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The Ball is in Our Court: Conducting Visualization Research with Sports Experts

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***Abstract*—Most sports visualizations rely on a combination of spatial, highly temporal, and user-centric data, making sports a challenging target for visualization. Emerging technologies, such as augmented and mixed reality (AR/XR), have brought exciting opportunities along with new challenges for sports visualization. We share our experience working with sports domain experts and present lessons learned from conducting visualization research in SportsXR. In our previous work, we have targeted different types of users in sports, including athletes, game analysts, and fans. Each user group has unique design constraints and requirements, such as obtaining real-time visual feedback in training, automating the low-level video analysis workflow, or personalizing embedded visualizations for live game data analysis. In this paper, we synthesize our best practices and pitfalls we identified while working on SportsXR. We highlight lessons learned in working with sports domain experts in designing and evaluating sports visualizations and in working with emerging AR/XR technologies. We envision that sports visualization research will benefit the larger visualization community through its unique challenges and opportunities for immersive and situated analytics.**

DATA analytics in sports can be a game changer, as it enables its stakeholders to make clear-sighted decisions based on objective evidence [1]. One of the most successful stories is the MLB Moneyball, where Oakland Athletics General Manager Billy Beane, with a limited budget, used sabermetrics (i.e., a specific statistical analysis method in baseball) to measure player performance. He then used discovered insights to draft undervalued players and subsequently won games against rich teams like the New York Yankees. In modern sports, data-driven decision-making has become ubiquitous in most processes, such as player recruitment, performance evaluation, training, and tactic analysis [2].

However, data-driven decision making and sports data analysis is still often difficult to access for sports professionals. Imagine a college basketball player struggling to make free throws. The coaches tell them to improve their shooting trajectories, but that is hard to achieve when athletes are mostly practicing on their own. How could athletes get immediate and data-driven feedback directly on the court? Moreover, consider a basketball fan watching a game starring their favorite player. It is the 2nd quarter and the player is not performing well. The fan is getting worried and pulls up their phone to check the player's recent performance, but it is hard to find. Being distracted, the fan misses an all-star play of their favorite athlete, easily the best moment of the game. How could this game-watching experience have benefited from easily accessible data-based insights presented situated right next to the player? Lastly, consider a data analyst working for a basketball team. After collecting and analyzing spatio-temporal data for days, they have found some exciting insights. However, when presenting statistics and abstract graphs, the coaches have a hard time understanding the point and dismiss the insights. How could this data have been presented closer to its spatial and temporal context, to make insights easier to understand?

What do these three scenarios have in common? First, they are all based on real stories from sports practitioners we have worked with. Second, the visualizations in these three scenarios all come with a set of unique constraints in *space*, *time*, and *user* that make their adoption difficult. These constraints might not be present in all sports applications, however, when they are, conventional visualization solutions may no longer work. This is mainly because conventional sports analytics is often performed *off-line* and *off the court*. As a result, users cannot access the visualization at their preferred location and time, forcing users to change their workflow or making some application scenarios impossible.

On the positive side, sports visualization is currently reaching a pivotal moment in time. Novel sensors and data collection techniques and recent progress in human-computer interaction and mixed reality offer unprecedented possibilities for modern sports visualizations. For example, state-of-the-art computer vision (CV) technologies provide *real-time* data collection *in the court*, allowing applications that would not be possible without access to such data; the next generation of display and interaction devices (i.e., virtual and augmented reality or VR/AR) are capable of projecting an unlimited number of interactive 2D and 3D graphics into any space, and breaking the boundary between the physical and digital world [3]. With these advances in technology, basketball players who want to improve their shooting can obtain objective feedback through CV and AR techniques in real-time [4]; fans who want to access external information during a play can see the data embedded in the court [5]; and analysts who want to better explain their insights can create situated sports videos for more effective communication [6].

The purpose of this paper is to discuss the opportunities and challenges in modern sports visualization (or SportsXR [3]) research. We first elaborate the spatial, temporal, and user constraints to highlight the uniqueness of modern sports visualizations. We then share three projects we performed with different sports user groups (see Fig. 1) and finally discuss the lessons learned and potential future challenges we see from these projects.

WHAT MAKES SPORTS DIFFERENT?

