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[1,3]Yosra MLOUHI, [2]Najeh LAKHOUA, [3]Imed JABRI, [3]Taher BTATIKH

TELEVISION BROADCASTING IN SPORT EVENTS: TECHNOLOGIES, APPLICATIONS AND LIMITATIONS

[1] Esprit School of Business, Research Unit AI4U, Department of Computer Science and Applied Mathematics, Ariana, TUNISIA
[2] University of Carthage, National Engineering School of Carthage, ENICarthage, Research Laboratory, Smart Electricity & ICT, SEICT, Tunis–Carthage, TUNISIA
[3] University of Tunis, National Superior School of Engineering, Research Laboratory, Information & Communication Technologies & Electrical Engineering, Tunis, TUNISIA

Abstract: This paper explores television broadcasting within the context of sports events, focusing on the various technologies involved. It offers an in–depth analysis of how computer vision and augmented reality are currently leveraged to enrich visual content, support real–time data integration, and enhance audience engagement. Additionally, it discusses the implementation of image processing techniques specifically tailored for sports broadcasting. Finally, the paper highlights multiple research initiatives that apply these techniques across a range of sporting disciplines.
Keywords: TV Broadcasting, Augmented Reality, Image Processing, Sports events

INTRODUCTION

The history of broadcasting traces back to the early 1920s with the emergence of amplitude modulation (AM) radio, which marked a significant shift from earlier forms of electronic communication such as telegraph, telephone, and early radio that operated on a one-to-one basis.

AM radio introduced a one-to-many model, where audio content could be transmitted to a broad audience simultaneously. As the first technique for embedding sound into a radio wave, AM laid the groundwork for modern broadcasting and continues to be in use today.

Over time, it has faced increasing competition from frequency modulation (FM) and more recently from digital broadcasting systems, delivered via both terrestrial and satellite networks [1] [2].

In several countries, AM radio has become more focused on spoken content such as news, sports, and talk shows, largely due to its susceptibility to interference. In contrast, FM and digital platforms have become the preferred choices for music broadcasting due to their superior audio quality [3] [4] [5].

Terrestrial broadcasting, also known as over-the-air transmission, involves delivering radio and television programs from a broadcast station directly to home receivers using radio frequency spectrum. In most countries, this form of transmission is regulated and requires a broadcasting license. Other methods, such as cable television, which combine satellite links and wired infrastructure to distribute content including the retransmission of terrestrial channels with consent are also regarded as forms of broadcasting, though they typically operate under different licensing frameworks. While the term "broadcasting" is sometimes used more broadly today, its traditional definition remains tied to regulated, spectrum-based transmission systems [6] [7].

This paper aims to present a structured overview of the key techniques that underpin contemporary television broadcasting practices, while also highlighting recent research efforts involving the application of artificial vision and augmented reality technologies in this field.

MATERIALS AND METHODS

This section presents an overview of television broadcasting technologies, with a particular emphasis on the integration of computer vision and augmented reality methods and techniques.

Digital television, in this context, refers to the transmission of audio and video signals that are digitally encoded, processed, and multiplexed for efficient and high-quality delivery., offering a significant advancement over traditional analog broadcasting, which relied on separate channels and fully analog signals [8] [9] [10]. Unlike its predecessor, digital TV allows multiple programs to be broadcast within the same channel bandwidth, enhancing efficiency and content variety. This shift marks one of the most transformative developments in television since the introduction of color broadcasting in the 1950s [11].

Augmented reality, meanwhile, enables the real-time overlay of digital elements including graphics, audiovisual components, or geolocation data superimposed onto the physical environment, whether through direct visualization or mediated display. This technology belongs to the broader field of mediated reality, where a user's perception of the environment is dynamically altered by computer-generated elements, sometimes enhancing or even reducing elements of the real-world view. Consequently, this technology operates by modifying and enriching the user's real-time perception of their surroundings [12] [13].

Augmented reality enhances the physical environment by overlaying contextual information, such as live sports scores during broadcasts, whereas virtual reality fully immerses users in a simulated world. Advanced techniques like computer vision and object recognition enable real-world data to become interactive and digitally modifiable, allowing synthetic information to be superimposed seamlessly onto the user's perception.

