

Pitching-Motion: Pose-Based Pitch Trajectory Overlay System

Bor-Yao Tseng ^a, Hung-Tse Chiang ^a, Jiann-Liang Chen ^a, Han-Chuan Hsieh ^b,

^a Department of Electrical Engineering, National Taiwan University of Science & Technology, Taipei, Taiwan
(Lchen@mail.ntust.edu.tw)

^b Southern Region Campus, Industrial Technology Research Institute, Hsinchu, Taiwan
(hchsieh@itri.org.tw)

Abstract— This study reviews the current practical use of the electronic strike zone in baseball, which typically features a fixed high-low strike zone. This system deviates from the baseball rules, which dictate that the strike zone should be adjusted according to the batter's shoulder, waist, and knee positions. Consequently, This study proposes a system based on commonly used baseball game camera perspectives. Using YOLO-Pose technology, it automatically detects players' body structures. It combines them with the baseball nine-grid positioning principle to promptly establish a strike zone that complies with baseball rules and player positions. The accuracy of this system, as measured by the Intersection over Union (IoU) metric, is 0.8541, representing a 14.29% improvement over the current electronic strike zone's IoU metric of 0.7473. Considering both viewers' perspective and sports analysis requirements, the system integrates an automated pitch trajectory detection system. It can overlay multiple pitch trajectories, allowing for a visual comparison of their differences. Combined with the strike zone detection system proposed in this study, it provides a more comprehensive view of the overlap between pitch trajectories and the strike zone. This study aims to enhance baseball officiating and analysis by introducing a more accurate and visually informative system for determining the strike zone and analyzing pitch trajectories.

Keywords— Pose estimation, Sports video, Ball Trajectory, Kalman Filter, Position measurement

I. INTRODUCTION

The digitization of sports data is an increasingly popular and vital trend in sports. It enhances athletic performance and provides deeper insights, contributing to the improvement of game quality and athletes' training levels. Data research in the realm of sports is highly regarded [1]. Ball trajectory analysis has gained prominence in sports like tennis and badminton through systems such as Hawk-eye [2]. In baseball, the analysis of pitching trajectories is a crucial research area. Existing systems like TrackMan [3], PITCHf/x [4], and StatCast [5] are widely recognized and extensively utilized.

Moreover, innovations in trajectory analysis systems continue to emerge, exemplified by the integration of pitching trajectories with the electronic strike zone, as seen in K Zone [6]. This integration provides a clear and comprehensible representation of the relationship between pitching trajectories and the strike zone. Such systems exhibit a high level of accuracy in tracking pitching trajectories. However, the

corresponding strike zone remains fixed, while an accurate strike zone should vary based on the height of the batter's shoulder, waist, and knees, as stipulated by baseball rules. According to these rules, the lower boundary of the strike zone corresponds to the height of the batter's knees, while the upper boundary aligns with the height of the batter's shoulders and the center of the waistband. In order to enhance the alignment of electronic strike zone data with baseball regulations, this study introduces a computational mechanism and framework as a solution. Considering the batter's physique, it automatically detects the strike zone from images captured from common game perspectives. It overlaps different pitch trajectories from the same pitcher and generates images that comprehensively depict the differences between each pitch and its alignment with the strike zone data.

II. RELATED WORK

The digitization of sports data through technology has become commonplace, and it can effectively enhance the fairness of sports, which is why Hawk-eye [2] has become standard equipment for significant tennis competitions. In baseball, errors are inevitable because the home plate umpire relies solely on the naked eye to judge balls and strikes [7]. Various factors on the field can also influence the umpire's strike zone [8]. In recent years, baseball has also been experimenting with and testing systems similar to Hawk-eye, such as the electronic strike zone, which is currently being tested in Minor League Baseball in the United States. It is based on the high-precision pitch tracking analysis of TrackMan [3] to determine whether the ball has entered the strike zone. However, the current electronic strike zone has a fixed height and does not conform to the actual rules of baseball.

In current research related to automated strike zone analysis, Chen, HT. et al.[9] proposed using image processing to outline the batter's silhouette to analyze the positions of the batter's shoulders, waist, and knees. This data is used to determine the strike zone. However, this system does not meet the current market requirements regarding stability, execution speed, and automation. Y. Kanno et al. [10] automated the detection of the batter's shoulder, waist, and knee joint positions using deep learning with OpenPose [11]. Their research focused on analyzing the movement of the catcher's glove

during the catching process. The strike zone detection requires significant preprocessing on the input images, such as manually selecting the batter's batting zone. However, several aspects of their research are worth considering, such as the automation of deep learning detection and the detection of the baseball to determine the timing of the batter's batting stance. This study builds upon these foundations to improve the automation and data accuracy of strike zone detection while expanding its applicability.