Sports data, as well as sports domain users, have some unique traits that need to be considered when designing sports visualizations.

Spatial constraints. Most sports data are by nature *spatial*, either containing spatial coordi-

	(1) Basketball AR	(2) VisCommentator	(3) Omnioculars
Target user and workflow	Athletes **Motor-skill training**	Analysts **Analytic video creation**	Fans **In-game data analysis**
User Goal	Evaluate and improve on performance in training	Deliver analytic results in videos effectively	Consume game data to enhance game engagement
User Needs	Obtain immediate & precise feedback to analyze performance	Extract and integrate data into video authoring process	Access and analyze data in-game without being distracted from the game
User Research Methods	Initial interviews On-site field study Follow-up interviews	Initial Interviews Weekly meetings for a year	Online survey Follow-up interviews Real game walkthrough
Data Source	Shot tracking data by our tracking system	Data extracted from sports videos	NBA player tracking & game stats
Visualization	Real-time shot feedback with situated AR visualization	Data-driven augmented video authoring tool	Game viewing system with embedded visualization
Evaluation	Performance measurement Subjective user feedback	Case study Expert Interview	Case study Subjective user feedback

Figure 1. Three exemplary sports visualization projects we discuss in Sec 2. Each project targets a different user group and workflow, including athletes' motor-skill training, analysts' video creation, and fans' in-game data analysis. Different user goals and needs lead to tailored research and design approaches.

nates, such as the position of the basketball and players, or by being linked to physical objects or spaces [7]. For example, shooting percentages of a basketball player are linked to specific areas on the basketball court. Moreover, sports data are typically dynamic [8], with most entities (e.g., the players) moving all the time, making it challenging to design visualizations that allow viewers to easily track these changes.

Temporal constraints. Most sports are fast-paced, creating constant streams of time-sensitive data, such as updated player positions or velocities. Sports visualizations have to be able to support these time-sensitive data, to allow viewers to follow the temporal aspect of the sport. This requires visualizations to run at real-time on high-throughput data streams. At the same time, however, sports visualizations must limit the mental load on viewers, to allow them to digest the presented information in a limited time. Additionally, sports visualizations should not distract users from their primary tasks, which might be coaching a team, watching a game on TV, or practicing free shots. Instead of competing for their attention, sports visualization needs to be integrated into the user's workflow to support real-time data analysis.

User constraints. Common stakeholders in sports include athletes, coaches, analysts, fans, and journalists, and less common roles can be managers, sports doctors, and more. The diverse requirements of different user groups lead to completely different sports visualization designs. For ATHLETES, visualizations should enable them to connect the data back to their physical skills [4] (e.g., to improve their technique or tactics). For COACHES, visualizations should be deployed on mobile devices, to be looked at while being close to their athletes, next to the court, rather than in front of an office computer. ANALYSTS consider both the exploratory and explanatory aspects of sports data and need to be able to quickly and easily create different visualizations based on their specific purposes [6]. The wide variety of FANS, from novices to die-hard fans, adds even more challenges to the design of visualizations [5]. Finally, JOURNALISTS leverage visualizations to perform in-depth sports data exploration and communicate the generated data story to their readers [9]. These user groups vary widely in their visualization literacy and analytical background, but also in their motivation and the data they are interested in. Therefore, it is essential that visualization tools are customized to specific user groups, their data, and the goals they are trying to achieve.

Summary. The spatial and temporal constraints are often interconnected, and modern sports visualization has the potential to address them together. For example, creating visualizations situated in physical space allows viewers to consume spatially-embedded sports data faster and with less cognitive load. Other domains, outside of sport, share similar challenges and could benefit from SportsXR research, such as visualizing spatio-temporal data. We also foresee that applying existing techniques from computer graphics and computer vision, like optimizing camera placement and rendering, can advance sports visualization in certain scenarios. Some challenges have bigger implications but have been underexplored, such as the limited amount of time for users to perceive visual information, which has only been discussed preliminarily [3], [8].

SPORTSXR RESEARCH

In the following, we summarize three sports visualization projects that we have conducted with athletes, analysts, and fans, respectively (see Fig. 1). For each project, we summarize our initial user research, identified goals & tasks, design considerations, and evaluation.