This paper reviews key studies exploring these technologies in television broadcasting broadcasting, artificial vision, and augmented reality.

Zhou & al. [14] propose a two-stage method for detecting events in broadcast football videos. In the first stage, multiple action recognition models are fine-tuned on football datasets to capture high-level semantic features. The second phase employs a transformer-based temporal detection module to accurately localize specific events. This method has achieved leading results in both action spotting and replay detection tasks, as highlighted during the ActivityNet workshop at CVPR.

Extending this research, Zhang et al. [15] developed a multimodal neural network that leverages attention mechanisms to classify sports events by integrating visual sequences, audio commentary, and an additional training-specific modality. Their approach demonstrates a clear improvement in classification accuracy, outperforming existing transformer-based models in this domain.

In this context, Guo & al. [16] present an advanced framework for real-time analysis and immersive visualization of sports events within virtual and augmented reality environments. Their approach leverages multiple LiDAR sensors combined with camera arrays to collect comprehensive multimodal data, enabling precise multi-athlete tracking and three-dimensional pose estimation under limited supervision. The generation of highly detailed 3D player models, which are seamlessly embedded into virtual settings, enhances the spectator's experience while providing valuable support for sophisticated tactical analysis. The system demonstrated robust performance during experimental validation, and the authors plan to release their dataset and implementation to promote further research advancements in this area.

Finally, Liu & al. [17] explored hybrid models that combine visual perception and behavioral analysis to design adaptive cognitive interfaces in augmented reality for personalized sports coaching. Their approach enables the system to dynamically adjust the interface based on the user's actions, attention, and reactions, thus offering more fluid, contextual, and user-centered interactions in immersive training environments.

Building on this, videos remain a widely accessible medium for posture analysis and feedback in sports. However, many existing systems rely on fixed pose attributes, limiting flexibility and customization for non-expert users. Some compare poses directly but often fail to clearly highlight key differences. Furthermore, video-based feedback is constrained by fixed camera angles, which restrict motion analysis and can cause ambiguous results. To overcome these challenges, PoseCoach was developed a system allowing users to define relevant running posture attributes and visualizing differences using part-based 3D animations applied to a human model, this approach replicates the demonstration techniques of a human coach while minimizing constraints related to viewing angles. User studies and expert feedback have validated its effectiveness and usability.

In the context of enhanced television broadcasting of sporting events, augmented reality (AR) technologies are emerging as key enablers for strengthening the immersive experience of viewers.

Kendall & al. [18] proposed PoseNet, a CNN-based method for real-time 6-degree-of-freedom (6-DOF) camera relocalization. Their approach directly predicts estimation of the camera's spatial position and orientation derived from a single RGB image, enabling real-time performance with low latency. The method is robust against challenging conditions like lighting changes, motion blur, and varying camera intrinsics, making it well-suited for dynamic augmented reality environments. PoseNet is efficient, processing frames in about 5 milliseconds, and it generalizes effectively to unseen scenes with minimal additional training data.

In parallel, B. Wang & al [19] proposed AtLoc: Attention Guided Camera Localization, an innovative CNN approach that enhances real-time 6-DOF camera pose estimation by integrating a self-attention module to automatically emphasize geometrically robust image features. Compared to earlier methods like PoseNet, AtLoc self-regulates to focus on stable cues, improving both accuracy and robustness in complex and evolving environments

Zhao & al. [20] developed a real-time visual-inertial localization framework combining IMU data with semantic segmentation to enhance pose estimation in dynamic and cluttered environments. By filtering out unstable elements via semantic cues, the system maintains spatial coherence and improves robustness under fast motion minimizing drift and occlusion errors. The authors emphasize its utility in immersive technologies such as AR and VR, where maintaining stable and accurate tracking is critical for seamless user experiences in live and interactive scenarios.