The strike zone aims to determine whether the pitch result is a strike or a ball. Therefore, electronic strike zones need to be complemented by pitch-tracking technologies to demonstrate their effectiveness effectively. In order to achieve a complete 3D reconstruction of the entire batting area, points that are obscured or cannot be precisely captured in some views are estimated using re-projection to determine their 2D pixel coordinates. In baseball pitch tracking research, Labayen et al. [12] used high-speed cameras to detect the difference between the baseball and the background images through image processing to track the baseball's trajectory. H. Lee et al. [13] used two cameras for calibration and placed pillars with grids on the field to precisely calculate the pitch trajectory based on the positional relationship between the baseball in the image and the pillars. Bor-Jiunn Wen et al. [14] used YOLOv3-Tiny to detect the baseball trajectory automatically and could calculate pitch speed and spin rate from a single-angle image. H. -S. Chen et al. [15] detected the baseball trajectory based on brightness, size, and appearance in the image, and automatically extracted pitching and hitting video clips from game footage based on trajectory features, making pitch analysis more accessible. Combining pitch trajectories with electronic strike zones can visualize sports data and has significant potential for both commercial and research applications [16][17][18]. It can also enhance the viewer experience in 3D replays on the field [19] [20]. However, more data does not necessarily mean better viewer experience, as simplicity and clarity are often more appealing to the general audience [21]. Therefore, in this study, deep learning techniques are used to automatically detect pitch trajectories and overlay multiple pitch trajectories with the electronic strike zone to provide a clear and intuitive representation of the differences between pitch trajectories and the relationship with the strike zone.

III. STRIKE ZONE DETECTION

This study employs YOLO-Pose [22] technology for detecting human body poses in images. By identifying critical skeletal points in the human body, it aims to determine the batter's strike zone. As Figure 1 of the game footage shows, recognizing the human body poses skeletal points for the pitcher, batter, catcher, and umpire. In the game footage, since the pitcher's posture faces away from the camera, the skeletal point corresponding to the nose can be used to exclude the pitcher. Considering that the batter typically occupies the outermost region among the batter, catcher, and umpire, this study utilizes the distances between skeletal points to determine those at the outermost periphery.



Figure 1. Illustration of Actual Game Footage

By comparing the heights of the detected outermost individuals' nose or ear coordinates, it is possible to identify whether a skeletal point belongs to the batter using the highest coordinate point. Determining the batter's strike zone relies on the positions of the batter's shoulders, the upper edge of their pants, and their knee. Therefore, identifying the timing to assess the strike zone is crucial. In this study, we divide the process after the pitcher releases the baseball into two key moments, namely, the Release Frame and the Prepare Frame, as illustrated in Figure 2. The Release Frame is when the pitcher is about to release or has just released the baseball. The batter has already started preparing for the hitting motion and has assumed the corresponding hitting stance. We use YOLOv7 [23] to detect the initial frame of the pitched baseball to determine the exact timing of the Release Frame. The Prepare Frame is defined as the frame within the 20 frames preceding the Release Frame, where the batter's knee position is the lowest. This moment represents the batter in a standing position and provides more accurate information about the positions of the batter's shoulders, the upper edge of their pants, and their knees.

Once the Prepare Frame is detected, the upper limit of the strike zone is defined as the midpoint between the shoulder and hip skeletal points detected in the Prepare Frame. In contrast, the lower limit is the lower edge of the knee skeletal point. The width of the strike zone is determined manually by marking the width of the home plate, as shown in Figure 3. This strike zone, customized based on the batter's height, provides a more accurate basis for determining a good pitch.