Basketball AR: Motor-skill training for athletes

The goal of this project was to provide real-time visual feedback for basketball players practicing free-throw shooting. Through close collaboration with college basketball teams, we prioritized a minimal visual design and fast and accurate feedback to help improve players' motor skills [4].

Interviewing athletes to identify the gap in shot training. Through user interviews and in-person field studies with players and coaches, we found players desire precise quantitative feedback on their shots, which they typically do not get. They also have no way to precisely specify goals or evaluate their outcome in an actionable way, i.e., players cannot easily evaluate the shot angle of their free throws. Therefore, players were highly interested in accessing visual feedback during shot training.

We first characterized user goals and tasks to form a set of visualization design requirements. Basketball players wanted to have real-time quantitative feedback to increase shot consistency and refine their shot arc. We then identified four tasks a visualization system for free-throw training needs to support: T1) analyzing the target shooting arc before a shot, T2) analyzing one's shooting arc during and after each throw immediately, T3) comparing one's shooting arc to the target arc, and T4) adjusting one's target arc to get consistently closer to an ideal arc.

(a) Co-located 2D Visualization (b) AR Situated 3D Visualization

Figure 2. 2D and AR free-throw shot visualizations.

Real-time visual feedback through co-located and situated visualization. To fulfill the aforementioned design requirements, the visualization needs to support the three-dimensional reasoning of the shot, be located closely and easily accessible to the user. We implemented a shot tracking system to detect shot metrics in real-time and designed two visualization modalities. A *co-located 2D visualization* (Fig. 2a) presents the shot arc from a third-person view on a co-located monitor placed next to the shooter. A *situated AR 3D visualization* (Fig. 2b) presents the shot arc from a first-person view through an AR headset. Both visualizations present information about the shooter's target and actual shot arcs with different presentation dimensions (2D vs. 3D) and viewing perspectives (third-person vs. first-person).

Comparing the usefulness of 2D and AR visualizations for free-throw training. Our evaluation focused on characterizing unique aspects of applying our novel AR visualization to free-throw training. We conducted a comparative study of free-throw shot training with the 2D and AR visualizations with ten basketball players over four days each. We collected both quantitative and qualitative measures, such as shot metrics and user feedback. Our results suggest that the 2D and AR visualizations were considered useful for free-throw training, and users significantly

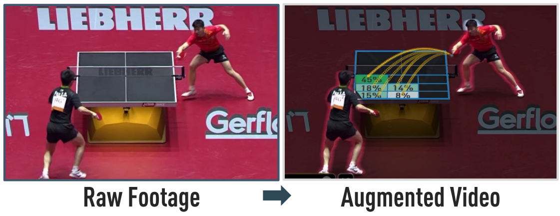

Figure 3. Augmented sports videos embed visualizations into videos to present data.

improved their shot angle consistency throughout the study. More interestingly, the AR visualization promotes an increased focus on body form as users prioritized "improve the shooting form" as their top training goal, as opposed to "improve shot accuracy" with the 2D visualization.

VisCommentator: Augmented sports video creation for analysts

In this project, we focused on enabling analysts to create augmented sports videos in a data-driven workflow (see Fig. 3) rather than a completely manual annotation process [6].

A Formative Study to Understand Constituents of Augmented Sports Videos. Augmented sports videos help in communicating analytical insights. However, creating augmented sports videos is often difficult, involving complex design decisions and video editing. To understand the design practices of augmented sports videos, we collected and analyzed 233 videos from TV, teams, and leagues. Based on our analysis, we propose a design space that characterizes augmented sports videos at element- and clip-levels with four design dimensions (i.e., Data Type, Visual Type, Data Level, and Narrative Order).

A Semi-Automated System to Create Augmented Sports Videos. Informed by the design space and the close collaboration with experts, we developed *VisCommentator*, a system that allows sports analysts to augment table tennis videos efficiently by selecting the data to visualize instead of manually drawing graphical marks. Given a raw table tennis video, VisCommentator first extracts sports data (e.g., players and ball positions, ball events) using a set of machine learning models. The extracted data are grouped together based on their semantic levels. Next, VisCommentator uses the extracted data to decorate the video objects and the video timeline, so that users can directly interact with the video objects and events to select the data to visualize. Finally, VisCommentator suggests visual effects for the user-selected data based on our design space and renders the visual effects into the video.