López-Barreiro & al. [21] proposed an AI-based recommendation framework that processes semantically rich metadata, user profiles, and environmental context to deliver highly personalized content in real time. Using adaptive filtering and dynamic user modeling, the system infers preferences and suggests tailored experiences. While initially focused on health promotion and active aging, the framework's scalability and modularity make it highly transferable to domains like sports broadcasting, AR/VR content delivery, and interactive media where contextual relevance and user engagement are critical.

Collectively, these contributions illustrate the ongoing evolution toward highly interactive and adaptive sports broadcasting systems, driven by multidisciplinary technological innovations.

RESULTS

This section presents the outcomes of automated analysis applied to sports video content. A variety of enhancement techniques in sports broadcasting rely on object-tracking algorithms like those used to follow the ball to generate informative visual overlays within the live broadcast. Additionally, elements like field markings and player positions are crucial for conducting semantic analysis, particularly in soccer video analysis [22].

The system uses ambiguous learning labels, from a video and subtitles, the system can locate and recognize faces from the front, where there are nearly 1 to 2 faces per image. Figure 1 shows the facial recognition. In this image, limit frames show the location of the faces, and the texts show the name of the character.

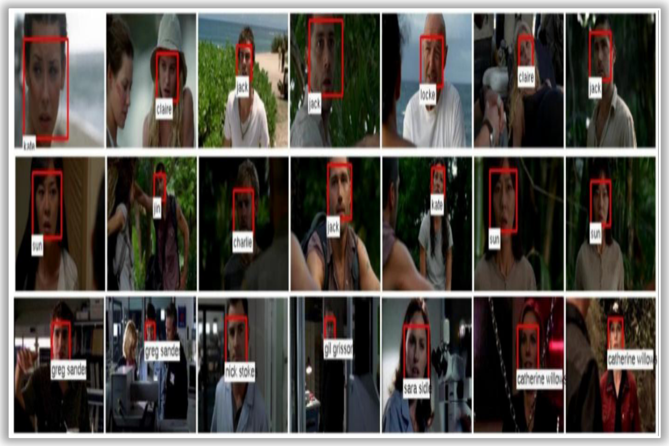

Figure 1. The facial recognition [22].

To perform the monitoring of multiple targets in a video sequence, the best-known approach is to apply multiple and independent mono tracking algorithms target to perform the monitoring of various targets. More specifically, it can initiate a single monitoring procedure target thanks to the initial location of the target and then ask him to follow the player in the video sequence (Figure 2).

The original location can be identified manually, or by an automatic object detection system. These follow-up procedures are independent because they do not know the existence of other procedures, and however it has no overall coordination between these follow-up procedures. For example, researchers have used the algorithm of mean-shift for the follow-up of football players, as shown in figure 3.

