immersive analytics toolkit. In *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*. IEEE, 200–209.

[17] Maxime Cordeil, Andrew Cunningham, Tim Dwyer, Bruce H Thomas, and Kim Marriott. 2017. ImAxes: Immersive axes as embodied affordances for interactive multivariate data visualisation. In *Proceedings of the 30th annual ACM symposium on user interface software and technology*. 71–83.

[18] Ciro Donalek, S George Djorgovski, Alex Cioc, Anwell Wang, Jerry Zhang, Elizabeth Lawler, Stacy Yeh, Ashish Mahabal, Matthew Graham, Andrew Drake, et al. 2014. Immersive and collaborative data visualization using virtual reality platforms. In *2014 IEEE International Conference on Big Data (Big Data)*. IEEE, 609–614.

[19] Tim Dwyer, Kim Marriott, Tobias Isenberg, Karsten Klein, Nathalie Riche, Falk Schreiber, Wolfgang Stuerzlinger, and Bruce H Thomas. 2018. Immersive analytics: An introduction. *Immersive analytics* (2018), 1–23.

[20] Jorge A. Wagner Filho, Wolfgang Stuerzlinger, and Luciana Nedel. 2020. Evaluating an Immersive Space-Time Cube Geovisualization for Intuitive Trajectory Data Exploration. *IEEE Transactions on Visualization and Computer Graphics* 26, 1 (Jan. 2020), 514–524. https://doi.org/10.1109/TVCG.2019.2934415

[21] Christophe Hurter, Nathalie Henry Riche, Steven M. Drucker, Maxime Cordeil, Richard Alligier, and Romain Vuillemot. 2019. FiberClay: Sculpting Three Dimensional Trajectories to Reveal Structural Insights. *IEEE Transactions on Visualization and Computer Graphics* 25, 1 (Jan. 2019), 704–714. https://doi.org/10.1109/TVCG.2018.2865191

[22] Yvonne Jansen and Pierre Dragicevic. 2013. An interaction model for visualizations beyond the desktop. *IEEE Transactions on Visualization and Computer Graphics* 19, 12 (2013), 2396–2405.

[23] Daniel Keim, Gennady Andrienko, Jean-Daniel Fekete, Carsten Gorg, Jorn Kohlhammer, and Guy Melançon. 2008. Visual analytics: Definition, process, and challenges. *Lecture notes in computer science* 4950 (2008), 154–176.

[24] Simon Kloiber, Volker Settgast, Christoph Schinko, Martin Weinzerl, Johannes Fritz, Tobias Schreck, and Reinhold Preiner. 2020. Immersive analysis of user motion in VR applications. *The Visual Computer* 36, 10-12 (Oct. 2020), 1937–1949. https://doi.org/10.1007/s00371-020-01942-1

[25] Matthias Kraus, Johannes Fuchs, Björn Sommer, Karsten Klein, Ulrich Engelke, Daniel A. Keim, and Falk Schreiber. 2022. Immersive Analytics with Abstract 3D Visualizations: A Survey. *Comput. Graph. Forum* 41, 1 (2022), 201–229. https://doi.org/10.1111/cgf.14430

[26] Benjamin Lee, Xiaoyun Hu, Maxime Cordeil, Arnaud Prouzeau, Bernhard Jenny, and Tim Dwyer. 2020. Shared surfaces and spaces: Collaborative data visualisation in a co-located immersive environment. *IEEE Transactions on Visualization and Computer Graphics* 27, 2 (2020), 1171–1181.

[27] Alexandre Maes, Xavier Martinez, Karen Druart, Benoist Laurent, Sean Guégan, Christophe H Marchand, Stéphane D Lemaire, and Marc Baaden. 2018. MinOmics, an integrative and immersive tool for multi-omics analysis. *Journal of integrative bioinformatics* 15, 2 (2018).

[28] Stefan Marks, Javier E Estevez, and Andy M Connor. 2014. Towards the Holodeck: fully immersive virtual reality visualisation of scientific and engineering data. In *Proceedings of the 29th International Conference on Image and Vision Computing New Zealand*. 42–47.