(a) Prepare Frame



(b) Release Frame

Figure 2. Illustration Frames

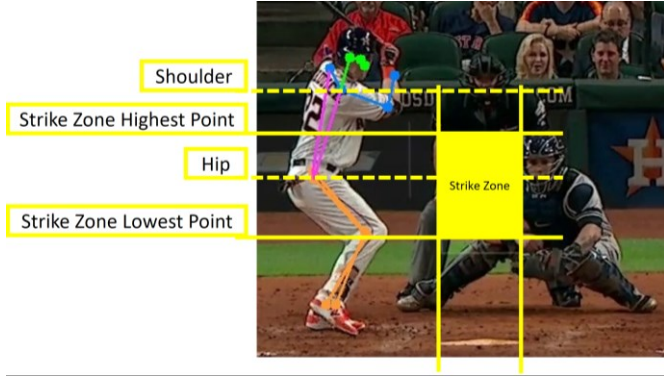


Figure 3. Strike Zone Diagram Based on Height

IV. BASEBALL PITCH OVERLAY

This study combines YOLOv7 and the Kalman filter (KF) to enhance the accuracy of flight trajectory prediction. The Kalman filter is a recursive algorithm applicable to linear systems, effectively addressing Gaussian noise issues induced by image processing. The system can also integrate multiple flight trajectories with the results of human body pose recognition and display them in the image. This provides coaches and pitchers with a better visual experience of flight trajectories.

The operation of the Kalman filter involves estimating the system's state by combining the system model and observed data. It consists of two main stages: prediction and update. In the prediction stage, the current state is predicted based on the previous moment's state as a reference. The predicted state is corrected in the update stage based on the current observed values. Through this recursive process, the accuracy of the estimation continuously improves. The critical assumptions of the Kalman filter are that both the system state and observations follow Gaussian distributions and have a linear relationship. Its advantages include efficient computation and precise estimation.

The state variable $\mathbf{x}_k$ and observation variable $\mathbf{z}_k$ refer to the variable settings in [24], which are used to represent the characteristics of the system state and observations. The forms of the state variable $\mathbf{x}_k$ and observation variable $\mathbf{z}_k$ are as follows:

$$\mathbf{x}_k = [u, v, s, r, \dot{u}, \dot{v}, \dot{s}]^T \quad (1)$$

$$\mathbf{z}_k = [u, v, s, r]^T \quad (2)$$

The variable k in the state variables represents different stages of the system. At the same time, u and v denote the ball's pixel positions in the horizontal and vertical directions. s signifies the area of the ball, and r represents the aspect ratio of the ball. Furthermore, $\dot{u}$, $\dot{v}$ and $\dot{s}$ correspondingly denote their velocities.

In the Kalman filter prediction stage, we assume that the state at time step k can be derived from the state at time step $k-1$. For the constant velocity motion of the baseball considered in this study, we can express the state equation as follows:

$$\mathbf{x}_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}_{k-1} \quad (3)$$

The purpose of the observation equation is to describe the relationship between the state variable $\mathbf{x}_k$ and the observation variable $\mathbf{z}_k$. Its mathematical form is as follows:

$$\mathbf{z}_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \mathbf{x}_k \quad (4)$$

The state variable $\mathbf{x}_k$ and observation variable $\mathbf{z}_k$ can be represented by the following two sets of equations:

$$\mathbf{x}_k = F_k \mathbf{x}_{k-1} + B_k \mathbf{u}_k + \mathbf{w}_k \quad (5)$$

$$\mathbf{z}_k = H_k \mathbf{x}_k + \mathbf{v}_k \quad (6)$$

F_k represents the state-transition matrix used to calculate the predicted state from past estimations. B_k is the control input model, and vector $\mathbf{u}_k$ denotes the controller input. $\mathbf{w}_k$ represents process noise. H_k is the observation matrix used to compute the predicted measurement based on the predicted state. $\mathbf{v}_k$ represents measurement noise.

The prediction stage and update stage can be expressed through the following seven equations:

$$\mathbf{x}_{k|k-1} = F_k \mathbf{x}_{k-1} + B_k \mathbf{u}_k \quad (7)$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \quad (8)$$

$$\mathbf{y}_k = \mathbf{z}_k - H_k \mathbf{x}_{k|k-1} \quad (9)$$

$$S_k = H_k P_{k|k-1} H_k^T + R_k \quad (10)$$

$$K_k = P_{k|k-1} H_k^T S_k^{-1} \quad (11)$$

$$\mathbf{x}_{k|k} = \mathbf{x}_{k|k-1} + K_k \mathbf{y}_k \quad (12)$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \quad (13)$$

Equations (7) and (8) represent the prediction stage, where P_k stands for the posterior estimation covariance matrix, and Q_k denotes the process noise covariance. The equations for the update stage are (9), (10), (11), (12), and (13), with R_k representing the observation noise covariance, $\mathbf{y}_k$ representing the innovation or measurement pre-fit residual, S_k representing the innovation covariance, and K_k representing the optimal Kalman gain.