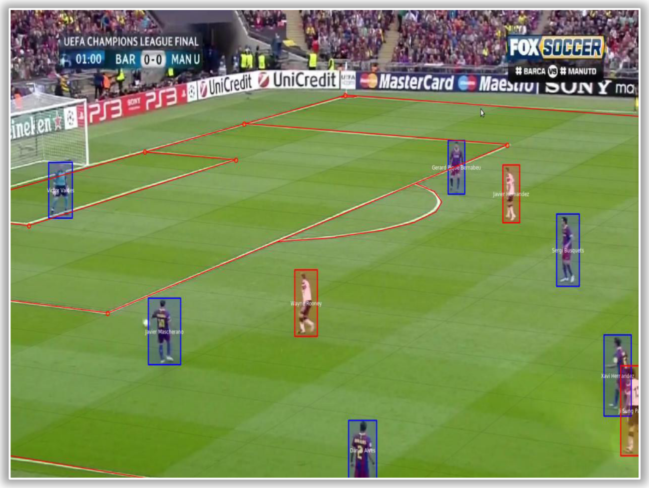

Figure 2. The follow–up of football players by particle filter started

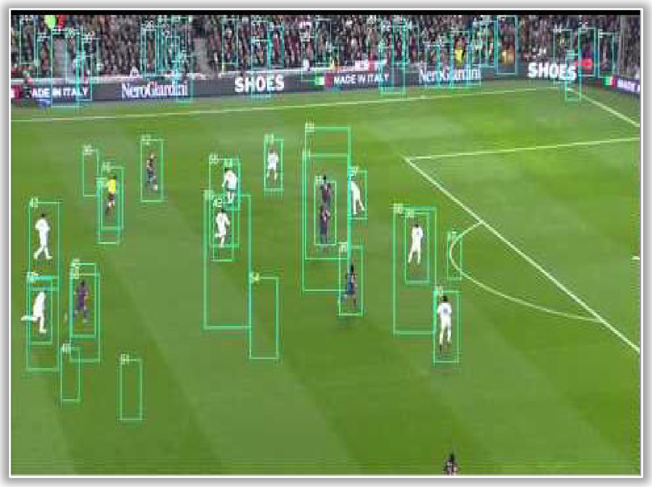

Figure 3. The follow–up of football players by the algorithm of mean–shift

Recently, others researchers have applied the Camshift (Continuously Adaptive Mean Shift) image segmentation algorithm for the follow-up of basketball players, as shown in figure 4.

Several studies have explored the application of image processing techniques in sports events. In particular, automated video analysis for team sports such as basketball has emerged as a rapidly growing research area, leveraging advanced computer vision and artificial intelligence methods to develop intelligent systems capable of contextual interpretation.

Figure 4. The follow–up of basketball players by Camshift image segmentation algorithm

Citraro & al. [23] propose a real-time camera pose estimation framework specifically designed for sports environments such as soccer fields. Their method focuses on accurately recovering both intrinsic parameters (such as focal length) and extrinsic parameters (camera orientation and position) without prior manual calibration. By leveraging a semantic understanding of the playing field, the system detects key geometric landmarks including arcs and field lines which serve as anchors for estimating a projective transformation between the field model and the image plane. The initial homography is refined through a combination of nonlinear optimization techniques and temporal filtering, incorporating visual cues from both the static layout and dynamic player keypoints. This robust estimation process enables the seamless overlay of virtual graphics onto the live video stream, ensuring spatial consistency across frames even under partial occlusions or moving camera conditions. This approach delivers robust accuracy and operational efficiency, making it an ideal solution for real-time augmented broadcasting applications in the domain of professional sports.

Chen & Little [24] introduce a novel camera calibration approach tailored for sports environments, leveraging synthetically generated data to overcome the limitations of traditional calibration techniques. Their method trains deep learning models on artificially rendered images of sports fields, enabling the network to infer camera parameters such as focal length, position, and orientation directly from a single image. By simulating diverse viewing angles, field layouts, and lighting conditions, the synthetic dataset ensures strong generalization to real-world broadcast footage. Unlike conventional methods that rely heavily on manual annotation or line detection, this data-driven strategy offers fast, automated, and scalable calibration, particularly well-suited for dynamic and multi-camera sports scenarios. The system demonstrates robust performance across different sports domains, paving the way for enhanced augmented reality overlays and tactical analysis in live sports broadcasting.

Puente & al. [25] conducted an in-depth analysis of the physical and physiological demands placed on experienced male basketball players during competitive matches. Utilizing GPS tracking and heart rate monitoring, they quantified key performance metrics such as running speed, body impacts, acceleration patterns, and cardiovascular load. The study revealed that players, particularly guards, sustain high-intensity efforts characterized by substantial distances covered at varying speeds and elevated heart rates nearing 90% of their maximum. The frequency of body impacts per minute further underscored the sport's dynamic and contact-intensive nature. These insights highlight the necessity for position-specific conditioning programs, emphasizing aerobic capacity and agility training to optimize game performance and manage fatigue effectively in elite basketball settings.

García & al. [26] investigated the variation in physical demands throughout the different quarters of professional basketball games, analyzing how these demands differ according to players' positions during official competitions.Using inertial tracking technology, they monitored players' movements and performance indicators such as distance covered, acceleration frequency, and high-intensity efforts throughout the four quarters of actual games. The study revealed a notable decrease in physical performance, particularly in the fourth quarter, suggesting the influence of fatigue as the game progresses. Additionally, significant differences were observed between positions: guards exhibited higher physical demands in terms of intensity and volume compared to forwards and centers. These findings underscore the importance of tailored training and conditioning strategies that consider both positional roles and temporal dynamics within games to sustain performance and mitigate fatigue.