[29] Kim Marriott, Falk Schreiber, Tim Dwyer, Karsten Klein, Nathalie Henry Riche, Takayuki Itoh, Wolfgang Stuerzlinger, and Bruce H Thomas. 2018. *Immersive analytics*. Vol. 11190. Springer.

[30] Tamara Munzner. 2014. *Visualization Analysis and Design* (0 ed.). A K Peters/CRC Press. https://doi.org/10.1201/b17511

[31] Keith Nesbitt. 2001. Interacting with stock market data in a virtual environment. In *Data Visualization 2001: Proceedings of the Joint Eurographics—IEEE TCVG Symposium on Visualization in Ascona, Switzerland, May 28–30, 2001*. Springer, 273–282.

[32] Huyen Nguyen, Florence Wang, Raymond Williams, Paulo de Souza, Ulrich Engelke, and Alex Kruger. [n. d.]. Immersive Visual Analysis of Insect Flight Behaviour. ([n. d.]).

[33] Charles Perin, Romain Vuillemot, Charles D. Stolper, John T. Stasko, Jo Wood, and Sheelagh Carpendale. 2018. State of the Art of Sports Data Visualization. *Comput. Graph. Forum* 37, 3 (2018), 663–686. https://doi.org/10.1111/cgf.13447

[34] Arnaud Prouzeau, Antoine Lhuillier, Barrett Ens, Daniel Weiskopf, and Tim Dwyer. 2019. Visual link routing in immersive visualisations. In *Proceedings of the 2019 ACM international conference on interactive surfaces and spaces*. 241–253.

[35] Dheva Raja, Doug Bowman, John Lucas, and Chris North. 2004. Exploring the benefits of immersion in abstract information visualization. In *Proc. Immersive Projection Technology Workshop*, Vol. 61. 69.

[36] Adrian Remonda, Sarah Krebs, Eduardo Veas, Granit Luzhnica, and Roman Kern. 2019. Formula RL: Deep Reinforcement Learning for Autonomous Racing using Telemetry Data. In *IJCAI Workshop on Scaling-Up Reinforcement Learning: SURL*.

[37] Kadek Ananta Satriadi, Barrett Ens, Maxime Cordeil, Tobias Czauderna, and Bernhard Jenny. 2020. Maps around me: 3d multiview layouts in immersive spaces. *Proceedings of the ACM on Human-Computer Interaction* 4, ISS (2020), 1–20.

[38] Jorge Segers. 2014. *Analysis Techniques for Racecar Data Acquisition*. SAE International.

[39] Richard Skarbez, Nicholas F. Polys, J. Todd Ogle, Chris North, and Doug A. Bowman. 2019. Immersive Analytics: Theory and Research Agenda. *Frontiers in Robotics and AI* 6 (Sept. 2019), 82. https://doi.org/10.3389/frobt.2019.00082

[40] Mel Slater et al. 1999. Measuring presence: A response to the Witmer and Singer presence questionnaire. *Presence: teleoperators and virtual environments* 8, 5 (1999), 560–565.

[41] Kerry Spackman. 1996. Programming the driver. *Race Tech Motorsport Engineering magazine* (1996).

[42] Manuel Stein, Thorsten Breitkreutz, Johannes Haussler, Daniel Seebacher, Christoph Niederberger, Tobias Schreck, Michael Grossniklaus, Daniel Keim, and Halldor Janetzko. 2018. Revealing the invisible: Visual analytics and explanatory storytelling for advanced team sport analysis. In *2018 International Symposium on Big Data Visual and Immersive Analytics (BDVA)*. IEEE, 1–9.

[43] Rajkumar Theagarajan, Federico Pala, Xiu Zhang, and Bir Bhanu. 2018. Soccer: Who has the ball? Generating visual analytics and player statistics. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*. 1749–1757.

[44] James J Thomas and Kristin A Cook. 2006. A visual analytics agenda. *IEEE computer graphics and applications* 26, 1 (2006), 10–13.