V. EXPERIMENT

The dataset utilized in this study is MLB-YouTube[25], which comprises 20 baseball game videos from the 2017 MLB postseason. These videos have a frame rate of 30 frames per second and a resolution of 1280 pixels by 720 pixels. The dataset is divided into two primary sections: activity recognition with segmented videos and activity classification with continuous videos. For this study, we selected the segmented videos used for activity recognition, from which segments containing successful pitches and batters performing hitting actions were extracted, as detailed in Table 1.

In our experiments, we employed YOLOv7[23] technology to identify the positions of Prepare frames, Release frames, and the baseball in the videos. Additionally, we utilized YOLO-Pose[22] as a human pose recognition technique to draw the strike zone based on the batter's height and to depict multiple trajectories of pitched baseballs. These visual elements were embedded into the videos, providing a visualization tool for coaches and pitchers to examine the relationships between pitch types and strike zones.

TABLE 1. EXPERIMENTAL DATASET

	Videos	Frame Numbers
MLB-YouTube[25]	101	14371

This study employed Intersection over Union (IoU) as a metric to measure the accuracy of human pose-based strike zone representation. IoU is a commonly used indicator for evaluating object detection accuracy and is widely employed in deep learning tasks, particularly in object detection. Its calculation involves two parameters: the first is the ground truth target range manually annotated in the dataset, and the second is the target range derived from the algorithm used in the experiment. IoU is computed by measuring the overlap between these target ranges and their union, then dividing it by the union to obtain the IoU value. The established ground truth by manually drawing the strike zone in the Prepare frame. Subsequently, this manually drawn strike zone was compared with the strike zone computed using the human pose recognition technique to calculate the IoU. This metric reflects the correlation between the ground truth and predictions.

Traditional electronic strike zones in televised baseball broadcasts are based on images captured by two high-speed cameras, which are used to calculate 3D coordinate space through triangulation techniques. This 3D strike zone is then displayed in the broadcast. The electronic strike zone technology currently uses a fixed-size strike zone without considering the batter's height factor. This study measured the accuracy of the strike zone drawn based on human pose recognition and tested the accuracy of the electronic strike zone. The testing methodology is the same as that used for drawing the strike zone based on human pose recognition, and the accuracy of the strike zone is shown in Table 2. The human pose recognition strike zone method proposed in this study demonstrated a 14.29% improvement in accuracy compared to the electronic strike zone. The comparison between the strike

zones drawn based on human pose recognition, electronic strike zones, and the ground truth is depicted in Figure 4.

TABLE 2. ACCURACY OF THE STRIKE ZONE

	IoU
YOLO-Pose Strike Zone	0.8541
Electronic Strike Zone	0.7473

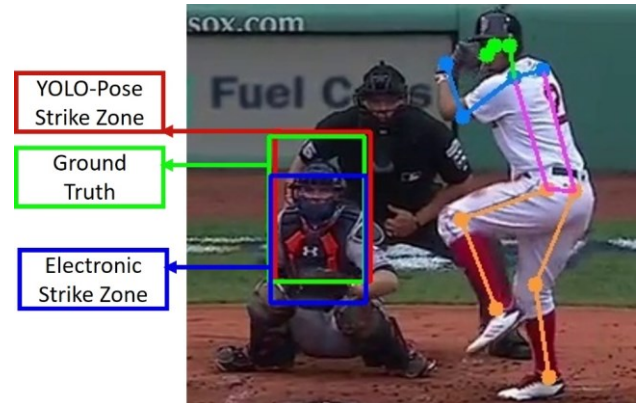


Figure 4. Illustrating the Assessment Range of the Strike Zone

This study goes beyond merely drawing a strike zone based on the batter's height; it also processes the trajectories of pitched baseballs, enhancing their accuracy using the Kalman filter. It allows us to precisely overlay the trajectories of baseballs pitched by the same pitcher against different batters in the same game and combine them with the respective batter's strike zone. It provides pitchers and coaches with a more accessible means of analyzing the different pitch types that pitchers deliver to different batters in the opposing team and how variations in batter height affect the effectiveness of the strike zone. It enables pitchers and coaches to adjust pitch types and strategies based on the characteristics of different batters. Such fine-grained analysis is expected to assist teams in making more strategic decisions, enhancing their competitiveness. The outcomes of this study are depicted in Figure 5.