Vázquez-Guerrero & al. explored the progressive physical demands faced by elite U18 basketball players across official competitive matches [27]. Utilizing high-resolution tracking through local positioning systems, the study quantified performance metrics such as sprint distance, acceleration frequency, and total player load throughout all four quarters. A consistent decline in these indicators was observed as the game progressed, particularly in the final quarter suggesting clear signs of fatigue accumulation. Additionally, positional differences revealed that guards experienced higher intensity demands than forwards or centers. The findings emphasize the need for targeted conditioning especially aerobic and agility-focused training in junior basketball to maintain high performance levels and mitigate fatigue during competition.

Koshkina & al. [28] developed an unsupervised method for classifying players into their respective teams using only video input, without relying on prior knowledge of jersey colors or manual annotations. Their approach is based on contrastive learning, which trains a lightweight segmentation network to produce pixel-level embeddings. These embeddings are optimized so that features from players on the same team cluster closely, while those from opposing teams are separated in feature space. The method demonstrates high performance, achieving up to 94% accuracy from a single frame and nearly 97% after 500 frames of gameplay. Though evaluated on ice hockey footage, the system's adaptability makes it suitable for team-based sports like basketball, especially in scenarios involving occlusions and varied camera perspectives. Additionally, the method generates team-specific heatmaps to analyze player spatial behavior.

In the domain of visual recognition, Balaji & al. [30] propose a jersey number recognition framework tailored for low-quality sports broadcast videos. Their approach relies on an intelligent keyframe selection step that identifies frames with sufficient visibility of the jersey number. These selected frames are then processed by a spatio-temporal network combining CNN and Vision Transformer architectures, leveraging both visual context and temporal continuity to estimate the digits displayed. A multi-task learning strategy enables independent prediction of each digit. Evaluated on the SoccerNet dataset, their method achieves substantial improvements, increasing accuracy by over 37%, demonstrating the effectiveness of this pipeline for number recognition under real-world conditions such as blur, low resolution, and occlusion.

Finally, the synthesis of these approaches is embodied in the work of Lakhoua & al. [31] [32] and Wang & al. [33], who developed integrated systems for multi-object detection and tracking with robust re-identification. These systems ensure precise and continuous localization of players across the entire court, despite challenges posed by occlusions and fast, unpredictable movements.

Together, these multidisciplinary contributions combine computer vision, multisensory data processing, and artificial intelligence to push the boundaries of automated sports analytics. They provide sophisticated technological tools that not only improve understanding of game dynamics but also enable real-time optimization of athletic performance and strategic decision-making. From an applied perspective, these advances support the development of intelligent platforms that enhance the experience of coaches, analysts, and spectators, while establishing a methodological foundation for extending these innovations to other domains that require fine-grained and adaptive analysis of complex phenomena in dynamic environments.

DISCUSSION

Compared to conventional television production techniques, live TV broadcasting presents several compelling advantages. First, it enables real-time interaction between the production team and the audience, offering viewers not only the ability to watch but also to actively engage with and influence the content. Second, it transforms the traditional role of the TV director into that of a content conductor, where pre-recorded and live materials can be orchestrated into multiple simultaneous broadcast streams. This approach allows audiences to customize their viewing experience by choosing among different content flows. Third, live broadcasting benefits from intelligent systems, such as content and behavior analysis, which further personalize and enhance the viewing experience.

Augmented reality has become an integral part of modern sports broadcasting. Using tracked camera feeds; broadcasters overlay digital elements onto live footage to enrich the viewer's perception of the game. A widely recognized illustration is the virtual yellow "first down" line in American football, which marks the yardage the offensive team needs to cover to achieve a first down.. Similar applications are used in football and other sports to superimpose advertisements or sponsor logos onto the playing surface. In rugby and cricket, virtual branding is displayed on the field, while in swimming events, graphic overlays often show the current world record pace, enabling spectators to visually compare live performances with historical benchmarks.