Expert evaluation. To evaluate the usability of *VisCommentator*, we conducted a qualitative user study with seven sports analysts. We tasked participants with reproducing target augmented videos and recorded the completion time and success rate for each task, and subjective feedback. All participants could successfully reproduce the augmented videos.

Omnioculars: In-game data analysis for fans

In this project, we focused on improving the experience of sports fans in live game watching scenarios by embedding visualizations into basketball games.

We investigated the design space of embedding visualizations into live game videos and developed an interactive game-viewing prototype with personalized embedded visualizations to support fans' in-game data analysis [5].

Characterizing basketball fans' data needs during a live game. We first deployed an online survey to collect fans' data needs in a live game and interviewed six fans about their game viewing experiences. We found that fans seek data in various contexts during games, which we characterized into three components, including SCENARIOS (*when* fans desire to look for data), DATA (*what* in-game data fans look up), and TASKS (*why* fans look for data). Based on this framework, we derived design requirements under specific game contexts. All interviewees confirmed their habits of looking up game stats on separate screens during live games, which introduces context switching and reduces game engagement.

Design exploration of embedded visualizations in sports games. To present contextual data with embedded visualization in game videos, we designed an interactive game viewing system, *Omnioculars*. Based on the design feedback from fans, we prioritized five game contexts to drive our embedded visualization designs, including shooting, offense, defense, player performance, and team performance (Fig. 4).

Using embedded visualizations for in-game

(a) SHOT LABEL (b) OFFENSE TRAJECTORY (c) DEFENSE FORM (d) SHOT CHART (e) TEAM PANEL

Figure 4. Embedded visualizations for five selected game contexts, including (a) shooting performance, (b) offense player trajectories, (c) defenders' movement, (d) player performance, and (e) team performance.

data analysis. To evaluate our system for in-game data analysis, we conducted a user study with simulated basketball game clips in two parts. The participants evaluated each of the five embedded visualizations and then freely combined different visualizations to derive game insights.

Participants considered all five embedded visualizations useful and novel. Moreover, participants used different interaction approaches based on their game focus and preferences (i.e., configuring a fixed set of visualizations ahead of time or altering visualizations on-the-fly based on context). They could derive distinct game insights with their chosen embedded visualizations. Overall, they found Omniocluars helpful and fun to use, felt in control of their experience, and were likely to use it in live games.

LESSONS LEARNED

Theme 1: Working with Sports Experts

The entry barrier is high due to the *required domain knowledge*, *seasonality of sports leagues*, and *limited data availability*.

Without personal connections and a deep understanding of the sport, it is difficult to find collaborators and keep them engaged. For our basketball AR project, the collaboration with the varsity teams only started because the lead author had experience working with a professional basketball team and was introduced to the coach through a mutual connection. Similarly, the augmented video project was only initialized because of the researcher's prior experience with table tennis visual analytics systems. At the very least, coaches, analysts, or fans usually expect the researchers to have a good understanding about the sport, such as the rules of the game and the composition of the professional league or collegiate tournament. For example, when interviewing NBA fans, they often refer to specific players or teams and technical terms (e.g. pick-and-roll, floater) to describe their game-viewing experiences. It is crucial that researchers show understanding and enthusiasm to encourage the conversation and extract more insights from the interviewees.

In addition, sports leagues are seasonal and follow strict timelines. Researchers need to be aware of the constrained availability of experts when planning project phases. For example, in the basketball AR project, the varsity teams were able to support us throughout the design phases, but they were competing in a tournament at the later phase. Therefore, we had to find other intramural teams to support our user testing. We planned our Omniocluars project to align with the NBA season to increase our chances to find passionate fans and keep them in the loop throughout the entire project.

Lastly, access to sports data is usually proprietary to the team or league. Since the nature of sports is competitive, teams and athletes try to get advantages over others through data collection and analysis. Therefore, sharing data is usually not encouraged or even impossible. For example, all teams we collaborated with explicitly asked us not to publicize their data and process. Similarly, when designing embedded visualizations for basketball game viewing, we could not obtain up-to-date player tracking data from the NBA and had to use previously collected game data. A workaround could be to build our own camera tracking system and train computer vision models to extract data. However, this would require expertise in CV and considerable resources.