Figure 5. Illustrating Overlapping Baseball Trajectories and Strike Zone

VI. CONCLUSIONS

In this study, a review of current electronic strike zone systems and strike zone detection research was conducted. A novel strike zone detection system, YOLO-Pose Strike Zone, was proposed to address the issue of electronic strike zones not conforming to baseball rules in practical applications. The YOLO-Pose Strike Zone achieved an IoU (Intersection over Union) score of 0.8541, a 14.29% improvement in accuracy compared to the current electronic strike zone system with an IoU score of 0.7473. Furthermore, it enhances detection efficiency through automation. In terms of visualizing pitch trajectories, this study considered both the viewer experience and practicality. Overlapping pitch trajectories provides an intuitive way to visualize differences between pitch trajectories and their relationship with the strike zone. This system offers a practical and feasible approach for electronic strike zone-related systems, ensuring that strike zone values align more closely with baseball rules. Additionally, it has the potential for future use in data visualization methods such as 3D replay systems on the field, ultimately enhancing the viewer experience and increasing the precision of baseball data analysis. In the future, we can integrate the data from this system with 3D modelling technology to accurately recreate the pitching trajectory. Coupled with a 3D strike zone model, this will allow us to visualize the fine details of the pitching trajectory with greater precision.

REFERENCES

- [1] G. Thomas, R. Gade, T.B. Moeslund, P. Carr and A. Hilton, "Computer vision for sports: current applications and research topics", *Comput. Vis. Image Underst.*, vol. 159, pp. 3-18, June 2017.
- [2] N. Owens, C. Harris and C. Stennett, "Hawk-eye tennis system," *Proceedings of the International Conference on Visual Information Engineering VIE 2003*, pp. 182-185, Guildford, UK, 2003.
- [3] J.J. Martin, "Evaluation of doppler radar ball tracking and its experimental uses," 2012.
- [4] M. Fast, "What the heck is PITCH f/x?" *The Hardball Times Baseball Annual*, pp. 153-158, 2010.
- [5] M. Lage, J. P. Ono, D. Cervone, J. Chiang, C. Dietrich and C. T. Silva, "StatCast Dashboard: Exploration of Spatiotemporal Baseball Data," *Proceedings of the IEEE Computer Graphics and Applications*, Vol. 36, No. 5, pp. 28-37, Sept.-Oct. 2016.
- [6] A. Gueziec, "Tracking pitches for broadcast television," in *Computer*, vol. 35, no. 3, pp. 38-43, March 2002.
- [7] Dale L. Zimmerman, Jun Tang, Rui Huang, "Outline analyses of the called strike zone in Major League Baseball," *Ann. Appl. Stat.* pp. 2416 - 2451, December 2019.
- [8] Jyhhow Huang & Hwai-Jung Hsu "Approximating strike zone size and shape for baseball umpires under different conditions," *International Journal of Performance Analysis in Sport*, pp. 133-149, 2020.
- [9] Chen, HT., Tsai, WJ. & Lee, SY. "Contour-based strike zone shaping and visualization in broadcast baseball video: providing reference for pitch location positioning and strike/ball judgment," *Multimed Tools Appl*, pp. 239-255, 2010
- [10] Y. Kanno, H. Shishido, M. Shinya, Y. Kameda and I. Kitahara, "Detection of Mitt Movement Trajectory in Catcher Framing Using Baseball Video," 2022 IEEE 11th Global Conference on Consumer Electronics (GCCE), pp. 139-143, Osaka, Japan, 2022.
- [11] Z. Cao, G. Hidalgo, T. Simon, S. E. Wei and Y. Sheikh, "OpenPose: Realtime Multi-Person 2D Pose Estimation Using Part Affinity Fields," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 43, no. 1, pp. 172-186, 2021.
- [12] Labayen, M., Olaizola, I.G., Aginako, N. et al. "Accurate ball trajectory tracking and 3D visualization for computer-assisted sports broadcast," *Multimed Tools Appl*, pp. 1819-1842, 2014.
- [13] H. Lee, J. Kim, J. Kim and W. -Y. Kim, "A Method of Measuring Baseball Position at the Strike Zone," 2020 International Conference on Electronics, Information, and Communication (ICEIC), Barcelona, Spain, pp. 1-3, 2020.
- [14] Bor-Jiunn Wen, Che-Rui Chang, Chun-Wei Lan, and Yi-Chen Zheng, "Magnus-Forces Analysis of Pitched-Baseball Trajectories Using YOLOv3-Tiny Deep Learning Algorithm," *Applied Sciences* 12, no. 11: 5540, 2022.
- [15] H. -S. Chen, H. -T. Chen, W. -J. Tsai, S. -Y. Lee and J. -Y. Yu, "Pitch-by-Pitch Extraction from Single View Baseball Video Sequences," 2007 IEEE International Conference on Multimedia and Expo, pp. 1423-1426, Beijing, China, 2007.
- [16] Du, M., Yuan, X. "A survey of competitive sports data visualization and visual analysis," *J Vis*, pp. 47-67, 2021.
- [17] V. Bhatt, U. Aggarwal and C. N. S. V. Kumar, "Sports Data Visualization and Betting," 2022 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), Bangalore, India, pp. 1-6, 2022.
- [18] Huang, J.-H., & Hsu, Y.-C. "A Multidisciplinary Perspective on Publicly Available Sports Data in the Era of Big Data: A Scoping Review of the Literature on Major League Baseball," *SAGE Open*, 2021.
- [19] C. Dietrich, D. Koop, H. T. Vo and C. T. Silva, "Baseball4D: A tool for baseball game reconstruction & visualization," 2014 IEEE Conference on Visual Analytics Science and Technology (VAST), Paris, France, pp. 23-32, 2014.
- [20] M. Lage, J. P. Ono, D. Cervone, J. Chiang, C. Dietrich and C. T. Silva, "StatCast Dashboard: Exploration of Spatiotemporal Baseball Data," in *IEEE Computer Graphics and Applications*, vol. 36, no. 5, pp. 28-37, Sept.-Oct. 2016.
- [21] Zheng, Meng-Cong, and Chih-Yung Chen, "Types of Major League Baseball Broadcast Information and Their Impacts on Audience Experience," *Informatics* 9, no. 4: 82, 2022.
- [22] D. Maji, S. Nagori, M. Mathew and D. Poddar, "YOLO-Pose: Enhancing YOLO for Multi Person Pose Estimation Using Object Keypoint Similarity Loss," *Proceedings of the 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pp. 2636-2645, New Orleans, LA, USA, 2022.
- [23] C. Y. Wang, A. Bochkovskiy and H. Y. Mark Liao. "YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 7464-7475, 2023.
- [24] A. Bewley, Z. Ge, L. Ott, F. Ramos and B. Upcroft, "Simple online and realtime tracking," *Proceedings of the 2016 IEEE International Conference on Image Processing (ICIP)*, pp. 3464-3468, Phoenix, AZ, USA, 2016.
- [25] A. Piergiovanni and M. S. Ryoo, "Fine-Grained Activity Recognition in Baseball Videos," *Proceedings of the 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pp. 1821-18218, Salt Lake City, UT, USA, 2018.