CONCLUSION

In this article, we have provided a comprehensive survey of the current landscape of television broadcasting in sports events. We explored various applications of artificial vision and augmented reality technologies, alongside an analysis of how image processing techniques are integrated to enhance the quality and effectiveness of the broadcasting experience.

Together, these innovations contribute to transforming how sports content is produced, delivered, and experienced by audiences. Some results of automatic analysis of sport videos are presented (the follow-up of players by particle filter started; by the algorithm of mean-shift; by Camshift image segmentation algorithm…).

REFERENCES

[1] Janghak K., Jeounglak H. and Bumsuk C., "Design and Implementation for Interactive Augmented Broadcasting System," IEEE Transaction. https://doi.org/10.1145/3391614.3393649

[2] Saeghe A. B., Weiler A. and Röderer N., "Augmented Reality and Television: Dimensions and Themes," Proceedings of the ACM International Conference on Interactive Media Experiences (IMX '20), ACM, 2020, pp. 22–33.

[3] Y. H. Bae, "Queueing Analysis of Deadline–Constrained Broadcasting in Wireless Networks," IEEE Communications Letters, 2015, Vol. 19, No. 10, pp. 1782–1785.

[4] N. Nomikos, T. Charalambous, Y.–A. Pignolet and N. Pappas, "On the Interplay Between Deadline–Constrained Traffic and the Number of Allowed Retransmissions in Random Access Networks," IEEE Transactions on Communications (prépublication ou version arXiv), 2022

[5] N. Nomikos, T. Charalambous, N. Pappas and Y.–A. Pignolet, "Deadline-constrained Bursty Traffic in Random Access Wireless Networks," Proceedings of the IEEE International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Kalamata, Greece, June 2018, 5 pp.

[6] M. Salman and M. K. Varanasi, "Capacity Results for the K–User Broadcast Channel with Two Nested Multicast Messages," arXiv preprint arXiv:1812.10520, publié le 27 décembre 2018.

[7].Khissti A. and Tae L., "Private Broadcasting Over Independent Parallel Channels", IEEE Transactions on Information Theory, 2014, Vol.60, Issue: 9, pp. 5173–5187.

[8]. S. Zhang, et al., "FootyVision: Multi–object tracking, localization and augmentation for football videos," ACM Transactions on Multimedia Computing, Communications, and Applications, 2023, Vol.19, Issue 1, pp. 1–25

[9]. J. Smith and M. Brown, "Investigation into tracking football players from video streams produced by cameras set up for TV broadcasting,"American Journal of Engineering Research (AJER), 2017, Vol 6, Issue–11, pp–95–104

[10]. P. Campr, M. Herbig, J. Vanek, and J. Psutka, "Sports Video Classification in Continuous TV Broadcasts," 12th IEEE International Conference on Signal Processing (ICSP), Hangzhou, China, October 2014, pp.

[11]. M. Graham, M. A. Zook, and A. Boulton, "Augmented reality in urban places: Contested content and the duplicity of code," Transactions of the Institute of British Geographers, 2013, Vol. 38, Issue 3, pp

[12]. C.–Y. Ong, J. Song, C. Pan, and Y. Li, "Technology and Standards of Digital Television Terrestrial Multimedia Broadcasting," IEEE Communications Magazine, 2010, Vol. 48, Issue 5, pp. 119–127

[13]. J. Song, Z. Yang, and J. Wang, Digital Terrestrial Television Broadcasting: Technology and System, Wiley–IEEE Press, 2015, 456 pages.

[14]. X. Zhou, L. Kang, Z. Cheng, B. He, and J. Xin, "Feature Combination Meets Attention: Baidu Soccer Embeddings and Transformer based Temporal Detection," arXiv, 28 juin 2021

[15]. Y. Zhang, B. Li, H. Fang, and Q. Meng, "A Multi–Modal Transformer Approach for Football Event Classification," Proceedings of the IEEE International Conference on Image Processing (ICIP), 2023, pp

[16]. Wenxuan Guo, Zhiyu Pan, Ziheng Xi, Alapati Tuerxun, Jianjiang Feng, & Jie Zhou, "Sports Analysis and VR Viewing System Based on Player Tracking and Pose Estimation with Multimodal and Multiview Sensors," arXiv, 2 mai 2024.