Educating sports experts to use new techniques is hard since some experts are *reluctant to try alternatives* while others may *overestimate the capabilities of emerging techniques*.

Oftentimes, sports experts have well-established workflows and are reluctant to consider alternatives. In VisCommentator, even though our proposed authoring system can support fast prototyping of augmented videos, some analysts still preferred using traditional court diagrams. To this end, we sought to find motivating factors in the target users. For example, collegiate teams usually are open to collaborating with school research labs because innovation appeals to student athletes, which may also enhance their recruitment process.

On the other hand, sports experts may overestimate the capabilities of emerging technologies that are still in an evolving stage but are advertised as omnipotent (e.g., universal artificial intelligence). In the AR free-shot project, for example, some experts were disappointed as they found that the HoloLens1 was far from mature and thus provided biased negative feedback for the visualizations in the user study. It is crucial to properly *manage experts' expectations* of the emerging techniques to obtain unbiased and useful feedback.

Theme 2: Evaluating Immersive Visualizations

Identifying the benefits of visualizations in the analytic workflow. A key consideration during the design process is to distinguish between the added values from the data versus visualization designs. When presented with a novel analytic system, sports experts may find the system useful because of the data they were able to obtain. To identify the design values, it is important to evaluate them explicitly. In our free-shot project, we present the same shot tracking data in the 2D and AR visualizations. The direct comparison between different visual representations allowed us to separate the benefit of immersive visualization, leading to more generalizable design guidelines.

Using Wizard-of-Oz user testing allows us to focus on the visualization research questions. Considering the high implementation costs of AR, we advocate for developing a subset of target scenarios and using the Wizard-of-Oz method for evaluation. In the VisCommentator project, we focused on a selected game video instead of trying to implement a complete solution for all game videos. On the other hand, in the Omniocular project, we aimed to evaluate how people use embedded visualizations to analyze a basketball game. Instead of tackling CV problems beyond our expertise, we designed a simulated game environment with 3D models and manually crafted player animation for selected game scenarios. We also used a Wizard-of-Oz method to evaluate how users interact with different visualizations through verbal commands. In both cases, we have obtained valuable insights from users interacting with our visualization tools under realistic use cases without being blocked by implementation details.

Evaluating sports visualizations requires consideration for individual user differences and contexts. It is often insufficient to evaluate sports visualizations using general quantitative measurement with simplified tasks. One mitigation is to use qualitative methods across user groups, contexts, and times. For example, we evaluated Omniocular with novice and hardcore fans and recorded their interaction patterns. We also evaluated visualizations under different game contexts, such as under shooting or clutch time scenarios. In AR basketball training, we collected user feedback at the beginning, during, and after training. This allowed us to evaluate the usefulness of visualizations at a finer granularity with considerations for various factors on top of the standard quantitative measures.

Evaluating skill transfer and long-term adoption are still lacking in sports visualizations. As much as we are excited about the new SportsXR solutions, it is difficult to convince sports experts to change their workflow without evidence for long-term improvement and adoption. Long-term evaluations of visual analysis tools for sports are still lacking. However, to have a meaningful impact on the sports domain, it is necessary to show evidence of skill transfer through longitudinal evaluation. We thus envision and advocate for sports visualization research to expand its impact through collaborations with other research areas, such as Kinesiology and Sports Sciences.

CONCLUSIONS

Exploring new possibilities in sports visualization with modern computing and display technologies is extremely exciting, especially when seeing its impact on sports practitioners. However, designing SportsXR applications is not a trivial task. Sports is a data-rich scenario for visualization that comes with many specific design considerations and constraints. Although there are some inspiring discussions and preliminary studies [7], [8], [10], fundamentally, it is still unclear how existing visualization principles can best be applied to modern sports visualizations, and there is a lack of established guidelines. We need to invest more in understanding human factors in sports visualizations and closely collaborate with other communities (e.g., CV, ML, NLP) to improve the current workflows in sports. Furthermore, we envision that with visualization becoming ubiquitous in space and time, there will be more and more scenarios that share similar challenges as we have discussed here for sports. Ultimately, research in different applications can complement empirical knowledge, guidelines, and techniques from different perspectives, forming a complete ecosystem for future visualization applications.

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