Bor-Yao Tseng was born in Taiwan, in 1999. He received the B.S. degree from Fu Jen Catholic University (FJCU), in 2022. He is currently pursuing the M.S. degree in electrical engineering with the National Taiwan University of Science and Technology (NTUST), Taipei. His main research interests include Artificial Intelligence, Internet of Things (IoT), Sports data analysis, Image Stitching, and Cybersecurity.



Hung-Tse Chiang was born in Taiwan, in 2000. He received the B.S. degree from National Taiwan University of Science and Technology (NTUST), in 2022. He is currently pursuing the M.S. degree in electrical engineering with the National Taiwan University of Science and Technology (NTUST), Taipei. His main research interests include Artificial Intelligence, Internet of Things (IoT), Sports data analysis, Image Stitching, and Cybersecurity.



Jiann-Liang Chen Prof. Chen was born in Taiwan on December 15, 1963. He received the Ph.D. degree in Electrical Engineering from National Taiwan University, Taipei, Taiwan in 1989. Since August 1997, he has been with the Department of Computer Science and Information Engineering of National Dong Hwa University, where he is a professor and Vice Dean of Science and Engineering College. Prof. Chen joins the Department of Electrical Engineering, National Taiwan University of Science and Technology, as a Distinguished professor and Dean now. His current research interests are directed at cellular mobility management, cybersecurity, personal communication systems and Internet of Things (IoT).



Han-Chuan Hsieh received the BSEE degree from National Taipei University of Technology (NTUT) in 1998, and the MS degree in Communication Engineering from Tatung University (TTU), Taipei, Taiwan, in 2008. He received his PhD in EE from National Taiwan University of Science and Technology (NTUST) in 2018. He joined ICL, ITRI in 2012, working on experimental research that mainly covers 4G Networks. He has recently devoted himself to the integration of 5G networks, Computer Vision and IoT applications.