[17] J. Liu, N. Saquib, Z. Chen, R. H. Kazi, L.–Y. Wei, H. Fu, and C.–L. Tai, "PoseCoach: A Customizable Analysis and Visualization System for Video–based Running Coaching," arXiv preprint, 2022

[18] A. Kendall, M. Grimes, and R. Cipolla, "PoseNet: A Convolutional Network for Real–Time 6–DOF Camera Relocalization," arXiv preprint, 2015.

[19] B. Wang, C. Chen, C. X. Lu, P. Zhao, N. Trigoni, and A. Markham, "AtLoc: Attention Guided Camera Localization," Proceedings of the AAAI Conference on Artificial Intelligence, 2020, Vol. 34, No. 07, pp. 10605–10613.

[20] X. Zhao, C. Wang, and M. H. Ang, "Real–Time Visual–Inertial Localization Using Semantic Segmentation Towards Dynamic Environments," IEEE Access, 2020, Vol. 8, pp. 51701–51714

[21] J. López–Barreiro, J. L. García–Soidán, L. Álvarez–Sabucedo, and J. M. Santos–Gago, "Artificial Intelligence–Powered Recommender Systems for Promoting Healthy Habits and Active Aging: A Systematic Review," Applied Sciences, 2024, Vol. 14, Issue 1, Article 284

[22] Maallej L., "Vision Artificielle et Réalité Augmentée Appliquées à l'Analyse et à la Retransmission Télévisuelle des Rencontres Sportives", Thèse, ENSIT, Université de Tunis, 2015.

[23] Citraro S., Palazzo S. and Spampinato C., "Real–Time Camera Pose Estimation for Sports Fields," Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 13655–13664.

[24] Chen J. and Little J.J., "Sports Camera Calibration via Synthetic Data," Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2019, pp. 1076–1084.

[25] Puente C., Abián–Vicén J., Gómez M.–Á., et al., "Physical and physiological demands of experienced male basketball players during a competitive game," European Journal of Sport Science, 2017, Vol. 17, Issue 8, pp. 1076–1083.

[26] García F., Vázquez–Guerrero J., Castellano J., Casals M. and Schelling X., "Differences in Physical Demands between Game Quarters and Playing Positions on Professional Basketball Players during Official Competition," Journal of Sports Science and Medicine, 2020, Vol. 19, No. 2, pp. 256–263.

[27] Vázquez–Guerrero J., Fernández–Valdés B., Jones B., Moras G., Reche X., and Sampaio J., "Changes in physical demands between game quarters of U18 elite official basketball games," PLoS ONE, 2019, Vol. 14, No. 9, e0221818.

[28] Koshkina M., Pidaparthy H., and Elder J.H., "Contrastive Learning for Sports Video: Unsupervised Player Classification," arXiv preprint, 2021.

[29] Balaji B., Bright J., Prakash H., Chen Y., Clausi D.A. and Zelek J.Z., "Jersey Number Recognition using Keyframe Identification from Low–Resolution Broadcast Videos," Proceedings of the 6th International Workshop on Multimedia Content Analysis in Sports, 2023, pp.

[30] Balaji, R., Alagappan, K., Choudhary, A., "Jersey Number Recognition using Keyframe Identification from Low–Resolution Broadcast Videos," Proceedings of the 6th International Workshop on Multimedia Content Analysis in Sports, 2023.

[31] Mlouhi Y., Maalej L., Lakhoua M.N., Jabri I. and Battikh T., "Augmented reality and image processing solutions for sport events and training", IEEE International Conference on Information Technologies and Smart Industrial Systems ITSIS, 2022, July 15–17, Paris, France.

[32] Mlouhi Y., Maalej L., Lakhoua M.N., Jabri I. and Battikh T., "Localization for PMTTA algorithm at sport events: from concept to application", IEEE International Conference on Information Technologies and Smart Industry

[33] Wang Y., He X. and Fu Y., "Occlusion–Resilient Multi–Player Tracking with Re–identification in Team Sports", IEEE Transactions on Image Processing, 2024.

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