[45] Christian Tominski and Hans-Joerg Schulz. 2012. The Great Wall of Space-Time. *Vision* (2012), 8 pages. https://doi.org/10.2312/PE/VMV/VMV12/199-206 Artwork Size: 8 pages ISBN: 9783905673951 Publisher: The Eurographics Association.

[46] Christian Tominski and Hans-Joerg Schulz. 2012. The great wall of space-time. (2012).

[47] Andries Van Dam, David H Laidlaw, and Rosemary Michelle Simpson. 2002. Experiments in immersive virtual reality for scientific visualization. *Computers & Graphics* 26, 4 (2002), 535–555.

[48] Eduardo Veas, Raphaël Grasset, Ioan Ferencik, Thomas Grünewald, and Dieter Schmalstieg. 2013. Mobile augmented reality for environmental monitoring. *Personal and ubiquitous computing* 17 (2013), 1515–1531.

[49] James A Walsh and Bruce H Thomas. 2011. Visualising environmental corrosion in outdoor augmented reality. In *Proceedings of the Twelfth Australasian User Interface Conference-Volume 117*. 39–46.

[50] Jiachen Wang, Kejian Zhao, Dazhen Deng, Anqi Cao, Xiao Xie, Zheng Zhou, Hui Zhang, and Yingcai Wu. 2019. Tac-simur: Tactic-based simulative visual analytics of table tennis. *IEEE transactions on visualization and computer graphics* 26, 1 (2019), 407–417.

[51] Sean Michael White. 2009. *Interaction and presentation techniques for situated visualization*. Columbia University.

[52] Wesley Willett, Yvonne Jansen, and Pierre Dragicevic. 2016. Embedded data representations. *IEEE transactions on visualization and computer graphics* 23, 1 (2016), 461–470.

[53] Jiang Wu, Ziyang Guo, Zuobin Wang, Qingyang Xu, and Yingcai Wu. 2020. Visual analytics of multivariate event sequence data in racquet sports. In *2020 IEEE conference on visual analytics science and technology (VAST)*. IEEE, 36–47.

[54] Yalong Yang, Maxime Cordeil, Johanna Beyer, Tim Dwyer, Kim Marriott, and Hanspeter Pfister. 2020. Embodied navigation in immersive abstract data visualization: Is overview+ detail or zooming better for 3D scatterplots? *IEEE Transactions on Visualization and Computer Graphics* 27, 2 (2020), 1214–1224.

[55] Yalong Yang, Tim Dwyer, Bernhard Jenny, Kim Marriott, Maxime Cordeil, and Haohui Chen. 2018. Origin-destination flow maps in immersive environments. *IEEE transactions on visualization and computer graphics* 25, 1 (2018), 693–703.

[56] Yalong Yang, Tim Dwyer, Bernhard Jenny, Kim Marriott, Maxime Cordeil, and Haohui Chen. 2019. Origin-Destination Flow Maps in Immersive Environments. *IEEE Transactions on Visualization and Computer Graphics* 25, 1 (Jan. 2019), 693–703. https://doi.org/10.1109/TVCG.2018.2865192

[57] Yalong Yang, Bernhard Jenny, Tim Dwyer, Kim Marriott, Haohui Chen, and Maxime Cordeil. 2018. Maps and globes in virtual reality. In *Computer Graphics Forum*, Vol. 37. Wiley Online Library, 427–438.

[58] Shuainan Ye, Zhutian Chen, Xiangtong Chu, Yifan Wang, Siwei Fu, Lejun Shen, Kun Zhou, and Yingcai Wu. 2021. ShuttleSpace: Exploring and Analyzing Movement Trajectory in Immersive Visualization. *IEEE Transactions on Visualization and Computer Graphics* 27, 2 (Feb. 2021), 860–869. https://doi.org/10.1109/TVCG.2020.3030392

[59] Stefanie Zollmann, Denis Kalkofen, Christof Hoppe, Stefan Kluckner, Horst Bischof, and Gerhard Reitmayr. 2012. Interactive 4D overview and detail visualization in augmented reality. In *2012 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. IEEE, 167–176.